Patterns of Cropland Management Systems for Assessment of Global Change

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von
Vera Porwollik, M.Sc.

Kommissarischer Präsident der Humboldt-Universität zu Berlin
Prof. Dr. Peter Frensch

Dekan der Lebenswissenschaftlichen Fakultät der
Humboldt-Universität zu Berlin
Prof. Dr. Dr. Christian Ulrichs

Gutachter:

1. Prof. Dr. H. Lotze-Campen
2. Prof. Dr. S. Siebert

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Zusammenfassung

Die Landwirtschaft liefert einen Großteil der Nahrungsmittel und Rohstoffe für den menschlichen Verbrauch. Der Sektor wird zum einen durch die prognostizierte steigende Nachfrage aufgrund globaler Dynamiken des Bevölkerungswachstums, Änderungen der Ernährungszusammensetzung, aber auch durch Auswirkungen des Klimawandels herausgefordert. Gleichzeitig hat die intensive landwirtschaftliche Produktion oft erhebliche Auswirkungen auf die Leistungen und Funktionen von Ökosystemen. Agrarökosystemmodelle können verwendet werden, um Auswirkungen der Landwirtschaft über verschiedene zeitliche und räumliche Skalen hinweg zu quantifizieren. Globale Bewertungen werden jedoch, durch die begrenzte Verfügbarkeit von Daten einzelner agronomischer Maßnahmen und dem limitierten Wissen über die damit verbundenen biophysikalischen und biogeochemischen Prozesse, erschwert.

Ziel dieser Doktorarbeit ist es, das Verständnis über Anforderungen an Daten von landwirtschaftlichen Produktionssystemen und über Methoden ihrer Anwendung in globalen Modellierungsstudien zu erweitern. Darüber hinaus zielt die Arbeit darauf ab, die räumliche Ausdehnung, Verteilung, Umweltwirkung und Potenziale von unterschiedlichen Bewirtschaftungsmethoden auf globalem Ackerland abzuschätzen.

In der ersten Studie wird untersucht, inwiefern die Anwendung unterschiedlicher Datenprodukte für die Aggregation von grid-basiert simulierten Ernteerträgen, zu Durchschnittserträgen auf nationale und globale Skalen, zu Unsicherheiten in den Ergebnissen von Modellstudien führen kann. Die Unsicherheit ergibt sich demnach, aus den Unterschieden in der angegebenen Menge und räumlichen Verteilung der Ernteflächen zwischen den vier angewendeten Datensätzen, und in der räumlichen Heterogenität der Ertragsmuster, die von den 14 Modellen generiert wurden. Die Aggregationsunsicherheit beträgt ~ 10 % der Unterschiede in durchschnittlichen Ernteerträgen auf globaler Ebene, kann jedoch für einzelne Länder und Fruchtarten erheblich höher sein.

Die zweite Studie präsentiert eine Klassifikation von weltweit sechs relevanten Bodenbearbeitungssystemen, deren ermittelten Merkmale zur Parametrisierung in globalen Agrarökosystemmodellen verwendet werden können. Ökologische und sozioökonomische Daten werden als räumliche Proxy-Indikatorvariablen verwendet, um die grid-basierte Kartierung der Bodenbearbeitungssysteme auf globalem Ackerland zu leiten. Dazu wurde eine Mischung aus regel- und wahrscheinlichkeitsbasierten Ansätzen verwendet. Die Studie zeigt, dass jährlich ein Großteil der weltweiten Ackerfläche intensiver Bodenbearbeitung unterliegt. Es wird auch gezeigt, dass die pfluglose Bodenbearbeitung von einem Anteil von ~10 % an der globalen Ackerfläche um das Jahr 2005, potenziell auf mehr als 40 % ausgeweitet werden könnte. Der generierte Open-Access-Datensatz ermöglicht die räumlich variierende Darstellung und Bewertung von Bodenbearbeitungssystemen für 42 Fruchtarten auf der globalen Ackerfläche.

In der dritten Studie werden die Auswirkungen unterschiedlicher Bewirtschaftungsmethoden auf die Kohlenstoff-, Stickstoff- und Wasserdynamiken auf globalem Ackerland mit Hilfe des prozessbasierten Modells LPJml5.0-tillage-cc abgeschätzt. Im Vergleich zur Referenzsimulation mit vegetationsfrei gehaltener Brache, zeigen die Simulationen mit Zwischenfruchtanbau einen erhöhten Kohlenstoffgehalt des Bodens und eine Reduzierung der Stickstoffauswaschungsrate von mindestens 50 % auf dem Großteil der globalen Ackerfläche für den 50-jährigen Simulationszeitraum auf. Die global aggregierten Durchschnittserträge von Weizen, Mais und am meisten die von Reis, sind mit Zwischenfruchtanbau verringert, mit Ausnahme einer erhöhten Sojabohnenproduktivität, im Vergleich zur Simulation mit Schwarzbrache. Weiterhin wird gezeigt, dass Ertragseinbußen bei der nachfolgenden

Hauptfrucht, die durch den Anbau von Zwischenfrüchten entstehen können, weitgehend durch Bewässerung, pflugloser Bodenbearbeitung und Mulchen auf Grund wassersparender Effekte, abgemindert werden können. Darüber hinaus liefert die Studie eine Abschätzung der bio-physikalischen und bio-geochemischen Umweltwirkungen von Zwischenfruchtanbau kombiniert mit pflugloser Bodenbearbeitung auf der generierten jährlich dynamischen globalen Ackerlandfläche mit ‚Conservation Agriculture' für den historischen Zeitraum 1974-2010.

Die Ergebnisse dieser Dissertation zeigen, dass die zeitlichen und räumlichen Muster von Bewirtschaftungsmethoden und deren Effekte auf Kohlenstoff- Stickstoff- und Wasserdynamiken, auf globaler Ackerlandfläche stark variieren. Es wird auch gezeigt, dass eine erhöhte Vielfalt umweltbedingter und sozioökonomischer Bedingungen der landwirtschaftlichen Produktion in globalen Modelstudien berücksichtigt werden kann. Die jeweiligen Bewirtschaftungsmethoden bestimmen erheblich die Agrarumweltleistung eines landwirtschaftlichen Produktionssystems, indem sie entweder als Quelle von Verschmutzung und Degradation oder als Kohlenstoffsenke wirken können. Alternative Bewirtschaftungsmethoden können dazu verwendet werden, durch Techniken zur erhöhten Kohlenstoffbindung im Ackerboden, die gleichzeitig die Bodeneigenschaften und -fruchtbarkeit verbessern, die Auswirkungen der landwirtschaftlichen Produktion abzuschwächen und Treibhausgasemissionen zu kompensieren. Eine Vielzahl von Datenprodukten und Modellimplementierungen zur Prozessdarstellung von ackerbaulichen Maßnahmen stellt einen Teil des Unsicherheitsbereichs von Wirkungsergebnissen dar. Dennoch kann gefolgert werden, dass diese Vielfalt auch als Lernquelle in zukünftigen Modellvergleichsstudien betrachtet werden kann, um die Bewertungen des globalen Wandels zu unterstützen.

Abstract

Agricultural production provides food, feed, fiber, and fuel, and is challenged by projected increasing demand due to dynamics of population growth, changes in dietary compositions, and climate change impacts. At the same time, intensive agricultural production practices have various environmental externalities, which negatively affect ecosystems' services and functions.

Agroecosystem models can be used to quantify impacts of cropland use across various temporal and spatial scales, but global assessments are hampered by the limited availability of land management data and of knowledge regarding associated biophysical and biogeochemical processes and functions.

The objective of the thesis is to increase the understanding of agricultural management data requirements and implications for their usages in global modeling studies. Further, the thesis aims to identify types, spatial distribution, as well as to estimate impacts, and potentials of cropland management practices to support sustainable development.

In the first study, it was assessed in which way the application of different harvested crop area datasets for the aggregation of modeled crop yield outputs from the grid cell to country and global scale, induces uncertainty to the results. The aggregation uncertainty is found due to differences in magnitude and spatial distribution of harvested area between the applied datasets in conjunction with the spatial heterogeneity of yield pattern obtained by each of the included global gridded crop models. The aggregation uncertainty accounts for about 10 % of differences in derived average crop productivity at the global scale but can be substantial for individual crop types and countries.

The second study presents a global classification of soil management systems and the derived characteristics can be used for parameterization over a range of intensity levels in global modeling studies. Environmental and socio-economic data are used as spatial proxy indicators variables to guide the mapping of the tillage types to global cropland, employing a mix of rule- and probability-based approaches. It is found that annually, the majority of global cropland is tilled intensively. Further, it is found that no-tillage could be extended from a share of 10 % on global physical cropland reported in the year 2005 to a share of more than 40 % of the area estimated as suitable for the practice. The generated crop-type specific tillage system dataset facilitates the assessment of six different tillage systems on global cropland for 42 crop types.

In the third study different cropland management practices were assessed using LPJml5.0-tillage-cc, with a modified code for the representation of cover crops growing as grass on cropland between two consecutive main crop growing seasons. In comparison to bare soil fallowing, cover crop practices exhibit enhanced soil carbon contents and reduced nitrogen leaching rates by at least 50 % on the majority of global cropland during the 50 year simulation period. With cover crop and tillage practices global aggregated average yields of wheat, maize, and mostly of rice are lowered, whereas the crop productivity of soybean mostly is found higher. The declines in cereal crop productivity with cover cropping, are found largely countered if combined with irrigation, no-tillage, and mulching practices due to beneficial soil water effects. Further, the study provides an estimate of impacts of cover crops combined with no-tillage on mapped annual dynamic Conservation Agriculture cropland for the historical period 1974-2010.

The findings of this thesis demonstrate that the pattern of cropland management systems are heterogeneous due to the spatial and temporal differences of environmental and socio-economic farming conditions. It is demonstrated that a higher variability of cropland management can be accounted for in datasets and models for global change assessments. Crop management practices determine considerably the agri-environmental performance of a farming system, either acting as a source of pollution and degradation or as a carbon sink and mitigating production impacts. A diversity of global cropland management data products and model implementations of associated process representation, constitute parts of the uncertainty range of assessment results. Since validation efforts are hampered at the global scale, it can serve as a source of learning to improve estimations of anthropogenic impact on global carbon, nitrogen, and water dynamics.

Schlagwörter

Ackerland, Bewirtschaftungsmethoden, Folgenabschätzung, Agrarökosystemmodell, Unsicherheiten, pflügen, Zwischenfrüchte, Conservation Agriculture

Keywords

Cropland, land management practices, impact assessment, agroecosystem modeling, uncertainty, tillage, cover crops, Conservation Agriculture

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List of Abbreviations

ACCMIP	Atmospheric Chemistry and Climate Model Intercomparison Project
AgMERRA	Agricultural Modern-Era Retrospective Analysis for Research and Applications
AgMIP	Agricultural Model Intercomparison Project
APSIM	Agricultural Production Systems Simulator
C	Carbon
CA	Conservation Agriculture
CBD	Convention on Biological Diversity
CESM	Community Earth System Model
CFT	Crop Functional Type
CLM	Community Land Model
CO_2 eq.	Carbon dioxide equivalent emissions; assuming the molecular weight of carbon dioxide to carbon ratio as 44 to 12
CSM	Cropping System Model
CTIC	Conservation Technology Information Center
DGVM	Dynamic Global Vegetation Model
DM	Dry matter
DSSAT	Decision Support System for Agrotechnology Transfer
EPIC	Environmental Policy Integrated Model or Erosion Productivity Impact Calculator
ESM	Earth System Model
FACE	Free Air Carbon Dioxide Enrichment
FAO	Food and Agriculture Organization of the United Nations
GADM	Database of Global Administrative Areas
GAEZ	Global Agro-Ecological Zones
GCM	General Circulation Model
GGCM	Global Gridded Crop Model
GGCMI	Global Gridded Crop Model Intercomparison
GHG	Greenhouse Gas
GLADIS	Global Land Degradation Information System
GLC	Global Land Cover
GLOBIOM	Global Biosphere Management Model
GNI	Gross National Income
HI	Harvest Index
HYDE	History Database of the Global Environment
IFPRI	International Food Policy Research Institute
IIASA	International Institute for Applied Systems Analysis
IMPACT	International Model for Policy Analysis of Agricultural Commodities and Trade
IPCC	Intergovernmental Panel on Climate Change
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project
LAI	Leaf Area Index

LPJ-GUESS	Lund-Potsdam-Jena General Ecosystem Simulator
LPJmL	Lund-Potsdam-Jena managed Land
LUH	Land-use Harmonization
M3	harvested area and yields of 175 crops by Monfreda et al. (2008)
MADRaT	May All Data be Reproducible and Transparent
MAgPIE	Model of Agricultural Production and its Impact on the Environment
MIRCA	Monthly Irrigated and Rainfed Crop Area
N	Nitrogen
NOAA	National Oceanic and Atmospheric Administration
PFT	Plant Functional Type
RCP	Representative Concentration Pathway
SDGs	Sustainable Development Goals
SI	Sustainable Intensification
SPAM	Spatial Production Allocation Model
SSP	Socio-economic Scenario Pathway
UNEP	United Nation Environmental Program (UNEP)

1 Introduction

1.1 Global change effects on agriculture

Agriculture is the main source of food, fiber, fodder, and fuel provision with considerable demands for natural resources. Arable land production comprise market-oriented, subsistence production systems, or mixes of both depending e.g., on the size of the land holding, financial assets, and technology available (Herrero et al., 2017; Lowder et al., 2016; Samberg et al., 2016). The global demand for agricultural products is projected to increase due to human population growth dynamics, urbanization trends, as well as switching of diets to more processed food and richer in calories (Alexandratos and Bruinsma, 2012; Godfray et al., 2010; Tilman, 2001). Food security is defined by availability, access to, and of sufficient nutritional value (FAO, 2003). Food security is shaped by the natural production basis of a crop production system but also by culture, traditions, regulations, laws, trade dynamics, and political agreements and as a result can be influenced by price shocks, social unrest, or as currently by global health insecurities (pandemics), which can distort established supply and distribution systems (Laborde et al., 2020a).

Agriculture is projected to be affected by dynamics of climate change, such as increased frequencies and intensities of extreme weather events as floods, storms, and droughts, leading to yield instability and crop failures resulting in lower crop production (Lesk et al., 2016). Projected climate change impacts on agriculture production are associated to increasing CO_2 concentrations in the atmosphere, elevated temperatures, and changing precipitation patterns in terms of intensity, amount, duration, frequency, timing, and location (Sillmann et al., 2013).

Positive responses for grain crops yield to elevated CO_2 concentration levels in flux tower crop trials', due to the 'fertilization effect' are found by Kimball (2016) and Toreti et al. (2020). Nevertheless, increased biomass production in response to elevated CO_2 concentration and temperature maybe associated with a reduction in nutritious values of the food produced per mass unit, as thinning of contents (Müller et al., 2014), which in turn may constitute another relevant concern to future food security. Higher temperature enhance the productivity of plants only to certain levels if water and nutrients are not limiting growth processes. When crop type or cultivar specific physiological temperature optima are exceeded, plant response processes lead to yield declines, e.g. through shortening of the phenological grain-filling period of crops (Challinor et al., 2015; Minoli et al., 2019b), or through direct damage from increased heat stress (Teixeira et al., 2013). Atmospheric evaporative water demand is expected to increase under rising air temperature (Donohue et al., 2010), so that cropping systems in already water limited environments are expected to experience increased water stress when soil water is depleted additionally to higher water demands assumed for CO_2-fertilized crop growth (Wullschleger et al., 2002). The local setting of temperature, water availability, and crop management conditions also drive the decomposition rates of soil organic carbon (Friend et al., 2014), reducing cropland soil fertility and therefore being highly relevant for the yield declining effects expected under climate change. Challinor et al. (2015) find impacts of climate change on crop productivity well discussed but results on future cropping intensity and harvested area pattern less understood. Due to expected continuing global temperature increase, cropping systems at higher latitudes in the northern hemisphere may see extended growing periods with earlier starting and ending later also enabling new crop types to be cultivated there (Peltonen-Sainio et al., 2009). The prolongation of favorable growing conditions for crops may lead to increased cropping intensity, i.e. the cultivation of an additional crop per year on the same field (Zhang et al., 2013). Productivity impacts are found distributed spatially variable, affecting certain crop types typically grown and regions more than others, such as in South Asia and Southern Africa, (Lobell et al., 2008b).

1.2 Impacts of agriculture on the environment

Agriculture accounted for 18-29 % of total annual anthropogenic greenhouse gas emissions, including carbon, methane, as well as nitrous oxide from arable production and livestock rearing activities, combined with land use change for food provision during the years 2007-2016 (Rosenzweig et al., 2020). Methane is emitted from livestock, i.e. released after digestion due to enteric fermentation (Herrero et al., 2011) but also from paddy rice fields often managed under flooded soil conditions (Linquist et al., 2012; Sass et al., 1992). Rice is one of the most important staple food crop and its cultivation practices affect large shares of global cropland (Carlson et al., 2017). Nitrous oxide emissions mostly originate from organic (Davidson, 2009) and mineral fertilization (Gerber et al., 2016).

Area for arable production and livestock rearing activities currently covers about 38 % of the global land surface, of which about a third is estimated as cropland (FAOSTAT, 2021). Up to the first half of the 20th century agriculture production volume increases were mainly a function of area expansion through conversion of natural ecosystems to cropland, pastures, and rangeland (Ellis et al., 2010; Hurtt et al., 2006; Ramankutty and Foley, 1999). Emissions from land use and land cover change for agricultural production are estimated as 9 % CO_2 eq. yr^{-1} (FAO, 2020) and are related to land clearing and cultivation techniques, such as deforestation, drainage, burning, and mowing (Friedlingstein et al., 2020; Houghton et al., 2012; Pugh et al., 2015; Rosenzweig et al., 2020).

Croplands' net primary production (NPP) is quantified to be in the range of a natural Savanna ecosystem (Krausmann et al., 2013). However, Carvalhais et al. (2014) show that vegetation carbon stock on cropland is in the range of a boreal forest biome. Human-induced decline in biomass productivity have been observed on 25 % of global cropland for the historic period until year 2005 (Le et al., 2016). A large fraction of the vegetative biomass produced on cropland is usually exported from the fields as harvest of grains and residues, lowering the organic inputs to the soil resulting in declined soil organic carbon content (Drewniak et al., 2015; Mills and Fey, 2003). Historically, the usage of cropland products for human consumption, livestock fodder, and energy production, grew in correlation to global population growth, whereas with the current increasing reliance on bioenergy provision (Krausmann et al., 2013) with conventional land management practices this trend may cause further soil nutrient mining. Cropland entails relatively lower soil organic carbon (Ren et al., 2020) than the ecosystems they replace and Stockmann et al. (2013) find it generally lower than under natural forest or grasslands. Carvalhais et al. (2014) find that cropland soil has about a third of total global mean soil carbon density. Also traditional cropland cultivation techniques such as drainage and tillage were modifying soil carbon stocks (McDermid et al., 2017). Through altering soil structure and water holding capacity, the soil microbial activity is enhanced and oxidation processes of soil organic matter are caused, releasing carbon emissions from soils (Baker et al., 2007). Mechanization and industrialization accelerated impacts of agricultural land management on the environment over the course of the 20th century (McDermid et al., 2017). The use of machinery with uncontrolled traffic on fields are identified to drive soil compaction (Batey, 2009; Hernandez-Ramirez et al., 2021). Under conditions of the 'Green revolution' since about the 1960s, raised agricultural productivity is found increasingly associated to the application of industrial fertilizer, pesticides, insecticides, and herbicides (Lee and Thierfelder, 2017; Therond et al., 2017) often combined with high yielding crop varieties preventing common crop failures. Agroecosystem under conventional intensification are found to be associated to lower species richness (Beckmann et al., 2019), providing less complexity in habitats and food chain elements. Intensive agriculture and especially pesticides have been identified to be main drivers of declining insect populations (Sánchez-Bayo and Wyckhuys, 2019). The extensive use of mineral and organic fertilizers but also insufficiently managed livestock manure and waste management cause rising rates of emissions but also nitrate leaching from croplands resulting in freshwater pollution, algae bloom, and associated eutrophication of surface waters (Potter et al., 2010). Also cropland irrigation was found a potential contributor to soil surface crusting (Oster and Schroer, 1979) and soil salinization (Rengasamy, 2006), if not managed appropriately.

The conversion of natural ecosystems to cropland and its intensive usage are drivers of soil fertility decline, ecosystem degradation, and desertification (Lal, 2002; Squire et al., 2015), which may cause land abandonment (Gibbs and Salmon, 2015) and require further land use change.

1.3 Policy and contextual framework of agricultural land management

Within the 'planetary boundaries' analyses framework (Rockstrom et al., 2009; Steffen et al., 2015) largest anthropogenic alteration of ecosystem stocks and flows are identified with respect to biodiversity loss, the disturbance of the global nitrogen cycle, and climate change. Agricultural production is subject to several global policy frameworks, setting targets and guidelines for its sustainable development.

First to mention is the Convention on Biological Diversity (CBD), wherein during the United Nation Environmental Program (UNEP) summit in Rio de Janeiro in year 1992, signing parties agreed on implementing measures towards global and national environmental protection, as well as restoration of degraded ecosystems, and habitats. The associated concept of 'land sparing' and 'land sharing' (Phalan et al., 2011), describes the critical evaluation of saving land from anthropogenic use for ecosystem protection or the integration of both on the same land unit. Jung et al. (2021) estimate that 30 – 70 % of the terrestrial land surface require conservation attention for compliance with objectives of biodiversity and climate conventions.

Agricultural activities are found among the main contributors to the current transgression of boundaries of a safe operating space regarding biogeochemical flows (nitrogen and phosphor cycles) and biosphere integrity (Campbell et al., 2017). Additionally, agricultural production is going to be affected stronger by impacts of climate change in developing regions, already insufficiently able to meet current food demand and showing low resilience towards shifting system elements (Aggarwal et al., 2019). The members of the United Nations formulated the Sustainable Development Goals (SDGs) targeting a "Zero Hunger" world through mutual endeavors until the year 2030 (Blesh et al., 2019).

Undersigning parties of the Paris climate agreement dedicated themselves to self-set goals formulated in their NDCs (Nationally Determined Contributions) to reduce emissions, mitigate climate change impacts, and adapt their sectors (Rogelj et al., 2016). About 10 countries mention 'soil organic carbon' in context of their agricultural NDCs, whereas about 40 countries mention 'practices affecting the protection or sequestration of soil organic C on cropland', i.e. including management of manure, residues, or measures to promote agroforestry and the restoration of degraded ecosystems (Wiese et al., 2019). The '4 per 1000' initiative has set the goal to guide transition of agricultural cropland use and management techniques towards a C sink to mitigate climate change effects, reduce environmental degradation, and reverse impacts in form of ecosystem restoration (Corbeels et al., 2018; Minasny et al., 2017).

1.4 Agricultural management data and the role of uncertainty

1.4.1 Sustainable agricultural management practices

Sustainable Intensification (SI) includes the promotion of sustainable agriculture production practices, which at the same time improve food security (Garnett et al., 2013; Pretty and Bharucha, 2014; Rockström et al., 2017; Ruiz-Martinez et al., 2015; Tilman et al., 2011). SI includes principles of increasing efficiencies (e.g. reduced waste in food chain, fertilizers-smart technologies), substituting inputs (e.g. new cultivars or seeding techniques), and system redesign by transferring or using existing natural processes to enhance certain desired effects (Pretty et al., 2018) (e.g. introducing N fixing legumes, replacing pesticides, and supporting natural enemies). According to Pretty et al. (2018) these forms of SI are already practiced on 453 million ha of agricultural crop and pasture land, which correspond to about 9 % of total global land area.

Precision agriculture practices can promote SI, such as by facilitating optimized, site-specific, and temporal more targeted fertilizer application rates on fields but are also found challenging due to high informational, financial, and technological requirements (Lindblom et al., 2017).

Agricultural land management practices mutually can support mitigation and adaptation efforts (Morais et al., 2019; Rosenzweig et al., 2020; Smith et al., 2019). In the year 2005, about 306 million ha of global cropland was found irrigated (Siebert et al., 2015), whereas the majority of global crop production is rainfed. Irrigation can be used to avoid or lower water stress to close yield gaps (Mueller et al., 2012), but also to reduce the canopy temperature of a crop stand. Reduced tillage, increased irrigation and leaf area index, are shown to have mutual direction of physical cooling effects on global land surface (Lobell et al., 2006; Lobell et al., 2008a). Further, a study by Hirsch et al. (2017) finds larger cooling effects for irrigation measures than for crop albedo enhancement by leaving residues on top of the soil, which's albedo is usually higher than the soil they cover (Davin et al., 2014). However, the albedo effect of snow cover of cropland soil versus darker surfaces in winter when covered with biomass, is found to lead to a winter warming effect in certain regions (Lombardozzi et al., 2018). Schauberger et al. (2017) state that the negative impact of projected elevated temperature on crop yields with climate change, can only partly be compensated by the positive response of plant growth to higher CO_2 concentration and that the potential off-set were much higher when increasing irrigation measures. Jägermeyr et al. (2015) estimate considerable water saving potentials with improved crop water management measures, such as rainwater harvesting, mulching, and shifts to more water use efficient irrigation techniques, to maintain current crop productivity levels with climate change, especially in water limited environments.

Keestra et al. (2018) considers cropland management practices as 'nature based solutions' that target the improvement of soil organic matter content, and farming structure to enable increased soil water infiltration rates, lower runoff, and erosion prevention. The Intergovernmental Panel on Climate Change (IPCC) estimate for cropland management a potential carbon sequestration rate of 0.8 Gt CO_2 eq. yr^{-1}, excluding rice production and agroforestry systems by the year 2030 (Smith et al., 2007). Stockmann et al. (2013) consider conservation tillage, cover cropping, integrated nutrient management (including manuring), and improved grazing as best cropland management practices currently available, to assess the technical and potential soil carbon sequestration on cropland. However, also the application of biochar may lock in C in the soil and at the same time improve soil fertility (Werner et al., 2018). Conservation Agriculture (CA) practices are found in line with the goals of SI (Hobbs, 2007; Laborde et al., 2020b; Lal, 2019) and as a climate-smart technology benefiting mitigation and adaptation of cropping systems to climate change (Findlater et al., 2019; Giller et al., 2015; Reicosky, 2003). CA practices comprise minimal mechanical soil disturbance, cropping diversification, and maintaining a permanent biological ground cover (Friedrich et al., 2012; Kassam et al., 2019). Mayer et al. (2018) analyzed modeled effects of Conservation Agriculture practices on global surface temperature, finding a potential warming reduction of 0.1 K in the year 2100 due to soil carbon sequestration rate of 0.68 Gt C yr^{-1} for the 85 year simulation period. Through carbon accumulation the soil hydraulic properties and nutrient cycling are improved within the agroecosystem with a positive impact on main crop yields (Hobbs et al., 2008; Knapp and van der Heijden, 2018). Conservation Agriculture builds on principles of 'agroecology' which concept is aligned to 'nature' or 'ecosystem based solutions' for improving agricultural management and achieving food security (Sonneveld et al., 2018). Griscom et al. (2017), elaborating on CA as a 'natural climate solutions' as well, estimate potential mitigation 0.31-0.52 Gt CO_2 eq. yr^{-1} in 2030 for cover crop practices, which is one of the practices promoted under CA.

1.4.2 Availability of agricultural management data

The type and intensity of crop production practices shape the state of natural resources and processes within an agroecosystem but also beyond (Erb et al., 2014; Friedlingstein et al., 2020; Haberl et al., 2009; Levis et al., 2014; Lobell et al., 2006; Mayer et al., 2018; Pugh et al., 2015; Stockmann et al., 2013). Cropping systems are characterized by the type of crop cultivated, their area coverage, and the employed agronomic measures to attain a certain crop yield. Throughout this thesis, different agronomic treatments within cropping systems are jointly referred to as cropland management practices, including the type of cultivated crop, area covered by the crop, type of water regime (rainfed or irrigated), seedbed preparation, cultivation, harvest, crop residue management, fallowing practices, as well as manure and inorganic fertilizer application.

Global assessments require complex and detailed data on cropland management practices regarding the type, location, intensity, timing, duration, frequency, as well as associated biophysical and biogeochemical processes (Hutchings et al., 2012; Pongratz et al., 2018; White et al., 2010), which can have various sources.

Usual reporting formats of cropland management data are via (sub-)national reports, statistics, or more recently increasing in the literature via open access data repositories. Satellite and remote sensing data are increasingly used as sources for input data to modeling studies although mostly up to regional scales (Zheng et al., 2014), approving of their higher temporal coverage (daily to annual) and level of spatial detail (<10 km resolution) (Kim et al., 2021). However, global assessment studies are challenged by the level of access to them, due to related data property and protection policies or national security issues. Current efforts towards open access data may increase the usage of agricultural management data by increasing the availability and transparency of applied methodologies regarding data processing steps, as well as assumptions made beforehand. Citizen science approaches (Fraisl et al., 2020) can supplement the top-down reporting schemes of nations. Fritz et al. (2015), present a global gridded cropland and field size dataset, which included the assessments of satellite pictures of land use by participants in online campaigns using GEOWIKI for input data generation as well as the for the validation of sampled computed values.

Alternative sources of agricultural management information can be from measurements, models, surveys, delineations from other variables using statistical relations between variables of interest, or hybrid versions of any combination of the aforementioned. For data resulting from field and farm trials, frameworks are proposed to assess data quality for the usage in agroecosystem modeling (Boote et al., 2016; Kersebaum et al., 2015). They define a minimum standard and three data quality categories differing by information complexity, i.e. site-based data to be ranked according to the level of detail on soil, climate, and management information described in the respective meta-data.

During the last decade most advancement is found improving the availability of data on land use, land use change, crop types, crop productivity, and cropland fertilizer application rates (Kim et al., 2021). The data often relies on fusion methods of reported data from (sub-)national statices and other sources of information, such as the global gridded crop type specific harvested area datasets MIRCA (Portmann et al., 2010) and M3 (Monfreda et al., 2008) for around the year 2000 or SPAM available for the years 2000, 2005, and 2010 (Yu et al., 2020). Available datasets may also include land use or integrated model projections, such as the land-Use Harmonization (LUH) dataset, reporting on historical and future extent of land use types and the spatial distribution of crop groups, such as C3, C4, annuals, and perennials respectively, as well as nitrogen-fixing plants (e.g. soybean) for the years 850-2100 (Hurtt et al., 2020). Eitelberg et al. (2015) review potentially available global cropland area projections and find a large range of estimates between 1552 to 5131 million ha, including existing cropland of about 1550 million ha.

Siebert et al. (2010) generated an open-access global gridded dataset on cropping intensity and estimate 28 % of global cropland area was left temporal fallow around the year 2000. Waha et al. (2020) find that 12 % of global cropland area is multiply cropped the same year, whereas both studies use MIRCA2000 as their main input data source. Further, global gridded crop management datasets that are available to the modeling community, comprise crop sowing dates (Sacks et al., 2010; Waha et al., 2012), as well as major crop growing seasons provided by Minoli et al. (2019a) and MIRCA2000 (Portmann et al., 2010). Global cropland irrigation patterns are included in MIRCA (Portmann et al., 2010), SPAM (Yu et al., 2020) as well as in the time series data on irrigated land by Siebert et al. (2015) covering the years 1900-2005. Nitrogen and phosphorous application rates of fertilizer and livestock manure are provided by Potter et al. (2010). Zhang et al. (2017) provides a global gridded time series of total N mass excreted by livestock, finding a significant increase during the past 150 years from 3.6 Tg N in year 1860 to 24.5 TgN in 2014. Time series for fertilizer application rates on cropland for the past and projected future are also included in the LUH data, which was harmonized for their reported land use pattern (Hurtt et al., 2020). Lu and Tian (2016) present a time series (years 1900-2013) for synthetic N and phosphorous fertilizer application on cropland whereas Nishina et al. (2017) present a time series on historical global N fertilizer application (including NH_4 and NO_3) at 0.5 degree resolution for the period 1961–2010.

1.4.3 Data and model uncertainty

The responses of agricultural production to changing environmental and socio-economic conditions can be evaluated using land surface, dynamic vegetation, agroecosystem, and integrated models. These models can capture effects across a variety of temporal scales, such as past, current, or possible future scenarios and across diverse spatial resolutions, such as point, grid cell, region, country, or global scale. Global process based vegetation models have an emphasis on representing biophysical and biogeochemical interactions between natural soil and vegetation but also with anthropogenic resource use and management practices. Analyzing spatially explicit and temporal complex processes can reveal synergies but also trade-offs between impacts of agricultural management practices and targeted production outputs, such as soil fertility versus food production (West et al., 2010).

There are different sources of uncertainties associated to global biosphere modeling assessments, which propagate through the modeling chain from data usage, over model structure, and their application methods (Reyer et al., 2015; Wallach et al., 2015). Here the term ‘uncertainty’ can be defined as: “Any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system” (Walker et al., 2003, p. 5). Uncertainty is also

described as a situation of inadequate information, resulting from three sorts: “inexactness, unreliability, and border with ignorance” (Funtowicz and Ravetz, 1990, p. 23)
Input data uncertainty in modeling studies, is associated to differences in method applied to generate the individual data products, their sources of information, as well as to their spatial, and temporal coverage. In the absence of common criteria for cropland monitoring data at appropriate temporal and spatial resolution, the global modeling community relies on data which are reported for other purposes as statistics at country or sub-regional scales. Folberth et al. (2016), applying the EPIC model, find that different soil input data can even outweigh effects of climate change projections on simulated crop yields. Other studies found considerable uncertainty induced by aggregation or disaggregation of climate and soil input data and their effects on simulated model results (Folberth et al., 2012; Hoffmann et al., 2016). Maharjan et al. (2019) calculated differences between regional yields up to 60% when comparing simulations with different resolution of climate and soil input data to their model runs for two analyzed regions. Theses authors find increasing aggregation error in regional crop yields (winter wheat and maize) with decreasing resolution of the model input data (climate, soil). Further, they find that aggregated crop yields across their study region in the Mediterranean climate zone differed larger than for the one in the temperate humid climate zone. They also show that the aggregation of soil type data (dominant soil type was chosen) resulted in larger aggregation error than aggregated climate (arithmetic averaging per aggregation unit) input data at coarser resolutions.
Missing input data for agroecosystem model simulations need to be filled by inter- or extrapolation, or, if not existent at all, circumstanced otherwise with rough and sometimes non-transparent assumptions made by the modeler. This maybe the case, if for example the sowing date of a crop type in a certain region is not known, one may set the sowing date to a model default value, e.g. the beginning of month, year, or other fixed date (Schewe et al., 2019). Modeling uncertainty might arise from different assumptions made by the person running the model and interpreting protocol demands.
Another source of uncertainty relates to structural differences between agroecosystem models (Marin et al., 2015; Tao et al., 2018). Models may differ in amount, complexity, and level of detail of processes representation.
Current available climate models still perform rather poorly when simulating the precipitation pattern of the monsoon (Yang et al., 2019) to facilitate the assessment of climate seasonality and resulting cropping intensity pattern. Schewe et al. (2019) find a strong underestimation by simulated historical impacts of a heat wave and drought event across European countries in the year 2003 for all assessed sectors. They find that crop yields simulated by a set of agroecosystem models reveal mixed responses for analyzed countries due to mixed models’ skills to reproduce the variations in rainfall at sufficient temporal resolution, such as within and between seasons affecting inter-annual yield variability. Schauberger et al. (2019) found the effect of ozone being underrepresented in global assessments and when implemented in the LPJmL model, found a considerable decreasing effect for simulated soybean and wheat yield.
There is a large data requirement for model parameterization and calibration to improve the representation of biophysical and biogeochemical processes associated to agricultural production as well as for validation and comparison of modeled outputs (Ewert et al., 2015). This kind of data can be based on measurements derived from experimental or field trials, sensor, and satellite data. For example, process description and effects of photosynthesis in response to elevated CO_2 under climate change are associated to considerable uncertainty in global estimates (Toreti et al., 2020), which reveal further need of improved modeling approaches integrating measurement results from experimental trials (Medlyn et al., 2015). Current models may include stomatal closure

reaction as plant response to elevated temperature due to changing climate but the rubisco-enzyme response to and its faith at increased availability of atmospheric carbon remain less well described. Enzyme activity may increase vegetative carbon production only to a certain threshold and then maybe halt instead of a linear increase as could be delineated from an FACE experiment with fluctuating CO_2 concentrations, resulting in depressed photosynthesis rates (Allen et al., 2020). Adaptation of rubisco-activity to elevated CO_2 availability (also described as photosynthetic acclimatization) may be better overcome, if the associated rising N demand can be met by the plant, which is realized by N-fixing plants rather than by non-N-fixing plant species, resulting in increased growth and photosynthetic rate (Ainsworth and Rogers, 2007).

Folberth et al. (2019) discuss and show the effect of parameter uncertainty induced by using different soil parameters and crop management configurations in the EPIC model on maize yield simulations. Friend et al. (2014) analyzed the effect of climate change on NPP (finding that it will most probably rise) simulated with seven global vegetation models. These authors find that the different modeling of soil carbon residence time was leading to a larger uncertainty and even to different directions of simulated effects under climate change scenarios especially with temperature increases beyond 4K. Another source of uncertainty is induced by calibration methods of model results to assumed base data, such as using FAOSTAT production data in the evaluation and benchmarking. This calibration step maybe reasoned by the fact, that the majority of current model functionalities do not capture yield limiting effects on growth, such as erosion, weed, pest, diseases, damage, crop failures as found under natural or variability due to local specific agricultural management practices. Therefore, in global simulations studies crop productivity often is regarded as 'potential yield' instead of 'actual yield' levels and efforts of calibration may persist in being a rather non-transparent procedure.

A variety of representative concentration pathways (RCPs) of possible future atmospheric CO_2 concentration levels (Kyle et al., 2014; Moss et al., 2010; van Vuuren et al., 2012) can be found, which are projected under differing shared socio-economic pathways (SSPs) (Kriegler et al., 2010). Using these storylines of possible futures, Nelson et al. (2010) provide future food demand scenarios for 2050 based on simulations with the IMPACT model. Popp et al. (2017) present a set of future land use projections based on results of socio-economic scenarios (SSPs) and differing assumptions of representative concentration pathways (RCPs) of atmospheric CO_2-concentration levels using the global land use model MAgPIE. Balkovič et al. (2014) quantified modeled global crop production in response to climate change using the EPIC model with a variety of RCPs, finding sufficient intensification potential for current irrigation infrastructure to off-set negative climate change impacts on productivity and to meet projected future wheat demand at the global scale. In their meta-analysis on productivity impacts of different CO_2 concentration pathways, Aggarwal et al. (2019) find yield declining effects for rice, wheat, and maize, even stronger for if no adaptation measures were taken. Globally, they find crop production in the tropics more affected by declining effects than in temperate regions and in developing countries more than developed countries. Lastly, uncertainty may rise in global change assessments if a wide span of simulation scenarios (increased spread of variance) is chosen or in case of a biased selection of possible future development pathways.

1.5 Knowledge gaps

It is found that cropland use often is represented as an aggregate of crop types and associated management practices (Morais et al., 2019). However, to analyze the current state and potentials of crop production, local specific differences in crop and land management practices across a variety of socio-economic and environmental conditions need to be considered. Agricultural management decisions are usually pursued at the field to farming system scale, which may extend up to a landscape or larger regional ecosystem unit. Land management representation in models are found challenging because of their spatial heterogeneity (Silva and Giller, 2021) and temporal variations (inter- and intra-seasonal and inter-annual) (McDermid et al., 2017). Increasing resolution, detail of process understanding, as well as the improved model representation of soils and land management practices are found crucial for the quantification of historical emissions associated to agricultural land use (Erb et al., 2016; McDermid et al., 2017; Müller et al., 2017a; Pongratz et al., 2018). Historical emissions related to land use change for agriculture and cultivation are found underestimated, when impacts from land management practices are not accounted for as additional emission sources (Levis et al., 2014; McDermid et al., 2017; Pugh et al., 2015).

Soil carbon contents are found to have declined over the course of historical cropland cultivation (Levis et al., 2014; Tivet et al., 2013). McDermid et al. (2017) synthesize that fertilizer, soil amendments, and crop residue management play a crucial role for modeling effects of agricultural production on cropland soil C dynamics. Pugh et al. (2015) calculate an underestimation of historical ecosystem C loss due to missing accounting for tillage, irrigation, harvest, grazing, as well as crop residue removal of up to 1 Gt C yr^{-1}, and also report a cumulative 40.8 Gt C loss from arable soils in the last 50 years. These authors found increased heterotrophic respiration in tilled soils, which additionally to the extraction of biomass through harvest and resulting missing inputs to cropland soil, both are driving soil C stocks to move towards a lower equilibrium state, releasing emissions and increasing the soil legacy flux.

1.6 Aims and scope of the thesis

The overall objectives of this thesis are:

(1) To identify requirements of cropland management data and implications of their usages in global modeling studies, and

(2) To add knowledge on types and impacts of cropland management practices as well as determinants of their spatial and temporal pattern to improve assessments of global change.

1.6.1 Overview of the individual chapters of the thesis

The thesis comprises five chapters. The introduction (Chapter 1) gives an overview of the research problem, scientific background, and motivation to study the pattern of cropland management systems.

The two overall objectives of this thesis have been addressed with a set of three standalone research studies, here compiled as Chapters 2, 3, and 4, respectively. At the time of submission of this thesis two of the articles were published (Chapters 2 and 3) and the third was submitted for peer-review process to an open-access journal and therefore included as a preprint text version (Chapter 4).

The objectives of the individual studies were:

Chapter 2: Spatial and temporal uncertainty of crop yield aggregations.

- ➢ To identify causes for uncertainty associated to the aggregation of gridded crop productivity model outputs using different crop-specific harvested area datasets
- ➢ To estimate the magnitude of effects for results of average crop productivity at national and global scale across the simulated historical period, and

- To formulate recommendations to account for aggregation uncertainty in global gridded crop modeling studies.

Chapter 3: Generating a rule-based global gridded tillage dataset.

- To derive a classification of global tillage type practices for the improved parameterization of practices in agroecosystem models
- To develop a rule-based and probability based approach to map tillage types, using environmental and socio-economic spatial proxy indicator data variables and thresholds derived from the literature, and
- To provide estimates of the extend and spatial distribution pattern of tillage system types across global cropland.

Chapter 4: The role of cover crops for cropland soil carbon, nitrogen leaching, and agricultural yields – A global simulation study with LPJmL (V. 5.0-tillage-cc)

- To improve the representation of cropland management practices in the LPJmL model,
- To quantify the effects of simulated cover crop cultivation on cropland soil carbon and nitrogen dynamics, as well as crop productivity in comparison to bare soil fallowing practices
- To assess historical impacts of Conservation Agriculture practices on biophysical and biogeochemical processes at the global scale.

In Chapter 5, an overall synthesis of the thesis is provided. Key outcomes of the three studies are summarized, highlighting how they are inter-related and jointly address the overall objectives of the thesis. Finally, conclusions from this thesis' findings are drawn and discussed for implications within the context of agricultural production impact and climate change mitigation.

2 Spatial and temporal uncertainty of crop yield aggregations

The original and edited version of this chapter has been published as: Porwollik, V.; Müller, C.; Elliott, J.; Chryssanthacopoulos, J.; Iizumi, T.; Ray, D.K.; Ruane, A.C.; Arneth, A.; Balkovič, J.; Ciais, P.; Deryng, D.; Folberth, C.; Izaurralde, R.C.; Jones, C.D.; Khabarov, N.; Lawrence, P.J.; Liu, W.; Pugh, T.A.M.; Reddy, A.; Sakurai, G.; Schmid, E.; Wang, X.; de Wit, A.; Wu, X. Spatial and temporal uncertainty of crop yield aggregations. European Journal of Agronomy. 88,10-21, http://dx.doi.org/10.1016/j.eja.2016.08.006., 2017.

Abstract

The aggregation of simulated gridded crop yields to national or regional scale requires information on temporal and spatial patterns of crop-specific harvested areas. This analysis estimates the uncertainty of simulated gridded yield time series related to the aggregation with four different harvested area data sets. We compare aggregated yield time series from the Global Gridded Crop Model Intercomparison project for four crop types from 14 models at global, national, and regional scale to determine aggregation-driven differences in mean yields and temporal patterns as measures of uncertainty. The quantity and spatial patterns of harvested areas differ for individual crops among the four data sets applied for the aggregation. Also simulated spatial yield patterns differ among the 14 models. These differences in harvested areas and simulated yield patterns lead to differences in aggregated productivity estimates, both in mean yield and in the temporal dynamics. Among the four investigated crops, wheat yield (17% relative difference) is most affected by the uncertainty introduced by the aggregation at the global scale. The correlation of temporal patterns of global aggregated yield time series can be as low as for soybean ($r = 0.28$). For the majority of countries, mean relative differences of nationally aggregated yields account for 10% or less. The spatial and temporal difference can be substantial higher for individual countries. Of the top-10 crop producers, aggregated national multi-annual mean relative difference of yields can be up to 67% (maize, South Africa), 43% (wheat, Pakistan), 51% (rice, Japan), and 427% (soybean, Bolivia). Correlations of differently aggregated yield time series can be as low as $r = 0.56$ (maize, India), $r = 0.05$ (wheat, Russia), $r = 0.13$ (rice, Vietnam), and $r = -0.01$ (soybean, Uruguay). The aggregation to sub-national scale in comparison to country scale shows that spatial uncertainties can cancel out in countries with large harvested areas per crop type. We conclude that the aggregation uncertainty can be substantial for crop productivity and production estimations in the context of food security, impact assessment, and model evaluation exercises.

2.1 Introduction

Crop models are increasingly applied at the global scale to study how agricultural yields and total production over regions might be affected by global phenomena such as market dynamics and climate change. Simulations of crop productivity (yield) at different spatial and temporal scales have been used for example in the context of food security, land use, and climate change research (Asseng et al., 2015; Challinor et al., 2014; Mueller et al., 2012; Nelson et al., 2014a,b). Uncertainties associated with crop model projections have been widely recognized and discussed, including those attributed to input uncertainty (Roux et al., 2014), as to differences in climate forcing data (Rosenzweig et al., 2014), model structure and parameterization (Rötter et al., 2012), and assumptions on the effectiveness of CO2-fertilization on crop yields (Deryng et al., 2016). The uncertainty in cropland extent and its implications for land use modeling have been addressed before by Eitelberg et al. (2015), Fritz et al. (2015), and See et al. (2015). Gridded cropping system data sets on the spatial distribution of crops at the global scale have been reported by Leff et al. (2004), and more recently by Iizumi et al. (2014), and Ray et al. (2012) including distinct data on crop-specific harvested area. Anderson et al. (2015) directly compared four gridded cropping system data sets as MIRCA2000 (Portmann et al., 2010), SPAM2000 (You et al., 2014), GAEZ (Fischer et al., 2012), and M3 (Monfreda et al., 2008). They conclude that the data sets' differences in harvested area and yield could be attributed mainly to the input data used and the downscaling method applied, and report that the disagreement between data sets was largest in areas with minimal harvested area. Different schemes for the interpolation of site-specific yields for the aggregation to agro-climatic zones have been discussed by van Wart et al. (2013) within the context of yield gap and production analysis. Global gridded crop model (GGCM) results e.g. yield (t/ha) are typically reported in a standardized half degree grid format. This output is aggregated at annual time steps to different spatial scales within the context of model skill assessment, impact studies, or as input variable to land use models. It is used for example when comparing different countries or evaluating modeled yields against agricultural statistics that are only available at the aggregated scale of administrative units. For this kind of aggregation, data sets on spatial patterns of crop-specific harvested area are applied, which are typically derived from data on cropland extent, national and sub-national census data, and allocation rules. To date, little attention has been paid to the uncertainty of aggregation of gridded crop model simulations induced by the choice of crop-specific harvested area data set. Thus the objective of this study is to assess this aggregation uncertainty at different spatial scales. We use the term "crop mask" in the following as a short version of "gridded crop-specific harvested area data set". The uncertainty in simulated yields related to aggregation masks is determined by two factors: a) the differences in quantity and spatial patterns of crop-specific harvested area data sets, and b) the spatial and quantitative heterogeneity of simulated crop yields, which is specific to individual GGCMs.

2.2 Material and methods

2.2.1 Model input data and crop yield simulations

In the Global Gridded Crop Model Intercomparison (GGCMI) project Phase 1 (http://www.agmip.org/ag-grid/ggcmi/) of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) 14 modeling groups performed historical global crop growth simulations according to the modeling protocol of Elliott et al. (2015). Crop growth has been simulated using the bias-corrected historical weather input data sets AgMERRA (Ruane et al., 2015) and the atmospheric CO2-data based on the Mauna Loa Observatory time series (Thoning et al., 1989). AgMERRA provides daily data for the time period 1980–2010 and had been aggregated from the original resolution of 0.25◦ to 0.5◦ before being supplied to modelers. The Mauna Loa Observatory time series reports observed annual and monthly values of the atmospheric CO2-mixing ratio, so that models simulated crop growth with a CO2-mixing ratio of 339–390ppmv (here stating annual averages 1980–2010). Four crop types were simulated by the modeling teams: maize (Zea mays L.), wheat (Triticum aestivum L.), rice (Oryza sativa L.), and soybean (Glycine max (L.) Merr.) These crops had been categorized in the GGCMI project as Priority 1 crops, because of their importance as agricultural commodity in terms of their global harvested area covered, production amount, level of trade, and direct or indirect contribution to human diet. The participating models cover a broad range of model types and of implemented processes. Their basic characteristics and key literature references are listed in Table 1 (more details in SI Appendix Tables A.1–5). For the crop growth simulations initial conditions of soil water, minerals, crop residues, and soil organic matter were derived by applying different soil input data and spin-up runs individual to each of the modeling groups (SI Appendix Table A.3). Modelers were asked to model all crops wherever a given crop can grow and at least on all current agricultural land. The GGCMI project distinguishes three levels of model harmonization with respect to agricultural management. We here used the simulations of the "default" model configuration if available, where every modeling team used their own assumptions on agricultural management (varieties, growing season, fertilizer etc.). The EPIC-TAMU model was run at the global scale for the first time and ORCHIDEE-crop never globally simulated soybean before and thus could not provide a "default" simulation. These teams used the global input data on sowing and maturity dates, and fertilizer data provided within the context of the GGCMI project for a rather harmonized simulation, so that for this study their "fullharm" model configuration was used. The modeling teams reported two separate yield time series per configuration type—one assuming rainfed and the other fully irrigated production conditions everywhere. The irrigated crop growth simulations were run assuming unlimited water supply without conveyance or application losses. As a second step we used crop yield simulations of seven models for the same four crop types of the Intersectoral Impact Model Intercomparison (ISI-MIP) and The Agricultural Model Intercomparison and Improvement Project (AgMIP) fast track (Rosenzweig et al., 2014) obtained from the open-access impact model data archive of ISI-MIP (http://esg.pik-potsdam.de/). These models were driven by output data from five climate models here for the RCP 8.5, including the suite of processes related to "CO2- fertilization" for the future period 2070–2099 (modified carboxylation, and in some models reduced stomatal closure). Note that the seven models: EPIC-BOKU (in ISI-MIP/AgMIP fasttrack refer to the name "EPIC"), GEPIC, GAEZIMAGE, LPJ-GUESS, LPJmL, pDSSAT, PEGASUS which took part in the ISI-MIP/AgMIP fast track, also participated in this GGCMI phase 1 study (model details are listed in SI Appendix Tables A.1–5), except the GAEZ-IMAGE model.

Table 2-1. Participating models in the study.

Crop model	Model type	Key literature
CGMS-WOFOST	Spatially distributed site-based process model (based on WOFOST)	de Wit and van Diepen (2008)
CLM-Crop	Global ecosystem model	Drewniak et al. (2013)
EPIC-BOKU	Site-based process model (based on EPIC)	EPIC v0810 - Izaurralde et al. (2006); Williams (1995)
EPIC-IIASA	Site-based process model (based on EPIC)	Izaurralde et al. (2006); Williams (1995)
EPIC-TAMU	Site-based process model (based on EPIC)	EPIC v1102- Izaurralde et al. (2012)
GEPIC	Site-based process model (based on EPIC)	EPIC v0810 - Liu et al. (2007); Williams (1995)
LPJ-GUESS	Global ecosystem model	Lindeskog et al. (2013); Smith et al. (2001)

LPJmL	Global ecosystem model	Waha et al. (2012), Bondeau et al. (2007)
ORCHIDEE-crop	Global ecosystem model	Wu et al. (2015)
pAPSIM	Site-based process model	APSIM v7.5 - Elliott et al. (2014); Keating et al. (2003)
pDSSAT	Site-based process model	pDSSAT v1.0 - Elliott et al. (2014); DSSAT v4.5 - Jones et al. (2003)
PEGASUS	Empirical/process hybrid	v1.1- Deryng et al. (2016), v1.0 - Deryng et al. (2011)
PEPIC	Site-based process model (based on EPIC)	EPIC v0810- Liu et al. (2016), Williams (1995)
PRYSBI2	Empirical/process hybrid	Sakurai et al. (2014)

2.2.2 Crop masks

Four crop masks were used to aggregate simulated gridded yields: MIRCA2000 (Portmann et al., 2010), Iizumi (Iizumi et al., 2014), Ray (Ray et al., 2012), and SPAM2005 (You et al., 2014). Data sources and main characteristics of the original cropping system data sets were summarized in Table 2. All four data products were based on the cropland extent (ha) per grid cell by Ramankutty et al. (2008), who merged sub-national and national inventory data with two global satellite based land cover products. MIRCA2000 and Iizumi rely on the harvested area data of Monfreda et al. (2008) who used about 50% of sub-national and also FAO-based national data averaged over the time period 1997–2003. SPAM2005 is the update of the former SPAM2000 data set, wherein the share of sub-national data collection for harvested area was about 50% and Ray's share of that was 70–90% − the rest of both had been complemented with FAO national data as well. MIRCA2000, Iizumi, and SPAM2005 report static harvested area data per grid cell (circa 2000 or 2005) whereas Ray provides a dynamic annual time-series (1961–2008). MIRCA2000 and SPAM2005 independently report the spatial distribution of irrigated and rainfed harvested areas (ha) per crop type, which is an important feature for crop modeling and aggregation but are based on different baseline years (2000 vs. 2005). The Iizumi and Ray data sets do not further distinguish harvested areas into irrigated and rainfed fractions. The four data sets display differences in spatial patterns of harvested area as highlighted by Fig. 1 for maize (for the other crops see SI Appendix, Fig. B.1–4) .

2.2.3 Pre-processing the crop masks

The Iizumi data set, originally reported at a spatial resolution of 1.125°, was interpolated to 0.5°. MIRCA2000, SPAM2005, and Ray originally provided data at 5 arc minutes resolutions, which we aggregated to 0.5°. The original information on cropland extent and harvested area around the year 2000 from MIRCA2000, Iizumi, and SPAM2005 data sets, were kept constant and used to aggregate the simulated yields for the time period 1980–2010. The original Ray data set covered all simulated years up to 2008 and the aggregated yield time series used for this analysis thus spanned only the years 1980–2008. All aggregations with SPAM2005 and MIRCA2000 were performed with their own shares of rainfed and irrigated areas. In the case of the Ray and Iizumi data sets, their harvested area per grid cell were split into irrigated and rainfed fractions using MIRCA2000's relative shares for a given crop in each 0.5° grid cell. Grid cells, for which MIRCA2000 specifies no harvested area for the crop of interest, were assumed to be without irrigation if they contained crops in the original Ray or Iizumi data sets.

2.2.4 Aggregating gridded yield data

The GGCMs simulations provided crop yield data in tons of dry matter per hectare (t/ha) for four crop types under fully rainfed and fully irrigated conditions in annual time steps within the time period 1980–2010. These grid cell-specific yield estimates have been aggregated to time series at three spatial scales: global, country, and food production unit (FPU, major river basins crossed with countries) (Cai and Rosegrant, 2002) using the four crop masks as weights in the averaging (Eq. (1)):

$$yield_{aggregated} = \frac{\sum_{i=1}^{n} yield_{i\_i} * area\_irrigated_i + \sum_{i=1}^{n} yield_{i\_r} * area\_rainfed_i}{\sum_{i=1}^{n}(area\_irrigated_i + area\_rainfed_i)} \quad (1)$$

i: any grid cell in the aggregation unit, n: number of grid cells in the aggregation unit, $yield_{i\_i}$: simulated yield (t/ha) under full irrigated conditions in grid cell i, $yield_{i\_r}$: simulated yield (t/ha) under rainfed conditions in grid cell i, $area\_irrigated_i$: irrigated harvested area (ha) in grid cell i, $area\_rainfed_i$: rainfed harvested area (ha) in grid cell i To derive the productivity (t/ha) per year and aggregation unit, each rainfed yield, simulated by the models in a corresponding grid cell, is multiplied with the rainfed harvested area. The same procedure was carried out for the irrigated yields. Then the sum of all rainfed and irrigated production is divided by the total sum of harvested area reported by the individual data sets of that spatial aggregation unit, resulting in the aggregated mean yield (t/ha) per year and aggregation unit. Grid cells were assigned to countries according to the boundary information of Global Administrative Areas (GADM-0, http://gadm.org/), assigning grid cells to the country that has the largest area share in that grid cell. Here we used information on crop specific harvested areas, which can be larger than the physical cropland extent in multiple cropping systems with several harvests per year, which was accounted for in the harvested area data sets. The GGCMs simulated only a single growing period per grid cell, which we assume to be representative for the different growing periods due to current state of implementation of cropping management systems in the models.

Table 2-2. Major features of the four harvested area data sets applied for aggregation.

Feature	MIRCA2000	Iizumi	SPAM2005	Ray
Harvested area based on	Monfreda et al. (2008) - with modifications, circa 2000	Monfreda et al. (2008) - circa 2000	FAOSTAT, AGROMAPS and own sub-national data collection, circa 2005	Sub-national data collection (70% to 90%) 1961-2008
National areas	ESRI 2004	Dominant country code per 0.5° grid cell	Same national total areas as in MIRCA2000 (You et al., 2014)	As in Ramankutty et al. (2008)
N° of crops covered	26 crop classes	Maize, soybean, wheat, and rice	20 major crops	Maize, soybean, wheat, and rice
Original resolution	5 arc minute, 0.083° (~10km)	67.5 arc minute, 1.125° (~120km)	5 arc minute, 0.083° (~10km)	5 arc minute, 0.083° (~10km)
Irrigation data based on	Global Map of Irrigation Areas v.4 (Siebert et al., 2007; 2005), AQUASTAT national data	None	Global Map of Irrigation Areas v.5 (Siebert et al., 2007; 2005)	None
Cropland extent based on	Ramankutty et al. (2008)	Ramankutty et al. (2008)	Ramankutty et al. (2008)	Ramankutty et al. (2008)
Data inclusion method	Collection of statistical data and literature	Yield estimation model	Cross entropy approach with spatial allocation model optimization	Administrative bottom-up statistical data inclusion

For an assessment of aggregation uncertainties in projections of future changes in crop productivity, simulated gridded future yields of the ISI-MIP/AgMIP fast track are aggregated to country scale by three different time slices

(1961, 1984 and 2008) of the Ray data set. In order to quantify the differences between the different crop mask aggregations, we display absolute (t/ha) and relative (%) differences between yield aggregated with each of the four masks: MIRCA2000 (further abbreviated as MIRCA), Ray, Iizumi, and SPAM2005 (in the following abbreviated as SPAM) for selected regions/countries as well as by computing the yield time series differences over time. The correlation coefficients between the differently aggregated time series were used to describe how yield aggregates of individual years are affected by the different crop masks and how this affects variability over time. If all years were affected equally, aggregated yield time series differ in their mean but are highly correlated. Data analysis was conducted in R (R Development Core Team, 2014) using the standard Pearson correlation (Becker et al., 1988).

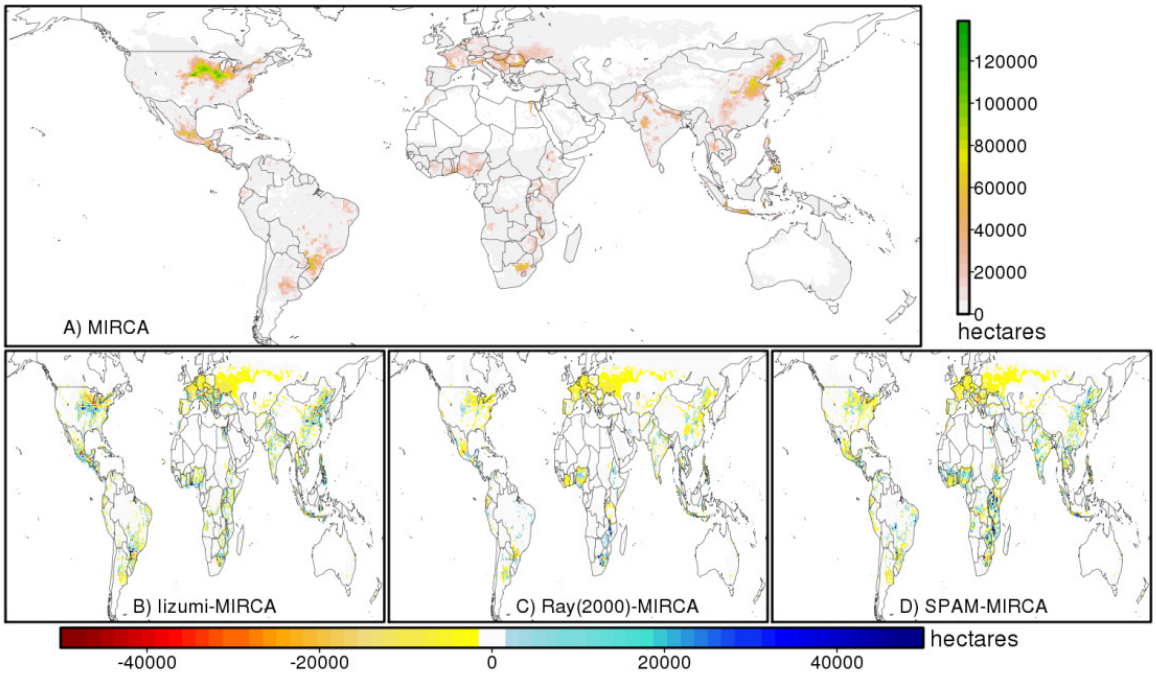

Figure 2-1. Maps of spatial patterns of total harvested maize area according to MIRCA2000 (panel A) and the absolute differences in ha over 0.5◦ grid cells between Iizumi (panel B), Ray (time slice for the year 2000 in panel C), and SPAM2005 (panel D) and MIRCA2000 respectively. See the same figure for irrigated areas only in SI Appendix, Fig. B.1

2.3 Results

The different crop masks lead to different yield estimates for individual years at all spatial scales (global, national, and FPU). The mean relative differences among aggregated global yields reach up to 6% for maize, 17% for wheat, 14% for rice, and 10% for soybean across the different crop models (further details at bottom of Tables 3–6). The ranges depended on the heterogeneity of the simulated spatial yield patterns by the GGCMs and how strongly opposing deviations in different regions compensate each other. The aggregation with different crop masks also affects the simulated temporal dynamics, with minimum correlation coefficients between the global aggregated yield time series of $r = 0.77$ for maize, $r = 0.85$ for wheat, $r = 0.64$ for rice, and $r = 0.28$ for soybean (Tables 3–6).

Table 2-3. Lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) between the aggregated maize yield time series (t/ha) calculated from the 14 models, during the AgMERRA time period, aggregated for the top-10 producer countries with one harvested area data set in relation to the aggregation with each of the other three masks (see more detailed results for all countries in SI Appendix Table D.1).

maize top-10 producer countries	lowest value of relative difference (%)	masks lowest value of relative difference	highest value of relative difference (%)	masks highest value of relative difference	minimum correlation (r)	masks minimum correlation	Share on global production (%)
USA	-3	SPAM-MIRCA	2	Ray-MIRCA	0.98	Ray-Iizumi	35.74
China	-11	SPAM-MIRCA	8	Ray-SPAM	0.94	Ray-SPAM	21.54
Brazil	-9	SPAM-MIRCA	7	Ray-SPAM	0.95	Ray-Iizumi	7.04
Argentina	-7	Iizumi-MIRCA	10	Ray-Iizumi	0.93	Ray-Iizumi	2.54
Mexico	-14	SPAM-MIRCA	17	Ray-SPAM	0.71	Ray-SPAM	2.38
India	-21	SPAM-MIRCA	38	Ray-SPAM	0.56	MIRCA-Ray	2.38
Ukraine	-11	Iizumi-MIRCA	20	Ray-SPAM	0.96	Iizumi-SPAM	2.18
Indonesia	-8	Iizumi-MIRCA	6	Ray-MIRCA	0.85	Iizumi-SPAM	2.06
France	-20	Iizumi-SPAM	28	SPAM-MIRCA	0.95	MIRCA-Iizumi	1.70
South Africa	-37	SPAM-MIRCA	67	Iizumi-SPAM	0.75	MIRCA-SPAM	1.34
global	-5	Ray-Iizumi	5	Iizumi-MIRCA	0.77	MIRCA-Ray	100

Table 2-4. Lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) between the aggregated wheat yield time series (t/ha) calculated from the 14 models, during the AgMERRA time period, aggregated for the top-10 producer countries with one harvested area data set in relation to the aggregation with each of the other three masks (see more detailed results for all countries in (SI Appendix Table D.2).

wheat top-10 producer countries	lowest value of relative difference (%)	masks lowest value of relative difference	highest value of relative difference (%)	masks highest value of relative difference	minimum correlation (r)	masks minimum correlation	Share on global production (%)
China	-19	SPAM-MIRCA	19	Iizumi-SPAM	0.82	SPAM-MIRCA	17.26
India	-16	SPAM-MIRCA	33	Iizumi-SPAM	0.89	Iizumi-SPAM	12.77
USA	-8	Iizumi-MIRCA	7	Ray-Iizumi	0.77	Iizumi-SPAM	8.61
Russia	-6	Iizumi-SPAM	6	Iizumi-SPAM	0.05	SPAM-MIRCA	7.29
France	-5	Iizumi-SPAM	6	Ray-Iizumi	0.85	Iizumi-MIRCA	5.60
Canada	-28	Ray-SPAM	41	SPAM-MIRCA	0.41	Iizumi-SPAM	4.09
Australia	-21	Iizumi-SPAM	16	SPAM-MIRCA	0.87	Iizumi-SPAM	3.62
Pakistan	-19	SPAM-MIRCA	43	Iizumi-MIRCA	0.79	SPAM-MIRCA	3.52
Germany	-4	Iizumi-MIRCA	5	Ray-Iizumi	0.94	MIRCA-Ray	3.50
Turkey	-17	Iizumi-SPAM	15	SPAM-MIRCA	0.72	MIRCA-Ray	3.05
global	-17	SPAM-MIRCA	10	Ray-SPAM	0.85	MIRCA-Ray	100

Table 2-5. Lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) between the aggregated rice yield time series (t/ha) calculated from 11 models, during the AgMERRA time period, aggregated for the top-10 producer countries with one harvested area data set in relation to the aggregation with each of the other three masks (see more detailed results for all countries in SI Appendix Table D.3). Note that the models PEGASUS, PAPSIM, and EPIC-TAMU did not simulate rice.

rice top-10 producer countries	lowest value of relative difference (%)	masks lowest value of relative difference	highest value of relative difference (%)	masks highest value of relative difference	minimum correlation (r)	masks minimum correlation	Share on global production (%)
China	-25	Iizumi-MIRCA	14	SPAM-MIRCA	0.71	MIRCA-Ray	27.99
India	-10	Iizumi-SPAM	13	SPAM-MIRCA	0.88	MIRCA-Ray	20.97
Indonesia	-5	Iizumi-MIRCA	4	Ray-SPAM	0.95	Iizumi-SPAM	9.36
Bangladesh	-15	Iizumi-SPAM	17	SPAM-MIRCA	0.97	MIRCA-SPAM	6.97
Vietnam	-33	Iizumi-SPAM	42	SPAM-MIRCA	0.13	MIRCA-SPAM	5.81
Thailand	-29	Iizumi-SPAM	35	SPAM-MIRCA	0.78	Ray-SPAM	4.97
Myanmar	-11	Iizumi-SPAM	10	Ray-SPAM	0.92	MIRCA-SPAM	4.18
Philippines	-33	Iizumi-SPAM	38	SPAM-MIRCA	0.77	Ray-SPAM	2.37
Brazil	-9	Ray-Iizumi	8	Iizumi-SPAM	0.32	MIRCA-Ray	1.69
Japan	-18	Ray-Iizumi	51	Iizumi-MIRCA	0.79	MIRCA-Ray	1.48
global	-14	Iizumi-SPAM	11	SPAM-MIRCA	0.64	MIRCA-Ray	100

Table 2-6. Lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) between the aggregated soybean yield time series (t/ha) calculated from 13 models, during the AgMERRA time

period, aggregated for the top-10 producer countries with one harvested area data set in relation to the aggregation with each of the other three masks (see more detailed results for all countries in SI Appendix Table D.4). Note that the model EPIC-TAMU did not simulate soybean.

soybean top-10 producer countries	lowest value of relative difference (%)	masks lowest value of relative difference	highest value of relative difference (%)	masks highest value of relative difference	minimum correlation (r)	masks minimum correlation	Share on global production (%)
USA	-4	Ray-SPAM	9	Ray-MIRCA	0.91	Ray-SPAM	34.52
Brazil	-8	Iizumi-MIRCA	23	Ray-Iizumi	0.07	Ray-SPAM	27.48
Argentina	-22	Ray-Iizumi	25	Iizumi-MIRCA	0.8	Ray-Iizumi	17.51
China	-8	SPAM-MIRCA	14	Iizumi-SPAM	0.83	Ray-SPAM	5.53
India	-13	SPAM-MIRCA	48	Ray-SPAM	-0.08	Ray-MIRCA	4.85
Paraguay	-41	SPAM-MIRCA	82	Iizumi-SPAM	0.83	SPAM-MIRCA	2.61
Canada	-16	SPAM-MIRCA	20	Ray-SPAM	-0.23	SPAM-MIRCA	1.77
Uruguay	-16	Ray-SPAM	27	Iizumi-SPAM	-0.01	Ray-SPAM	0.88
Ukraine	-9	SPAM-MIRCA	12	Ray-SPAM	0.82	Ray-SPAM	0.80
Bolivia	-68	SPAM-MIRCA	427	Ray-SPAM	0.45	Ray-SPAM	0.78
global	-6	SPAM-MIRCA	10	Ray-SPAM	0.28	Ray-SPAM	100

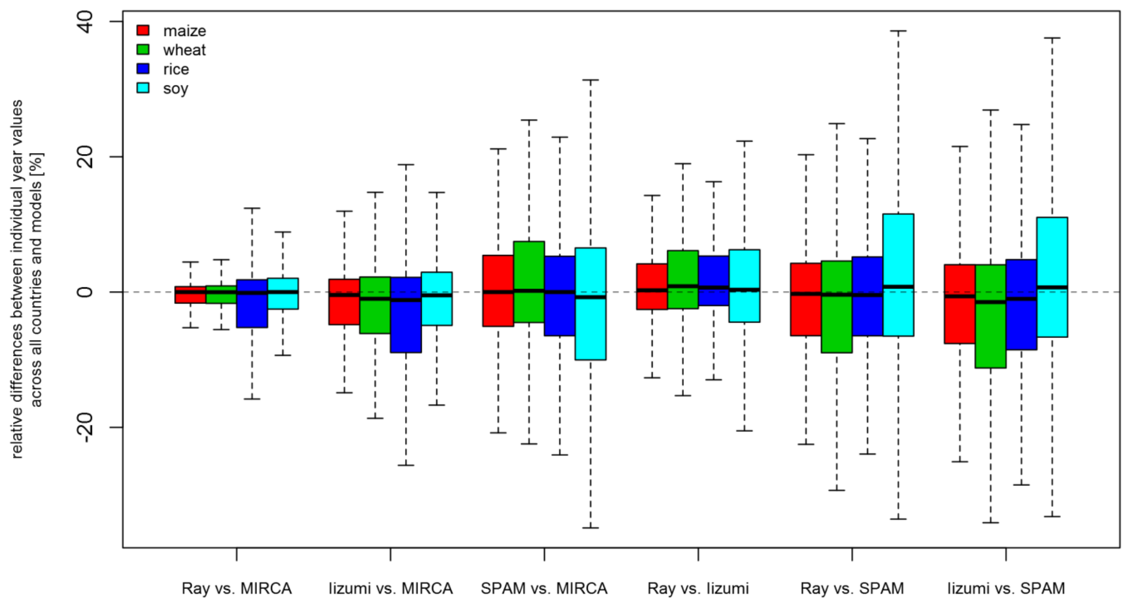

Figure 2-2. Boxplots of relative differences (%) between aggregated yield time series (t/ha) over 208 countries, 14 GGCMs and 31 years of the weather data set AgMERRA for the four crop types (n = 357365 for maize, n = 290061 for wheat, n = 214617 for rice, n = 202619 for soybean). Boxes show the interquartile (25–75%) range across the GGCMs used, whiskers expand to 1.5 times of inner-quartile range of national aggregated yield, and black lines within the boxes display the median value (outliers are not displayed).

Across 208 countries, 14 GGCMs, and 31 years, aggregation induced differences between nationally aggregated yield estimates for the four crop types can be very large (>10 DM t/ha), but the majority is below 10% of relative difference (<0.3DM t/ha in absolute terms). The aggregations with Ray show least differences to aggregations with MIRCA, whereas SPAM-based aggregations show strongest differences to MIRCA, Iizumi, and Ray-based aggregations (Fig. 2). Largest relative differences in yield sets can be found for soybean especially in comparison of SPAM to each of the other three aggregated sets. Aggregated maize yield are least affected by the aggregation uncertainty. When accounting for differences in total crop area, e.g. when looking at differences in production (t) rather than in productivity (t/ha), the relative differences between country scale aggregations are even stronger (Fig. C in the SI Appendix). This is caused by differences in quantity and spatial pattern of the harvested area data set applied for the aggregations. At the national level, the crop cover mask can be of greater importance. In Tables

3–6, the effects of different aggregations on country scale are displayed for the top-ten producer (for all countries and the four crops Tables D.1–4 in the SI Appendix). Differences over the 31 years are shown as the percentage minimum and maximum mean relative difference between the aggregations with Ray, Iizumi, SPAM, and MIRCA-based aggregation. Differences in temporal dynamics induced by the different crop masks applied for the aggregation are shown by the minimum correlation coefficient (r) between aggregated national time series (one per GGCM). Countries were ranked by their share on global production as averaged over the years 2009–2013 (FAO, 2014). Of the top-10 maize producers (United States, China, Brazil, Argentina, Mexico, India, Ukraine, Indonesia, France, and South Africa) - South Africa, India, and France show stronger sensitivity to the choice of the aggregation mask, while the USA (SI Appendix Fig. F.3) is less sensitive to the choice of crop mask (for all countries see SI Appendix Table D.1). Of the top-10 maize producers, yield simulations can be strongly affected by the national aggregation mask by up to 67% (South Africa), 38% (India) or 28% (France, Fig. 3).

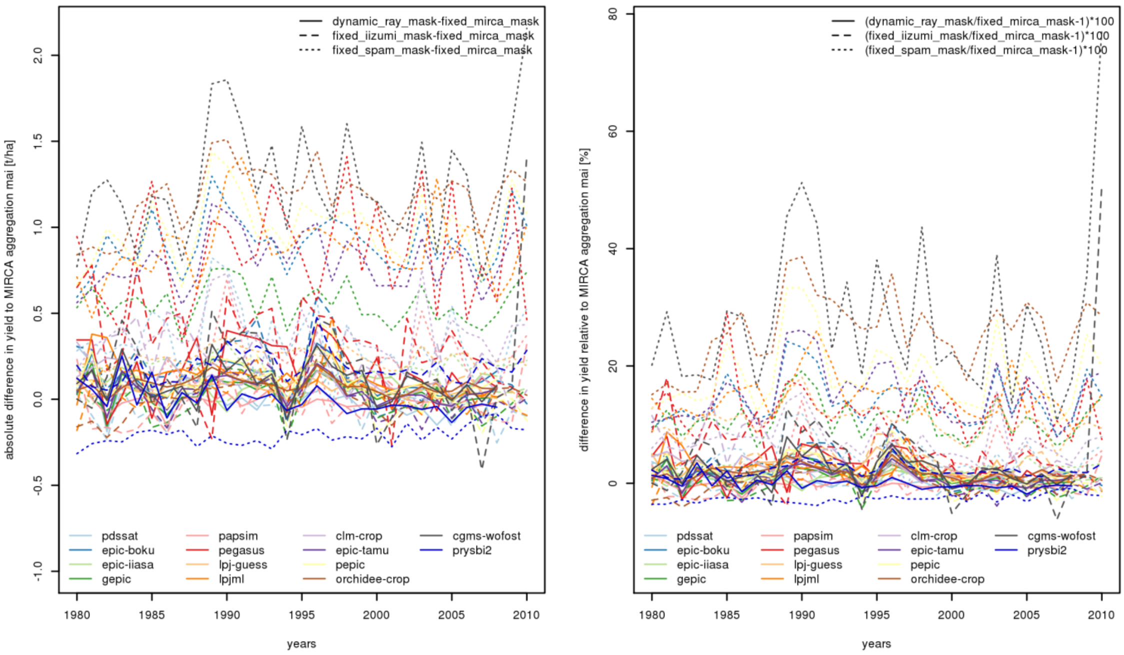

Figure 2-3. Absolute (t/ha) (left panel) and (right panel) relative difference (%) between nationally annual aggregated yield time series displayed for the example case of maize yield (DM t/ha) in France. Difference per model, year, and mask from the four aggregation sets is largest with the SPAM aggregation (dotted lines) and for most models accounting for about one additional t/ha.

Individual years can be affected more strongly, so that the correlation between the MIRCA-based aggregated time series and the ones obtained with the Ray mask can be low, as in India ($r = 0.56$), while the correlation is not necessarily low if there are stronger differences in mean yields (e.g. France with minimum $r = 0.95$). From the top-10 wheat producer countries (Table 4) Canada with −28–41% has the largest span of relative yield difference as well as a low correlation coefficient of $r = 0.41$ (Iizumi-SPAM). For Pakistan, differences in mean yield of up to 43% can be observed for the MIRCA-based aggregation compared to the one with Iizumi. Only the mean relative difference between aggregated yield sets for Russia, United States, France, and Germany are about 15% or less. For the case of wheat productivity in Russia low differences in yields are shown but the correlation coefficient reaches as low values as $r = 0.05$ displaying the larger deviations of temporal patterns in aggregated yield sets (MIRCA-SPAM). In the case of rice productivity (Table 5), relative differences between aggregations sets for Indonesia and Brazil are below 10%. Indonesia has fairly high correlation across all masks pairings but for Brazil the correlation between the MIRCA and Ray-based aggregations is as low as r = 0.32. Rice yields for Vietnam, Philippines, Thailand, and Japan show very strong relative differences between aggregated yield sets. For rice in Vietnam also the temporal dynamics are affected by the choice of aggregation mask, reflected by a very low correlation coefficient of r = 0.13 when comparing MIRCA- to SPAM-based aggregations. For soybean several countries show large relative differences attributed to the crop mask and the modelled yield patterns across the country. For soybean in Bolivia the relative difference between the Ray and the SPAM-based aggregation reach 427%, for Paraguay 82% between Iizumi- and SPAM-based aggregations, followed by India with 48% relative yield difference between the Ray- and the SPAM-based aggregation. China and the United States show the lower sensitivity to the crop mask applied with ranging around 10% relative difference between the different aggregated yield sets. Although soybean yields of Brazil show relatively low sensitivity to the aggregation mask effects with 23% as maximum relative difference, but the correlation coefficient of r = 0.07 between the Ray- to SPAM-based aggregation is very low, displaying little agreement in temporal pattern between the time series. Temporal dynamics of soybean productivity in Uruguay, Canada, and India are greatly affected by the aggregation mask and can reach even negative correlation coefficients. The differences due to aggregation can become exceptionally high in countries with pronounced differences in crop-specific harvested area information (SI Appendix Tables G.1–2) and where GGCMs simulate heterogeneous yield patterns, as reflecting strong gradients in climatic conditions or crop management practices. Strong yield gradients between grid cells within a country can also derive from model-specific calibration processes of e.g. simulated yields to observations of field experiments or country-specific reference data sets (SI Appendix Table A.5). The effect of calibration may even increase the aggregation uncertainty, which is exemplified by maize yield aggregations in Egypt (Fig. 4, SI Appendix Fig. E.1).

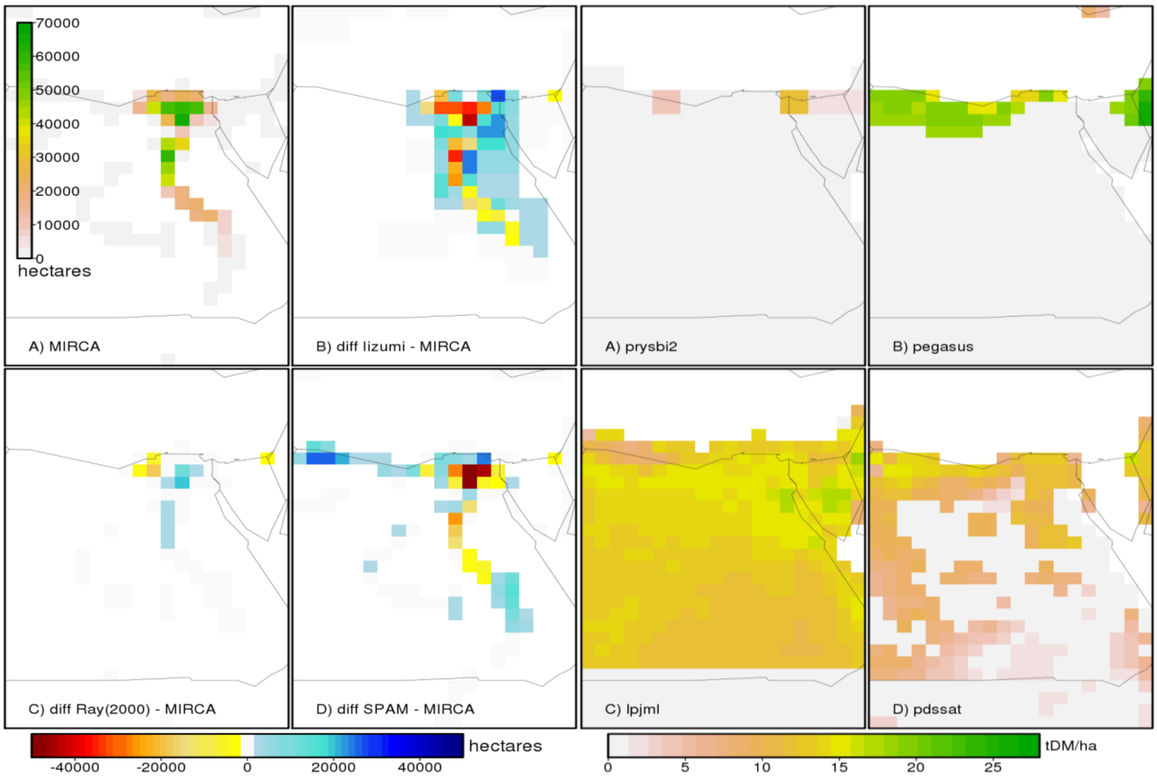

Figure 2-4. (Left panel) For irrigated maize harvested areas (ha) in Egypt, spatial patterns and quantities differ between the crop masks. The maps show grid cell scale harvested area as reported by MIRCA2000 (A), and the absolute differences between harvested areas of Iizumi (B), Ray (C), and SPAM2005 (D) and MIRCA2000, respectively. (Right panel) Spatial patterns of simulated irrigated maize yields, as means over the AgMERRA

weather data time period and before any masking by crop-specific harvested area data, supplied by four models A) PRYSBI2, B) PEGASUS, C) LPJmL, and D) pDSSAT before being masked by a harvested area data set. The gray shaded areas indicate grid cells where the climate conditions were regarded as unsuitable to grow irrigated maize by a model.

In Egypt almost the entire maize production is irrigated. In Fig. 4 we show GGCM simulations of four different models. PEGASUS and PRYSBI2 simulate very heterogeneous yield patterns, whereas pDSSAT assumes more homogeneous and LPJmL simulates very homogeneous yield patterns, assuming national uniform crop production intensities. In the case of model PRYSBI2, the only area with higher yields is around Port Said, for which only the Iizumi crop mask reports some larger harvested area for maize (Fig. 4, SI Appendix G.1–2). PRYSBI2 calibrates several parameters (more details in SI Appendix Table A.5) on grid cell level to best match the yields to the Iizumi et al. (2014) yield reference data set in their "default" simulation. Consequently, aggregated PRYSBI2 yields are very low, except when aggregated with the Iizumi crop mask, which results in an aggregated annual yield being up to 250% more productive compared to the other aggregations. For the model PEGASUS, the productive harvested area is located along the Mediterranean coastline. Calibration in PEGASUS consisted in tuning the radiation use efficiency factor (ß) to select a proper crop variety to best match the yield data of Monfreda et al. (2008) according to the Willmott (Willmott et al., 1985) index of agreement (Deryng et al., 2011). The aggregated national result for PEGASUS's yields shows stronger differences for the SPAM aggregation, which reports less harvested maize areas along the Mediterranean coast line. LPJmL calibrates its parameters: maximum leaf-area-index under unstressed conditions, harvest index, and factor (alpha) for up-scaling leaf-level-photosynthesis to stand level, at country scale, to best match the national yields reported by the FAO. LPJmL thus simulated a very homogeneous yield pattern for irrigated maize in Egypt, as climatic conditions are similarly very hot and dry − but irrigated across the area. The yields of pDSSAT are calibrated to field experiment results. The maize yield pattern of pDSSAT for Egypt is less homogeneous than LPJmL as it takes into account more spatial detail on fertilizer application and other management parameters. Further analysis reveals that sub-regions of larger producing countries, as in individual FPUs of the USA, show a mixed response. Major production areas of the USA along the Mississippi (SI Appendix Fig. F.1), the Missouri, and the Ohio River catchments show very little sensitivity to the choice of the crop mask. Other FPUs, such as the Colorado River catchment (SI Appendix Fig. F.2) or California, show larger discrepancies between the aggregated yield sets. At the national scale, these regional discrepancies do not show, as the national aggregated productivity is numerically dominated by the major production areas, which show little sensitivity to the choice of the aggregation mask (SI Appendix Fig. F.3) Assuming static crop masks in the assessments of climate change impacts on agricultural productivity can also strongly affect the projected impact on crop yields. We demonstrate this by aggregating the climate change impact projections on yields of the ISI-MIP/AgMIP fast track (Rosenzweig et al., 2014) with different time slices of the Ray crop mask (years: 1961, 1984, and 2008) as if the assessment had been conducted in these years, assuming 'current' crop masks. We find strong effects on the projected future yield changes in response to climate and elevated atmospheric CO_2 for individual crops in some countries. Fig. 5 shows the differences in projected relative yield changes (percentage change of the period 2070–2099 relative to the 1980–2009 baseline) between the country scale aggregation with the 1961 mask and the aggregation with the two other masks (1984 and 2008) for all seven models that contributed to the ISI-MIP/AgMIP fast track (Rosenzweig et al., 2014). The differences in the five climate projections affect the heterogeneity of simulated yields and thus the sensitivity of aggregated yield changes to the crop mask (bars and whiskers in Fig. 5). For aggregated maize yield projections in India most models show a positive trend with time in projected changes in yields. The projected difference in relative yield change simulated by EPIC-BOKU, GEPIC, and pDSSAT models are considerably higher for the aggregation with Ray's harvested area time slice of 2008 compared to the 1961 as the relative yield change of the aggregated yield with the 1984 mask compared to 1961er. For the case of wheat in Australia the projected yield changes agree quite well, showing only slightly median differences between the time slices used for aggregation. Only the EPIC-BOKU projections show a high variability and maximal difference of yield change of up to −10% with the 2008er in comparison to the 1961 mask but only 4% difference for the 1984 in comparison to the 1961 time slice. This is because the crop-specific harvested area regions in the former case have changed a lot with significant expansion of harvested maize areas in southern India, whereas in Australia the regions have remained roughly similar. In the case of rice productivity in Brazil, aggregations with the crop mask of 2008 lead to higher difference in yield change projections than the 1984 mask (except for GEPIC) compared to the aggregation with the 1961 time slice. For soybean in Argentina the magnitude of differences in projected yield change are less pronounced between the time-slices' aggregation used but are very different among models as for pDSSAT, and LPJ-GUESS up to 20% but more than 40% for PEGASUS. Differences in climate change impact projections for all other countries of the top-10 producer countries are lower than for those countries displayed in Fig. 5.

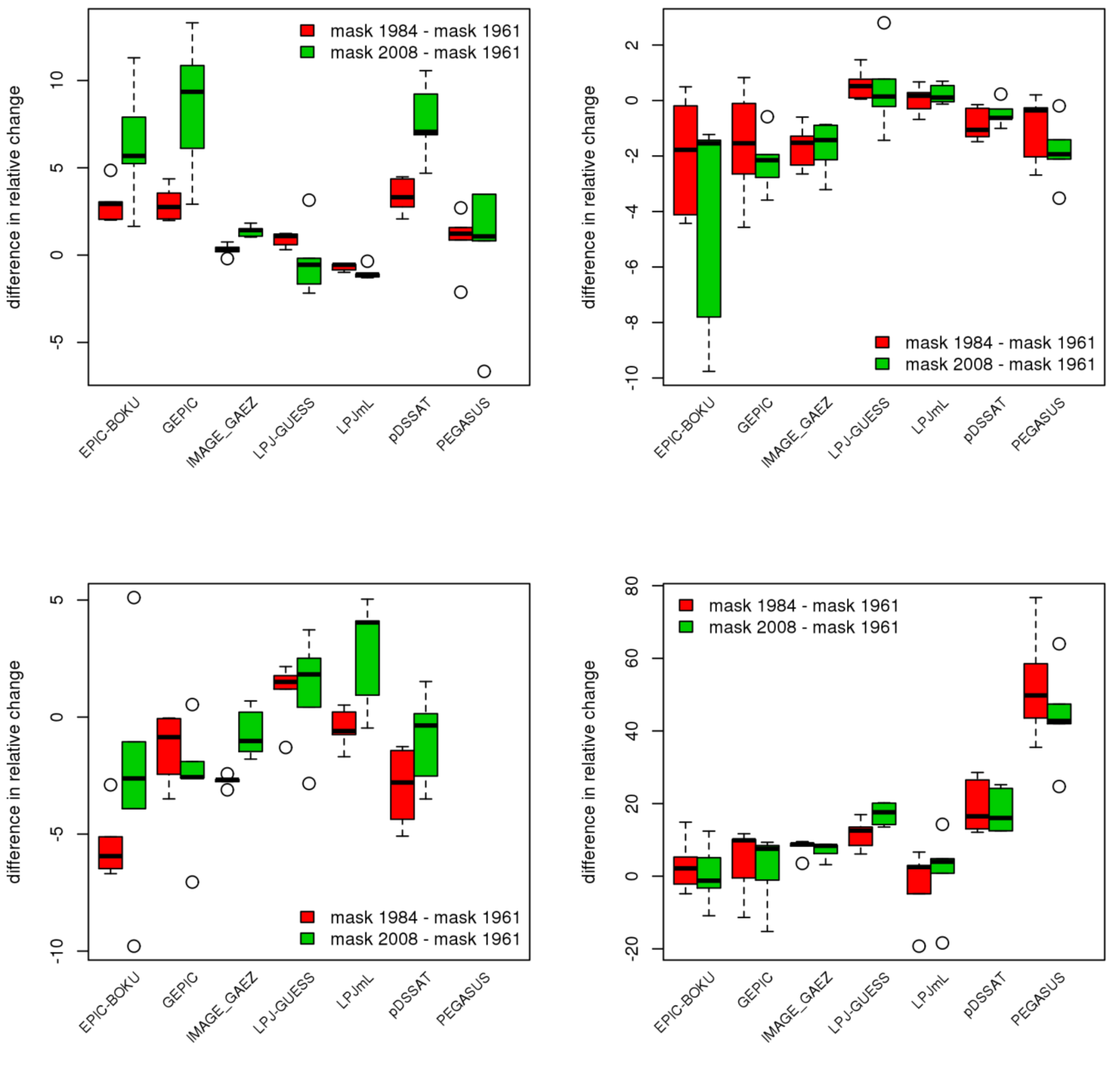

Figure 2-5. Differences in projected relative yield changes (percentage change of the period 2070–2099 relative to 1980–2009) between the aggregation with the Ray crop mask of 1961, and that of 1984 (red) and 2008 (green).

The panels display aggregated yields for one of the top-10 producer countries for each of the four crops: (Upper left panel) India for maize, (upper right panel) Australia for wheat, (bottom left panel) Brazil for rice, and (bottom right panel) Argentina for soybean. Boxes show the interquartile (25–75%) range across the five GCMs used, whiskers expand to 1.5 times the inner-quartile range of national aggregated yield and outliers are depicted as dots. Black lines within the boxes display the median value. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.4 Discussion

We find that differences in crop masks affect not only the mean bias of aggregated yield time series but also the temporal dynamics, resulting in low or even negative correlations between the differently aggregated time series (Tables 3–6, and D.1–8 in the SI Appendix). This is of particular concern, as model skill is often determined by comparing temporal dynamics rather than mean yields. Large difference between aggregated yield time series occur, when areas suitable for crop growth (determined by the individual model) are combined with a large harvested area reported by one mask but rather little by another (Fig. 4, SI Appendix, Tables G.1–2). Developers of GGCMs need to analyze the spatial variability of their simulations for plausibility. Models that tend to simulate very heterogeneous patterns of crop yields due to calibration, flexible parameter specifications, and assumptions on management practices (e.g. cultivar choice, fertilizer application, sowing dates) were more sensitive to the choice of crop mask (SI Appendix, Table A.5). Further differences between the aggregated productivity time series result from the fact, that spatial location of national borders of the various original crop masks are different due to different data products included by the authors (Table 2). When applying publicly available statistics for down-scaling data to a grid cell (as the authors did to produce the harvested area data sets) its accuracy is also limited by the fact, that the historical development of states cannot be well reflected in a timely manner. Also, we assume that each grid cell always belongs to a single country, whereas often the simulated grid cell level results would need to be attributed as fractions to multiple countries. However, since we treat this consistently across the different crop mask data sets used, we consider the resulting error as not relevant in the comparison of the different crop masks in the aggregation process. The spatial patterns of crop-specific harvested areas as provided by the four data sets here used for aggregation, and the information on where irrigation is applied for these crops is central to large-scale crop modeling. The crop-modelling community requires more complex and updated data on the spatial and temporal dynamics of agricultural production systems. The Ray data set is the only crop mask that is dynamic in time and it also is typically the aggregation mask that shows the largest differences in the temporal dynamics between the aggregated yield time series (low correlation coefficients). We conclude that each of the four harvested area data sets has its unique features and none can be identified as particularly superior by our study. For particular regions spatial aggregations should be performed with alternative crop masks to assess the effects of aggregation uncertainty and to avoid drawing erroneous conclusions on model skill or projected impacts. Reporting productivity is what is typically done to communicate or analyze climate change impacts on agriculture (e.g. Müller et al., 2015; Osborne et al., 2013; Wheeler and von Braun, 2013) or to inform land use change models (Müller and Robertson, 2014; Nelson et al., 2014a,b; Schmitz et al., 2014). With some exceptions, as e.g. GLOBIOM (Havlík et al., 2012, 2011) and MAgPIE (Dietrich et al., 2014; Lotze-Campen et al., 2008), these models require information on changes in agricultural productivity aggregated to their simulation units (because of their often coarser resolution, as e.g. national or supra-national regions). General shifts of cropping areas towards higher productive areas are very likely (Beddow and Pardey, 2015) as can be investigated by land use models, which project changes in land use and production as socio-economic responses to changes in agricultural productivity. Future land use uncertainty can also be addressed by aggregating simulated changes in productivity with external land use scenarios as in Pugh et al. (2015) and remain a challenge for further crop modeling studies.

2.5 Conclusions

This study shows quantitative differences between the aggregated gridded yield time series revealing the uncertainty induced by the aggregation applying differing harvested area data sets. The effects of aggregation uncertainty are the shift of the multiannual mean national yield and an influence on the variability over time, depending on the heterogeneity of simulated yield patterns by the models and the differences between crop masks. This uncertainty is already significant in global aggregations of grid cell scale yield simulations and can be very large for some aggregation unit-crop-model-year combinations. Aggregation uncertainty of gridded yields becomes even more important when taking into account production instead of productivity. For projections of future agricultural production, this aggregation uncertainty will likely be small compared to given uncertainties in future climate change, adaptation options, and capacities. The potentially large differences between different aggregations for individual countries or regions will have to be considered in future model evaluations and also in future crop yield projections. This requires considerable investment for building a transparent method for aggregation. The study also illustrates the need to transition from assuming static harvested areas towards dynamic projections that account for spatial shifts in crop distribution and production induced by changes in social and environmental conditions.

Author's contribution

The research question to this paper has been developed and proposed by the GGCMI coordinators J.E. and C.M. J.E. and J.C. performed the post-processing as aggregating the submitted data from grid cell-level to coarser spatial units. C.M. and V.P. conducted the analysis. V.P. wrote the manuscript with substantial contributions from C.M., P.C., D.R., T.I., J.E, D.D., R.C.I, and C.J. All co-authors provided data to the GGCMI project, discussed, and commented on the manuscript.

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Supplement

Supplementary data associated with this article can be found in the online version, at: http://dx.doi.org/10.1016/j.eja.2016.08.006.

Supplementary data and material associated to this Chapter 2 is provided in the Appendix A.

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3 Generating a rule-based global gridded tillage dataset

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Abstract

Tillage is a central element in agricultural soil management and has direct and indirect effects on processes in the biosphere. Effects of agricultural soil management can be assessed by soil, crop, and ecosystem models, but global assessments are hampered by lack of information on the type of tillage and their spatial distribution. This study describes the generation of a classification of tillage practices and presents the spatially explicit mapping of these crop-specific tillage systems for around the year 2005. Tillage practices differ by the kind of equipment used, soil surface and depth affected, timing, and their purpose within the cropping systems. We classified the broad variety of globally relevant tillage practices into six categories: no-tillage in the context of Conservation Agriculture, traditional annual, traditional rotational, rotational, reduced, and conventional annual tillage. The identified tillage systems were allocated to gridded crop-specific cropland areas with a resolution of 5 arcmin. Allocation rules were based on literature findings and combine area information on crop type, water management regime, field size, water erosion, income, and aridity. We scaled reported national Conservation Agriculture areas down to grid cells via a probability-based approach for 54 countries. We provide area estimates of the six tillage systems aggregated to global and country scale. We found that 8.67 Mkm2 of global cropland area was tilled intensively at least once a year, whereas the remaining 2.65 Mkm2 was tilled less intensely. Further, we identified 4.67 Mkm2 of cropland as an area where Conservation Agriculture could be expanded to under current conditions. The tillage classification enables the parameterization of different soil management practices in various kinds of model simulations. The crop-specific tillage dataset indicates the spatial distribution of soil management practices, which is a prerequisite to assess erosion, carbon sequestration potential, as well as water, and nutrient dynamics of cropland soils. The dynamic definition of the allocation rules and accounting for national statistics, such as the share of Conservation Agriculture per country, also allow for derivation of datasets for historical and future global soil management scenarios. The resulting tillage system dataset and source code are accessible via an open-data repository (DOIs: https://doi.org/10.5880/PIK.2019.009 and https://doi.org/10.5880/PIK.2019.010, Porwollik et al., 2019a, b).

3.1 Introduction to tillage

Global cropland covers an area of about 15 Mkm^2 (Ramankutty et al., 2008), which is approximately 13 % of global ice-free land. Cropland and associated land management contribute about 4.5 % of global anthropogenic GHG emissions accounting for emissions from rice cultivation, peatland drainage, and nitrogen fertilizer application in the year 2000 (Carlson et al., 2016). Tillage and plowing (further jointly referred to as tillage) are practiced on most of this cropland (Erb et al., 2016; Pugh et al., 2015). Tillage comprises farm operations usually practiced for seedbed preparation, weed, and pest control, or incorporation of soil amendments. According to Schmitz et al. (2015), conventional tillage can be distinguished on the one hand into traditional systems with manual labor and tools and on the other hand into mechanized systems. Conventional tillage usually comprises inversion and mixing of the soil layers with the biophysical loosening of the soil, leading to altered temperature and soil moisture levels in the affected soil layer (S1 for further terms and definitions used in this study). Current global soil management practices trend towards a reduction of tillage operations and intensity (Derpsch, 2008; Smith et al., 2008). Reduced intensity of the tillage operation as either in the case of strip-, mulch-, ridge-, and no-tillage is also referred to as conservation tillage (CTIC, 2018). Reduced tillage practices are especially suitable for agricultural production (a) of grain crops such as cereals, legumes, and oilseed crops (Giller et al., 2015); (b) on large, mechanized farms to save labor (Mitchell et al., 2012; Ngwira et al., 2012), fuel (Young and Schillinger, 2012), and machine wearing (Saharawat et al., 2010); (c) under arid climate conditions, because of its soil moisture preserving effect (Kassam et al., 2009; Pittelkow et al., 2015); and (d) on soils with high erosion rates (Govaerts et al., 2009; Schmitz et al., 2015).

Up to now there has been only little effort in the classification and area assessment of tillage systems at the global scale. Erb et al. (2016) reviewed data availability of land management practices at the global scale and found that there was no continental or global dataset on area, distribution, and intensity of tillage practices. They report 7.43 Mkm^2 to be under high-intensity tillage comprising the cropland area of annual crops and 4.73 Mkm^2 of area under low-intensity tillage, which comprises the cropland area of perennial crops, zero-tillage as stated by Derpsch et al. (2010), and young and temporal fallow cropland area as reported by Siebert et al. (2010).

The only global statistical data on a kind of tillage system area are provided by the FAO for the extent of Conservation Agriculture (CA) area (FAO, 2016) at the national scale. CA is a soil management concept comprising minimum soil disturbance (through direct seeding techniques), a permanent organic soil cover as mulch or green manure, and a diversified crop rotation (Kassam et al., 2009). It is applied to about 10 % of the global cropland area (FAO, 2016). The widest area spread of CA practice is reported for South America, followed by North America (accounting for over 84.6 % of the total global CA area), where it has been originally developed. Adoption of CA is much lower in Europe, Asia, Australia, and New Zealand, and with the lowest adoption rate in Africa (1.1 %, 2.3 %, 11.5 %, and 0.3 % of reported total global CA area, respectively) (Derpsch et al., 2010). The top three adopting countries of CA in terms of area are Argentina, Paraguay, and Uruguay (73.51 %, 66.67 %, and 46.13 % of their arable land, respectively) (FAO, 2016).

Prestele et al. (2018) mapped reported national values of CA area from Kassam et al. (2015) to cropland of the History Database of the Global Environment database (HYDE; Klein Goldewijk et al. (2017)) for the year 2012. Based on literature findings, Prestele et al. (2018) developed a CA adoption index per grid cell composed of a set of spatial predictors such as aridity, field size, soil erosion, market access, and poverty for downscaling reported national CA area values. Their resulting global map of CA area at a spatial grid resolution of 5 arcmin can be applied for impact assessments in global model simulations.

Data on tillage practices are available, e.g., for the USA through the reporting of the National Crop Residue Management Survey published by the Conservation Technology Information Center (http://www.ctic.purdue.edu/CRM/crm_search/, last access: 21 August 2018). The survey was pursued at national level until 2004 and continued for a subset of counties for subsequent years reporting on farming area managed under conventional, reduced, and conservation tillage (with further sub-categories of no-, ridge-, and mulch-tillage). For Europe, tillage practices have most recently been assessed by the Survey on agricultural production methods (SAPM) in 2010 based on census and sample survey data and published by EUROSTAT (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Survey_on_agricultural_production_methods_(SAPM), last access: 23 August 2018). In the EUROSTAT data portal farm type and size, and their corresponding area managed under the tillage categories, conventional, conservation tillage, and zero-tillage (often used as a synonym for no-tillage as referring to direct seeding techniques) are reported. Analyzing tillage practices in the EU-27 for the year 2010, it has been found that on average the share of conservation and zero-tillage practices increases with the size of the arable land area of a farm holding (EUROSTAT, 2018).

Soil, crop, vegetation, erosion, and Earth system models (ESMs) (in the following jointly referred to as ecosystem models) can be applied to assess the effect of different tillage practices on ecosystem elements, fluxes, and stocks. Some global carbon studies assess the climate mitigation potential of soils managed with no-tillage compared to conventional tillage, which was simulated as a temporally limited enhancement of the decomposition factor on the soil carbon pools under cultivated cropland (Levis et al., 2014; Olin et al., 2015; Pugh et al., 2015; Smith et al., 2008). More process-based representations of the tillage effect are applied in models such as the decision support system for agrotechnology transfer–cropping system model (DSSAT–CSM, White et al. (2010)) and the crop growth simulator (CROPGRO-soybean, Andales et al. (2000)) with direct and indirect biophysical effects on soil, water, crop yield, and emissions. Another field of global-scale studies assessing the tillage effect refers to the analysis of albedo enhancement perceived in cases of no-tillage in conjunction with associated increased residue levels left on the soil surface (Hirsch et al., 2017; Lobell et al., 2006). Furthermore, tillage is important in soil erosion assessment studies, often represented within the context of the land management factor amplifying sub-factors such as surface cover and roughness (Nyakatawa et al., 2007; Panagos et al., 2015).

McDermid et al. (2017) reviewed regional and ESMs' approaches of representing agricultural management practices and land use conversion with a focus on climate and land surface interactions, including tillage modifying carbon stocks in the soil as well as biogeophysical surface attributes. They reveal sources of uncertainty due to missing land management data and limited representation of processes in current assessment models. In regard to the tillage effect, they elaborate on the findings of Levis et al. (2014), who found decreased soil carbon levels below cropped and cultivated land compared to land without cultivation. McDermid et al. (2017) mention a potential overestimation of the efficacy of no-tillage practices' contributions to mitigating anthropogenic carbon by enhanced carbon stock based on findings of Powlson et al. (2014).

Pongratz et al. (2018) also reviewed data availability and process implementations within ESMs for 10 land management practices and conclude tillage to be currently underrepresented. They recommend simple and complex methods to model tillage effects on albedo, soil moisture, respiration, and the resulting impact on soil carbon stocks and fluxes. In the absence of detailed tillage area and type information, the global ecosystem modeling community currently can assess differences of contrasting tillage practice impacts just in the form of stylized scenarios, simulating the effect on the entire cropland area (Del Grosso et al., 2009; Olin et al., 2015;

Pugh et al., 2015). One recent exception is the assessment by Hirsch et al. (2018), who estimate the effects of an altered albedo from residues used for soil cover on CA areas, using the spatial data of Prestele et al. (2018).

The objective of this study is to (a) increase the understanding of differences in tillage practices at the global scale, (b) formulate rules to spatially map tillage systems to the grid scale, and (c) develop an open source and open data crop-specific tillage system dataset for the parameterization of tillage events and area in global ecosystem models and assessments. In order to do so we develop a global tillage system classification. Further we analyze underlying causes of the occurrence of different tillage systems and make use of available data in order to map them to a global grid of 5 arcmin resolution.

3.2 Data and method

3.2.1 Tillage system classification

Globally tillage systems differ by the kind of implement used, soil depth, and share of soil surface affected, mixing efficiency, timing, frequency, and by their purpose within the relevant cropping systems (Table 1).

Table 3-1. Six tillage systems and suggested parameterization for model applications (note that (a) several values per tillage system refer to each single tillage event within each tillage system in the same order as mentioned under frequency per year, and (b) for reduced tillage the inversion and mixing efficiency depends on the specific form of practice as mentioned above).

Tillage system	Conventional annual tillage	Rotational tillage	Conservation Agriculture	Traditional annual tillage	Traditional rotational tillage	Reduced tillage
Soil management components	Tillage for seedbed preparation, cultivation, post-harvest tillage	Tillage for seedbed preparation, cultivation, post-harvest tillage	Minimum mechanical soil disturbance with direct seeding	Hoe or cutlass for seedbed preparation, cultivation, post-harvest tillage	Hoe or cutlass for seedbed preparation, cultivation, post-harvest tillage	Tillage for seedbed preparation, cultivation, post-harvest tillage
Soil layer inversion	Yes, no, yes	Yes, no, yes	No	Yes, no, yes	Yes, no, yes	(Yes), no, (yes)
Frequency and timing per year	1 before seeding, 1 to 2 cultivation (10 days to 2 weeks after establishment), 1 after harvest	1 before seeding, 1 to 2 cultivation, 1 after removal	1 at seeding	1 before seeding, 1 to 2 cultivation (10 days to 2 weeks after establishment), 1 after harvest	1 before seeding, 1 to 2 cultivation, 1 after removal	1 before seeding, 1 to 2 cultivation (10 days to 2 weeks after establish-ment), 1 after harvest
Depth (cm)	20, 5, 20	20, 5, 20	5	10, 5, 10	10, 5, 10	<20, 5, <20
Mixing efficiency (%)	90, 20, 90	90, 20, 90	5	50, 20, 50	50, 20, 50	90, 20, 90
Soil surface affected (%)	100, 33, 100	100, 33, 100	20 to 25	100, 33, 100	100, 33, 100	100, 33, 100
Soil surface covered by residues after planting (%)	<15	<15	>30	<15	<15	15-30

Conventional tillage, often done with a moldboard plow, refers to the inversion and mixing of soil layers for seedbed preparation, incorporation of soil amendments and weed, pest, and residue management. In traditional tillage systems soils are usually managed with hand tools, e.g., hoe or cutlass (Schmitz et al., 2015), which is very labor and time intensive. The application of animal-drawn plows or the use of a moldboard plow attached to some motorized vehicle results in increased soil depth and mixing efficiencies of the tillage operation compared to traditional tillage implements. In the case of CA, there is only a minimal mechanical soil disturbance by direct seeding equipment or none in the case of broadcasting seeds.

The soil depth affected by the tillage operation is determined by the soil depth to bedrock, the implement used to till the soil, and by the purpose of the tillage event. A moldboard plow usually inverts and mixes the soil layers up to 20–30 cm depth. Pimental and Sparks (2000) state the minimum soil depth for agricultural production to be 15 cm, whereas Kouwenhoven et al. (2002) find that, for burying green manure and annual weed, a minimum tillage depth of 12 cm to be necessary and suggest 20 cm for the management of perennial weeds. We decided for a minimum depth of mechanized tillage of 20 cm. For traditional tillage with manual labor, tillage is assumed to reach only to a lesser depth, because of limited capacity to penetrate the soil profile (Schmitz et al., 2015). The affected depth by minimum soil disturbance practices under CA is assumed to be as deep as the seed placement requires, which is stated as approximately 5 cm by White et al. (2010) for no-tillage systems.

In conventional tillage systems, the tillage implement is usually applied to the entire soil surface to be effective. In contrast to that, no-tillage under CA may affect at most 20 % to 25 % of the soil surface during the direct seeding procedure (Kassam et al., 2009; White et al., 2010). On the field, reduced tillage as partial disturbance of the soil surface in the case of strip-, mulch-, or ridge-tillage can be achieved by applying either an inverting implement to a lesser soil depth or a lower share of soil surface affected, by using harrows or disks, or by fewer field passes. Reduced tillage practice can be simulated in the form of lower soil disturbance, frequency, depth, mixing efficiency, or higher residue share left on the soil surface ranging between values of conventional and no-tillage (15 % to 30 %).

Tillage mechanically loosens the soil by decreasing the bulk density of the soil. Soil bulk density and pore space determine the levels of surface contact between seeds and soil particles, root growth, and water infiltration. The mixing efficiency of tillage describes the degree of homogeneity achieved, e.g., when burying crop residues and redistributing soil particles in the affected soil horizon. The type of soil, its moisture content, and the speed of the tillage practice are further determining factors for the mixing efficiency of tillage (White et al., 2010) under field conditions. Too intensively or inappropriately tilled soils over a longer time period exhibit the destruction of soil aggregates by increasing bulk density leading to compaction or crusting (White et al., 2010). The mixing efficiency can be modeled as a factor modifying the homogeneity level of soil components and associated characteristics.

Conventional tillage in both mechanized and traditional farming systems leaves a low portion of residues covering the soil surface after seeding – usually less than 15 % (CTIC, 2018; White et al., 2010). Reduced tillage may leave 15 %–30 %, whereas in CA systems minimum soil surface covered by organic mulch is defined as at least 30 % after the seeding operation (CTIC, 2018). Timing and frequency of soil disturbance by tillage depend on the type of cropping system. For annual crops, tillage is performed annually at the time of establishment, after harvest, or both. When modeling perennial crops, the interval of the main tillage events on fields should reflect the length of the perceived entire plantation cycle. During the growing period less intense tillage may be necessary for weed management or intended inter-cropping purposes several times. This soil management is locally restricted to the space between the rows of the main crop and can be replaced by herbicide applications. Within CA-managed systems disturbance of the soil occurs only at the time of seeding. Weed in CA systems is either managed by sustaining a permanent soil cover of either mulch or cover crops, by diversified rotations, or by application of herbicide so that no further mechanical soil disturbance is necessary during the growing season.

Based on the literature findings mentioned above, we consider six different tillage systems, namely no-tillage in the context of Conservation Agriculture, conventional annual, rotational, traditional annual, traditional rotational, and reduced tillage (Table 1).

3.2.2 Datasets used for mapping tillage systems to the grid

To map the six tillage systems, spatial indicators on the basis of several environmental and socio-economic datasets are applied (Table 2). The basic data layer to this mapping study is the cropland dataset by the spatial production allocation model further referred to as SPAM2005 by the International Food Policy Research Institute and International Institute for Applied Systems Analysis (IFPRI/IIASA, 2017b). It reports physical cropland area for 42 crop types (Table S2 in the Supplement for a list of crop types) for the year 2005. SPAM2005 is a result of a disaggregation of national and sub-national data sources in a cross-entropy approach. The SPAM2005 dataset comprises four technology levels of crop production, distinguishing high input irrigated from purely rainfed with further distinction of rainfed into high input, low input, and subsistence production per crop type and grid cell (You et al., 2014). In this study only the entire physical cropland and the separated irrigated and rainfed cropland were used per grid cell. Adding up the reported cropland area of SPAM2005 for 42 crop types results in a total sum of 11.31 Mkm^2.

Table 3-2. Gridded and national-scale datasets used for mapping tillage.

Global gridded dataset	Resolution (arc-minutes)	Temporal coverage (year)	Source
Crop-specific cropland	5	2005	SPAM2005: IFPRI/IIASA (2017b)
Soil depth to bedrock	6	1990-2014	SoilGrids: Hengl et al. (2014)
Field size	0.5	2005	Fritz et al. (2015)
Water erosion	5	1990-2011 (~2000)	GLADIS: Nachtergaele et al. (2011)
Aridity	10	1961-1990	FAO (2015)
National data			
Conservation Agriculture (CA) area	country	2002-2013	FAO (2016)
Income level	country	2005	World Bank (2017)

The grid cell allocation key to countries accompanying the SPAM2005 cropland dataset (IFPRI/IIASA, 2017a) was applied in this study for any grid cell aggregation to country scale. Sub-national aggregations of grid cells to state or province level were done with the Global Administrative Areas database (Global Administrative Areas, 2015).

The dataset on soil depth to bedrock (Hengl et al., 2014) has been retrieved from SoilGrids, which is a soil information system reporting spatial predictors of soil classes and soil properties at several depths. It has been derived on the basis of the United States Department of Agriculture (USDA) soil taxonomy classes, World Reference Base soil groups, regional and national compilations of soil profiles, and several remote sensing and land cover products using multiple linear regressions. The dataset reports on the absolute depth to bedrock (centimeters) per grid cell.

The global gridded field size dataset by Fritz et al. (2015) has been derived and validated on the basis of a crowd-sourcing campaign. It reports four field size classes as “very small” (smaller than 0.5 ha), “small” (0.5 to 2 ha), “medium” (2 to 100 ha), and “large” (larger than 100 ha) (Herrero et al., 2017) for the year 2005. The field size and the SPAM2006 datasets both use the cropland extent presented in Fritz et al. (2015).
The Global Land Degradation Information System (GLADIS) (Nachtergaele et al., 2011) reports land degradation types and their spatial extent around the year 2000. From this database the global gridded water erosion data have been selected. The water erosion data report the sediment erosion load (t ha^{-1} yr^{-1}) per grid cell which the authors derived by applying the Wischmeier equation (Wischmeier and Smith, 1978). Values of the data range from 0 to 12 110 t ha^{-1} yr^{-1}, with the highest water erosion levels occurring in mountainous areas.
The aridity index dataset was retrieved from the Food and Agriculture Organization Statistics (FAO, 2015). The aridity index was calculated as the average yearly precipitation divided by the average yearly potential evapotranspiration (PET), based on Climate Research Unit (CRU) CL 2.0 climate data averaged for the years from 1961 to 1990 applying the Penman–Monteith method. It reports values per grid cell ranging from 0 to 10.48, where values smaller than 0.05 are regarded as “hyper arid”, 0.05–0.2 as “arid”, 0.2–0.5 as “semi-arid”, 0.5–0.65 as “dry humid”, and values larger than 0.65 as “humid”.
The AQUASTAT online database reports annually the spread of Conservation Agriculture (CA) practices at the national scale (FAO, 2016). From this data source, national CA area values were retrieved for all 54 countries that reported any CA with the total area sum of 1.1 Mkm^2. Not all of these countries reported values for the year 2005, so that values closest to 2005 were selected from the available set, giving preference to data availability over matching the year 2005.
The average farm size per country dataset (n=133) (Lowder et al., 2014) is based on FAO farm size time series data. National average farm size was largest in land-rich countries, with the top three countries being Australia (3243.2 ha), Argentina (582.4 ha), and Uruguay (287.4 ha) (Lowder et al., 2014). The authors found average farm size to increase with the elevated income level of a country.
Furthermore, we retrieved the income level per country by the World Bank (2017) for the year 2005. The data refer to four categories of countries' gross national income (GNI $capita^{-1}$ yr^{-1}), as “Low income” (less than USD 875), “Lower middle income” (USD 876–3465), “Upper middle income” (USD 3466–10 725), and “High income” (more than USD 10 725).

3.2.3 Processing of input data and mapping rules

For calculation purposes, all gridded input datasets mentioned above were harmonized in terms of spatial extent, resolution, and origin. The spatial extent of the target dataset comprises all cropland cells reported by SPAM2005 (IFPRI/IIASA, 2017b). The targeted resolution is 5 arcmin, which partially required resampling and (dis)aggregation of the applied datasets using R (R Development Core Team, 2013) version 3.3.2 loading packages “raster” (Hijmans and van Etten, 2012), “fields” (Nychka et al., 2016), and “ncdf4” (Pierce, 2015). More details on the input data harmonization and processing can be found in the accompanying R code (Porwollik et al., 2019a).
We developed several mapping rules to allocate the six tillage systems to the grid-cell scale, employing a decision tree as shown in Fig. 1. The decision tree approach has also been applied in other spatial mapping exercises, e.g., in Verburg et al. (2002) and Waha et al. (2012). Hierarchical classification procedures based on expert rules can be used to distribute data of a larger spatial (e.g., administrative) unit to the grid cell level (Dixon et al., 2001; Siebert et al., 2015; van Asselen and Verburg, 2012; van de Steeg, 2010).

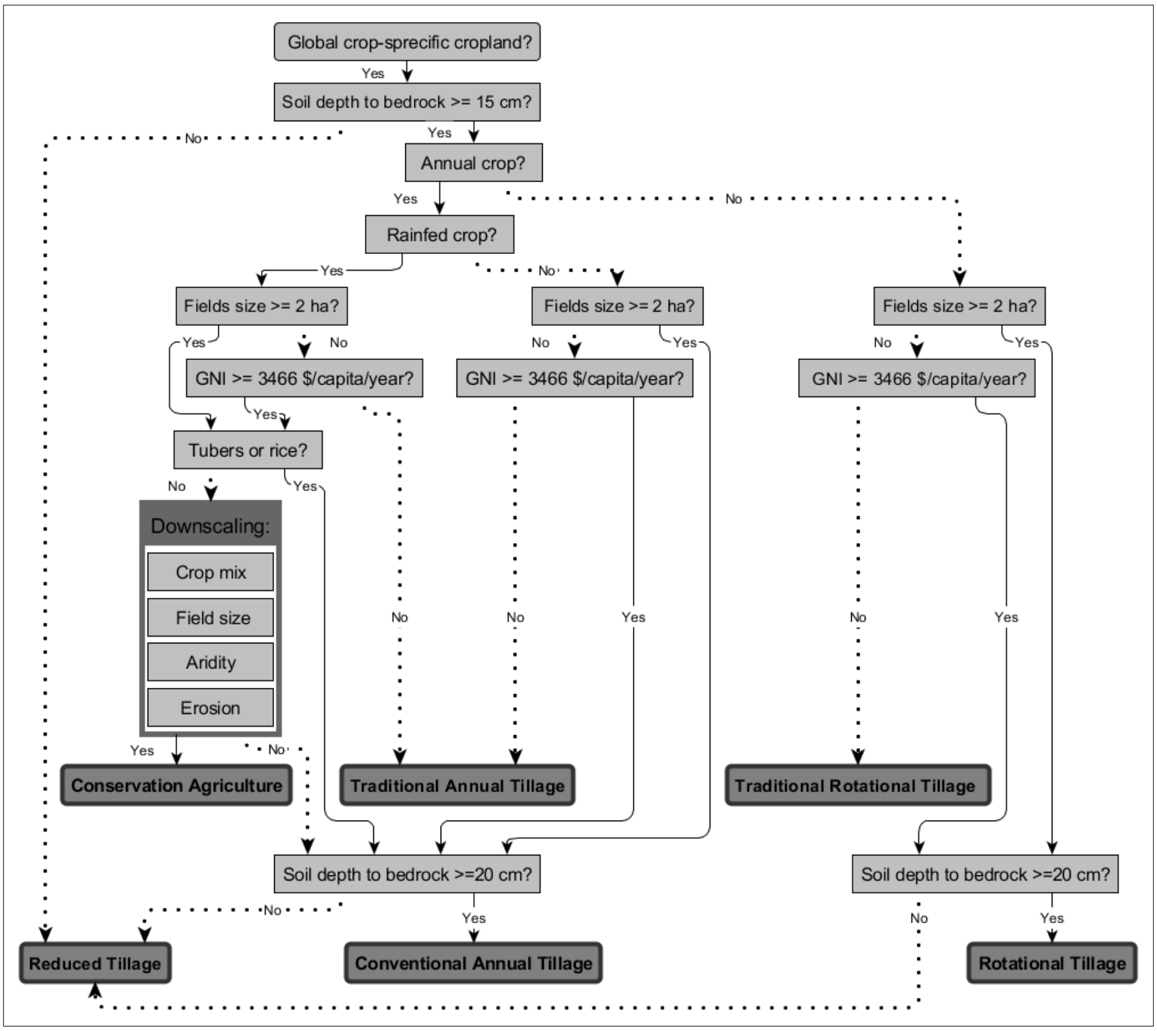

Figure 3-1. Decision tree for allocating cropland to six derived tillage systems. The data processing and mapping were pursued as depicted from top to bottom of the diagram. Each box represents a check on a grid cell of whether reporting values from the different data layers meet the derived thresholds or specific cropland features. The arrows with solid lines indicate a "yes" and arrows with dotted lines a "no" in the allocation procedure of crop-specific area to tillage systems. The box indicating the "Downscaling" represents our probability and suitability indicators applied to downscale national CA area values to a spatially heterogeneous pattern at per grid cell. Boxes with darker grey background shading and thicker frames show the derived types of tillage systems. (Abbreviation of gross national income as GNI).

As a first step, the SPAM2005 cropland dataset is masked for grid cells reporting cropland but soil depth to bedrock of less than the required 15 cm for agricultural production according to Pimental and Sparks (2000) (Fig. 1). This contextual mismatch between these two datasets may be caused by different input data used by the producers or by their method of averaging values within one grid cell, in which the soil depth to bedrock is heterogeneous. The entire cropland of these shallower grid cells is allocated directly to the reduced tillage system area, where ridging or raised beds may be practiced by the farmer because of physical hindrance for inverting tillage practices at increased depth.

The remaining cropland is treated separately for annual and perennial crops following Erb et al. (2016)'s findings, differing between plant-type associated tillage by intensity in terms of frequency and timing of the tillage operation (Table S2 for crop-type classification).

As a further step, we distinguished tillage practices per water management regime. We assumed that soils of irrigated crops are more regularly exposed to some level of mechanical soil surface alteration, i.e., leveling off of the surface in order to distribute irrigation water most efficiently and homogeneously over the field. We allocated all irrigated annual cropland either to traditional or conventional annual tillage area depending on field size and income level (Fig. 1).

Annual and perennial tillage systems are both further distinguished by the level of mechanization and commercial orientation of the crop production. We follow the definition of smallholder farming used in Lowder et al. (2016) if cultivation area is smaller than 2 ha. According to Fritz et al. (2015), field size can be regarded as a proxy for agricultural mechanization and human development. Further, Levin (2006) found that field size and farm size are positively related. Based on these findings, we apply the field size dataset as a proxy for farm size and mechanization. We categorize cropland per grid cell reporting field size equal to or larger than 2 ha as "large" scale assuming access of the farmer to mechanized farming equipment, and field size smaller than 2 ha as "small" scale farming with rather manual labor. Field size data are not available for all grid cells where SPAM2005 reported cropland. Consequently we interpolated for missing field size grid cell values using the mean of surrounding grid cell values. The spatial distance to the Hawaiian islands was too far for this operation, so there field size was set to a value of 2 ha, assuming a land restriction to field size due to the islands' geographic pattern and in the absence of any alternative information.

We further assume that animal draught power and mechanized soil management practices on a farm also occur as a function of income, indicating the financial capital a farmer might have access to. Therefore, we additionally apply the national average income level dataset to differentiate between small field sizes in higher-income countries, where access to financial capital for investment in farm equipment is perceived to be easier than for farmers with small field sizes in lower-income countries. In order to do so, we reclassified countries reported in the income dataset considered "low" and "lower-middle income" as "low income", and those countries formerly considered "upper-middle income" and "high income" as "high income", in this study. In grid cells reporting newly derived small field size and low income, we then allocated perennial cropland to traditional rotational tillage and annual cropland to traditional annual tillage. In high-income countries or in a grid cell reporting field sizes larger than 2 ha situated in low-income countries, perennial cropland was assigned to rotational tillage and annual cropland to conventional annual tillage assuming a rather commercially oriented farming system with access to market, financial capital, and therefore mechanized soil management equipment (Fig. 1).

We applied a downscale algorithm of national reported CA area values to a subset of rainfed annuals' cropland area (see Fig. 1, box "Downscaling"; see the following Sect. 2.4 for more details). The remaining rainfed annuals' cropland not being assigned to CA area is checked again for soil depth to bedrock. In case it was shallower than 20 cm, the cropland was also assigned to reduced tillage, assuming less depth, frequency, mixing efficiency, or alternative cultivation practices. In the case of a soil depth to bedrock of 20 cm or more, the remaining cropland depending on crop type was either mapped to the conventional annual or to the rotational tillage system.

3.2.4 Downscaling reported national CA area to the grid cell

Mapping rules for downscaling CA

Generally it can be assumed that the entire cropland is suitable for some kind of sustainable farming technique, but in the following we refer to "potential CA area" as the area where we regard the adoption of CA as more likely than for the remaining cropland where CA adoption would require additional assistance or support for the farmer. Potential CA area is derived from the cropland of 22 rainfed annual crops in grid cells reporting dominant large field size in low-income countries and all field sizes in high-income countries. Cropland areas of annually planted rainfed crop types were considered suitable for CA practice following the finding of Kassam et al. (2009), who

state that much of the CA development to date has been associated with rainfed arable crops. We selected the following annual crop types reported by SPAM2005 as suitable for CA in this study: barley, beans, chick peas, cotton, cowpea, groundnut, lentil, maize, other cereals, other pulses (e.g., broad beans, vetches), pearl millet, pigeon pea, rapeseed, rest (e.g., spices, other sugar crops), sesame seed, small millet, sorghum, soybean, sunflower, tobacco, vegetables (e.g., cabbages and other brassicas), and wheat (see Table S2), following Giller et al. (2015)'s findings on CA suitability of (dryland) grain crop types. All annual rainfed root, tuber, and rice cropland is excluded from the potential CA area following Pittelkow et al. (2015), who reported larger yield penalties for these crop types when applying no-tillage practices. Rice is often produced as paddy rice, requiring puddling, which is a practice modifying the soil aggregates a lot in order to facilitate the flooded condition, e.g., to suppress weed growth. A conversion from puddled to dryland rice production as well as improved drainage of tuber crop production area may require additional management steps by the farmer in order to achieve comparable yield levels with no-tillage to under conventional production methods. The resulting potential CA area amounts to 4.65 Mkm^2.
As stated by Powlson et al. (2014) for the Americas and Australia, by Rosegrant et al. (2014) in general on no-tillage, by Scopel et al. (2013) for Brazil on CA, and by Ward et al. (2018) on CA, the largest adoption rates of minimum soil disturbance management principles can be found on medium to large farms. There is low adoption of CA or no-tillage among small-scale farms, with the exception of Brazil (Rosegrant et al., 2014), where adoption of CA was supported through policies and technological investments.

We developed a linear regression with the “stats” package of R (R Development Core Team, 2013), applying the linear correlation model (“lm function”) to assess the statistical relation between national average farm size (Lowder et al., 2014) and percentage share of CA area (FAO, 2016) on arable land. The functional relation exhibits an increase in the national share of CA on arable land with an increase in average farm size over the country sample (Fig. S3).

Based on the literature findings and regression results, we assumed that no-tillage in the context of CA was highly probable for cropland in grid cells with large fields (here serving as a spatial proxy for large farm size and mechanization).

Furthermore, we considered no-tillage to be suitable for arable production under arid conditions (Kassam et al., 2009; Pittelkow et al., 2015), because of less aeration, more stable pores, and soil aggregates compared to soils managed with conventional tillage. In CA systems, the evapotranspiration is additionally reduced by a continuous biomass cover of at least 30 % of the soil surface, which promotes yield stability in drought-prone production environments.

As a last allocation criterion, CA was regarded as suitable for crop production in areas with elevated erosion levels. Basso et al. (2006) find that farmers may make use of green or residue cover to protect the soil surface during high-intensity rainfall events. Our mapping rule too is in line with the finding of Kassam et al. (2009) stating that wind and water erosion were major drivers of CA adoption in Canada, Brazil, and the USA. According to Schmitz et al. (2015) and Govaerts et al. (2009), Asian and African agricultural producers could also benefit from the positive effects of CA in erosion-prone areas.

Logit model for downscaling national CA

Cropland, field size, water erosion, and aridity data per grid cell are used as predictors determining the spatial distribution of national reported CA area within a country (Fig. S4.1–4). We developed a logit model to transform and combine these four spatial predictors into probability values per grid cell, indicating the likelihood of CA area occurrence. The logit model was chosen because different ranges of the spatial predictor datasets are made comparable at equal weights without losing much detail.

From the potential CA area data layer we computed the input variable "crop mix" as the ratio of the area sum of 22 CA-suitable crop types over the sum of total cropland area per grid cell. We assume an increasing probability for CA area occurrence in grid cells with an increasing cultivated area share of CA-suitable crop types. This was based on the assumption that cropland within a grid cell belongs to one management regime under which rotations with CA-suitable crops are practiced and a similar set of soil working equipment is employed. The assumptions also takes into account peer group influence and knowledge spillover effects from early adopters of a new technology (here CA practice) on their neighbors (Case, 1992; Maertens and Barrett, 2013).

Regarding the statistical relation between farm size and CA adoption, we assume that the larger the field size, the higher the CA probability, especially for field sizes equal to or larger 2 ha depending on the income level of a country, taking 2 ha as the midpoint of the transformed field size logit curve.

We set missing water erosion values in grid cells reporting potential CA area to the neutral value of 12 t ha^{-1} yr^{-1}, since it depends on very small-scale conditions, e.g., slope. When transforming the water erosion values to logit, we set 12 t ha^{-1} yr^{-1} as the midpoint value of the function. Here the corresponding mapping approach was to assume increased probability of CA practices in cells which report water erosion values exceeding 12 t ha^{-1} yr^{-1} as the upper bound of the soil loss tolerance value (*T*-values) defined by the USDA (Montgomery, 2007).

The midpoint of aridity's logit regression curve is chosen at 0.65, resulting in higher probabilities of CA area occurrence for grid cells reporting arid (values smaller than 0.65) rather than humid (values larger than 0.65) growing conditions. We interpolated missing aridity values in grid cells where SPAM2005 reports cropland, except for one island near Madagascar, which we set to the logit-neutral value of 0.65 because we assumed very special climatic conditions there.

We tested for (Pearson) correlation among the four spatial predictor variables with the R "base" package (R Development Core Team, 2013), in order to prevent autocorrelation effects (Table 3).

Table 3-3. Correlation coefficients (r) according to Pearson between spatial predictor variables (crop mix, field size, erosion, and aridity) across all grid cells containing potential CA cropland globally.

(r)	**Field size**	**Erosion**	**Aridity**
Crop mix	0.322	-0.104	-0.241
Field size		-0.356	-0.141
Erosion			-0.002

Generally correlation coefficients (*r*) among the datasets are low and mostly negative, except for field size and crop mix.

Those four cropping system indicators are used as explanatory variables in the regression to get the probability of cropland in a grid cell to be CA area as a value between 0 and 1. The probability of CA in a grid cell is derived via the following Eq. (1):

$$CA_{Grid\ cell} = \frac{1}{1+\exp(-\sum_{i=1}^{4} k_i\,(vx_i - xmid_i))} \quad (1)$$

where *i* represents the input datasets of water erosion, aridity, crop mix, and field size (proxy for farm size), k_i refers to the slope value, $xmid_i$ to the central points of each of the logit curves, and vx_i to grid cell values of the referring input dataset.

A sensitivity analysis has been conducted to assess the explanatory power of each of the four input variables and the uncertainty of our parameter set and combination (Fig. S5). The first step was to vary our chosen reference slope (k_i) of each of the input dataset values by factors of 2 and 0.5 (+100 %, −50 %). As a next step each of the variables is dropped, and finally each of the variables is used individually in the logit model. The sensitivity test was conducted at the global scale and also for each of the 54 CA reporting countries.

Mapping CA area per country

The downscaling of total national CA area values entailed subsetting all grid cells with CA-suitable area per CA area reporting country (FAO, 2016). Then these grid cells were sorted in decreasing order according to their CA probability values derived with the logit equation. As a next step, grid cells with the highest logit model results were selected step-wise while adding up the corresponding potential CA area until the reported national CA area threshold was reached. We received a heterogeneous pattern of allocated CA area at 5 arcmin resolution grid within a CA reporting country according to the likelihood of CA area occurrence based on the logit results, statistical data, and literature findings.

Scenario CA area

Similar to the “bottom-up scenario” of Prestele et al. (2018), we deduced “scenario CA area” indicating the maximum area extent of CA adoption, under assessed current socio-economic and biophysical conditions. We add the subset of 22 annual rainfed crop-specific areas in grid cells with large field sizes in low-income countries and all field sizes in high-income countries from reduced tillage to the potential CA area to calculate scenario CA area per grid cell.

3.3 Spatial pattern of six tillage systems

We allocated global cropland of SPAM2005 to the six tillage systems at a spatial resolution of 5 arcmin according to a set of rules (Table 4). In terms of area, conventional (Fig. 2) and traditional (Fig. 3) annual tillage globally constitute the most widespread tillage practices. Both systems are applied for annual crops, which are globally growing on the largest cropland fraction, are traded, and are consumed most. Large parts of the cropland under traditional annual tillage for rainfed and irrigated annuals are located in South-East Asia, with especially high cropland area shares in India followed by sub-Saharan Africa and then South America (Table S9 for aggregated tillage system areas to country scale). Conservation Agriculture globally constitutes the third largest tillage system area (Table 4 and the following Sect. 3.1). Rotational tillage (Fig. 4) is in fourth position in the ranking of tillage system areas, followed by traditional rotational tillage area (Fig. 5). Most traditional rotational tillage system area can be found across the tropical region of South-East Asia and western Africa. Reduced tillage has the smallest area extent (Table 4), which we find mostly in a narrow band between 10 and 20° northern latitude (Fig. 6). It occurs in Mexico and south of the Sahel region, but mostly is found on cropland in India (Table S8 for further metrics across tillage system areas; Table S9).

Table 3-4. Global aggregated tillage system areas and shares on total cropland (IFPRI/IIASA, 2017b).

Tillage system	Tillage system area sum (km^2)	Share of tillage system area on total cropland (%)
Conventional annual tillage	4,650,498	41.10
Traditional annual tillage	4,015,279	35.49
Conservation Agriculture	1,101,899	9.74

Rotational tillage	741,798	6.56
Traditional rotational tillage	650,509	5.75
Reduced tillage	154,403	1.36
World	**11,314,386**	**100**

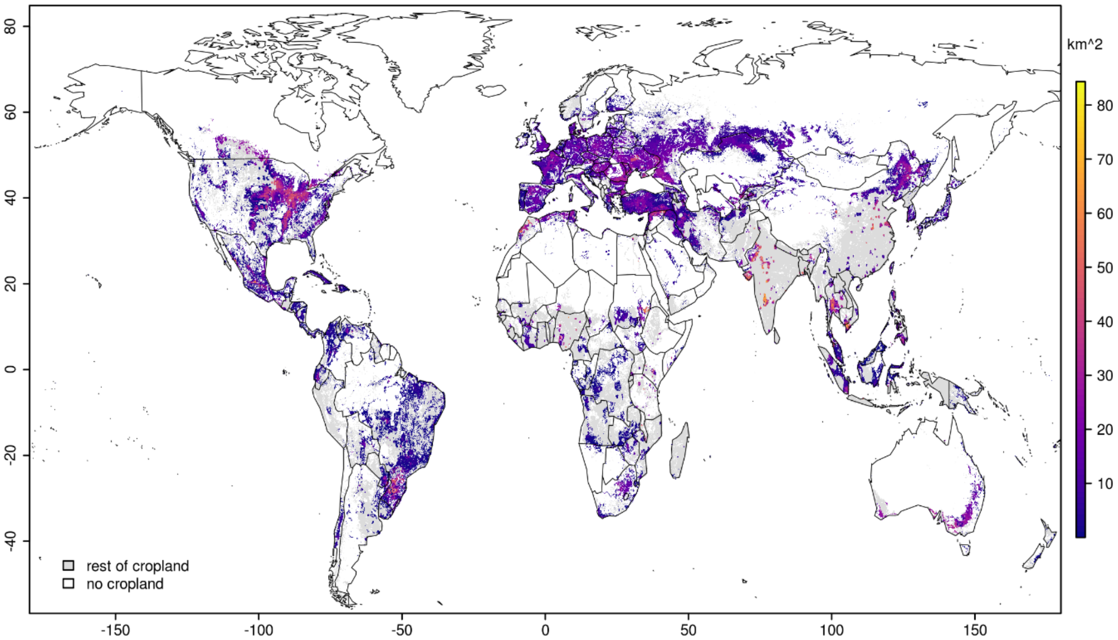

Figure 3-2. Conventional annual tillage area, which has been allocated to the majority of the global physical cropland area.

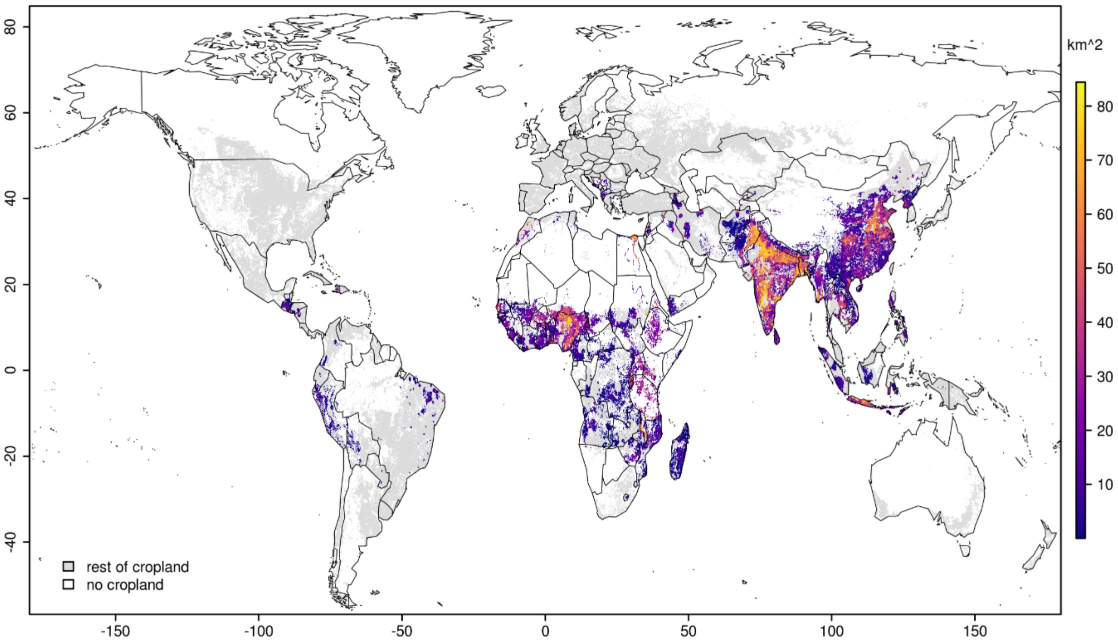

Figure 3-3. Traditional annual tillage area as sums over 29 annual crop types' areas in grid cells reporting dominant field sizes smaller than 2 ha and in countries classified as low income in this study.

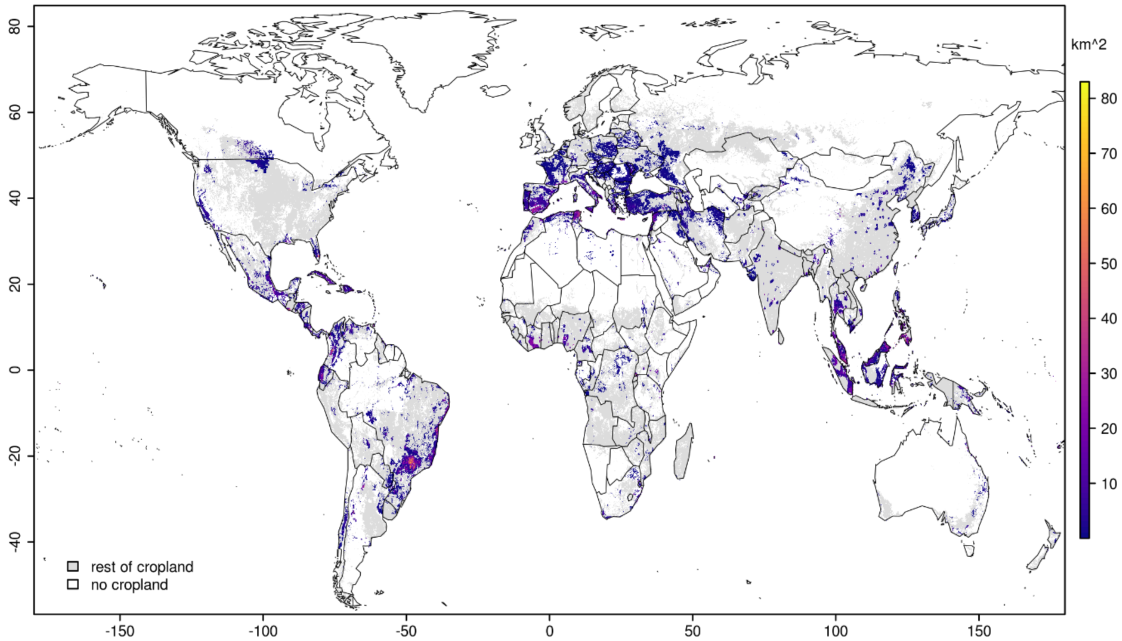

Figure 3-4. Rotational tillage area on cropland area of 13 perennial crop types in grid cells with dominating field sizes of minimum 2 ha or larger in low-income countries or all field sizes in high-income countries.

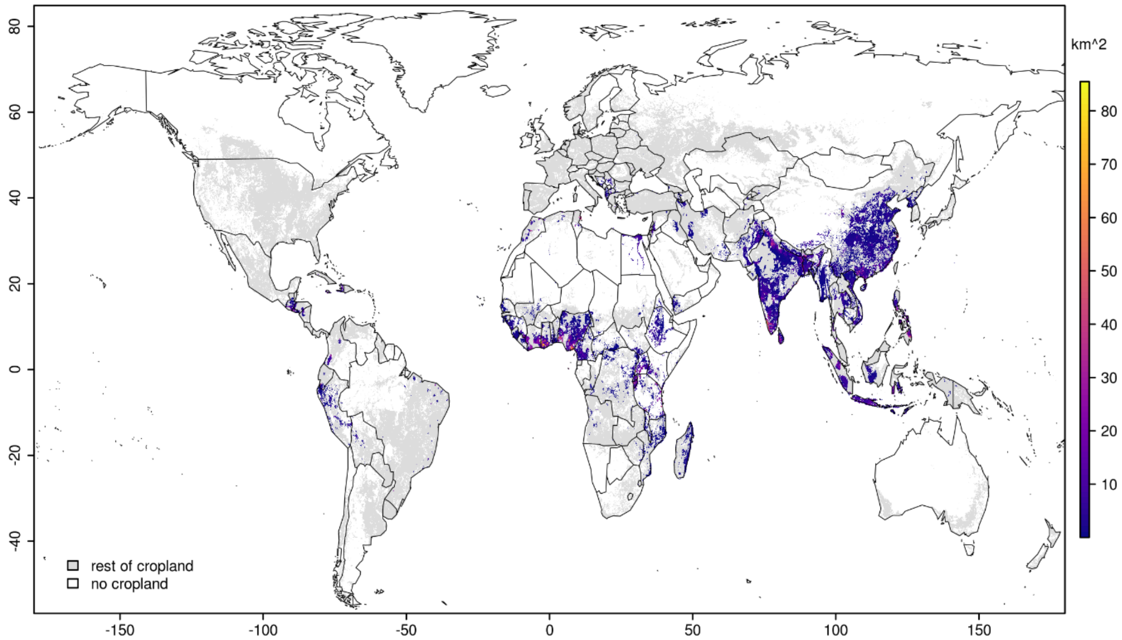

Figure 3-5. Traditional rotational tillage area as cropland of 13 perennial crop types in grid cells characterized by field sizes smaller than 2 ha in countries considered low income in this study.

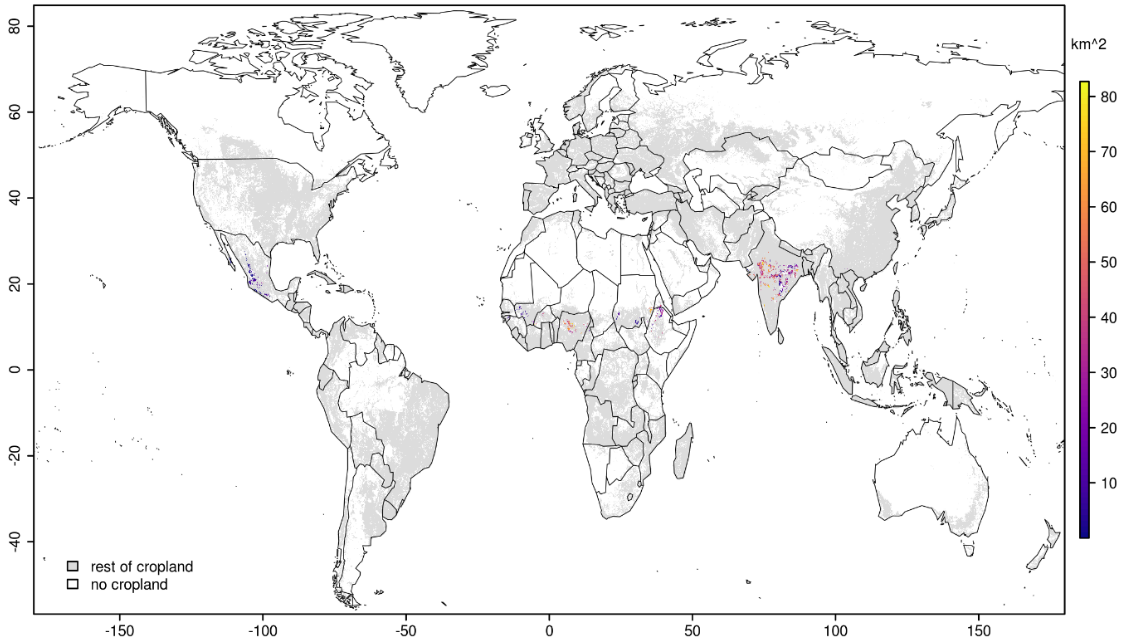

Figure 3-6. Reduced tillage area where soil depth to bedrock is limiting the depth of tillage.

3.3.1 Conservation Agriculture area

The results of the logit model

We deduced the likelihood of CA area in a grid cell via the logit model approach according to the indicators crop mix, field size, water erosion, and aridity (Fig. 7). The geographical pattern of the logit results (further referred to as ref-logit) exhibits higher probabilities for cropland in grid cells outside the tropical climate zone and in rather continental regions. Probability of CA is higher for cropland in grid cells reporting large field sizes, which are mostly found in developed and land-rich countries, i.e., in the USA, Australia, and large parts of Europe. Grid cells in the tropics receive rather low logit results due to their humid conditions, smaller field sizes, lower income levels, and crop types cultivated. In India, China, and Pakistan the majority of cropland showed very low CA likelihood.

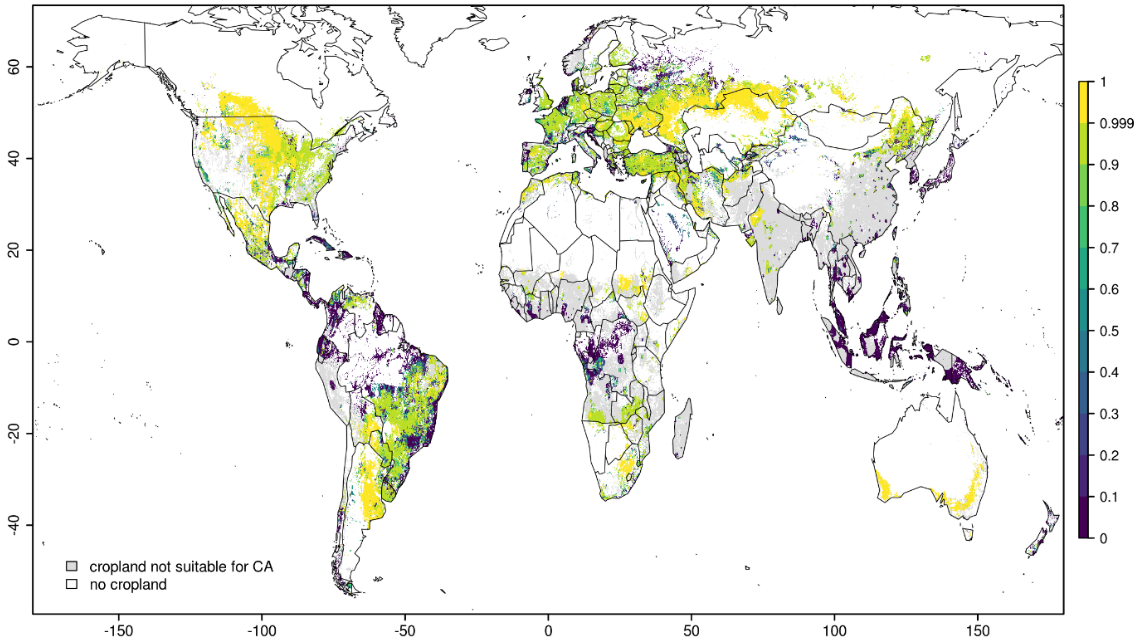

Figure 3-7. Probabilities of Conservation Agriculture area per grid cell with high values as green to yellow and low ones in blue to purple colors (white color indicates the absence of cropland, and grey the cropland (IFPRI/IIASA, 2017b) which is excluded from the potential CA area due to soil depth, crop type, irrigation, field size, or income level).

Results of the sensitivity analysis of the logit model

The sensitivity analysis of the logit model shows mixed responses to the perturbations of slope or variable combination (Table 5, Fig. S5). Rank correlation (*r*) to the ref-logit is much lower when taking one variable only compared to each of the other drop-variable settings or slope modifications. Regarding modifications of the slope parameters of the input variables, we calculated the lowest rank correlation coefficient for increasing the slope of aridity by +100 % and for decreasing the slope of crop mix by −50 % compared to changing the slopes of the other three variables, respectively.

Table 3-5. Logit model input parameters, as midpoint (xmid) and slope (k) of the four logit model input datasets (columns 1 and 2), which are altered per sensitivity setting. Correlation coefficients (r) for ranks according to "Spearman" between the reference case (Logit-ref) and the perturbed slope and variable combinations of the logit model results are given, illustrating the sensitivity of the grid cell likelihood of potential CA area (columns 3 to 6).

Variable	Logit-ref (xmid)	Logit-ref (k)	Logit-ref/ and k+100 % (r)	Logit-ref/ and k-50 % (r)	Logit-ref/ and drop one variable (r)	Logit-ref/ and one variable only (r)
Field size	20	0.25	0.975	0.988	0.944	0.555
Erosion	12	0.017	0.992	0.997	0.989	-0.119
Aridity	0.65	-5	0.966	0.982	0.901	0.607
Crop mix	0.50	10	0.981	0.971	0.773	0.826

Erosion has the lowest explanatory power, as can be interpreted from the very high correlation coefficient with ref-logit when dropping it – but even negative correlation when taking it into the logit equation only. This finding is in line with the findings of the sensitivity tests performed by Prestele et al. (2018), who find erosion to be the variable with the smallest explanatory power as well.

Crop mix has the largest explanatory power in the logit equation, as shown by the lowest correlation coefficient value when dropping it but highest when taking that variable only (Table 5). We additionally report on the sensitivity results for the 54 CA reporting countries, where the effects of slope and variable perturbation show very different patterns per country (Table S6). However, as national CA areas are allocated within individual countries, the sensitivity of ranking within countries is of greater importance than the global rank correlation.

Downscaled CA area

Total downscaled CA area (1 101 899 km^2, Fig. 8) is slightly lower than FAO reported total CA area for these countries (1 102 900 km^2). This difference occurs because of our algorithm, which assigned the entire CA-suitable cropland area per grid cell to CA, taking the cropland of the following grid cell in or out of consideration striving for least deviation from the threshold per country (Table S7 for comparison of reported and downscaled country values). A further difference is due to the insufficient potential CA area in North Korea and New Zealand, resulting in the fact that only part of the national reported CA area could be allocated to.

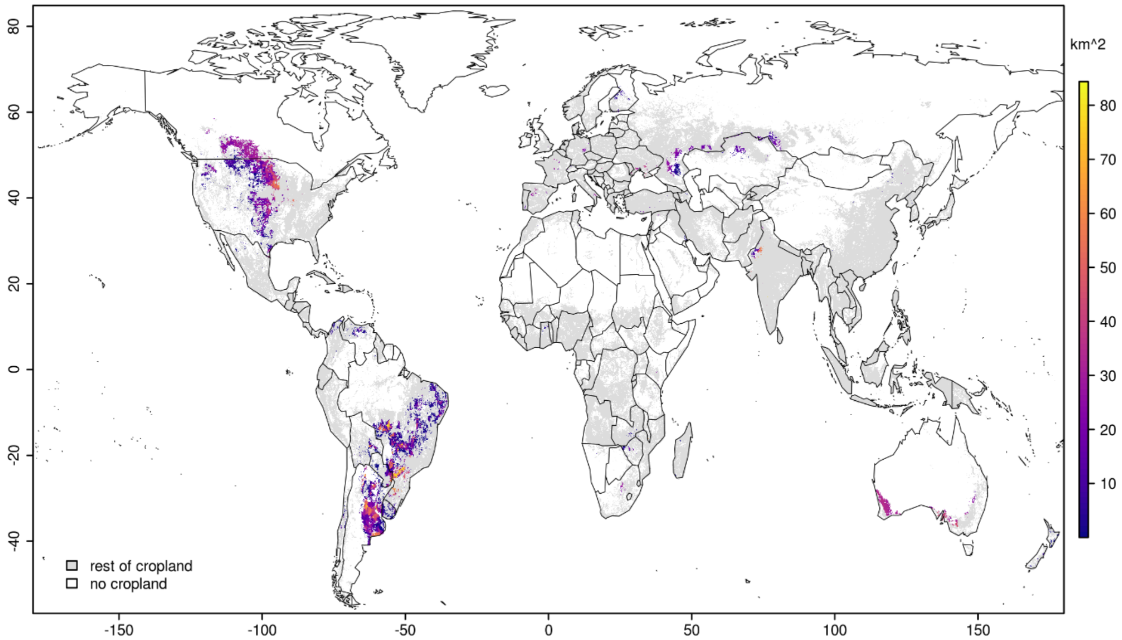

Figure 3-8. Downscaled Conservation Agriculture area (km2) (colored) on total cropland (grey) per grid cell for 54 reporting countries around the year 2005.

Aggregated crop-specific CA area values reveal that most downscaled CA area was allocated to area cultivated with soybean, followed by wheat and then maize (Table 6). These three crops are among the most important produced, traded, and consumed agricultural goods, making their production highly competitive, and therefore the incentive to reduce operational costs (e.g., regarding tillage) is high. Another reason for soybean and maize being among the crops mostly produced under CA may be the usage of high yielding or genetically modified crops, coming along with improved pesticide resistances, which make them more suitable for possible herbicide applications (Giller et al., 2015) replacing tillage operations on-field. In Argentina, soybeans are found to be the most common plant cultivated under CA, with usually lower residue coverage than required for being a CA system (Pac, 2018). Subsistence farming crops, e.g., peas and millet, contributed only a little cropland to the downscaled CA area (Table 6), because they are more drought resistant (Jodha, 1977), and of rather regional importance in terms of food security, while being traded less on the international markets (Andrews and Kumar, 1992).

Table 3-6. Global sums over 22 CA suitable crop-type areas, sorted decreasing shares of downscaled CA area values on the identified potential CA area, and crop-specific downscaled CA areas.

Crop type	Potential CA area (km^2)	Share of downscaled on potential CA (%)	Downscaled CA area (km^2)
Soybean	740,797	48	359,205
Wheat	1,341,590	24	321,305
Maize	762,415	19	143,432
Barley	485,428	12	57,959
Rapeseed	144,601	31	45,363
Sunflower	186,310	20	36,716
Sorghum	97,918	24	23,816
Bean	119,902	20	23,535
Other cereals	231,384	10	22,109
Cotton	84,069	25	21,121
Other pulses	76,869	21	15,932
Lentils	19,015	45	8,565
Pearl millet	56,062	11	5,938
Rest	82,063	5	4,081
Groundnut	47,208	7	3,308
Chicpea	28,489	11	3,227
Small millet	13,419	21	2,859
Vegetables	90,535	2	1,834
Tobacco	13,678	7	916
Sesameseed	17,940	3	502
Pigeonpea	6,411	2	129
Cowpea	6,317	1	48
World	**4,652,419**	**24**	**1,101,899**

Scenario CA area

We deduced the total global potential CA area of 4.65 Mkm^2 (see above). Additionally, we identified 0.02 Mkm^2 of 22 rainfed annual crop types' areas on large fields in low-income countries and all field sizes or in high-income countries from the reduced tillage system area, which potentially could be converted to CA area as well. We calculated a total scenario CA area of 4.67 Mkm^2, where perceived driving forces, e.g., CA adoption supporting agricultural policies, targeted mechanization efforts, and knowledge dissemination approaches could lead to an area expansion of CA practices.

3.4 Data availability

The presented tillage system dataset and source code are available under the ODBL (data) and MIT (source code) licenses. The tillage dataset can be downloaded from https://doi.org/10.5880/PIK.2019.009 (Porwollik et al., 2019b) and the corresponding R-code from https://doi.org/10.5880/PIK.2019.010 (Porwollik et al., 2019a). The dataset is provided in netCDF format (version 4) and consists of 42 layers, each reporting crop-specific tillage systems per grid cell. Additionally, we provide a layer indicating area, where adoption of Conservation Agriculture could be facilitated (scenario CA area). The dataset can be used as a direct input or be applied as a mask or overlay for identifying tillage area. The R-code is provided to increase the transparency of our methods, but also to enable other modeling groups to adjust our tillage area mapping algorithm to their needs, e.g., for different input data or scenarios.

3.5 Discussion

3.5.1 Comparison of results to other studies

In the absence of alternative tillage area datasets for validation at the global scale we here want to discuss the way our tillage system area results relate to other studies' findings.

We compare the spatial pattern of our added traditional tillage system area to the one reported by the cropland subsets of SPAM2005 for low-input and subsistence production. According to You et al. (2014), both production levels are characterized by a low level of mechanization, or rather manual labor and low input usage. The sum of our traditional tillage systems' (rotational and annual) areas (4.63 Mkm^2) is slightly higher than the sum of SPAM2005 subsistence and low-input technological-level cropland (4.55 Mkm^2). We deduced more traditional tillage system area in South-East Asia, Sub-Saharan Africa, and Peru than SPAM2005 reported under low and subsistence farming (see the difference map in Fig. S10). Further comparison reveals a moderately lower amount of area under traditional tillage in our dataset for Europe, the Middle East, South America, and Australia, i.e., in countries which are regarded as emerging or developed economies. The spatial difference may be due to the fact that SPAM2005 is a product of a sub-cell cross-entropy optimization approach to distribute cropland of the same crop species into several production levels per grid cell. In contrast to this, we used the field size and gross national income as spatial indicators of un-mechanized tillage systems by masking out cropland either per entire grid cell or country-wise according to our derived thresholds. We calculated the spatial correlation via a regression of the added area values of our traditional tillage system and of the sum of low-input and subsistence production level cropland reported by SPAM2005. We found a regression factor (r^2) of 0.54 (p<0.001, slope of 1.139) among both datasets' values.

Our estimate of a traditional tillage system area in turn is lower than the finding by Lowder et al. (2016), stating 5.87 Mkm^2 to be under management of farms smaller than 2 ha in size (~12 % of their arable cropland assumption). In order to compare our results to the findings of Erb et al. (2016) on tillage intensity areas, we added up our reduced, both rotational tillage system, areas, and the downscaled CA area to represent the "low intensity" tillage area, whereas conventional and traditional annual tillage are summed up to the "high intensity" tillage area. Since the description of what is included in their "low intensity" area is inconsistent within their main text, tables, and Supplement, we state two different estimates of our results – both exhibiting different absolute values and shares compared to the findings of Erb et al. (2016) (Table 7).

Table 3-7. Tillage system area results compared to estimates of Erb et al. (2016) on tillage intensity areas. The first two columns show our aggregated tillage system area values; columns 3 and 4 additionally include the young and temporal fallow cropland area by Siebert et al. (2010), a cropland area not represented in SPAM2005 and therefore added to our total cropland as well as to the "low intensity" category as described in Erb et al. (2016). Note that Siebert et al. (2010) state that about 4.4 Mkm2 of cropland was young and temporal fallow (< 5 years) around the year 2000.

Tillage system	Tillage area this study (km^2)	Tillage area this study (%)	Tillage area this study + fallow (km^2)	Tillage area this study + fallow (%)	Tillage area (km^2) (Erb et al., 2016)	Tillage share (%) (Erb et al., 2016)
Low intensity	2,648,610	23.4	7,048,610	44.9	4,730,000	38.9
High intensity	8,665,776	76.6	8,665,776	55.1	7,430,000	61.1
World	**11,314,386**	**100**	**15,714,386**	**100**	**12,160,000**	**100**

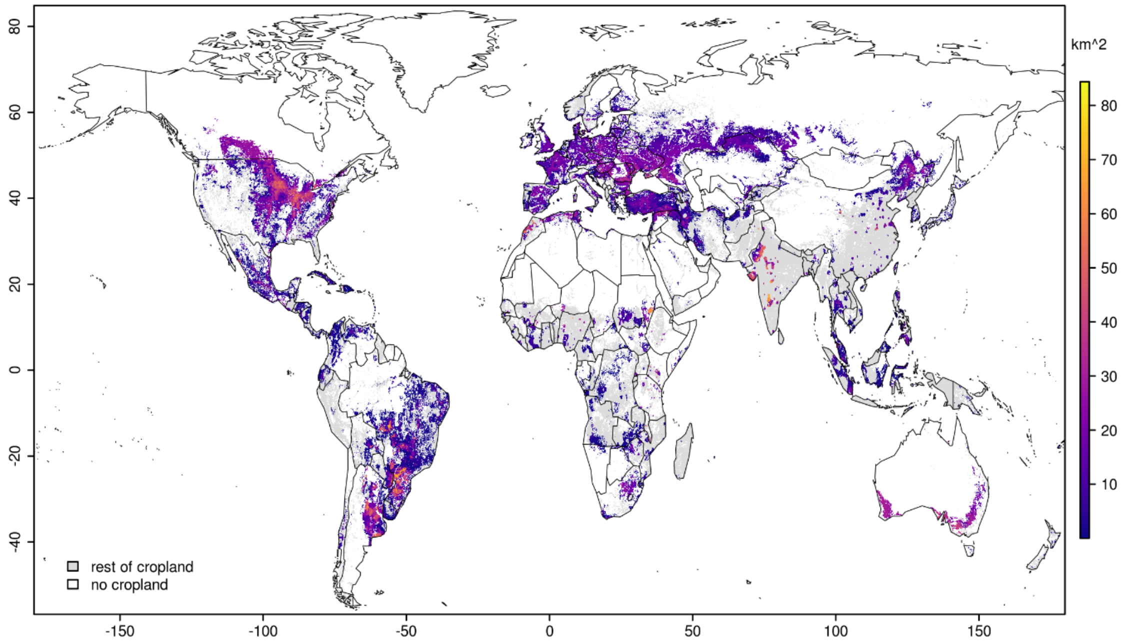

Figure 3-9. Scenario Conservation Agriculture area (km2) (colored) on total cropland (grey) per grid cell.

Prestele et al. (2018) analyzed CA area time series data by FAOSTAT and found an increasing trend of CA adoption within countries and to more countries since the 1970s. This trend is likely going to continue as farm holdings increase in size while decreasing in number in upper-middle- and high-income countries (Lowder et al., 2016). At the same time, the adoption rate of CA in smallholder farming systems in low-income countries (e.g., in Sub-Saharan Africa) may continue to be low, where average farm size reveals a decreasing trend (Jones, 2017). Adoption of CA practices by smallholder farmers is hampered by competition for residue use (Scopel et al., 2013), missing knowledge, as well as restricted access to inputs and financial capital (Kassam et al., 2009), making them more risk-averse towards adoption of new technology than large-scale farmers (Schmitz et al., 2015).

Prestele et al. (2018) state their potential CA area to be 11.3 Mkm^2 in their "Bottom-up" and 5.33 Mkm^2 in their "Top-down" scenarios until the year 2050. Our estimate of scenario CA area of 4.66 Mkm^2 is lower but on the same magnitude as their "Top-down" scenario. Prestele et al. (2018) used another cropland product, targeted another time period, pursued a slightly different CA mapping approach, and had different assumptions about the scenario design, which might be causing the main area differences compared to our derived scenario CA area. In order to take into account that other modeling groups may apply other cropland inputs than SPAM2005 as presented here, we made the tillage dataset and source code flexible in a way that each modeling group may adjust it according to their individual crop mix per grid cell.

3.5.2 Potentials, limitations, and implications for applications of the dataset

A limitation to our presented mapping approach is that the input datasets applied cover different time periods, e.g., GLADIS reports water erosion values for approximately the year 2000, SPAM2005 and the field size dataset for the year 2005; the aridity spans to the reference climate data of the period from year 1961 to 1990, and for some countries we extracted the only CA reporting year by FAO (2016) from years 2002 up to 2013. By using SPAM2005, field size for 2005, and setting the objected year for the produced tillage dataset to 2005 as well, we tried to minimize inconsistencies in time coverage at least for the cropland extent. GLADIS uses the Global Land

Cover dataset (GLC2000, Bartholomé and Belward, 2005) as land-use information, thus reporting water erosion values as an average over the different ecosystem and land-use types per grid cell. Land use as well as land management are results of dynamic socio-economic and environmental processes. Local mismatches in the cropland extents between these datasets might be on the one hand due to abandonment as a result of shifting cultivation or on the other hand due to extension of cropland to converted other land-use types between the years 2000 and 2005. Further mismatches might exist due to different assumptions about crop types and area between different data products. The choice of crop to be cultivated is usually taken under consideration of rotations for weed and pest management, household demand, and market conditions, together leading to different cropping patterns between the years 2000 and 2005. The aridity dataset does not consider any land-use information, but relies on averages of climatic data and parameters. Another source of uncertainty is the used rule-based approach for mapping the tillage system areas. We statistically proved the relation between national average farm size and CA adoption (S3). Whereas statistical relations between field and farm size can be found in the literature, the mapping rules of distinguishing traditional from mechanical tillage and the suitability of CA for erosion and aridity-prone agricultural production environments are based on qualitative literature findings and warrant further research and scrutiny if new data become available.

The tillage dataset presented here can be employed in various applications, depending on the type of model, context, and objective of the user. Agricultural land management practices are determined not only by environmental factors, but are also embedded in local to regional systems of culture, traditions, and markets. This mosaic of farming conditions can only be taken into account at high spatial resolution. The developed tillage dataset is an effort to better account for heterogeneous patterns of agricultural soil management across and within countries by using socio-economic and biophysical data in conjunction. The resolution of the generated dataset of 5 arcmin is quite high. Global ecosystem models are currently mostly run at a coarser resolution than our dataset's resolution, and the tillage data may have to be aggregated in such cases. This could introduce further uncertainty to the area under a certain tillage system.

A challenge to the full usage of this dataset is the limited implementation of the 42 crop types reported in SPAM2005 in global ecosystem models. Especially perennial crop types are hardly ever parameterized in ecosystem models, or if so rather address regional-scale applications (Fader et al., 2015). One reason for the missing implementation may be their relatively small cultivation areas globally (~10 % of global cropland, Erb et al., 2016). Woody and other perennial plant species entail potential in the aspect of sustainable agricultural practices because they keep the soil covered for longer periods and thus better protect it from erosive and radiative forces, promote soil organic carbon accumulation (Smith et al., 2008), and stabilize soils more than annually planted crop types.

Another challenge for the application of our tillage dataset in model simulations is the differentiation of soil depth affected by the tillage operation. Some models may be able to differentiate between 20 or 30 cm depth affected by the tillage operation mostly when having a site-based background and therefore a very detailed representation of agricultural management practices (White et al., 2010). The LPJ-GUESS global dynamic ecosystem model and the Community Land Model (CLM) have implemented the tillage routines as a tillage factor accelerating the decomposition rate of the different soil carbon pools (Levis et al., 2014; Olin et al., 2015), so that implementations of spatial variability in depth or mixing efficiency are not straightforward.

White et al. (2010) elaborate on the problem of generally implementing a three-dimensional aspect as “surface affected” by the tillage practice, which would be the case for simulating reduced tillage practices as strip-, mulch-

, or ridge-till, managing weeds during the growing period of the main crop, or preparing the seedbed for inter-cropping cultures. The reduction relates to depth, surface affected or both, for which White et al. (2010) recommend an intermediate model implementation mode which distinguishes two zones as one share of the soil being affected and the other one not.

Some authors mention partial adoption of CA as referring to the minimal soil disturbance practice only (Giller et al., 2015; Scopel et al., 2013) where residues are not always retained (Pittelkow et al., 2015). This no-tillage practice tries to benefit from saving energy, work hours, machine wearing, and field passes when skipping tillage. No-tillage without a sufficient biological mulch is reliant on the application of increased amounts of herbicides to comply with weeds (McConkey et al., 2012; Mitchell et al., 2012) compared to conventional tillage systems. Leaving the soil unprotected exposes the soil surface to erosive forces and enhances nutrient leakage, especially under high rainfall intensities. Crusting and compaction of the soil can only be addressed by tilling these fields rotationally, as has been discussed in Erb et al. (2016). This rotational tillage may lead to a decrease in soil organic matter (SOM) due to increased mineralization under aerated conditions, and the advantages of no-tilling during the other years disappear (Powlson et al., 2014). The effects of SOM increase under no-tillage, only in conjunction with a certain level of residue inputs, may appear relevant after a transition time of about 10 to 20 years of continuous practice until a new equilibrium state of SOM dynamics is re-established (Sá et al., 2012). The other often missing aspect to the full implementation of the CA practice is the rotation of diverse crop types, inter-cropping, or other green manuring practices. It remains unclear to what extent countries reporting CA area to FAO may rather refer to partially adopted practice of CA, i.e., no-tillage only.

Applying the presented tillage system dataset in global assessment is a major step forward compared to globally rather homogeneous assumptions on tillage systems (Hirsch et al., 2017; Levis et al., 2014) or a total ignorance of soil management practices (Folberth et al., 2016; Rosenzweig et al., 2014). The rule-based approach and the publication of the underlying data processing scripts allow for extensions of this work if further relationships can be identified or improved data become available. It also allows for construction of future scenarios, consistent with other scenario frameworks on climate, economic development, and land-use change (e.g., Popp et al., 2017). Further research is needed to generate global land management datasets with high resolution on crop rotations, residue management, and multiple cropping, so that the full set of CA principles can be simulated and biophysically assessed in comparison to further sustainable land practices.

Author contributions

VP, CM, SR, and JH developed the tillage system dataset. VP collected the input data and wrote the scripts for processing and analyzing the data. CM and JH suggested the CA area downscaling procedure, whereas JH proposed the application of the logit model. VP prepared the manuscript with contributions from all the co-authors with respect to interpretation of the results and writing of the final paper.

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Supplement

The supplement related to this article is available online at: https://doi.org/10.5194/essd-11-823-2019-supplement. Supplementary data and material associated to this Chapter 3 is provided in the Appendix B.

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4 The role of cover crops for cropland soil carbon, nitrogen leaching, and agricultural yields - A global simulation study with LPJmL (V. 5.0-tillage-cc)

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Abstract

Land management practices can reduce the environmental impact of agricultural land use and production, improve productivity, and transform cropland into carbon sinks. We applied the global vegetation model LPJmL5.0-tillage-cc with a modified representation of cover crop practices. We assessed simulated responses to cover crop practices on agroecosystem components in comparison to bare soil fallow between two consecutive primary crops' growing seasons on global cropland for a simulation period of 50 years. With cover crops and tillage, we obtained annual global median soil carbon sequestration rates of 0.52 and 0.48 t C ha^{-1} yr^{-1} for the first and last decades of the entire simulation period, respectively. We found that cover crops with tillage reduced annual nitrogen leaching rates from cropland soils by a median of 39 % and 54 % but also the productivity of the following main crop by average of 1.6 % and 2 % for the two analyzed decades. Largest reduction of productivity were found for rice, modestly lowered for maize and wheat, whereas soybean yield revealed an almost homogenous positive response to cover crop practices during fallow periods.

Further, the results suggest that no-tillage is a suitable complementary practice to cover crops, enhancing their environmental benefits and reducing potential trade-offs with the main crop productivity due to their impacts on soil nitrogen and water dynamics. For cover crops applied in conjunction with no-tillage across the mapped Conservation Agriculture cropland area for the period 1974-2010, we estimated a cumulative soil carbon net-accumulation of 1.4 PgC, an annual median reduction of soil nitrogen leaching by 57 %, as well as mostly enhanced yields of the following main crop.

The spatial heterogeneity of simulated impacts of cover crops on the variables assessed here was related to the time period since the introduction of the management practice as well as to environmental and agronomic conditions of the cropland. This study supports findings of other studies, highlighting the substantial potential contribution of cover crop practices to the sustainable development of arable production.

4.1 Introduction

The agricultural sector is challenged to provide more food, feed, and fuel to meet an increasing demand due to global human population dynamics as well as changes in diet composition (Alexander et al., 2017; Bodirsky et al., 2015; Godfray et al., 2010). Simultaneously, it is expected to consume fewer resources either by direct savings or by increasing general efficiency of applied inputs (Lal, 2004a; Springmann et al., 2018). Agricultural production accounts for ~10 % (mean of the years 2007 to 2016) of the annual global anthropogenic greenhouse gas emissions, including carbon (C) dioxide, methane from ruminant animals, as well as nitrous oxide emissions from crop production (i.e. fertilizer) and livestock rearing activities (Rosenzweig et al., 2020). A loss of 30 to 40 % soil organic C was estimated due to the historic cultivation of croplands (Poeplau and Don, 2015). Additional to the estimated 1.6 ± 0.7 PgC yr^{-1} emissions from land use and land-use change for the decade 2010-2019 (Friedlingstein et al., 2020), about 1 PgC yr^{-1} of emissions can be attributed to harvest, grazing, and tillage on global cropland in the period since year 1850 (Pugh et al., 2015). At the same time, agricultural land management practices can be employed to reduce or reverse detrimental environmental impacts of agricultural production as well as facilitate the regeneration of degraded ecosystem functions (Rosegrant et al., 2014). Conservation Agriculture (CA) practices have been proposed to improve cropland soil fertility and to sustain productivity (Scopel et al., 2013; Thierfelder et al., 2018; Tittonell et al., 2012). CA comprises minimum mechanical soil disturbance, the maintenance of a permanent vegetative soil surface cover, and a diversified crop rotation (Kassam et al., 2019). The latter two aspects can be accomplished by the integration of a secondary crop, which depending on the position and purpose in the rotation, can be referred to as green manure, intercrop, or as intermediate, companion, catch, and cover crop (term further used in this study). For farming systems cultivating annual crop types, cover crops can be grown between two consecutive main cropping seasons, whereas for perennial woody crops, cover crops are rather found as groundcovers between trees (Gonzalez-Sanchez et al., 2019). Cover crops exhibit several environmental benefits such as decreasing nitrogen (N) leaching from agricultural systems (Abdalla et al., 2019; Thapa et al., 2018; Tonitto et al., 2006; Valkama et al., 2015). The N recovery rate of excess fertilizer left in the soil after harvest of a main crop is found to be higher for non-leguminous species (such as grasses, e.g. ryegrass (Florentín et al., 2011) and brassicas, e.g. radish) than for leguminous (e.g. peas and beans) cover crop species (Dabney et al., 2011). Leguminous types are able to improve the N balance of the soil (Kaye and Quemada, 2017) through additional N fixation and by this may reduce fertilizer input requirements in the long term (Nouri et al., 2020; Thierfelder et al., 2018). Last but not least, cover crops constitute a suitable measure for weed control and against soil compaction (SARE, 2019), as well as erosion prevention through extending the vegetative coverage of the soil surface (Kaye and Quemada, 2017). Cover crops are terminated either naturally (e.g. by frost), chemically (e.g. by herbicide application), or mechanically (e.g. by mowing, roller, tillage) (Kaye and Quemada, 2017). The corresponding biomass of the cover crops can be harvested for off-field usages, grazed by livestock, or if left on the field, be used to build up the soil's humus layer (Florentín et al., 2011). Cover crops are an important practice to manage soil fertility and weed in organic farming systems (Keestra et al., 2018).

According to the Farm Structure Surveys and the Survey on Agricultural Production Methods (SAPM), which are carried out on a 10 year interval as a census in the EU-28 countries, the soil surface of arable land during winter of the year 2010 was covered: 44 % with normal winter crops, 5 % with cover or intermediate crops, 9 % with plant residues, and 25 % left as bare soil. The remaining 16 % missing reporting share comprise areas under glass and areas not cultivated during the reference year (e.g. temporary grassland, hops) (EUROSTAT, 2018a). Poeplau and Don (2015) report that current shares of cropland with cover crops range between 1-10 % for countries in

Europe and the US. Further, these authors estimate ~400 million hectares cropland area suitable for cover crop practices as half of the global winter or off-season fallow cropland, by excluding 50 % of the total area covered with winter cereals and further 25 % of the off-season fallow area due to climatic or agronomical constraints. This area estimate is also used in Kaye and Quemada (2017), who find the mitigation potential of cover crop practices mainly due to the combined effects of soil C sequestration, reduced fertilizer application rates, and changes in surface albedo, corresponding to an off-set of about 10 % of the estimated annual emissions from agriculture. Cover crop practices encompass potential to contribute to climate change impact mitigation through soil C sequestration (Abdalla et al., 2019; Corsi et al., 2012; Poeplau and Don, 2015). Largest potentials for the realization of C sequestration on global cropland soils were identified for areas with high natural potential soil C stocks and with strongest C depletion due to duration and intensity of historical agricultural land use and management (Sommer and Bossio, 2014), resulting in a larger saturation deficit (West and Six, 2007). Cover crop practices serve adaptation through improving the efficiency of applied inputs (i.e. fertilizer) and increasing the resilience of cropland production (Kaye and Quemada, 2017; Rosenzweig et al., 2020).
The objectives of this study were to: i) Assess the temporal and spatial pattern of cover crop impacts simulated with LPJml5.0-tillage-cc on global cropland soil C stocks, N leaching rates, and agricultural productivity, ii) Quantify responses to the practices applied with tillage and the influence of management duration, and iii) Estimate the effects of cover crops combined with no-tillage for mapped CA cropland as well as their potential contribution to mitigation and adaptation efforts.

4.2 Methods and data

4.2.1 Simulating cover crop practices with LPJmL5.0-tillage-cc

For the assessment of cover crop cultivation impacts, we applied the dynamic global vegetation model LPJmL5.0-tillage-cc, representing biophysical and biogeochemical processes of the biosphere for the quantification of human-nature interactions as well as of their impacts on natural and managed ecosystems. A detailed description of water, soil, and plant dynamics of a preceding model version 4, including a comprehensive evaluation of model skills, is provided in Schaphoff et al. (2018a); (2018b). The here used model version additionally includes processes associated to global N dynamics in soils and plants (von Bloh et al., 2018), as well as an explicit representation of tillage types and crop residue management (Lutz et al., 2019). Herzfeld et al. (2021) examine global soil carbon dynamics affected by historical land-use change, tillage, and crop residue management, based on simulations with LPJml5.0–tillage2 comprising a similar model code and management representation as applied here.
We used LPJmL5.0-tillage-cc with a modified code for the representation of cover crop management. It is built on an earlier version of the model accounting for 'intercrops', as the options to simulate either vegetated (natural grass) or bare soil fallow dynamics on cropland area in the period between two consecutive primary crops' growing seasons (Bondeau et al., 2007). The functionalities make use of three 'grass' plant functional types (PFTs), already implemented in LPJmL for the natural vegetation, growing on fallow cropland area according to their bio-climatic limits as tropical C4, temperate C3, and polar C3 grass (Forkel et al., 2014). In the model, biophysical and biogeochemical dynamics on off-season cropland within a grid cell, are accounted for in routines of the 'setaside stand'. The 'intercrop' carbon-only version of LPJmL and 15 other agroecosystem models were included in the study of Kollas et al. (2015). They find only minor ability of the model ensemble, to reproduce the slight positive main crop yield effect, which was observed in the experimental sites for rotations with intermediate crops.

We modified the functionalities for the establishment of cover crop (grass), so that it occurs on each crop specific off-season cropland fraction after harvest of the main crop (CFT) within a grid cell. The initial biomass of the cover crop grass sapling (0.05-0.07 g C m^{-2}) was changed to be taken from the respective C and N pools of the soil litter layers. We did so, to avoid imposing artificial fertilization effects (Olin et al., 2015), from simply adding contained amounts of the sapling's C and N to the simulated system with the default CFTs establishment model routines, which assume crop seeds as external inputs.

In this model version, C and N are allocated to the different organs (root and leaf pools) of the cover crop grass plants on a daily basis, using routines of 'managed grassland' dynamics described in Rolinski et al. (2018) and von Bloh et al. (2018). Any management of the cover crops growing as grasses on fallow cropland area was excluded. Cover crops are terminated at the beginning of the following main crop growing season. The corresponding aboveground grass plant biomass is either left at the soil surface, or transferred to the incorporated soil litter pools, depending on the tillage setting. The root biomass of the terminated cover crops is added to the respective belowground litter pools. Soil and vegetation C, N, and water fluxes in the main crop growing period as well as during vegetated or bare fallow off-season were summarized in model outputs for the entire cropland. More details of the model functionalities, and input data used, are provided in the Supplement (Sect. S1).

4.2.2 Simulation setup land management scenarios

All simulations were run at a spatial resolution of 0.5 x 0.5 arc degrees. As a first step, we conducted a 7000 years spin-up simulation with LPJmL5.0-tillage-cc, in order to get natural vegetation pattern and soil pools into a dynamic equilibrium state, recycling the first 30 years of climate input data following the procedures described in von Bloh et al. (2018).

Subsequently, we ran a second spin-up simulation, with fixed cropland distribution pattern and most of the land management as provided by the model input data for the year 2010 (Sect. S1.2). We assumed bare soil fallow on cropland during the main crops off-season periods as well as tillage to be the default historical management practices. By keeping land use and management constant during these simulation steps, we assume that cropland had been already cultivated for a longer period at the beginning of the actual simulation period so that results can be more easily compared to literature values e.g., obtained from experiments conducted on already established cropland area plots. Starting with cropland soil pools from this spin-up procedure, we simulated the control scenario as reference (REF) maintaining all settings as during the land use spin-up. Three alternative management scenarios were generated with cover crops (CC), no-tillage (NT) applied as single, and as combined practices (CCNT) on global cropland for a 50 year simulation period (see Supplement Table S1.3 for more details on simulation setup). On the one hand, this time frame has been stated as minimum duration required to re-establish a new steady state in soil C pools after the introduction of a new soil management practice involving altered biomass input levels (Kaye and Quemada, 2017; Poeplau and Don, 2015). On the other hand, the 50 years were chosen for analysis because of spanning the maximum duration found for values in literature and here used for evaluating simulated responses.

4.2.3 Post-processing model outputs

Model output data was post-processed and analyzed with R version 3.3.2 (R Development Core Team, 2016), applying functions developed by Kowalewski (2016) as well as by using the packages 'raster' (Hijmans and van Etten, 2012), 'reldist' (Handcock, 2016), and 'ncdf4' (Pierce, 2015).

Soil C stock change was quantified up to a 30 cm soil depth by adding C pool model outputs for the litter, the first soil layer (0-20 cm soil depth), and one third of the second soil layer (20-50 cm soil depth). Responses of cropland soil C stock to altered management scenario in comparison to the control (REF) were generated, assuming a 'paired plot' (West et al., 2004) or 'synchronic' approach (Corbeels et al., 2018). The calculations follow the equation 3.3.4B of the guidance from the Intergovernmental Panel on Climate Change (IPCC, 2006) for annual changes in mineral soil C stock on remaining cropland as Eq. (1):

$$\Delta p_{s,i,t} = (p_{s,i,t} - p_{REF,i,t})/T_{i,t} \ , \qquad (1)$$

where $\Delta p_{s,i,t}$ is the annual soil C sequestration rate in t C ha^{-1} yr^{-1} per alternative scenarios s, in grid cell i, and time step t, as the absolute difference between the annual absolute soil C stock $p_{s,i,t}$ in t C ha^{-1} yr^{-1} in each of the alternative scenarios and the baseline $p_{REF,i,t}$, divided by management duration T, as the number of years (1 to 50) since introduction of the alternative practices.

Simulated annual productivity output data for the four crop types: wheat, maize, rice, and soybean were averaged, as area-weighted mean of irrigated and rainfed yield in kg DM ha^{-1} yr^{-1}, per crop-specific cropland area in grid cell i, and time step t.

Responses to altered management of crop-specific average yield in kg DM ha^{-1} yr^{-1} and N leaching rates kg N ha^{-1} yr^{-1} , respectively, were computed as Eq. (2):

$$\Delta v_{s,i,t} = ((\frac{v_{s,i,t}}{v_{REF,i,t}}) - 1) * 100 \ , \qquad (2)$$

where $\Delta v_{s,i,t}$ is the relative difference in percent (%) between the assessed variable $(v_{s,i,t})$ per alternative management scenario s compared to the baseline value $(v_{REF,i,t})$, per hectare of cropland area in grid cell i, and time step t.

We report global aggregates of values and differences as area-weighted median (Q2 as q = 0.5 as $\Delta\tilde{v}_{s,i,t}$), the first (Q1 as q = 0.25) and third quartile (Q3 as q = 0.75) per scenario s, per time step t. Time step t is annual (yr^{-1}) either reported for the first (years 1 to 10) and last (years 41 to 50) decade of the 50 simulation years to contrast short from long term effects, or for an else indicated time period. For area-weighting of the global aggregates, we applied the physical cropland distribution pattern of land use model input data of the year 2010 (see Sect. 2.2, S1.2). Although many studies present averages across experiment sites and years (Nyawira et al., 2016), we computed median (and quartiles) changes to exclude outliers stronger influence on global spatial aggregated mean values.

To assess historical global impact of Conservation Agriculture on agroecosystem components, we employed a time series dataset of global gridded CA physical cropland area. This CA data was generated, using annual national reported CA cropland area data in hectares (FAO, 2016) and employing methods described in Porwollik et al. (2019) and further in the Supplement (Sect. S1.4). The simulation cover crops combined with no-tillage (CCNT) was assumed a proxy for the suite of CA practices. Computed changes per variable, grid cell i, time step t for the CCNT scenario compared to the control (REF), were remapped to match the historically evolving spatial and temporal pattern of the CA cropland area time series data. We quantified impacts of CCNT on variables as global aggregated total and as area-weighted median change per hectare of CA cropland area for the years 1974 to 2010. During this assessed historical period the CA area grew from a share of 0.2 to 10 % of the global cropland area (FAO, 2016).

4.3 Results

4.3.1 Overview of aggregated responses to cover crops

Simulated cover crop impacts exhibit positive soil carbon sequestration rates and reduced N leaching rates, but at the cost of lowered average yield in both analyzed decades (Table 1). The here estimated changes of agroecosystem components due to cover crops (CC) compared to bare fallow (REF) on cropland between two consecutives main crop growing seasons, are consistent with the magnitude and direction of effects reported in other studies (Table 1, see Supplement Table S2.1 for an extended comparison to literature values).

Table 4-1. Responses to cover crops (CC) in comparison to the control scenario with bare fallow (REF) on cropland during main crop off-season periods as annual aggregated area-weighted median and in the parenthesis the quartiles (Q1, Q3) for the first and last decades of the 50 year simulation period, respectively, (see Sect. 2.3 for equations used). In the latter two columns values from other studies as well as their considered duration of cover crop management are reported.

Response Variable	Unit per year	Simulated ΔCC first decade median (quartiles)	Simulated ΔCC last decade median (quartiles)	Literature ΔCC range of values (min.-max.)	Management duration (years)
Soil C sequestration rate	t C ha^{-1}	0.52 (0.03, 1.04)	0.48 (0.24, 0.78)	0.01 - 0.56[a]	1 - 54
N leaching rate	%	-39.3 (-64.2, -3.6)	-54.3 (-74.4, -35.8)	-70 - (-50)[b]	1 - 17
Wheat yield	%	-0.7 (-3.5, 0)	-1.4 (-5.3, -0.1)		
Rice yield	%	-5.6 (-9.9, -0.3)	-5.6 (-9.8, -2.5)		
Maize yield	%	0 (-6.0, 0.1)	-1.2 (-11.5, 0.6)	0 - 9.6[c]	5
Soybean yield	%	0.1 (0, 1.0)	0.4 (0, 2.7)	2.8 - 11.6[d]	5
Average yield	%	-1.6	-2.0	-4 - 0[e]	1 - 28

[a] Jian et al. (2020); Lal (2004b); Paulsen (2020); Poeplau and Don (2015); Sommer and Bossio (2014); Stockmann et al. (2013)
[b] Thapa et al. (2018); Tonitto et al. (2006); Valkama et al. (2015)
[c] Marcillo and Miguez (2017); SARE (2019)
[d] SARE (2019)
[e] Abdalla et al. (2019); Thapa et al. (2018); Tonitto et al. (2006); Valkama et al. (2015)

4.3.2 Soil carbon responses to altered management and duration

We found increased cropland soil carbon stocks in the three alternative management scenarios compared to the control (REF), indicated by positive annual area-weighted spatial aggregated median soil carbon sequestration rates (Fig. 1, for respective spatial patterns see Fig. S2.3.1). During the first decade the median soil C sequestration rates in the three alternative management scenario simulations CC, CCNT and NT were higher (0.52, 0.72, and 0.08 t C ha^{-1} yr^{-1}) than during the last decade (0.48, 0.54, and 0.01 t C ha^{-1} yr^{-1}). The maximum annual median soil C sequestration rates within both cover crop scenarios CC and CCNT (0.79, 1.03 t C ha^{-1} yr^{-1}) were reached in the sixth year of the analyzed 50 year simulation period, whereas in NT (0.11 t C ha^{-1} yr^{-1}) already in the third year since introduction of altered management. After these peaks within each of the scenarios, the annual soil C accumulation effect persist over the course of the remaining simulation period, but with lower rates.

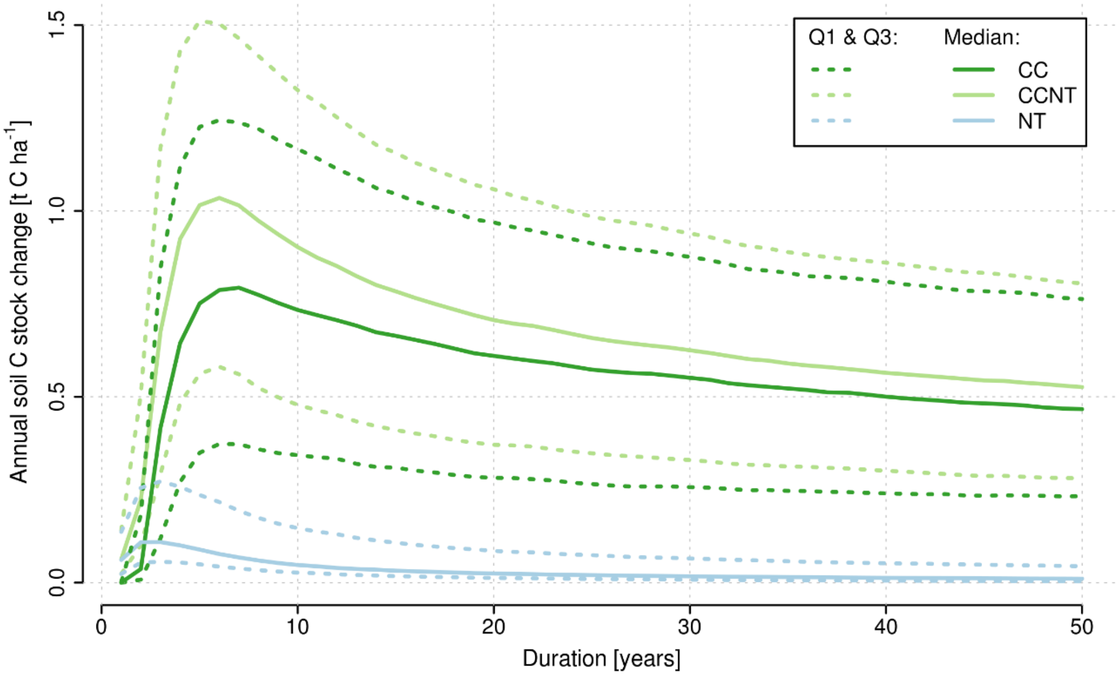

Figure 4-1. Area-weighted median across global cropland of average annual soil C sequestration rates (Eq. 1) in t C ha^{-1} yr^{-1} as solid lines and the first (Q1) and third (Q3) quartiles as dashed lines per alternative soil management scenario (CC: dark green, CCNT: light green, NT: light blue) compared to the baseline (REF) over the 50 year simulation period.

4.3.3 Impacts of management type and duration on soil N and water dynamics

All three alternative management scenarios exhibit higher transpiration but lower evaporation rates than found in the baseline (Fig. 2 a and b). In both cover crop simulations (CC and CCNT) the transpiration rates are higher because of the extended vegetative growth per cropland area unit compared to scenarios with the bare soil fallow during primary crop off-season periods (REF and NT). With CC, transpiration increased more strongly than evaporation was reduced, so that total evapotanspiration water fluxes were higher than in REF. In CCNT and NT, we found lowerded evaporation rates outweighing elevated transpiration rates compared to in REF with tillage. Cover crops in CC and CCNT led to lower but still positive median N net-mineralization rates (as the difference of soil N gross mineralization and immobilization rates) compared to bare soil fallowing practices in REF and NT (Fig. 2 c). This decline is driven by larger increases of the soil N immobilization than of gross mineralization rates, especially within the first 10 years after introduction of cover crop practices (Fig S2.2). In both cover crop scenarios (CC and CCNT) N leaching rate shares of applied mineral N fertilizer were decreased faster and more strongly than in NT compared to in REF over the course of the simulation period (Fig. 2 d). After the first three initial years the response is stabilizing for all three alternative scenarios.

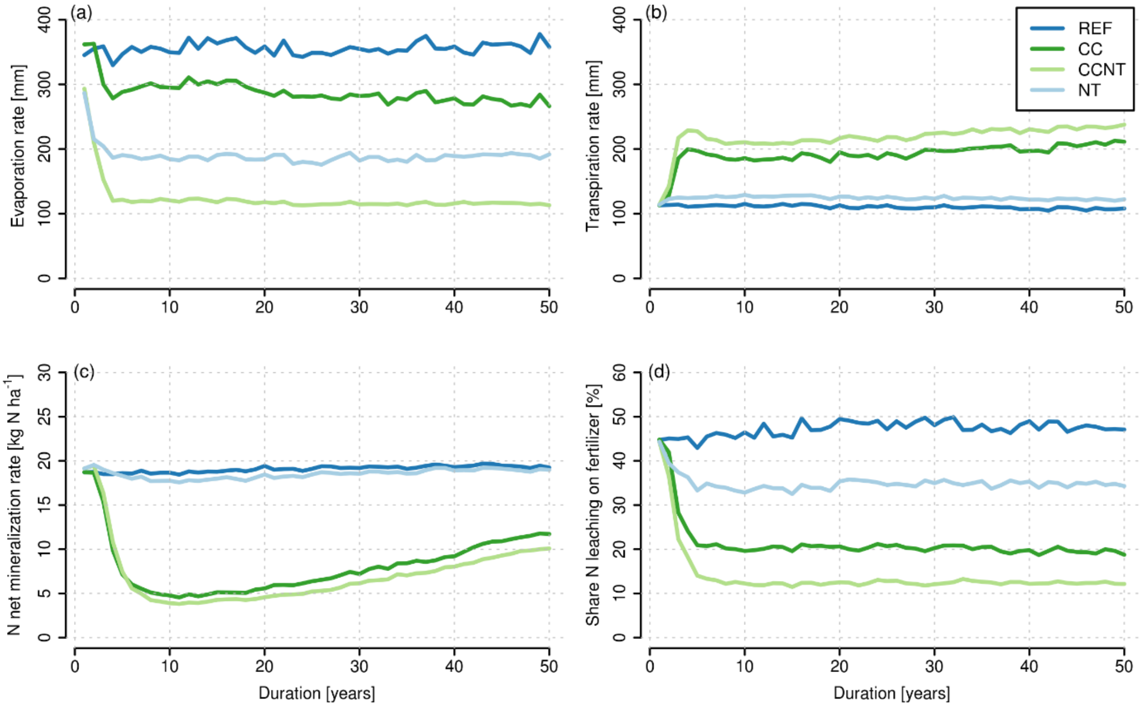

Figure 4-2. Plots in panel display the time-series for the 50 years simulation period of the annual global spatial aggregated area-weighted median per hectare cropland area as lines per management scenario (REF: dark blue, CC: dark green), CCNT: light green, and NT: light blue) for: (a) Evaporation rate in mm, (b) Transpiration rate in mm, (c) Soil N net mineralization rate in kg N ha^{-1} (derived as absolute difference between soil gross N mineralization and immobilization rates), and (d) Shares of annual soil N loss through leaching of applied mineral N fertilizer rate in percent (%).

The relative differences in soil N leaching rates compared to the baseline (REF) are illustrated in Fig. 3 and indicate a reduction on the majority of global cropland in all three alternative soil management scenarios (for the respective spatial pattern see Fig. S2.3.2). Larger reductions and lower spatial variation are generally found during the last than during the first decades. Median reductions in N leaching rates in simulations including cover crops (CC and CCNT) were about two to three times higher than in NT.

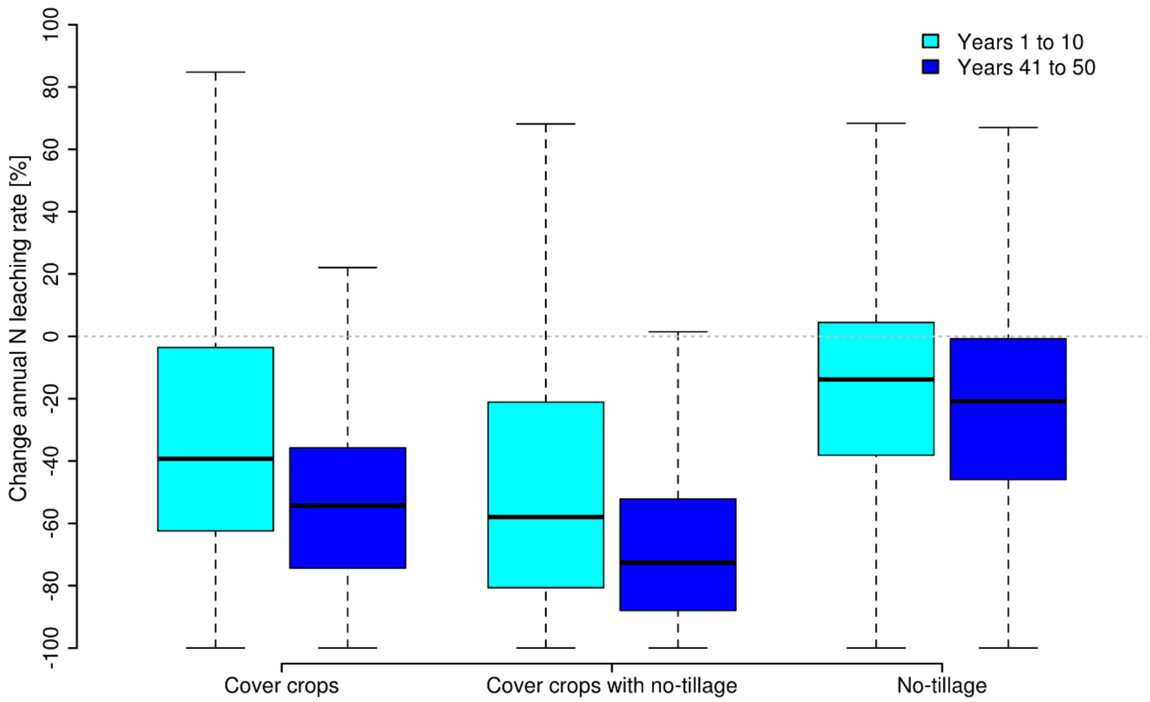

Figure 4-3. Boxplots of relative differences (%) per hectare cropland area between annual N leaching rates in each of the simulated alternative management scenarios (CC, CCNT, and NT) compared to the baseline (REF) in the first (left bars, cyan) and last decades (right bars, blue) of the 50 year simulation period. The black midlines of boxes indicate the median responses per period, hinges of boxes show the first (Q1) and third (Q3) quartiles, and whiskers extend both to the minimum and maximum values within 1.5 times the interquartile range (IQR) of the distribution (outliers, defined as values outside this range are not shown here).

4.3.4 Yield change of following main crop due to altered management and duration

Whereas the impact of cover crop (CC) on main crop yield exhibited a quite consistent temporal pattern when analyzing per crop type (Table 1), the spatial variance was larger (Fig. 4). The productivity for maize and rice in northern cold and tropical humid climates is lowered with cover crops (CC), whereas drier temperate regions e.g., in the Western USA and Mediterranean reveal prominently enhanced yield effects for the four assessed crop types.

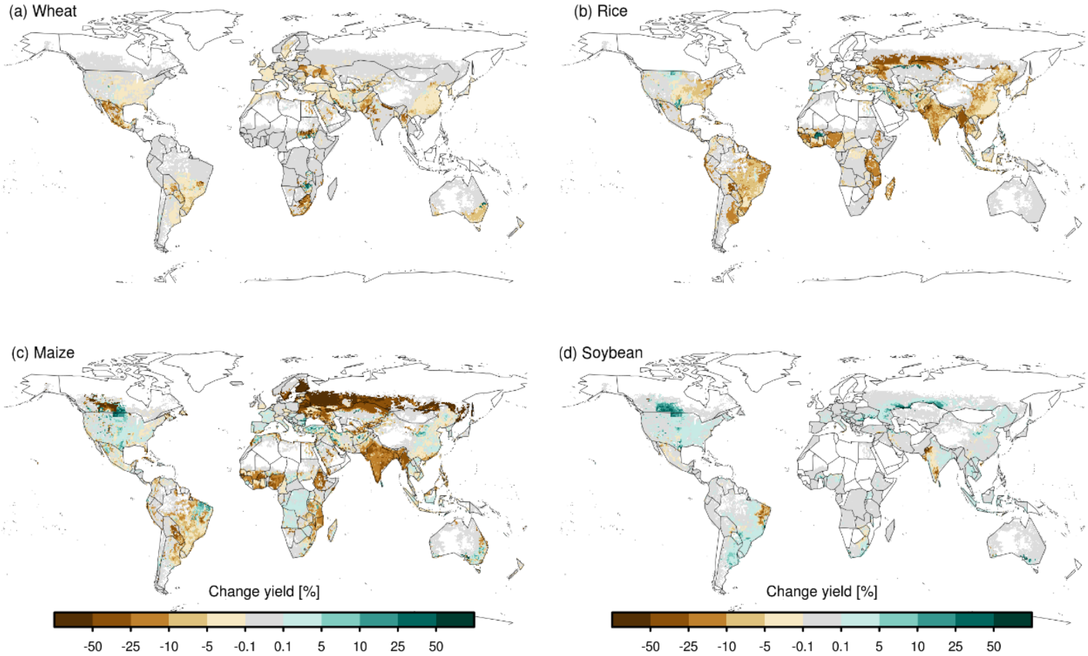

Figure 4-4. Maps showing changes of averaged rainfed and irrigated productivity in response to cover crops (CC) compared to bare fallow on cropland area during main crop off-season periods (REF) as annual median relative differences in percent (%) per hectare of crop-specific cropland area and grid cell of the year 2010 for: (a) Wheat, (b) rice, (c) maize, and (d) soybean for the 50 year simulation period.

Comparing the changes across the management treatments, main crop productivity decreased most strongly in CC and increased most in NT relative to the baseline with tillage and bare soil fallow practices (REF) (Fig. 5 a-d). In CC, rice yield declines were largest, whereas reduction for this crop type was halved on the majority of global cropland when combined with no-tillage practices (CCNT). In contrast to lowered maize yield in CC, we found positive median responses for this crop type in CCNT but with higher spatial variability of impact magnitude and direction. Wheat yield responses to any of the three alternative managements were very low in overall magnitude, being slightly reduced in both cover crop scenarios, but improved in NT. Soybean yield responded positively to all alternative management, around 9 % higher median in CCNT and NT compared to in REF.

Exploring management impacts on productivity separated by water regimes revealed larger spatial variability of management responses for rainfed than for irrigated crop yields (Fig. S2.4). Soybeans in irrigated systems show no response to altered management practices. For the other crops, median yield responses to cover crop practices (CC, CCNT) were found to be either more negative or changing from a positive to a negative response in irrigated systems compared to rainfed systems.

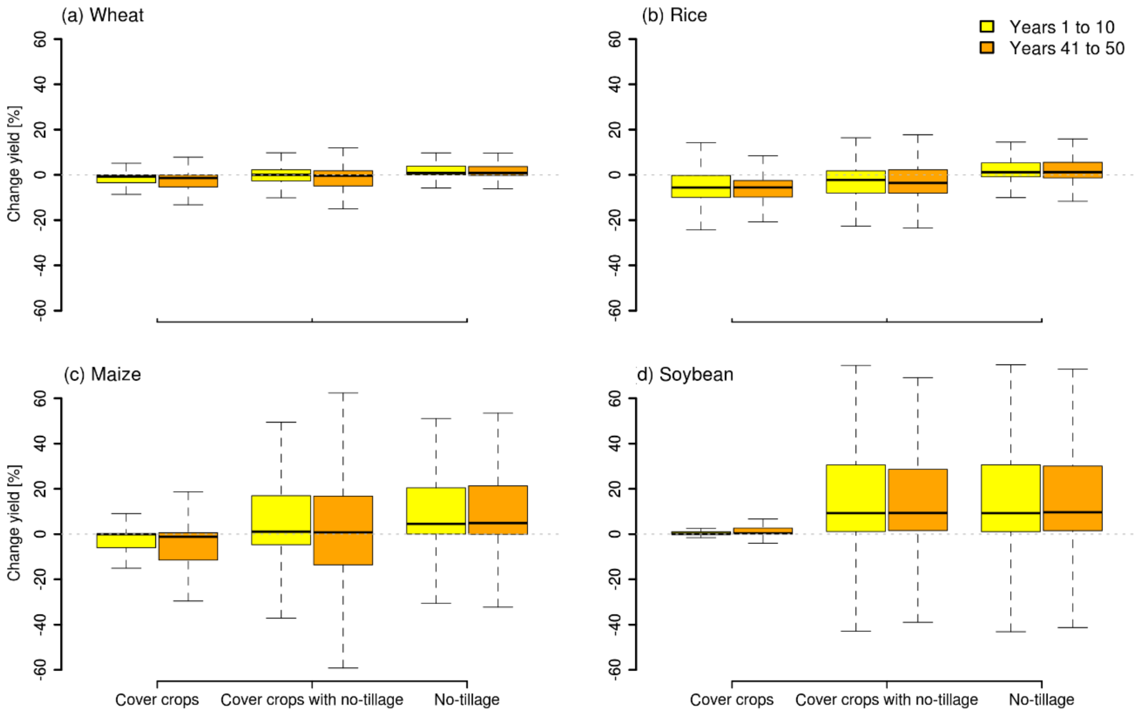

Figure 4-5. Panels (a-d) displaying changes in wheat, rice, maize, and soybean average yield as boxplots of relative differences in percent (%) area-weighted by crop-specific physical cropland, due to alternative management practices (CC, CCNT, and NT) compared to the baseline (REF) for the first (left bars, yellow) and last decades (right bars, orange) of the 50 year simulation period. Boxes' black midlines indicate the spatial median across the distribution of responses, the lower and upper edges of the boxes the first and third quartiles, and whiskers extending both to the minimum and maximum values within 1.5 times the interquartile range, respectively from each Q1 and Q3 (outliers, defined as values outside this range are not shown here).

4.3.5 Cover crop and no-tillage impacts on Conservation Agriculture cropland

In response to cover crops applied with no-tillage practices (CCNT, Fig. S2.5), which we used as proxy for the full set of CA practices, positive yield changes dominate in areas of Conservation Agriculture (Fig. S1.4). Calculating median (quartiles) for yield changes on CA areas only, we found that the productivity for wheat, maize, and soybean was almost exclusively enhanced (6.4 (0.2, 29.4); 23.7 (3.3, 84.1); 27.8 (3.1, 79.0) %, respectively). Although rice yield largely increased with the combined practices but can be lowered as well (5.6 (-3.1, 34.8) %). Applying the CCNT change metrics for soil C (Fig. 1) to the temporal and spatial pattern of the mapped CA cropland time series data (Sect. S1.4), we estimated 1.4 PgC total historical soil C net-accumulation in the period 1974-2010. The area-weighted median (quartiles) of average annual soil C sequestration rate was 0.85 (0.32, 1.42) t C ha^{-1} yr^{-1} on CA areas. For the N leaching rate, we find a reduction by -56.9 (-80.4, -13.4) % across global CA areas.

4.4 Discussion

4.4.1 Soil carbon sequestration

The generated median soil C sequestration rates of cover crops were within the upper end of range of values reported in the literature (Table 1, Table S2.1). Few regions in temperate and dry climatic conditions, e.g. in Western USA, Turkey, Iraq, Iran, reveal a neutral or declining trend (S2.3). In line with findings of West and Six (2007), we found highest soil C sequestration potential in tropical regions (e.g. South-East Asia and Central Western Brazil), whereas Stockmann et al. (2013) derive largest potential for temperate humid regions. Abdalla et

al. (2019) find both regions profiting from the practice, because there, water is a less limiting factor to biomass production and additional inputs produced by cover crops to the soil pools enhance soil C accumulation.
Assuming the median soil C sequestration rate of 0.55 t C ha^{-1} yr^{-1} during a period of 50 years for the estimated 400 million hectare cropland area potentially available annually for cover crop practices (Kaye and Quemada, 2017; Poeplau and Don, 2015), we estimated a global potential soil C sequestration rate of 0.22 PgC yr^{-1} in the top 30 cm. This is equivalent to about 7-11 % of the 2-3 PgC yr^{-1} annual sequestration on global agricultural soils until the year 2030 targeted by the '4per1000' initiative (Minasny et al., 2017). However, our estimate is higher than the 0.12 ± 0.03 PgC yr^{-1} (mean and standard deviation) found by Poeplau and Don (2015) simulating cover crops effects with the RothC model for a similar time frame but for 0 - 22 cm soil depth.
Lower annual median soil C sequestration rates with cover crops (CC) in the first three simulation years, reveal a time lag of response to altered management (Fig. 1). A similar effect is also apparent for N and water fluxes (Fig. 2). On the one hand, this may be because cover crops are first established at the end of the first main crop growing season, so that the full effect becomes visible in the second year only. On the other hand, a temporal delay of detectable cover crop impacts on soil organic C concentration within the first years of practice was also found in the review of ecosystem services of cover crop practices by Blanco-Canqui et al. (2015), due to the complexity of biophysical processes affected by changes in biomass inputs due to altered management practices. This suggests that cover crops need to be cultivated for at least three years to take effect. Duration, as the number of years a system has been under a management practice, was also identified as one of the most important factors to reap the benefits of altered soil physical properties from cover crops practices (Laborde et al., 2020b; Nouri et al., 2020; West and Six, 2007).
The higher soil C sequestration rates calculated for the first than for the last decade of the 50 year simulation period (Table 1, Fig. 1) are in line with other studies' estimates as well. For example Sommer and Bossio (2014), assumed their soil C sequestration rate functions for their simulations of cover crop impacts to peak between the third and seventh year of continuous practice and then to level off after about 20 to 40 years. Corsi et al. (2012) in their meta-analysis on effects of CA practices, found a decreasing rate of soil C sequestration between the fifth and twentieth years. The decreased change rates towards the end of the 50 year simulation period, suggest a saturation effect (for cover crops later than for no-tillage), when soil C and N pools approach a new equilibrium state, as discussed by Kaye and Quemada (2017); Poeplau and Don (2015); Smith (2016). However, the new equilibrium of soil C (Corbeels et al., 2018; Poeplau and Don, 2015) is not reached in our simulations for the majority of global cropland for CC or CCNT within the analyzed 50 years simulation period. For NT, half of global cropland reached the new equilibrium after 12 years.
The median soil C sequestration rate for both cover crop scenarios (CC and CCNT) were higher than for no-tillage (NT), which is in line with the review of Kaye and Quemada (2017). The effect of combined cover crop and no-tillage practices (CCNT) exhibited the largest soil C sequestration rate with median 0.72 t C ha^{-1} yr^{-1} in the first decade. Our result were higher than Franzluebbers (2010) finding a soil C sequestration rate of 0.45 ± 0.04 t C ha^{-1} yr^{-1} for experiments comparing cover crops combined with tillage and no-tillage in Southeast USA for about 11 years and were within the range stated in the meta-analysis of experiments from Brazil (0.4-1.9 t C ha^{-1} yr^{-1}) and France (0.1-0.4 t C ha^{-1} yr^{-1}) (Scopel et al., 2013) for experiments with a duration of 5-28 years. The higher effect of combined cover crops and no-tillage on soil C stock is also supported by Corbeels et al. (2018) finding higher soil C stocks in case of CA compared to conventionally tilled systems, whereas Abdalla et al. (2019) and Poeplau

and Don (2015), find no significant differences due to changed tillage practices with cover crops in their meta-analyses.

4.4.2 Nitrogen leaching

The derived N leaching rate reduction in CC were at the upper end of the -70 to -50 - % range of effects reported in literature (Table 1, Table S2.1). For the spatial effects of cover crops, it can be depicted, that most cropland can profit from about halved N leaching rates (Fig. 3, Fig. S2.3.2). One important driver of the size of the effect of cover crops is the length of the fallow season. In northern regions, main crop growing seasons are rather short and aligned across crop types, so that a lot of off-season cropland area is available for cover crops for relatively longer time. Largest N leaching rate reduction can be found in cold temperate regions (such as in Russia) and humid tropics (e.g., large parts in Africa), where external N inputs (i.e. mineral N fertilizer rates, also see Sect. S1.2 for rates used here) are rather low. On the one hand, the variance of cover crop effects across global cropland can be attributed to management intensity (e.g., fertilizer application rates), in this study prominently seen as differences at some national borders (USA and Canada). According to Wittwer et al. (2017) efficiency of cover crops to reduce N leaching is decreasing with management intensity (including fertilizer application rates and tillage practices). On the other hand, the spatial variance of cover crop effects within countries suggest differences due to soil and climatic conditions. Only few drier regions reveal either a neutral response or slight increase of N leaching rates due to cover crops (Fig. S2.3.2). This can be attributed to reduced growth of cover crops, limiting their capacity for N uptake of excess N remaining in the soil column after harvest of the main crop.

Because the plant material from cover crops that drives the C sequestration with the practices (Sect. 3.1, 4.1) has a wider C to N ratio than the soils, it leads to stronger immobilization of mineral N in the soil column (Fig. S2.2). Increased evapotranspiration and immobilization but also uptake of N by cover crop plants were found to reduce the soil N (Quemada et al., 2013; Thapa et al., 2018; Zhu et al., 2012), which would be susceptible to leaching from cropland soils during primary crop off-season periods (Abdalla et al., 2019; Alonso-Ayuso et al., 2014; Delgado et al., 2007; Tonitto et al., 2006). For their efficiency in N uptake, grass cover crop are also described as 'scavengers' (Blanco-Canqui et al., 2015). Therefore, cover crops can be regarded especially suitable for high-input farming systems, where surplus N left in the soil after harvest of the main crop, can be retained in the biomass of the cover crop. After termination, the C and N contained in the cover crops biomass, can serve as 'green manure' temporally fixed in compounds of the soil organic matter (Zomer et al., 2017).

4.4.3 Crop yields

The average yield change computed for cover crops (CC) were at the lower end of the range -5 to 11.6 % of values found in literature (Table 1, S2.1). Reduced productivity levels of the following main crop are reported mostly in the context of competition with the cover crops for water and nutrients (Abdalla et al., 2019; Tonitto et al., 2006; Valkama et al., 2015). The increased immobilization of soil N after the introduction of cover crops is thought to actually exacerbate N stress (Abdalla et al., 2019; Erenstein, 2003; Kuo and Sainju, 1998; Ranaivoson et al., 2019). Marcillo and Miguez (2017) assume that lower maize yields found with cover crops may also be caused by a temporal asynchrony between periods of soil N mineralization and high N demand of the main crop. Several authors (Marcillo and Miguez, 2017; Thapa et al., 2018; Tonitto et al., 2006) report no significant effects of non-leguminous cover crop species on yields of the subsequent main crop, which may be caused by the mainly intensively fertilized experiments considered, e.g. in Tonitto et al. (2006). This is in line with our findings for soybean, which is an N fixer (not subject to N limitations in LPJmL) and sees hardly any yield penalty from cover crops. Also, the mostly negative responses to cover crops for the three cereal crop types in irrigated systems (Fig. S2.4.2), where water is not a growth-limiting factor for the main crop, can only be explained by a decrease in N availability for the main crop. Several authors (Marcillo and Miguez, 2017; Thapa et al., 2018; Tonitto et al., 2006) report no significant effects of non-leguminous cover crop species on yields of the subsequent main crop, which may be caused by the mainly intensively fertilized experiments considered, e.g. in Tonitto et al. (2006).

Cover crops affect soil water in different ways: cover crops tend to increase transpiration (see Fig. 2 b), but at the same time reduce soil evaporation (Fig. 2 a) and increase infiltration (Dabney et al., 2001). Depending on the relative magnitude of these processes, soil water availability for the main crop can increase or decrease at different locations. This is clearly shown in Fig. S2.4, where yield responses to cover crops in rainfed systems reveal a much larger variability than in irrigated systems. The spatial variability of yield response to cover crops for different crops (Fig. 4 and 5) is the result of differences in how cover crops impact water availability of the main crop, how water limited the main crop is, and how strongly the cover crop the reduces N availability for the main crop. However, sensitivity to changes in water availability is highest in rainfed systems in water limited environments, on soil types of low soil water holding capacity, or insufficient recharge, which limits their applicability under such conditions (Marcillo and Miguez, 2017).

In contrast to CC, an enhancing effect on productivity was found with NT for all four crop types. Also Su et al. (2021) find for wheat, maize, and soybean, that although no-tillage could lead to yield declines in cooler and wetter regions, this loss to be more than compensated at the global scale by increased productivity in arid rainfed cropping areas. In our model, the yield increase can mainly be attributed to the water-saving effects simulated with no-tillage compared to both REF and CC scenarios with conventional tillage (Fig. 2, Fig. 5). This is caused by the built up of a litter layer due to no-tillage practices covering the soil as mulch, which increases infiltration rates as well as reduces evaporation and surface runoff rates (Jägermeyr et al., 2016; Lutz et al., 2019).

In CCNT, the effects of cover cops and no-tillage are combined, so that cover crops provide vegetative soil cover on cropland during main crop off-season, and when terminated serve as additional mulching material during the following main crop growing periods. This additional mulch layer in combination with no-tillage counteract the higher transpiration from cover crops by improving infiltration and reducing evaporation (Abdalla et al., 2019; Scopel et al., 2013). Enhanced maize and soybean yields, as well as less rice yield reductions found with CCNT than with CC compared to REF, reveal co-benefits of both practices (Fig. 5). The assumption of synergetic effects of both practices in CCNT were supported by the even higher median yield responses derived here for cropland with Conservation Agriculture practices (Sect 3.5, Fig. S2.5), which area was mapped with a higher likelihood to arid regions (Porwollik et al., 2019).

The here presented yield responses to different management settings (NT, CCNT) are only partly in line with findings of Pittelkow et al. (2015a), analyzing experiments lasting 1-31 years, who find largest declines (-9.9 %) when no-tillage was adopted alone and decreased negative effects (-6.2 %) when no-tillage was applied with crop rotation. However, cover crops as modelled in our CCNT scenario are only one aspect of crop rotation enhancement considered in the analyses by Pittelkow et al. (2015a), which limits the comparability between our and their findings.

4.4.4 Methodological limitations and implications

The results indicate in general reliability of the here used model version LPJml5.0-tillag-cc to reproduce ranges of reported temporal and spatial pattern, magnitude, as well as the sign of direction of cover crop impacts at the global scale (Table 1). However, aggregated changes due to CC presented here were not always matching other studies' findings (Table S2.1).

On the one hand, these deviations may result from different soil depth considered or meta-analyses reporting averages across different years and experiments (Nyawira et al., 2016). Further uncertainties are related to literature values, which may include experiment results from measurements during the main crop growing season only instead of covering the entire year (Quemada et al., 2013). On the other hand, important processes that determine the effect of cover crops in field trials, such as erosion, weeds, pests, or diseases, are not accounted for in this model version.

The high C sequestration rates calculated for CC, e.g. in the humid tropics (Fig. S2.3.1) may be due to an overestimation of the simulated fallow period length for cropland in this climatic region. In the model version used here, only the main representative growing season of a crop is simulated per year, so that multiple cropping practices for areas where several crop harvests per year are common (Siebert et al., 2010; Waha et al., 2020) are not well covered, resulting in distorted cover crop productivity levels and biomass input to the soil pools. The here applied model setting for the representation of irrigated cropland in the simulations, assuming unlimited water availability for irrigation practices, may cause an overestimation of main crop productivity as well as resulting main crop residue input amounts to the soil pools. The computed initial soil C pools do not represent the conditions on current croplands because our simulations excluded historical land use dynamics, to which responses in soil usually are slow and of long-term (Nyawira et al., 2016). Pugh et al. (2015) find that the soil legacy flux from land use and landcover change may dominate ecosystem carbon losses for a timescale up to a century. By starting the simulations from soil C pools in equilibrium, we aimed to make sure that the acquired response is due to altered management. The deviations in initial soil C and N pools was accounted for in this study by presenting responses to alternative management scenarios (CC, CCNT, NT) in relation to the baseline scenario (REF).

The potential trade-off between environmental benefits (reduced N leaching, soil carbon sequestration) and main crop productivity changes found here with cover crops and conventional tillage practices, suggest the requirement for the complementary modification of fertilizer management and the parallel adoption of irrigation or soil water preserving practices, such as no-tillage and mulching practices to maintain current main crop yield levels. Further global scale investigation of complementary land management practices may include leguminous (N fixing) cover crop species or mixes of them with the here presented grass type. Production costs associated to additional seed purchase for cover cropping (Alonso-Ayuso et al., 2020), and opportunity cost for field activities of the farmer in otherwise off-season periods (Lee and Thierfelder, 2017), need to be evaluated in integrated assessments against the environmental benefits from the practice (Blanco-Canqui et al., 2015). Further studies are needed for the quantification of cover crop impacts with climate change and to explore options for adaptation of the practice to regionally specific environmental and economic conditions, influencing farming decisions and land management practices.

4.5 Conclusion

This study presents the first global temporal and spatially explicit quantification of impacts of cover crops in combination with tillage practices. The routines of cover crops implemented into LPJmL, allow for consistent, global-scale assessments of biophysical, biogeochemical, and agronomic effects, such as on mapped CA cropland during the period 1974 to 2010 and for exploring potentials of sustainable cropland management practices.

We found, that cover crops enable soil C sequestration and reduce N losses through leaching on the majority of global cropland, except in few and mostly unproductive arid regions. Cover crop with conventional tillage practices increase evapotranspiration fluxes and decrease soil N net-mineralization rates compared to bare soil fallowing practices by lowering plant available soil water and nitrogen, leading to reduced growth and yield of the following main crop. Declining yield effects due to cover crops were found for rice, but also for maize, and wheat, most pronounced for cropping areas in northern cold climatic regions. Enhanced productivities with cover crops and tillage for these three staple crops were depicted for temperate regions with high mineral N fertilizer application rates and almost all soybean production.

The yield responses to altered management generated for all four crop types were rather constant over time, whereas for changes in soil N leaching rate and C sequestration pronounced temporal dynamics were found. For soil C sequestration and N leaching the sign of changes was mostly homogeneous across global cropland, whereas for productivity, the direction and magnitude of changes vary considerably among crop types and for different world regions.

For cover crops applied with no-tillage (CCNT), both the soil C sequestration rate and the reduction of N leaching were largest. The combined practices take advantage of the additional biomass production by cover crops and of the soil water saving effects associated to no-tillage, which results in increasing inputs to the soil, improved nutrient cycling, and substantially reduced rainfed crop yield penalties. We resume from the findings, that the heterogeneity of cover crop impacts on C, N, and water processes are determined by the primary crop type cultivated, water regime (rainfed or irrigated), tillage and mulching practices, location, as well as management duration. This study's results demonstrate the potential role of cover crop practices as a nature based solution (Keestra et al., 2018) to transform croplands to C sinks for climate change mitigation.

Code and data availability

The LPJml5.0-tillage-cc model code version, model output data, and R-scripts used for post-processing data accompanying this study are available online at the Zenodo data repository: https://doi.org/10.5281/zenodo.5178070 (Porwollik et al., 2021).

Author contributions

VP, CM, SR, and JH designed the research. VP and CM implemented the cover crops code functionalities with the support of all other authors. VP generated the CA cropland data set and conducted the simulations. VP and CM analyzed results. VP prepared the manuscript and all co-authors contributed by commenting and editing.

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Supplement

The supplement related to this article is available online at: https://bg.copernicus.org/preprints/bg-2021-215/bg-2021-215-supplement.pdf
Supplementary data and material associated to this Chapter 4 is provided in the Appendix C.

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5 Synthesis

Related to the overall thesis' objectives (Section 1.6), the three studies (Chapter 2-4) provide insights on requirements of agricultural management data and on implications for their usages in global change assessments. Chapters 3 and 4 include descriptions of the two soil management datasets, which were generated for improved representation of these practices with respect to type and spatial distribution pattern across global cropland. In the studies presented in the Chapters 2 and 4, respectively, global gridded crop model simulations were used to assess agricultural productivity at different temporal and spatial scales. In the scope of all three studies inter-relations between data and models reveal challenges regarding resolution and level of detail captured by each of them. In the following sections, key findings of the thesis are summarized, and their implications are discussed.

5.1 Single and combined effects of data and models

The first overall objective of this thesis relates to methodological aspects of agricultural management data usages, availability, and associated uncertainty within global modeling studies.

In the study of Chapter 2 aggregation uncertainty associated to the differences between results, when applying state- of-the-art harvested area datasets for the aggregation of gridded crop yield model outputs to average productivity at national and global scale. Aggregation uncertainty was found a compound effect of, first, the spatial heterogeneous pattern of crop yields simulated at the grid scale by each of the 14 individual models, and second of differences in the spatial pattern of harvested area reported in the datasets applied for aggregation. Aggregation uncertainty of global mean yields has been found below 10 % differences but can be substantial for certain crop types and individual countries.

The deduced recommendation from the study in Chapter 2 is to apply several harvested area datasets for gridded model output aggregation to check for plausibility and compliance with validation data, as is shown for combined effects on aggregated average crop productivity and for individual countries in Müller et al. (2017b). The aggregation uncertainty found in that study, cannot be reduced by any current available method, and should be considered when interpreting and communicating global aggregated crop model results. The findings of this analysis add aggregation uncertainty in the context of post-processing gridded model output data to other types of uncertainties already described in literature, such as related to input data (Folberth et al., 2016; Maharjan et al., 2019; Roux et al., 2014), model structure (Tao et al., 2018), model parameters (Challinor et al., 2009; Folberth et al., 2019; Wallach, 2011; Wallach et al., 2012), modeling assumptions, interpretation as well as to communication of data and modelled outputs (Palosuo et al., 2011).

Franklin et al. (2020) criticize that a larger number of represented processes in vegetation models, do not necessarily lead to higher accuracy of simulations, especially when including parameters with insufficient observations and data for validation. Modeling assessment studies should be conducted in an inter- and transdisciplinary way, including stakeholders and local knowledge to cover the spatial and temporal dynamics associated to arable land management practices. To increase the accuracy and robustness of global agroecosystem simulation results, modeling, observational, and experimental studies need to be linked in a better way for improved parameterization of processes to be covered in the models. Sensitivity analyses (Monod et al., 2006) and comparative scenario analyses (Moss et al., 2010) can be applied to estimate an outcome range, especially when simulating outside ranges of training data or when representing non-linear effects.

Global agroecosystem model performances are claimed to achieve higher accuracies of simulating observed values in the temperate zones and developed countries, caused by higher investment in research concerning agriculture in developed countries, but also due to historic development for field scale applications simulating plant growth under intensively managed conditions (Therond et al., 2017). Models, which have been used for biome simulations may be of less detail than point-scale models but can simulate interactions of natural biosphere components more comprehensively. Low-input subsistence production (Jones et al., 2016) and farming systems with a mix of arable and livestock production (Thornton and Herrero, 2015), which are characteristically for small-holder farming, are found underrepresented in global agriculture assessments (Ruane et al., 2017).

This is found associated to their characteristically higher cropping diversity (Challinor et al., 2018; Claessens et al., 2012), while covering comparatively small shares of global cropland, and lower significance of product types for global trade. In SPAM crop production data with a resolution of 0.083 degree resolution is distinguished for 42 crop types, per water regime as well as management intensity (high input, low input, and subsistence) at the sub-grid scale (You et al., 2014; Yu et al., 2020). It can be concluded that the SPAM crop production data and the recently published multiple cropping dataset by Waha et al. (2020) currently provide the most detailed information, which could be applied in global modeling assessments to address spatial heterogenous practices, such as found in small scale farms. Exemplary, the inclusion of high- and low-yielding crop cultivar types associated to different cropping system types has been assessed in Folberth et al. (2019) using the EPIC model. This may be due to failures to capture the inter-annual variability of climate variables especially regarding precipitation pattern (Ramirez-Villegas et al., 2013), missing input data on management practices for assessing agricultural production in highly variable climate regimes, such as in semiarid or tropical regions (McDermid et al., 2017),

Systematic model inter-comparison studies can reduce uncertainties in agricultural representations (McDermid et al., 2017) and serve as source of learning from differences for improvement of models and assessment results (Prentice et al., 2015). Comparing model outputs to ensemble members can reveal individual strength and weaknesses to gain an impression of the magnitude of uncertainty related to each element of the 'cascades' of uncertainties in modeling studies (Reyer et al., 2015). Model ensemble studies with harmonized input data and a common modeling protocol analysis, as shown for point-based (Asseng et al., 2013; Martre et al., 2015) and global scale simulations (Elliott et al., 2015; Frieler et al., 2017) are a way to minimize the variance in the model ensemble caused by differences in individual usages of model input data, parameterization, structure, and configurations. Different levels of model skills within an ensemble study can be addressed by offering different harmonization levels of simulation settings in the modeling protocol and then presenting results per model-group (Müller et al., 2019). With the help of model ensemble studies, it is possible to quantify ranges (variance, means, or medians) of model outputs, which reduce the risk of being totally off, regarding the direction or magnitude of simulated effects. Results of agroecosystem models can be supplemented with estimates of environmental impact from land management practices calculated via bookkeeping models, such as included in the annual publications of the Global Carbon Project on anthropogenic carbon emissions (Friedlingstein et al., 2019; Le Quéré et al., 2018), as a way to reduce bias of the model approach. Only if models can prove to sufficiently reproduce current and past processes, future projections can be made more trustful.

5.2 Methodological contributions and limitations

Whereas the exclusion of tillage practices in global assessments may lead to an underestimation of anthropogenic land use emissions from agricultural practices (Pugh et al., 2015), setting stylized default management such as conventional tillage everywhere, may result in an over-estimation of impact when simulating biophysical and biogeochemical processes on global cropland. The generated crop-specific cropland tillage dataset generated in the second study (Chapter 3) increases the availability of global spatial explicit gridded soil management data, as well as the methodological transparency by providing output data and R-script used for post-processing model output data as open-access assets to the article.

Within the scope of the second study (Chapter 3) existing knowledge and concepts of soil management was synthesized for a classification and more detailed representation of tillage practices in global assessments. Codes of existing global gridded agroecosystem models could be extended for representing also reduced tillage types, e.g. by scaling the model parameter of mixing-efficiency, soil depth affected, or fraction of crop residues' aboveground biomass submerged into the soil, as has been presented for tillage in the cropping system model (CSM) by White et al. (2010). Nevertheless, the tillage types derived in the second study (Chapter 3) are rather generalizations, so that local variations to seeding and harvest techniques, such as in subsistence production systems in tropical regions with all-year-round plant growing conditions, where farmers seed and harvest plants from fields throughout the entire year - resulting in irregular spatial limited soil disturbances, are not considered. For 'traditional' tillage system, further distinction according to the level of mechanization may increase the accuracy of process representation. Biophysical and biogeochemical impacts on agroecosystem components may differ considerably in magnitude between implements used for field operations, such as hand hoes and planting sticks (Thierfelder et al., 2018), animal drawn or tractor pulled plows.

The generated algorithm to map tillage types to the grid scale, included environmental (i.e. aridity, erosion) and socio-economic spatial proxy indicator data (i.e. crop type, water regime, field size, an GNI), because agricultural practices need to be analyzed with regard to their institutional context (Ostrom, 2011; Williamson, 1998). A rule based approach has been applied for the distinction of tillage type area using thresholds values derived from the literature. The downscaling of national reported CA area data to the grid scale was conducted according to the likelihood of no-tillage adoption similar to the mapping approach presented in Prestele et al. (2018). Spatial differences between the two CA area data products were found resulting from using different input data sources and targeting another year for representation in the maps.

The developed methodology for downscaling national reported CA area data in the second study (Chapter 3), was also applied to generate the annual dynamic CA cropland time series covering the period 1974-2010 for the third study (Chapter 4). The mapping of area with CA practices was performed at the grid cell scale with cropland, independent of the crop type, to match the simulation unit size and annual represented crop growth dynamics of LPJmL. This dataset then was used for weighting the generated changes in agroecosystem state and process variables due to combined cover crop and no-tillage practices accounting for the historically evolving pattern of mapped global annual CA area dynamics during the historical period.

For the majority of agroecosystem models employed in global agriculture assessments, the simulation resolution is 0.5 degree (about 50 by 50 km at the equator) (see Appendix A). The spatial resolution of current available agricultural management data mostly range between 0.083 to 0.5 degree, and daily to annual time steps of processes covered, whereas the application scale of provided input data strongly depends on the resolution of the simulating model. For agroecosystem data and models a trend towards 0.1 degree (10 by 10 km) resolution, maybe reasonable, e.g. for assessing food security on small Island affected by climate change or to capture the diversity of land management practices across spatially very heterogenous agroecosystem types. An alternative approach to increased resolution of simulation is presented by Hirsch et al. (2018), who find improved simulated surface energy fluxes with a more detailed representation of local agricultural practice in the Community Earth System Model (CESM). These authors implemented a sub-grid cell code routine, affecting evaporation and canopy conductance on the CA cropland fraction separately from the remaining conventional managed cropland within a grid cell. They find differences in directions and magnitudes of net-global warming responses to simulated CA practices with climate change when comparing results for model parameterization at the sub-grid and grid scale.

In the first study (Chapter 2) it was found that the aggregation of modeled output for crop yield for the historical 30 year period from the grid scale with the harvested area time series data by Ray et al. (2012) exhibited largest differences to the results obtained with the other three datasets, which were available only for the year 2000. The study's findings emphasize that the sensitivity of model output aggregations to the temporal and spatial pattern of crop management dataset used in modeling assessment can be high for certain combinations of crop type, country, and data product applied to aggregate modeled crop productivity. It can be concluded from these findings that in terms of temporal resolution, data time series on annual dynamic cropland use and management practices covering several years are more useful for global gridded crop modeling exercises than time slices reporting information only for one year, which impose the risk to represent an outlier or non-typical period. Even if the target year for a dataset maybe represented right, the modeling community then relies on recycling the time slice data as an annual input and for output aggregation, which induces further uncertainty to results if applied for non-targeted years of an applied dataset.

Within the scope of the third study (Chapter 4) tillage was coded in the LPJmL model to occur at the time of land use change after the natural vegetation spin-up simulation period (Appendix C) and annually on cropland before the seeding event at the beginning of a main crop growing season. Associated onset and frequencies of tillage events modelled maybe as uncertain as land use representation. Further research may explore the sensitivity to the timing and frequency of land management practices, as has been presented for intra-annual field operations, such as fertilization and tillage by Hutchings et al. (2012). The onset of utilizing hand tools has been assumed since about 6000 B.C., with animal drawn plows since about 1000 B.C., and with mechanically drawn implements for tillage on cropland soils since about the year 1920 (Hay, 1974). In current modeling studies, historical impacts of land use and management on agroecosystem components are usually approached with a simplified spin-up simulation. However, for tillage, as one of the first sedentary farming practice, it can be assumed that the respective time span even exceeds time covered by current land use data inputs available for modeling and though very likely tend to be either under- or over-estimated in effect size regarding its onset.

Agroecosystem models currently cannot predict the evolvement of new techniques or species under the simulated future scenarios. This effect can be approached by including compound factors to represent technological change (i.e. cultivar and crop type at field scale, crop mix at farm or regional scale) derived from past patterns, which trend may also be assumed for anticipated future periods (Dietrich et al., 2014). However, some factors influencing technological advancement but also acceptance and adoption of innovative practices cannot be entirely covered in a linear way, so that such a compound factor may rather reflect an average of effects.

Despite the interest in higher spatial exactness and temporal coverage of simulation results when applied at regions, increased resolution in the input datasets only propagate into model results, if models are capable to represent these processes with sufficient level of detail. This development is determined by personal and computational capacities as well as facilities of model teams. Assessment of agricultural production for global change remain in the squeeze between level of detail captured in the data and of complexity represented in the agroecosystem models, and their combined effects.

5.3 Importance of accounting for cropland management

Addressing the second overall objectives of this thesis the second study (Chapter 3) reveals that the majority of global cultivated cropland soil is tilled intensively at least on an annual basis, including the inversion, and mixing of the upper soil layer up to a depth of 30 cm. Conventional tillage submerges at least 85 % of the aboveground biomass of crop residues or killed weed from the surface into the soil. By this way weed pressure can be reduced but the bare soil surface is exposed to erosive processes of wind and water, which accelerate the decomposition of soil organic matter, resulting in declining soil hydraulic and physical properties (Carr et al., 2020; Naipal et al., 2015). Weed infestations after tillage reduction is found one of the major barriers to the adoption of reduced tillage practices as promoted under CA by farmers (Ward et al., 2018). However, it is argued that increased weed pressure, occurring during the initial years of transitioning to a less intensive tillage system, would decrease in the longer run and even enable lower pesticide application rates, especially when additionally practicing soil cover management and crop rotations (Friedrich, 2005). Biomass produced on the field which is not harvested, can be used for mulching, as another practice promoted under CA, e.g. to suppress weed growth (Thierfelder et al., 2018). The increasing substitution of mechanical weed control by herbicide application (Ward et al., 2018), can increase herbicide resistances, the development of weed infestations, and the pressure to use herbicide resistant crop cultivar types (Cerdeira et al., 2011). Since effects of weed, pest, and disease dynamics (Donatelli et al., 2017) are often not represented in agroecosystem models, the interaction with these processes with tillage, residue, and fallow period management practices are subject to further assessments of impact on ecosystem components and human health.

Within the scope of the third study, I also contributed to the model code development of LPJmL for a more detailed representation of cropland management practices, such as tillage, crop residue removal rates as well as manure and N fertilizer application. The impacts of the historical dynamics of these practices with land use change are analyzed in Herzfeld et al. (2021), who use LPJmL5.0-tillage2, which code is built on the same preceding model code version as LPJmL5.0-tillage-cc used in the third study of this thesis (Chapter 4).

The modified code representation of cover crop practices in LPJmL5.0-tillage-cc, exhibited improved compliance of simulation results with estimates reported in the literature (Appendix C). Generated estimates on soil carbon sequestration effects with cover crop and alternative soil management practices (Chapter 4), indicate considerable potentials to support sector-overarching and agricultural sector specific mitigation and adaptation efforts (Rosenzweig et al., 2020; Smith et al., 2019; Thorn et al., 2016; Waha et al., 2013). However, the analysis on cover crop practices reveals lowering impacts on cereal crop productivities due to evolving co-limitations of nutrients and water. For the local soil balance, it is necessary to compensate for ecosystem fixed and exported carbon and nutrients from agroecosystems to maintain soil fertility – also affecting land productivity and the food security of future generations. However, intensive agricultural production often is associated with negative environmental externalities, such as nutrient losses due to leaching, emissions, and resulting pollution of natural habitats and water bodies (Mueller et al., 2012). This could be improved by the adoption of cover crop practices (Chapter 4), or integrated fertilization schemes (Guardia et al., 2019). Whereas the Nitrate-Directive (91/676/EEC, year 1991) sets guidelines for compliance of field practices with the Codes of Good Agricultural Practice in member countries of the European Union, especially for cropland production near water courses or on sloping land, a common global policy regarding nitrogen fertilizer management is not yet agreed upon. The findings of the third article (Chapter 4) on reduced leaching levels of about 50 % on the majority of cropland with cover crop practices and increasing soil carbon show the superior performance over conventional bare soil fallowing practices. Internalizing and controlling important pollutant drivers, the sequestration of carbon in soils, but also through the integration of higher species and rotation diversity (i.e. by integrating secondary crop) on cropland (Malézieux et al., 2009), agriculture production may transition from a driver of decline of biodiversity and natural resource degradation, towards a promoter of local and global ecosystems functions and services.

In the second study (Chapter 3) it is shown that CA practices could potentially be extended from a share of 10 % of global cropland in the year 2005 to about 40 %, which estimate can be used in further studies to generate future scenarios. Prestele et al. (2018) derive adoption trends from historical country scale CA area data as functions, which could be used for extrapolation in time within future land use scenarios. Friedrich et al. (2012) find a global annual rate of 7 million hectare between the years 1999 to 2011, but with large regional differences. Historical levels of CA adoption rates were found larger in North and South America where governmental support for switching to no-till farming practices has been very effective, but the exponential growth rate of CA observed historically for South America cannot be expected to be applicable as a global trend for the future. Medium adoption rates are found for cropland in North America, Europe, and Oceania, due to lower economic constraints of farmers there (Prestele et al., 2018). Adoption rates of the CA practices are found rather low in developing countries (Kassam et al., 2014; Ward et al., 2018) and small-scale farming systems, due to lower levels of mechanization, weaker institutional embeddedness, financial and knowledge constraints, as well as limited access to market as further barriers (Andersson and D'Souza, 2014; Corbeels et al., 2014; Derpsch et al., 2016; Giller et al., 2011; Thierfelder et al., 2018; Thierfelder et al., 2015). In Sub-Saharan Africa adoption rates of CA are expected to remain rather low in the future, as subsistence farming is prevalent and knowledge transfer relies on the effectivity of agricultural research and extension programs (Giller et al., 2009). Low-tech solutions, enabling less soil disturbing practices on small scale farms, were developed, such as rippers or the jab planter (Thierfelder et al., 2018), which are hand tools for direct seeding techniques on small acreages, to counteract found limited access to mechanization. Knife rollers can be used to mechanically flatten standing biomass for usage on field as mulch (Friedrich, 2005) for weed suppression, and improved soil water management. In small scale agriculture, yields (and biomass) of main crops often are low and residues have relevant competing secondary off-field usages (Ward et al., 2018). As a result, in these farming systems less vegetative biomass can be left on field as may be recommended for CA (> 30 % soil cover). Long-term paybacks (delayed rewards) for additional field activities necessary under CA, as improving soil fertility by mulch or general soil cover management, are usually seen only attractive for smallholder farmers, if productivity is increased and risk reduced (Ngwira et al., 2012). Opposed to using highly controlled experimental field trial set-ups in research stations and farms, further assessments of CA should include inter-disciplinary, participatory farming system and on-site research approaches as well as dissemination approaches of knowledge on CA technology, which is adapted to the local conditions of the small scale farming systems and suiting the individual farmers' production targets (Hermans et al., 2020; Thierfelder et al., 2018).

The single adoption of no-tillage, intercropping but also of CA practices are found associated to better educated farmers, and to larger farms with market-oriented production (Derpsch et al., 2016; Ward et al., 2018) which may have a lower risk aversion, due to larger assets. By reduced tillage operations these farm types realize cost-savings, such as for fuel, machine wearing, and labor despite of possible increased costs for herbicide application (Thierfelder et al., 2015; Ward et al., 2018). This way they also reduce on-farm emissions which could not be entirely captured with the here applied agroecosystem models. In the case of applying the here presented tillage datasets (Chapter 3 and 4) in integrated or economic modeling studies, the monetary quantification of tillage versus no-tillage practices may reflect this factor dependency of no-tillage and CA adoption, having a bias in larger farms. However, missing rotations, due to the trend towards mono-cropping combined with no-tillage practices, as observed for commercial large farms in Southern American countries, imply that the benefiting effects of the full CA package cannot be exploited there (Friedrich et al., 2012). The modeling assessment of CA potentials may be improved, when accounting for the combined effect with temporal dynamic land use change for the historical period and under conditions of climate change. Beyond cover crop practices, future agroecosystem modeling studies may include a wider set of land management associated with CA, such as crop residue management (minimum of 30 % soil surface coverage) and crop rotations. Follow up research may include the complementary application of biochar (Bai et al, 2019), organic manure, or compost (Thierfelder et al., 2018), or other regenerative agricultural practices, such as agroforestry, and organic farming (Wittwer et al., 2017).

5.4 Conclusion and outlook

This thesis' findings reveal several points of applicability and transferability in the context of impact on the environment and food security. Insights into the composition of impacts related to cropland management practices, data, and model interaction, enable improved re-construction of historical trends as a basis for the construction of anticipated futures. On the one hand, this may expose possible risks of non-reversal changes in Earth system dynamics due to anthropogenic perceptions and actions. On the other hand, modeling studies, as used here, reveal the biophysical and biogeochemical potential of cropland management practices, which can be used to counteract critical trends in carbon and nitrogen dynamics.

The findings of the thesis may serve as a source of information on cropland management to improve estimates of emissions in policy decisions addressing climate change mitigation and adaptation (IPCC, 2014a, b). For the design of policy measures targeting the agricultural production sector, consideration of justice and equality should take into account allocation, distribution, and issues of scale (Daly, 1992). This can be achieved through the design of financial support schemes, which are directed at increasing the resilience of farming systems to global change induced risks and challenges. Public payments schemes for agroecological measures, such as the Common Agricultural Policy by the European Union, could serve as financial incentives for farmers' transition to more sustainable production practices. Furthermore, market based solution, such as payments for ecosystem services could be implemented, compensating for potential productivity losses when integrating on-farm measures for natural resource conservation or ecosystem regeneration. 'Carbon farming' comprises payments schemes promoting soil carbon sequestering practices and using cropland as tradable sinks for people interested in off-setting their emissions currently mostly up to regional scales (Paulsen, 2020). For this, monitoring and measurement schemes of on-farm progress in soil C sequestration need to be designed in a way to be comparable over time, across different sites and scales but also to be locally adapted enough to ensure success. The soil organic matter accumulated on agricultural land by certain land management techniques can be halted or even reversed (Powlson et al., 2011), when temporarily switching to other practices, which enhance soil carbon decomposition and shift the soil C pools to lower equilibria. There is a variety of reporting schemes of soil carbon and responses to land management in the literature, regarding soil depth or time period covered in the analysis. When only considering the short-term effect, studies may not account for the effect that the C sequestration is levelling off in soils approaching or already being close to their natural potential soil carbon content.

The reasoning for investigating at the global scale within the scope of this thesis was due to address global climate change and food security, which both have spatially and temporally diverse sources and impacts on cropland production and Earth System processes. The thesis findings highlight the importance of accounting for differences in cropland management practices, which result from the variance of environmental and socio-economic production conditions. It can be concluded from the thesis that cropland management practices can be employed, which promote existing ecological functions, while improving the environmental performance and facilitating sustainable crop production. In order to increase global food security in a sustainable way, increases in agricultural productivity need to be accomplished as a non-linear effect of natural resource usage to prevent the further loss of biodiversity and ecosystem function and services.

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Appendix A

Supplementary Information to Chapter 2: Spatial and temporal uncertainty of crop yield aggregations

Outline Supplementary Information:

A Details on crop models

Table A1. Global gridded crop models, data, participating research organization, and contact person.

Author name	Data/model	Research organization	E-mail contact
Alex C. Ruane	AgMERRA data	National Aeronautics and Space Administration, Goddard Institute for Space Studies	alexander.c.ruane@nasa.gov
Allard de Wit	CGMS-WOFOST	Alterra Wageningen University and Research Centre, Earth Observation and Environmental Informatics	allard.dewit@wur.nl
Peter J. Lawrence	CLM-Crop	National Center for Atmospheric Research, Earth System Laboratory	lawrence@ucar.edu
Erwin Schmid	EPIC-BOKU	University of Natural Resources and Life Sciences, Institute for Sustainable Economic Development	erwin.schmid@boku.ac.at
Nikolay Khabarov	EPIC-BOKU/EPIC-IIASA	International Institute for Applied Systems Analysis, Ecosystem Services and Management Program	khabarov@iiasa.ac.at
Juraj Balkovič	EPIC-IIASA	International Institute for Applied Systems Analysis, Ecosystem Services and Management Program	balkovic@iiasa.ac.at
Roberto C. Izaurralde	EPIC-TAMU	Joint Global Change Research Institute	cizaurra@umd.edu
Ashwan Reddy	EPIC-TAMU	University of Maryland, Department of Geographical Sciences	areddy01@gmail.com
Curtis D. Jones	EPIC-TAMU	University of Maryland, Department of Geographical Sciences	cujo@umd.edu
Christian Folberth	GEPIC	International Institute for Applied Systems Analysis, Ecosystem Services and Management Program	folberth@iiasa.ac.at
Thomas A.M. Pugh	LPJ-GUESS	Karlsruhe Institute of Technology, IMK-IFU	thomas.pugh@kit.edu
Almut Arneth	LPJ-GUESS	Karlsruhe Institute of Technology, IMK-IFU	almut.arneth@kit.edu
Christoph Müller	LPJmL	Potsdam Institute for Climate Impact Research, Research Domain II Climate Impacts & Vulnerabilities	cmueller@pik-potsdam.de
Philippe Ciais	ORCHIDEE-crop	Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ, Orme des Merisiers, 91191 Gif-sur-Yvette, France	philippe.ciais@lsce.ipsl.fr
Xuhui Wang	ORCHIDEE-crop	Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ, Orme des Merisiers, 91191 Gif-sur-Yvette, France	xuhui.wang@pku.edu.cn
Xiuchen Wu	ORCHIDEE-crop	Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ, Orme des Merisiers, 91191 Gif-sur-Yvette, France	xiuchen.wu@bnu.edu.cn
James Chryssanthacopoulos	pAPSIM & data post-processing pipeline	University of Chicago, Computation Institute	jchryssanthacopoulos@gmail.com
Joshua Elliott	pAPSIM, pDSSAT & data post-processing pipeline	University of Chicago, Computation Institute	jelliott@ci.uchicago.edu

Delphine Deryng	PEGASUS	University of Chicago, Computation Institute/NASA GISS & CCSR Earth Institute, Columbia University	deryng@uchicago.edu
Wenfeng Liu	PEPIC	Eawag, Swiss Federal Institute of Aquatic Science and Technology	wenfeng.liu@eawag.ch
Gen Sakurai	PRYSBI2	National Agriculture and Research Organization, Institute for Agro-Environmental Sciences, Tsukuba, 305-8604, Japan	sakuraigen@affrc.go.jp
Toshichika Iizumi	PRYSBI2 & Iizumi data	National Agriculture and Research Organization, Institute for Agro-Environmental Sciences, Tsukuba, 305-8604, Japan	iizumit@affrc.go.jp
Deepak K. Ray	Ray data	University of Minnesota, Institute on the Environment	dray@umn.edu

Table A2. Main features of crop models.

Model	**Type[1]**	**CO2 effects[2]**	**Stresses[3]**	**Fertilizer application[4]**	**Calibration[5]**	**Calibrated parameters**	**Outputs**
CGMS-WOFOST	Site-based	LF, TE	W, T	NA	Site-specific	Tsum requirements	Actual/potential yield and biomass
CLM-crop	Ecosystem	LF, TE	W,N,H	N	Uncalibrated	NA	Actual yield
EPIC-BOKU	Site-based	RUE, TE	W, T, A, N, P, BD, AL	automatic N input (max 200 kg Ha-1 yr-1) PK (national stat. IFA) dynamic application	Site-specific (EPIC 0810)	NA	Actual yield & yield gap
EPIC-IIASA	Site-based	RUE, TE	W, T, A, N, P, BD, AL	NP (sub-national stat by Balkovič et al. (2013); Mueller et al. (2012)); P timing: rigid; N timing: automatic (based on N stress)	Site-specific and global	F, HIpot (ric, mai) F (others)	Actual yield
EPIC-TAMU	Site-based	RUE, TE	W, T, H, A, N, P, BD, AL	NPK at planting	Site-specific and global	HIpot (maize)	Actual yield
GEPIC	Site-based	RUE, TE	W, T, A, N, P, BD, AL	NP (national stat: FertiSTAT), dynamic application of N, rigid application of P	Site-specific and global	F HIpot (for maize and rice)	Actual yield
LPJ-GUESS	Ecosystem	LF, SC	W, T	NA	Uncalibrated	NA	Actual yield

LPJmL	Ecosystem	LF, SC	W, T	NA	National	LAImax HI αa	Actual yield
ORCHIDEE-crop	Ecosystem	LF, SC	W,T,N	Automatic N input (IFA)	Uncalibrated	-	Actual yield
pAPSIM	Site-based	RUE	W, T, H, A, N	SPAM by You et al. (2014), (1/2 at planting, 1/2 at day 45)	Site-specific (APSIM)	NA	Actual yield
pDSSAT	Site-based	RUE (for wheat, rice, maize) and LF (for soybean)	W, T, H, A, N	SPAM by You et al. (2014), (1/2 at planting, 1/2 at day 45)	Site-specific (DSSAT)	NA	Actual yield
PEGASUS	Ecosystem	RUE, TE	W, T, H, N, P, K	NPK (national stat. IFA), annual application	Global	β	Actual yield
PEPIC	Site-based	RUE, TE	W, T, A, N, P, BD, AL	NP (national stat: FertiSTAT), three times of N, rigid application of P	Site-specific and global	F HIpot (for maize)	Actual yield
PRYSBI2	Ecosystem	LF, SC	W,T	NA	Global yield	TH, TC, TS, LR	Actual yield

Notes: (NA where not applicable)

[1] Site-based: site-base crop model; Ecosystem: global ecosystem model
[2] Elevated CO_2 effects: LF: Leaf-level photosynthesis (via rubisco or quantum-efficiency and leaf-photosynthesis saturation; RUE: Radiation use efficiency; TE: Transpiration efficiency; SC: stomatal conductance
[3] W: water stress; T: temperature stress; H: specific-heat stress; A: oxygen stress; N: nitrogen stress; P: phosphorus stress; K: potassium stress; BD: bulk density; AL: aluminum stress (based on pH and base saturation)
[4] Fertilizer application, timing of application; NPK annual application of total NPK (nutrient-stress factor); source of fertilizer application data; timing: annual or dynamic
[5] F: fertilizer application rate; HIpot: Potential harvest index; LAImax: maximum LAI under unstressed conditions; HI: harvest index; αa: factor for scaling leaf-level photosynthesis to stand level; β: radiation-use efficiency factor; TH: Total Heat unit required for the maturity; TC: Technological coefficient; TS: Temperature sensitivity of photosynthesis; LR: ratio of leaf to above ground biomass.

Table A3. Model inputs and agricultural management practices.

Model	**Spatial scale**	**Temporal scale**[1]	**Climate input variables**[2]	**Soil input data** [3]	**Spin-up** [4]	**Planting date decision** [5]	**Crop cultivars** [6]	**Irrigation rules**[7–8]	**Fertilizer application** [9]	**Crop residue** [10]
CGMS-WOFOST	0.5° lon x 0.5° lat	D	Ta Tmn Tmx P Rad Vap WS	FAO 1:5M DSMW AWC HYD	H2O (1)	Fixed planting day	GDD fixed	NA	NA	NA

CLM-crop	1° lon x 1° lat	D	T,P,WS, Q,SWRad	IGBP Global Soil Data Task 2000	NA	S	GDD+V	MIRCA 2000 (Portmann et al., 2010)	N	To litter pool
EPIC-BOKU	0.5° lon x 0.5 lat	D, H	Tmn, Tmx, P, Rad, RH, WS	ISRIC-WISE, ROSETTA, AWC, ALBEDO (Dobos, 2006), HYD (USDA and NRCS, 2015)	Soil OM, C, NH3, NO3, H2O, P(1)	S (fraction of PHU), fixed planting window	GDD - fixed	90/100/500/50/208 maximum applied irrigation: 500 mm yr-1	automatic N input (max 200 kg Ha-1 yr-1) PK (national stat. IFA) dynamic application	No, can be simulated
EPIC-IIASA	5" lon x 5"lat (default); 0.5° lon x 0.5° lat (harmonized)	D	Tmn, Tmx, P, Rad, RH, WS	ISRIC-WISE; ROSETTA; AWC; HYD (USDA and NRCS, 2015)	Soil OM, C, NH3, NO3, H2O, P, CR (50)	F (fixed planting window)	GDD, 3 cult for mai, 2 cult for wheat fixed	90/100/2000/500/0	NP (sub-national stat by (Mueller et al., 2012) P timing: rigid; N timing: automatic (based on N stress)	Yes
EPIC-TAMU	0.5° lon x 0.5° lat	D	Tmn, Tmx, P, Rad, RH, WS	ISRIC-WISE	Soil OM, C, NH3, NO3, H2O, P, CR (10)	S, planting delayed until 2 deg above base temp	GDD, 2 cultivars for mai	99/100/9999/100/25	NPK at planting	No
GEPIC	0.5° lon x 0.5° lat	D	Tmn, Tmx, P, Rad, RH, WS	ISRIC-WISE	Soil OM, C, NH3, NO3, H2O, P, CR (20)	S (fraction of PHU), clim. adapt	GDD, 2 cultivars for mai - fixed	90/100/2000/1000/0.018	NP (national stat. FertiSTAT), dynamic application of N, rigid application of P	Yes, Crop-specific
LPJ-GUESS	0.5° lon x 0.5° lat	D	Ta, P, cld (or Rad)	HWSD, STC HYD (Cosby et al., 1984), THM (Lawrence and Slater, 2008)	H2O (30)	S (Waha et al., 2012), fixed planting window	GDD+V (whe, sunfl, rapes); BT (mai); static (others) + clim. adap	200/90/100/100[7]	NA	Yes, does not affect yield

LPJmL	0.5° lon x 0.5° lat	D	Ta, P, cld (or Rad)	HWSD, STC HYD (Cosby et al., 1984), THM (Lawrence and Slater, 2008)	H2O, Tsoil (200)	S (Waha et al., 2012), fixed planting day after 1951	GDD+V (whe, sunfl, rapes); BT (mai); static (others) - fixed	300/90/100/varies[7]	NA	Yes, does not affect yield
ORCHIDEE-crop	0.5° lon x 0.5° lat	Half-hourly	Tmn, Tmax, P, Rad, RH, WS	NA	H2O (1)	F (Sacks et al., 2010)	Fixed	200/90/100/varies[7]	N(IFA)	Yes, does not affect yield
pAPSIM	0.5° lon x 0.5° lat	D	Tmn, Tmx,P, Rad	HSWD	NA	F (S is also possible)	GDD and/or latitude, 2-3 for each cell	NA	GGCMI	NA
pDSSAT	0.5° lon x 0.5° lat	D	Tmn, Tmx, P, Rad	HWSD	Soil OM, C, NH3, NO3, H2O (1)	S (Sacks et al., 2010) fixed planting window	GDD and/or latitude, 2-3 for each cell - fixed	40/80/100/757 ric: 30/50/100/100[7]	GGCMI	Yes, does not affect yield
PEGASUS	0.5° lon x 0.5° lat	D	Ta, Tmn, Tmx, P, cld (or sun)	AWC (ISRIC-WISE)	H2O (4)	S (Deryng et al., 2011) clim. adapt	GDD + clim. adapt	40/90/100/100[7]	NPK (national stat. IFA), annual application	NA
PEPIC	0.5° lon x 0.5° lat	D	Tmn, Tmx,P, Rad, RH, WS	ISRIC-WISE	Soil OM, C, NH3, NO3, H2O, P, CR (20)	Fixed planting day	GDD	90/100/1000/500/1	NP (national stat. FertiSTAT), three times of N, rigid application of P	Yes
PRYSBI2	1.125 ° lon x 1.125 ° lat	D	Tmn, Tmx, P, Rad, RH, WS	ISLSCP-II (Hall et al., 2006)	NA	F (Sacks et al., 2010)	GDD - fixed	NA	NA	No

Notes: (NA where not applicable)

[1] D: daily time-step; M: monthly time-step; H: hourly time-step; WG: use monthly climate data interpolated to daily using a weather-generator

[2] Ta: average temperature, Tmn: minimum temperature, Tmx: maximum temperature, cld: percentage of cloud cover, sun: fraction of sunshine hours; RH: relative humidity; WS: wind speed; Vap: vapour pressure, Rad: radiation

[3] Source of soil property inputs (e.g., source of basic soil properties), plus method for manipulation to derive parameters required by the model); AWC: Available Water Capacity (Van Genuchten et al., 1992) ; HYD:

hydraulic soil parameters; THM: thermal parameters; HWSD: Harmonized world soil database (Fischer et al., 2008); STC: soil texture classification based on the USDA soil texture classification (http://ufdc.ufl.edu/IR00003107/00001); ISRIC-WISE (Batjes, 2006) ; ROSETTA (Schaap and Bouten, 1996)
[4] Number of years for Spin up (x); OM: organic matter, C: carbon; NH3: ammonia; NO3: nitrate; H2O: soil water; P: phosphorus; CR: crop residues
[5] S: Simulate planting dates according to climatic conditions; F: fixed planting dates; source of planting date data if applicable; PHU: potential heat unit; fixed planting window (i.e., does not allow for adaptation to climate change); clim. adapt: dynamic planting window (adaptation to climate change)
[6] GDD: Simulate crop Growing Degree Days (GDDs) requirement according to estimated annual GDDs from daily temperature; Number of cultivars; GDD+V: GDD requirements and vernalization requirements computed based on past climate experience; BT base temperature computed based on past climate; fixed: static GDD requirement (no adaptation); clim. adapt: dynamic GDD requirement (adaptation to climate change)
[7] Irrigation rules: IMDEP: depth of soil moisture measured; ITHRL(): critical lower soil moisture threshold to trigger irrigation event; ITHRU(): upper soil moisture threshold to stop irrigation; IREFF: irrigation application efficiency
[8] Irrigation rules: EPIC and GEPIC models: BIR(): water stress in crop to trigger automatic irrigation; EFI(): irrigation efficiency - runoff from irrigation water; VIMX: maximum of annual irrigation volume; ARMX: maximum of single irrigation volume allowed; ARMN: minimum of single irrigation volume allowed
[9] Fertilizer application, timing of application; NPK annual application of total NPK (nutrient-stress factor); source of fertilizer application data; timing: annual or dynamic
[10] Remove residue or not (Yes/No)

Table A4. Biophysical processes covered by the crop models.

Model	**Leaf area development[1]**	**Light interception[2]**	**Light utilisation[3]**	**Yield formation[4]**	**Stresses involved[5]**	**Type of heat stress[6]**	**Crop phenology[7]**	**Type of water stress[8]**	**Evapo-transpiration[9]**	**Soil water dynamic[10]**	**Root distribution over depth[11]**	**Soil CN model [12]**	**CO2 effects[13]**
CGMS-WOFOST	DA	D	P-R	Prt	W T A	V	T DL V	S	PM	2	NON	NA	LF TE
CLM-crop	DA	D	P-R	Prt	W,N, H	V	T & DL	S	Turbulent Flux (Farquhar et al., 1980)	10	EXP	C/N	LF, TE
EPIC-BOKU	PS	S	RUE	HIws Prt B	W T A N P BD AL	V	T(HU) V O	E	PM	10	EXP W	C N B(1) P(6)	RUE TE
EPIC-IIASA	PS	S	RUE	HIws Prt B	W T A N P BD AL	V	T(HU) V O	E	PM	10	EXP W	C N B(1) P(6)	RUE TE
EPIC-TAMU	PS	S	RUE	HIws Prt B	W T H A N P BD AL	V	T(HU) V O	E	PM	3	EXP W	C N B(1) P(6)	RUE TE
GEPIC	PS	S	RUE	HIws Prt B	W T A N P BD AL	V	T(HU) V O	E	HAR	5	EXP W	C N B(1) P(6)	RUE TE

LPJ-GUESS	DA	S	P-R	HIws	W T	NA	T V	S	PT	2	LIN	NA	LF, SC
LPJmL	PS	S	P-R	HIws	W T	NA	T V	S	PT	5	EXP	NA	LF, SC
ORCHIDEE-crop	DA	S	P-R	Prt	WT N	VR	T(HU) DL O V	S	PT	11	EXP	NA	LF, SC
pAPSIM	DA	S	RUE, P-R(pasture only)	Gn, Prt, HIw (soy)	T,Dl, O, V	EXP	W,N, A,H	E, S	TE	5	EXP	C,N,P,B(3)	RUE, TE, NE
pDSSAT	PS(soy =DA)	S /D	RUE/ P-R	Gn	W T H A N	V R F	T V DL O	E	PT/PM	4	EXP	C N P(3)	RUE, LF, TE
PEGASUS	DA	S	RUE	Prt	W T H N P K	V F	T(HU)	E	PT	3	LIN W	NA	RUE TE
PEPIC	PS	S	RUE	HIws Prt B	W T A N P BD AL	V	T(HU) V O	E	PM	5	EXP W	C N B(1) P(6)	RUE TE
PRYSBI2	DA	S	P-R	HI	W T	V	HU	E	PM	2	EXP	NA	LF, SC

Notes: (NA where not applicable):

[1] DA: Dynamic simulation based on development and growth processes; PS: prescribed shape of LAI curve as function of phenology, modified by water stress & low productivity
[2] S: Simple approach: D: Detailed approach
[3] RUE: Simple (descriptive) radiation use efficiency approach; P-R: Detailed (explanatory) gross photosynthesis – respiration (for more details see Adam et al. (2011))
[4] Yield formation depending on: HI: fixed harvest – index; B: total (above – ground) biomass; Gn: number of grains and grain growth rate; Prt: partitioning during reproductive stages; HIws: HI modified by water stress
[5] W: water stress; T: temperature stress; H: specific-heat stress; A: oxygen stress; N: nitrogen stress; P: phosphorus stress; K: potassium stress; BD: bulk density; AL: aluminum stress (based on pH and base saturation)
[6] V: vegetative (source); R: reproductive organ (sink); F: number of grain (pod) set during the flowering period
[7] Crop phenology is a function of: T: temperature; DL: photoperiod (day length); O: other water/nutrient stress effects considered; V: vernalization; HU: Heat unit index
[8] E: ratio of supply to demand of water; S: soil available water in root zone
[9] PM: Penman – Monteith; PT: Priestley –Taylor; HAR: Hargreaves; TE: transpiration efficiency
[10] (x): x number of soil layers
[11] LIN: linear; EXP: exponential; NON: no roots-just soil depth zone; W: actuals water depends on water availability in each soil layer
[12] C model; N model; P(x): x number of organic matter pools; B(x): x number of microbial biomass pools
[13] Elevated CO_2 effects: LF: Leaf-level photosynthesis (via rubisco or quantum-efficiency and leaf-photosynthesis saturation; RUE: Radiation use efficiency; TE: Transpiration efficiency; SC: Stomatal conductance

Table A5. Model calibration and validation.

Model	Model origin[1]	Calibration method	Parameters for calibration[2]	Output variable and dataset for calibration[3]	Spatial scale of calibration	Temporal scale of calibration	Method for model evaluation [4]
CGMS-WOFOST	Site-based	Default parameters from site-specific analysis (WOFOST 6.0)	NA	NA	Field scale	Mostly trials from 1980-2000	NA
CLM-crop	Ecosystem	NA	NA	NA	NA	NA	NA
EPIC-BOKU	Site-based	Site-specific (EPIC 0810)	NA	Yield (FE & FAO)	Field scale & National	Various	NA
EPIC-IIASA	Site-based	Site-specific (EPIC 0810) & Global[5]	F, HIpot (ric, mai)F (others)	Yield (FE & FAO)	National	Around 2000	R2
EPIC-TAMU	Site-based	Site-specific	HIpot (mai)	Yield (SPAM 2000 by You et al. (2014))	Grid cell level	2000	various
GEPIC	Site-based	Site-specific (EPIC 0810) & Global[5]	F HIpot (mai, ric)	Yield (FE & FAO)	National	Average for 1997-2003	R2
LPJ-GUESS	Ecosystem	Uncalibrated	NA	NA	NA	NA	NA
LPJmL	Ecosystem	Global	LAImax HI alpha_a	Yield (FAO)	National	Average for 1998-2003	Wilmott
ORCHIDEE-crop	Ecosystem	Uncalibrated	NA	NA	NA	NA	NA
pAPSIM	Site-based	Default parameters from site-specific analyses	NA	NA	field scale	NA	NA
pDSSAT	Site-based	Site-specific (DSSAT)	NA	Yield (FE)	Field scale	Various	NA
PEGASUS	Ecosystem	Global	β	Yield (M3 by Monfreda et al. (2008))	Grid cell level (0.5° lon x 0.5° lat resolution)	Average for 1997-2004	Wilmott
PEPIC	Site-based	Default parameters from site-specific analyses of EPIC0810 Potential HI (maize)	NA	Yield (FAO yield statistics)	National	Average for 1998-2002	R2
PRYSBI2	Ecosystem	Global	TH, TC, TS, LR	Yield (Iizumi et al. (2014))	Grid cell level	1982-2006 (but the odd-numbered years were used as learning data for the	Log likelihood

						estimation for the even years, and vice versa)	

Notes: (NA where not applicable)

[1] site-base crop model, ecosystem: global ecosystem model
[2] F: fertilizer application rate; HIpot: Potential harvest index; LAImax: maximum LAI under unstressed conditions; HI: harvest index; αa: factor for scaling leaf-level photosynthesis to stand level; β: radiation-use efficiency factor; TH: Total Heat unit required for the maturity; TC: Technological coefficient; TS: Temperature sensitivity of photosynthesis; LR: ratio of leaf to above ground biomass
[3] FE: field experiments; FAO: FAOSTAT national yield statistic; M3: gridded data set of crop specific yields and harvested areas for the year 2000 (Monfreda et al., 2008)
[4] Willmott: maximise Wilmott index of agreement (d) and RMSEu>RMSEs (RMSE: root-mean-square error; RMSEu: unsystematic RMSE; RMSEs: systematic RMSE) (Willmott et al., 1985), R2: coefficient of determination
[5] GEPIC & EPIC-IIASA: Default parameters coming with the field scale model EPIC v0810 are mostly used. Potential HI has been adjusted for maize cultivars and rice based on literature (field trials). Fertilizer application rates have been modified for few countries that report very high yields and low fertilizer use, whereas most of these countries are known for their intensive use of manure.

B Crop specific harvested area maps

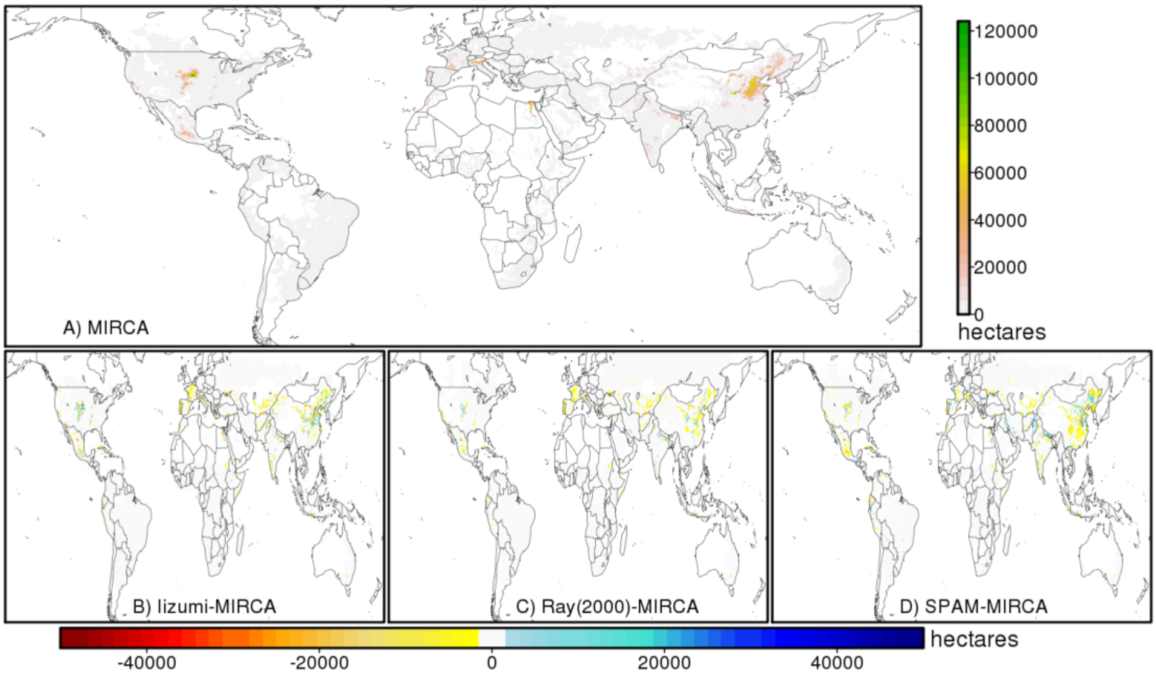

Fig B.1: Global spatial distribution of irrigated maize according to MIRCA2000 panel A). Panels B-D show absolute difference maps of irrigated maize harvested areas of Iizumi, Ray, and SPAM2005 in comparison to MIRCA2000 for the year 2000.

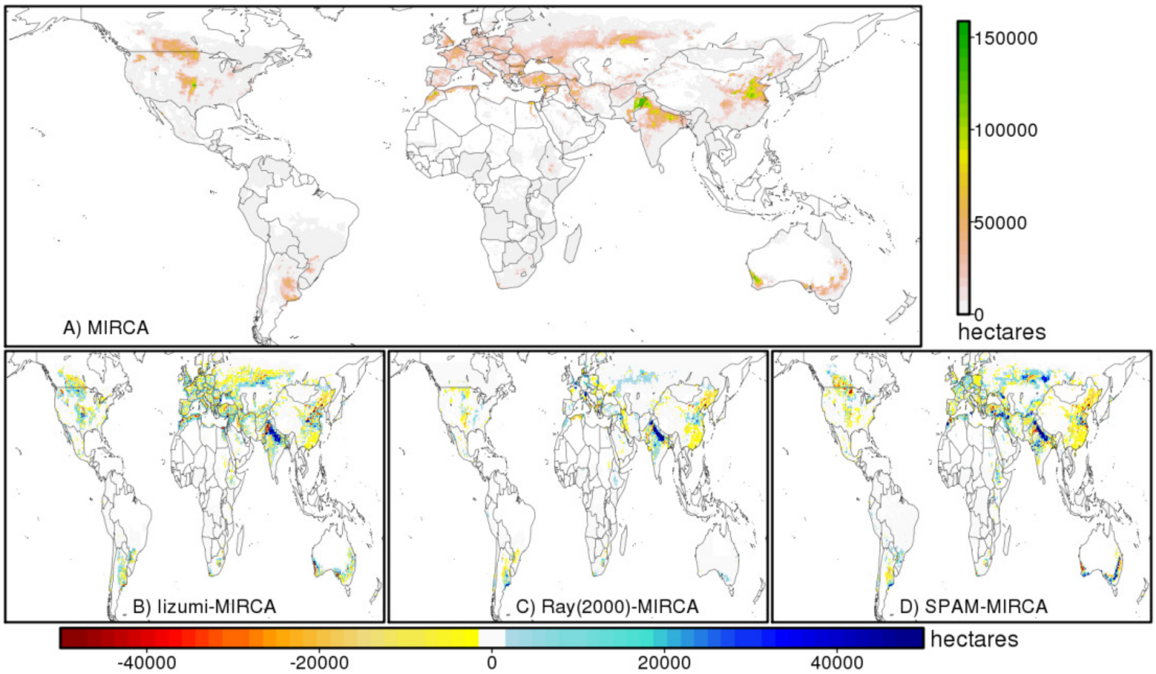

Fig. B.2: Global spatial distribution of total harvested wheat area according to MIRCA2000 in panel A). Panels B-D show difference maps of harvested wheat area of Iizumi, Ray, and SPAM2005 in comparison to MIRCA2000 for the year 2000.

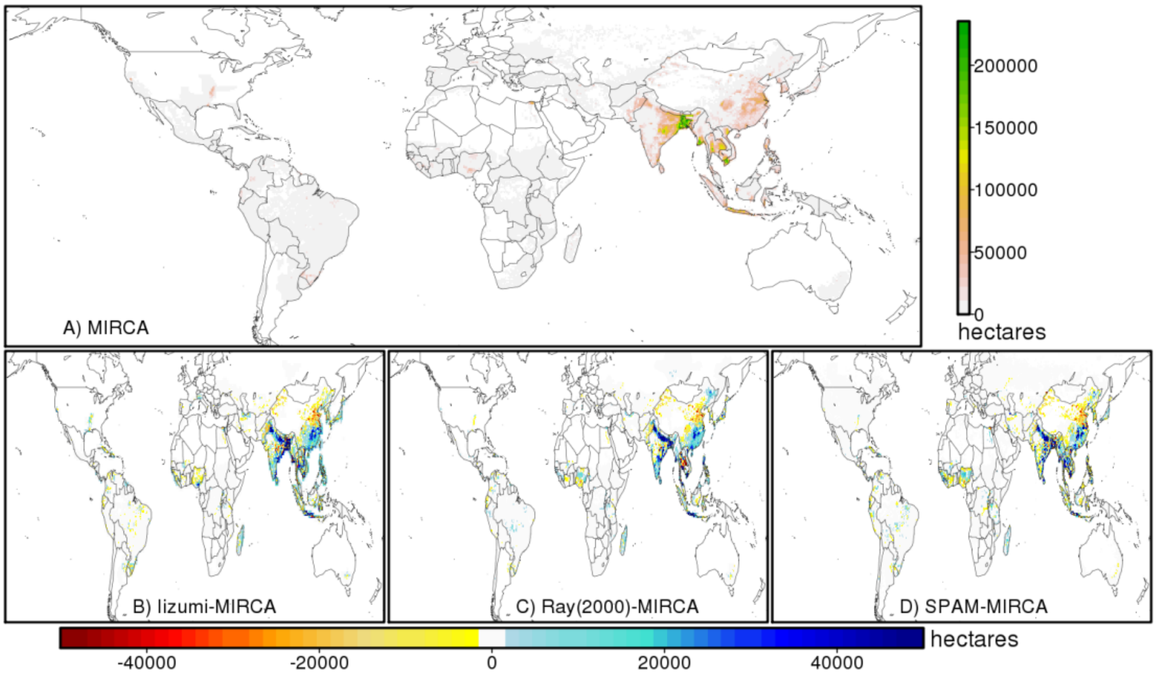

Fig. B.3: Global spatial distribution of total harvested rice area according to MIRCA2000 in panel A). Panels B-D show difference maps of harvested rice area of Iizumi, Ray, and SPAM2005 in comparison to MIRCA2000 for the year 2000.

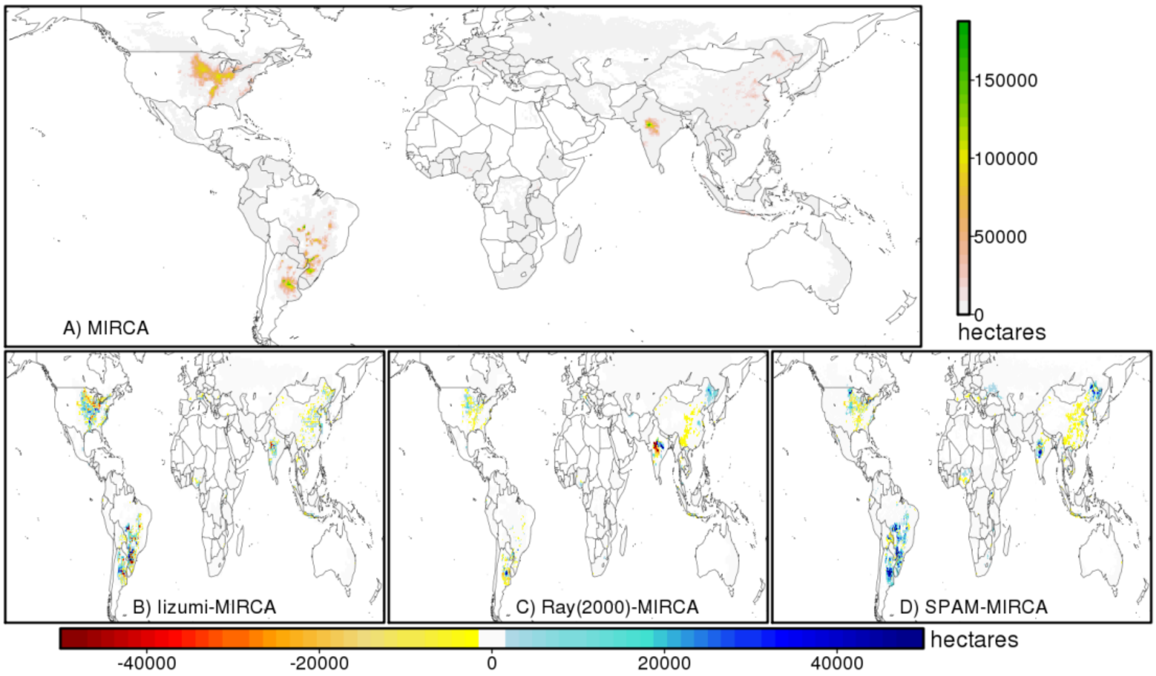

Fig. B.4: Global spatial distribution of total harvested soybeans area according to MIRCA2000 in panel A). Panels B-D show difference maps of harvested area of Iizumi, Ray, and SPAM2005 in comparison to MIRCA2000 for the year 2000.

C Relative difference between data sets of total production (t) aggregated to country scale

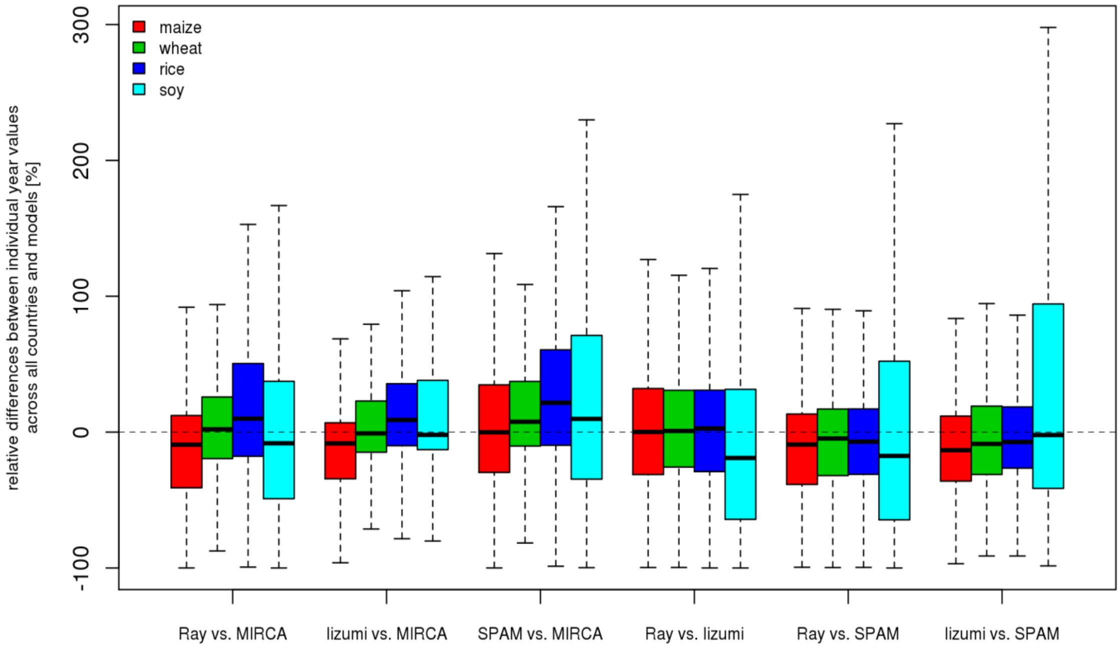

Fig. C: Boxplot of relative differences (%) between aggregated production time series (t) over 208 countries, 14 GGCMs and 31 years of the weather data set AgMERRA for the four crop types (n= 357365 for maize, n= 290061 for wheat, n= 214617 for rice, n= 202619 for soybeans). Boxes show the interquartile (25-75%) range across the GGCMs used, whiskers expand to 1.5 times of inner-quartile range of national aggregated yield, and black lines within the boxes display the median value (outliers are not displayed).

D Relative difference and correlation coefficient of national aggregated yields, production as well as total harvested area data

Table D.1: The table of the country data for maize shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of detrended yield (t/ha) time series calculated from one of the 14 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks). Countries are in ascending order according to their share (%) on global production based on FAOSTAT (FAO, 2014) average production for the period 2009-2013.

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Djibouti	35	-61	55	-43	-61	-96	88	-75	4472	457	3881	447	0,46	0,04	-0,27	0,08	-0,53	-0,47	0
Suriname	5	-1	89	-16	8	-22	21	-42	35	-8	142	-17	0,59	0,3	0,38	0,48	0,6	0,68	0
French Guiana	20	-15	2	-18	34	-50	21	-15	138	-29	96	-29	-0,06	0,84	0,75	-0,06	-0,18	0,52	0
Antigua and Barbuda	NA	NA	-1	-1	-1	-1	NA	NA	NA	NA	-1	-1	NA	0,9	0,98	NA	NA	0,98	0
Japan	1	-2	8	-88	22	-35	978	-8	57	-16	-3	-86	0,96	-0,13	0,16	-0,11	0,16	-0,29	0
Barbados	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0,99	1	0,99	0,98	0
Grenada	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
Puerto Rico	9	-2	5	-12	12	-73	14	-4	315	-3	255	-6	0,99	0,68	-0,77	0,7	-0,78	-0,66	0
Bahamas	0	0	17	-11	NA	NA	12	-14	NA	NA	NA	NA	1	0,95	NA	0,91	NA	NA	0
Vanuatu	0	0	2	-6	4	-4	6	-2	4	-4	1	-7	1	0,99	0,99	0,99	0,99	0,98	0
Fiji	0	0	9	-8	2	-2	9	-8	3	-2	11	-7	1	0,86	0,94	0,85	0,94	0,83	0
Algeria	-25	-94	-35	-91	145	-72	76	-65	112	-88	62	-82	-0,31	-0,04	-0,08	0,07	-0,23	-0,23	0
Qatar	NA	NA	771	-16	0	-85	NA	NA	NA	NA	1230	-9	NA	-0,05	-0,18	NA	NA	-0,12	0
Luxembourg	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
Jamaica	0	0	21	-7	19	-11	8	-18	12	-16	7	-4	1	0,83	0,97	0,81	0,96	0,92	0
Libya	0	-1	13	-34	25	-28	53	-5	39	-12	3	-11	1	0,49	0,54	0,43	0,53	0,65	0
New Caledonia	0	0	3	-4	3	-3	4	-3	3	-3	4	-6	1	0,97	0,97	0,97	0,97	0,94	0
Trinidad and Tobago	0	0	11	-13	1	-4	16	-10	4	-1	11	-10	1	0,55	0,99	0,54	0,98	0,5	0
Lebanon	0	-43	0	-52	799	-16	124	0	20	-88	20	-94	0,92	0,29	-0,02	0,22	-0,13	-0,19	0
Guyana	2	-1	19	-10	40	-21	10	-14	27	-27	15	-15	0,64	0,92	0,54	0,64	0,58	0,67	0
Niger	19	-22	4	-28	24	-12	51	-20	27	-14	14	-27	0,72	0,92	0,88	0,57	0,76	0,78	0
Montenegro	81	-11	49	-28	84	-11	26	-12	11	-33	33	-34	0,29	0,85	0,55	0,21	0,29	0,66	0
Guinea-Bissau	1	0	14	-25	7	-20	34	-12	26	-5	11	-15	0,95	0,94	0,9	0,9	0,89	0,94	0
Papua New Guinea	0	0	3	-4	22	-4	5	-2	7	-18	8	-18	1	0,77	0,4	0,76	0,32	0,22	0
Mauritania	6	-1	17	-5	13	-36	5	-10	68	-7	83	-4	0,84	0,88	0,8	0,83	0,65	0,71	0
Botswana	25	-8	15	-13	253	-44	43	-14	77	-60	83	-50	0,67	0,7	0,25	0,88	0,02	0,01	0
Kuwait	14	-32	1350	-46	342	-52	95	-50	134	-43	95	-34	0,59	0,51	0,06	0,08	0,03	-0,17	0
Armenia	17	-4	13	-70	179	-3	327	-14	13	-58	-24	-86	0,23	0,05	0,15	-0,22	-0,12	-0,16	0
Turkmenistan	35	-25	23	-34	16	-15	37	-22	16	-17	26	-32	0,2	0,15	0,75	0,66	0,61	0,33	0
Costa Rica	1	-1	1	-26	4	-11	37	-1	12	-4	12	-21	1	0,81	0,44	0,87	0,47	0,68	0
Jordan	99	-54	14	-40	-64	-99	155	-47	7372	63	8193	178	0,04	0,72	-0,4	0,12	-0,36	-0,51	0
Eritrea	36	0	7	-25	50	-33	82	-4	107	-31	14	-29	0,04	0,77	0,68	-0,07	-0,25	0,58	0
Dominican Republic	5	-1	43	-5	194	-45	5	-26	85	-64	87	-60	0,79	0,79	0,52	0,59	0,51	0,52	0
Sierra Leone	2	0	27	-9	4	-6	9	-19	9	-4	35	-6	0,99	0,92	0,97	0,93	0,95	0,85	0
Gambia	0	0	1	0	14	-7	0	-1	7	-12	7	-11	1	1	0,98	1	0,98	0,98	0

Gabon	0	-1	37	-19	52	-10	26	-27	15	-35	7	-9	0,99	0,72	0,7	0,7	0,66	0,59	0
Sudan	67	-66	78	-68	111	-67	27	-6	29	-59	28	-61	0,1	0,03	-0,13	0,55	0,05	0,25	0,01
Malaysia	3	-2	3	-4	5	0	5	-3	3	-6	3	-6	0,96	0,9	0,98	0,86	0,91	0,91	0,01
Belize	0	-1	8	-26	13	-5	35	-8	5	-12	13	-30	0,97	0,7	0,95	0,72	0,92	0,54	0,01
Namibia	52	-53	58	-56	98	-42	7	-19	138	-56	149	-46	0,51	0,63	0,39	0,88	0,03	0,23	0,01
Lesotho	2	-3	18	-20	31	-4	27	-17	9	-24	29	-30	0,99	0,83	0,55	0,85	0,57	0,48	0,01
Lithuania	11	-21	26	-66	17	-15	154	-17	9	-28	8	-60	0,39	0,32	0,81	0,34	0,08	0,03	0,01
Bhutan	5	-8	22	-24	9	-3	43	-15	9	-15	20	-24	0,98	0,67	0,89	0,61	0,86	0,45	0,01
Yemen	26	-36	9	-22	57	-30	17	-27	17	-21	24	-31	0,53	0,7	0,37	0,71	0,11	0,42	0,01
Swaziland	2	0	3	-8	7	-1	8	-3	3	-7	0	-14	1	0,96	0,63	0,96	0,61	0,8	0,01
South Korea	7	-6	5	-8	14	-12	17	-11	7	-6	20	-15	0,93	0,92	0,64	0,89	0,64	0,64	0,01
Israel	81	-62	6	-24	80	-96	138	-60	2010	-26	2012	-47	-0,43	0,36	-0,35	-0,36	-0,51	-0,5	0,01
Panama	1	0	16	-8	17	-27	8	-14	37	-14	39	-11	1	0,81	0,8	0,78	0,77	0,92	0,01
Saudi Arabia	132	-26	107	-24	133	-57	20	-14	73	-1	78	-17	-0,11	0,1	-0,05	-0,11	-0,13	0,27	0,01
East Timor	3	-11	56	-20	25	-2	29	-42	5	-29	25	-18	0,98	0,63	0,94	0,4	0,98	0,36	0,01
Taiwan	NA	NA	61	-5	5	-35	NA	NA	NA	NA	149	-5	NA	0,81	0,84	NA	NA	0,59	0,01
Somalia	0	-62	-14	-63	-8	-57	79	-1	111	-22	20	-32	0,04	0,22	0,28	0,76	-0,37	-0,2	0,01
Burundi	2	-4	15	-7	21	-10	10	-16	13	-17	9	-24	0,96	0,94	0,87	0,92	0,84	0,91	0,02
Switzerland	3	-1	24	-13	46	-3	15	-19	3	-31	2	-20	0,99	0,75	0,81	0,77	0,85	0,84	0,02
Central African Republic	1	0	14	-12	36	-21	15	-12	27	-25	19	-15	0,98	0,97	0,58	0,97	0,52	0,64	0,02
Tajikistan	44	-20	57	-20	40	-54	17	-23	102	-29	91	-18	0,53	0,47	0,02	0,68	0	0,08	0,02
Azerbaijan	25	-10	28	-28	20	-23	31	-7	35	-22	27	-28	-0,2	0,69	0,49	-0,05	-0,31	0,6	0,02
Sri Lanka	10	-3	6	-9	9	-42	18	-9	77	-5	66	-8	0,78	0,88	0,64	0,62	0,79	0,51	0,02
Morocco	12	-57	4	-55	16	-62	14	-18	21	-15	46	-25	0,38	0,64	0,29	0,85	0,82	0,55	0,02
New Zealand	34	-17	47	-27	172	-5	44	-10	-4	-50	-6	-50	0,76	0,17	0,33	0,24	0,39	0,26	0,02
Netherlands	9	-18	12	-17	16	-18	11	-11	-1	-10	3	-18	0,23	0,63	0,38	0,09	0,23	0,64	0,02
Senegal	1	0	48	-6	23	-4	7	-31	4	-18	21	-9	0,98	0,96	0,97	0,95	0,97	0,96	0,02
Syria	19	-17	28	-22	3	-45	17	-8	56	-6	63	-20	0,72	0,39	0,48	0,74	0,67	0,5	0,03
Uzbekistan	25	-9	27	-19	4	-12	12	-7	21	-2	23	-9	0,81	0,62	0,86	0,79	0,7	0,48	0,03
Georgia	0	0	19	-9	48	-12	10	-16	14	-33	5	-35	1	0,88	0,8	0,89	0,79	0,68	0,03
Chad	49	-7	34	-10	58	-23	13	-11	36	-37	20	-35	0,98	0,89	0,53	0,9	0,51	0,66	0,03
Iraq	14	-7	1	-25	5	-52	33	1	115	-5	89	-8	0,97	0,87	0,58	0,92	0,76	0,43	0,03
Slovenia	5	-8	13	-9	13	-12	6	-19	9	-7	25	-6	0,69	0,7	0,68	0,32	0,78	0,52	0,03
Afghanistan	40	-27	45	-25	48	-21	4	-9	26	-15	28	-9	0,37	0,39	0,48	0,92	0,46	0,55	0,03
Haiti	0	0	17	-26	29	-11	35	-14	12	-23	11	-23	1	0,85	0,97	0,85	0,97	0,89	0,03
Albania	4	-2	28	-24	5	-16	40	-21	23	-3	31	-18	0,63	0,72	0,69	0,41	0,59	0,29	0,04
Cuba	2	-9	5	-9	1	-68	6	-14	223	-1	214	-4	0,95	0,91	-0,05	0,95	0,06	0,18	0,04
Australia	12	-44	10	-45	10	-21	6	-3	2	-44	0	-44	0,33	0,48	0,53	0,81	0,43	0,32	0,05
Madagascar	0	0	8	-7	12	-14	7	-7	17	-11	22	-5	1	0,91	0,87	0,91	0,87	0,9	0,05
Uruguay	16	-2	7	-8	32	-4	18	-5	2	-22	2	-17	0,9	0,96	0,9	0,89	0,89	0,83	0,05
Rwanda	4	-1	6	-18	4	-5	26	-6	6	-5	12	-20	0,99	0,97	0,98	0,94	0,96	0,96	0,06
Kazakhstan	26	-26	34	-47	19	-18	52	-13	33	-14	55	-41	0,59	0,47	0,79	0,31	0,6	0,64	0,06
Nicaragua	2	-1	2	-5	4	-4	6	-1	5	-3	2	-6	0,99	0,98	0,96	0,98	0,97	0,96	0,06
Kyrgyzstan	52	-25	67	-31	-2	-22	11	-10	71	-19	89	-27	0,44	0,58	0,84	0,78	0,36	0,46	0,06
Honduras	2	0	21	-1	10	-7	2	-15	10	-8	30	-7	0,99	0,96	0,92	0,97	0,91	0,86	0,06
Guinea	2	-1	14	-13	19	-15	18	-13	18	-17	19	-14	0,99	0,83	0,56	0,81	0,71	0,41	0,07
Côte d'Ivoire	3	-2	2	-1	13	-35	4	-3	51	-10	55	-12	0,76	0,99	0,64	0,77	0,49	0,61	0,07
Togo	0	-6	7	-7	10	-13	6	-9	14	-14	8	-8	0,99	0,97	0,95	0,96	0,94	0,98	0,08
Portugal	24	-10	5	-4	13	1	18	-9	11	-19	-3	-12	0,95	0,97	0,88	0,95	0,8	0,88	0,08

Bosnia and Herzegovina	2	0	12	-7	9	-25	7	-8	23	-7	63	-6	0,86	0,91	0,3	0,88	0,27	-0,14	0,09
Belgium	4	-3	9	-11	67	-20	17	-10	22	-33	28	-31	0,86	0,95	0,56	0,74	0,56	0,59	0,09
Czech Republic	10	-5	10	-6	30	-9	15	-12	16	-19	20	-22	0,93	0,94	0,81	0,84	0,74	0,71	0,09
El Salvador	0	0	8	-8	16	-4	9	-7	5	-14	8	-12	1	0,98	0,97	0,97	0,95	0,98	0,09
Cambodia	69	-21	10	-5	15	-8	68	-22	79	-27	24	-16	0,32	0,86	0,63	0,32	0,37	0,68	0,1
Belarus	27	-23	9	-7	11	-7	17	-19	23	-25	6	-8	-0,12	0,98	0,93	-0,09	-0,07	0,94	0,1
Zimbabwe	0	0	3	-2	10	-13	2	-3	16	-8	14	-7	1	0,98	0,8	0,98	0,79	0,9	0,11
Bolivia	7	-7	12	-5	15	-13	4	-17	12	-12	28	-11	0,84	0,91	0,32	0,77	0,32	0,41	0,12
Angola	4	0	7	-11	142	-16	13	-7	20	-52	21	-54	0,98	0,94	0,35	0,94	0,33	0,16	0,12
Laos	2	-2	3	-8	8	-15	11	-5	22	-8	23	-12	0,83	0,9	0,81	0,79	0,7	0,92	0,12
Ecuador	14	-39	7	-10	9	-30	11	-33	40	-26	56	-4	0,62	0,9	0,62	0,6	0,79	0,61	0,13
Slovakia	6	-5	8	-5	2	-4	3	-12	4	-2	12	-3	0,99	0,93	0,99	0,96	0,97	0,88	0,13
Benin	1	0	2	-4	4	-35	6	-2	63	-3	62	-7	0,99	0,98	0,87	0,97	0,82	0,87	0,13
Democratic Republic of the Congo	1	-1	3	-12	12	-7	14	-2	7	-11	6	-17	1	0,91	0,21	0,9	0,29	0,16	0,13
Moldova	1	-1	2	-4	19	-32	4	-1	56	-12	58	-11	1	1	0,9	1	0,92	0,93	0,14
Bangladesh	1	-2	9	-15	11	-10	18	-9	10	-10	11	-9	0,78	0,71	0,9	0,68	0,68	0,79	0,14
Burkina Faso	0	0	2	-4	11	-5	4	-2	6	-10	6	-11	1	0,99	0,86	0,98	0,87	0,82	0,14
Chile	15	-11	0	-18	24	-39	29	-1	49	-5	45	-22	0,86	0,89	0,51	0,81	0,79	0,61	0,16
Myanmar	7	-3	4	-11	28	-40	17	-5	64	-15	71	-18	0,57	0,41	0,71	0,35	0,44	0,75	0,16
Mali	1	0	4	-2	5	-9	2	-3	11	-5	12	-7	1	0,99	0,96	0,98	0,95	0,96	0,17
Peru	7	-14	6	-15	48	-32	18	-5	48	-27	25	-32	0,31	0,71	-0,16	0,13	0,32	-0,37	0,18
Cameroon	3	-2	20	-21	41	-12	28	-17	14	-26	9	-16	0,95	0,95	0,79	0,92	0,8	0,91	0,19
Colombia	4	-15	13	-10	4	-29	6	-20	21	-4	51	-8	0,71	0,88	0,4	0,75	0,84	0,56	0,19
Guatemala	1	-2	2	-10	1	-18	11	-2	23	-2	25	-7	0,99	0,92	0,69	0,95	0,76	0,86	0,19
Mozambique	1	0	13	-9	17	-7	11	-11	9	-14	15	-7	0,96	0,84	0,88	0,65	0,93	0,59	0,2
Ghana	0	-1	1	-2	4	-8	2	-1	7	-4	7	-3	1	1	0,94	0,99	0,95	0,96	0,2
Croatia	8	-7	5	-8	24	-4	11	-11	5	-21	1	-19	0,79	0,97	0,85	0,8	0,79	0,94	0,21
North Korea	1	-1	5	-4	24	-32	5	-4	51	-8	55	-6	1	0,98	0,32	0,98	0,32	0,31	0,21
Bulgaria	8	-13	4	-12	52	1	16	-10	0	-40	3	-39	0,91	0,8	0,9	0,91	0,69	0,48	0,22
Venezuela	4	-6	8	-23	13	-53	25	-3	106	-6	65	-4	0,44	0,87	0,88	0,04	0,2	0,88	0,22
Nepal	2	-1	2	-11	121	-11	14	-2	16	-54	4	-59	0,97	0,94	0,05	0,96	0,16	-0,01	0,23
Greece	6	-23	3	-9	30	6	8	-19	-8	-33	-8	-24	0,01	0,9	0,8	0,16	-0,12	0,71	0,23
Austria	4	-1	11	-21	13	0	37	-8	6	-10	8	-28	0,96	0,56	0,78	0,24	0,73	0,56	0,24
Iran	-2	-27	7	-21	44	-20	10	-12	11	-37	23	-42	0,22	0,86	0,24	0,25	-0,14	0,09	0,26
Uganda	1	-1	4	-5	22	-14	7	-5	20	-19	12	-15	0,99	0,95	0,68	0,92	0,58	0,62	0,29
Zambia	1	0	5	-4	0	-6	4	-4	7	0	11	0	1	0,99	0,71	0,99	0,7	0,63	0,29
Poland	2	-4	4	-2	4	-5	1	-3	4	-4	5	-5	0,92	0,93	0,97	0,91	0,89	0,91	0,31
Paraguay	8	-14	8	-8	8	-37	8	-7	40	-4	51	-5	0,25	0,93	0,88	0,25	0,23	0,91	0,35
Kenya	0	-1	5	-14	108	-35	16	-5	54	-52	33	-49	0,99	0,95	0,18	0,94	0,23	0,27	0,37
Malawi	1	-1	5	-19	51	-16	24	-5	18	-26	14	-27	1	0,93	0,88	0,93	0,89	0,88	0,4
Spain	-2	-13	4	-18	53	2	11	-6	-4	-41	2	-46	0,39	0,9	0,59	0,48	0,22	0,57	0,45
Pakistan	4	-2	3	-8	56	-3	6	-2	1	-34	1	-36	0,98	0,9	0,49	0,93	0,53	0,46	0,46
Tanzania	0	-4	6	-8	13	-16	8	-6	15	-12	21	-18	0,99	0,97	0,88	0,98	0,88	0,82	0,51
Germany	20	3	30	-1	18	-12	7	-7	37	-11	47	-15	0,95	0,9	0,95	0,92	0,92	0,86	0,52
Turkey	3	-8	14	-17	29	-27	21	-19	42	-28	30	-11	0,22	0,53	0,09	0,21	0,05	0,72	0,52
Vietnam	3	-3	18	-2	7	-8	3	-16	7	-8	27	-5	0,78	0,97	0,89	0,77	0,6	0,89	0,54
Thailand	26	-10	1	-9	7	-14	40	-10	49	-11	6	-6	0,75	0,99	0,95	0,74	0,7	0,97	0,55
Ethiopia	27	-11	19	-7	30	-45	9	-24	137	-21	123	-20	0,99	0,9	0,59	0,87	0,6	0,56	0,62
Serbia	18	-11	5	-3	4	-15	17	-13	17	-12	26	-6	0,67	0,99	0,93	0,68	0,64	0,93	0,66

Russia	3	0	11	-4	40	-43	4	-8	84	-28	77	-25	0,99	0,92	-0,12	0,97	-0,14	-0,1	0,76
Hungary	1	-1	6	-4	4	-5	3	-6	5	-5	4	-6	1	0,99	0,92	0,99	0,94	0,96	0,76
Philippines	2	-7	1	-2	2	-6	1	-6	2	-1	5	-1	0,92	0,97	0,99	0,94	0,93	0,96	0,79
Egypt	2	-1	229	-9	12	-17	10	-67	21	-12	274	-14	0,99	0,65	0,5	0,65	0,46	0,51	0,81
Italy	3	-11	7	-13	1	-20	10	-9	20	-3	13	1	0,55	0,9	0,83	0,46	0,37	0,88	0,92
Nigeria	9	-2	4	-6	29	-8	5	-4	6	-16	4	-19	0,9	0,97	0,94	0,87	0,84	0,92	0,99
Romania	0	-1	6	-5	8	-1	5	-6	1	-7	3	-9	1	0,98	0,99	0,99	0,99	0,98	1,03
Canada	48	-2	50	-7	35	-5	7	-2	13	-10	14	-12	0,77	0,8	0,21	0,9	0,09	0,3	1,33
South Africa	4	-17	11	1	14	-37	-5	-19	34	-9	67	-2	0,8	0,78	0,75	0,93	0,89	0,85	1,34
France	3	0	5	0	28	-3	2	-3	3	-19	5	-20	0,98	0,95	0,95	0,98	0,96	0,95	1,7
Indonesia	6	-5	5	-8	6	-4	3	-2	4	-3	4	-5	0,86	0,96	0,91	0,89	0,95	0,85	2,06
Ukraine	9	-5	10	-11	3	-10	12	-6	20	0	7	-6	0,99	0,96	0,99	0,98	0,99	0,96	2,18
India	10	-2	1	-6	5	-21	17	-3	38	-7	18	-4	0,56	0,99	0,91	0,57	0,65	0,93	2,38
Mexico	4	-3	5	-3	0	-14	3	-4	17	1	17	1	0,79	0,97	0,85	0,79	0,71	0,82	2,38
Argentina	5	-1	8	-7	4	-5	10	-6	8	-2	7	-3	0,94	0,97	0,99	0,93	0,94	0,97	2,54
Brazil	0	-3	1	-4	5	-9	3	-3	7	-5	6	-5	0,96	0,99	0,98	0,95	0,96	0,99	7,04
China	1	-3	5	-6	2	-11	3	-3	8	-1	5	-2	0,96	0,98	0,97	0,95	0,94	0,97	21,54
United States	2	-2	2	-2	2	-3	2	-1	2	-1	2	-2	0,98	0,98	1	0,98	0,98	0,99	35,74
global	4	-3	5	-4	5	-5	1	-5	3	-1	5	-2	0,77	0,98	0,97	0,77	0,79	0,99	100

Table D.2: The table of the country data for wheat shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of detrended yield (t/ha) time series calculated from one of the 14 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks). Countries are in ascending order according to their share on global production based on FAOSTAT (FAO, 2014) average production for the period 2009-2013.

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Botswana	-5	-73	-5	-86	12	-89	122	-1	358	-14	303	-27	0,22	-0,06	-0,47	0,03	-0,19	0,03	0
New Caledonia	0	0	NA	NA	9	0	NA	NA	0	-9	NA	NA	1	NA	0,95	NA	0,94	NA	0
United Arab Emirates	21	-8	8	-28	11	-33	72	-14	61	-16	46	-20	0,75	0,83	0,21	0,62	0,38	0,28	0
Qatar	NA	NA	14	-67	12	-23	NA	NA	NA	NA	100	-65	NA	-0,11	0,4	NA	NA	-0,38	0
Venezuela	1	-1	31	-5	392	-38	6	-23	74	-79	74	-73	0,99	0,86	-0,25	0,87	-0,23	-0,24	0
Swaziland	14	-3	18	-2	1	-12	0	-8	29	-3	33	-3	0,99	0,93	0,99	0,97	0,97	0,89	0
Cameroon	175	-53	117	-50	70	-14	26	-10	62	-47	45	-43	0	0,18	0,81	0,67	0,18	0,31	0
Honduras	5	-3	15	-9	27	1	10	-9	3	-24	13	-23	0,46	0,96	0,92	0,35	0,44	0,91	0
Somalia	0	-58	46	-60	339	-63	32	-65	177	-85	163	-70	-0,1	-0,13	-0,01	0,3	-0,06	-0,02	0
Thailand	15	-9	46	-16	60	-19	17	-20	28	-29	15	-23	0,42	0,61	0,1	0,49	0,19	0,2	0
Kuwait	6	-16	10	-25	14	-48	29	-10	83	-6	93	-25	0,21	0,39	-0,16	0,18	-0,11	-0,04	0
Guatemala	7	-18	8	-18	95	-18	7	-11	3	-54	3	-49	0,86	0,81	0,6	0,93	0,31	0,6	0
Oman	12	-39	19	-25	18	-24	36	-49	20	-48	21	-23	0,47	0,55	0,48	0,18	-0,01	0,12	0
Malawi	9	-2	47	-12	76	-20	16	-26	23	-36	48	-30	0,48	0,78	0,67	0,49	0,47	0,53	0
Montenegro	81	-22	65	-23	115	-54	15	-11	68	-16	96	-25	0,12	0,79	0,3	0,2	0,16	0,4	0
Mauritania	0	0	7	-9	20	-6	10	-7	11	-14	12	-22	1	0,93	0,82	0,92	0,79	0,78	0
Angola	1	-17	5	-14	76	-33	10	-8	69	-39	89	-40	0,65	0,77	0,38	0,97	0,26	0,45	0

Taiwan	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Bhutan	10	-12	35	-46	22	-31	63	-19	59	-25	93	-50	0,41	0,4	0,47	0,56	0,03	-0,1	0
Niger	123	-33	89	-38	177	-39	16	-11	93	-27	109	-33	0,4	0,29	0,22	0,85	-0,34	-0,15	0
Burundi	4	-2	10	-10	32	-15	9	-6	17	-24	14	-31	0,8	0,9	0,89	0,8	0,76	0,89	0
Ecuador	151	-7	50	-11	232	-5	73	-16	11	-52	18	-61	-0,25	0,12	-0,21	0,45	0,4	0,23	0
Democratic Republic of the Congo	3	-8	14	-6	134	-4	5	-19	8	-59	7	-51	0,96	0,81	0,5	0,76	0,42	0,62	0
Madagascar	0	0	31	-1	253	-50	2	-23	101	-71	121	-62	1	0,95	0,33	0,93	0,34	0,35	0
Colombia	8	-28	4	-12	46	-51	15	-31	50	-37	120	-40	0,75	0,96	0,4	0,65	0,71	0,44	0
Namibia	36	-63	22	-63	43	-78	24	-12	410	-3	365	0	-0,25	-0,32	-0,37	0,91	0,42	0,44	0
Lesotho	3	-1	14	-6	8	-16	8	-11	21	-6	35	-12	0,99	0,96	0,9	0,97	0,83	0,84	0
Malta	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
Chad	252	-76	253	-77	38	-12	8	-7	230	-77	234	-78	-0,2	-0,24	-0,05	0,84	-0,23	-0,34	0
Mozambique	9	-24	25	-34	14	-19	18	-15	23	-28	28	-38	0,82	0,61	0,44	0,76	0,64	0,8	0
Zimbabwe	-4	-32	-1	-33	8	-21	3	-8	-4	-19	-1	-17	0,55	0,47	0,79	0,95	0,84	0,84	0
Uganda	2	-4	14	-7	47	-32	9	-12	54	-31	60	-30	0,8	0,94	-0,02	0,83	0,1	-0,01	0
Jordan	4	-16	29	-46	-11	-63	63	-22	177	10	218	-6	0,93	0,42	0,29	0,47	0,15	-0,11	0
Cyprus	NA	NA	21	-12	-6	-70	NA	NA	NA	NA	232	10	NA	0,37	-0,41	NA	NA	-0,14	0
Mali	22	-81	49	-77	111	-72	24	-70	25	-63	24	-47	-0,23	-0,02	-0,12	-0,08	-0,05	0,15	0
Eritrea	37	-9	16	-13	100	-23	57	-15	80	-54	16	-46	0,43	0,88	0,42	0,46	0,16	0,74	0
South Korea	6	-2	17	-17	12	-21	27	-15	35	-9	8	-24	0,25	0,88	0,85	0,24	0,28	0,71	0
Georgia	2	-2	21	-7	26	-13	8	-17	17	-20	14	-17	0,97	0,89	0,54	0,9	0,56	0,66	0,01
Rwanda	2	-2	18	-26	2	-9	34	-14	9	-3	18	-27	1	0,73	0,93	0,75	0,95	0,78	0,01
Portugal	0	-3	26	1	6	-5	0	-22	5	-8	27	-2	0,98	0,94	0,72	0,91	0,72	0,53	0,01
Luxembourg	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0,01
Tanzania	1	0	18	-16	65	-29	19	-15	41	-36	37	-31	1	0,97	0,86	0,97	0,86	0,88	0,01
Nigeria	13	-35	13	-32	34	-31	7	-11	71	-38	70	-34	0,56	0,56	0,46	0,78	0,33	0,13	0,02
Lebanon	3	-1	55	-40	171	0	68	-12	0	-60	0	-55	1	0,64	0,31	0,69	0,3	0,42	0,02
North Korea	20	-29	31	-30	17	-22	8	-8	25	-19	23	-17	0,89	0,88	0,88	0,98	0,8	0,82	0,02
Israel	14	-9	18	-25	16	-21	43	-22	47	-21	15	-21	0,91	0,51	0,73	0,39	0,46	0,7	0,02
Slovenia	15	-5	11	-3	9	-7	7	-15	14	-8	17	-4	0,51	0,86	0,66	0,57	0,55	0,84	0,02
Libya	13	-15	80	2	26	-28	-1	-48	80	-28	77	-1	0,94	0,23	0,48	0,11	0,45	0,38	0,02
Myanmar	1	-3	27	-6	99	-21	7	-23	24	-51	53	-35	0,7	0,87	0,25	0,66	0,14	0,46	0,03
Bolivia	6	-9	4	-1	48	-20	4	-11	19	-29	29	-31	0,82	0,92	0,64	0,8	0,63	0,42	0,03
Bosnia and Herzegovina	1	0	3	-7	10	-5	8	-4	6	-9	5	-15	0,99	0,98	0,98	0,96	0,96	0,96	0,03
Peru	20	-12	1	-7	59	-2	30	-8	-4	-24	-1	-39	0,71	0,93	0,7	0,7	0,38	0,63	0,03
Zambia	32	-25	21	-18	30	-25	15	-17	78	-33	55	-27	0,82	0,87	0,1	0,9	-0,04	0,09	0,03
Armenia	1	-1	1	-16	15	-5	18	-1	7	-13	3	-12	0,96	0,93	0,93	0,91	0,91	0,95	0,03
Yemen	8	-22	14	-29	46	-35	14	-23	24	-38	12	-22	0,86	0,76	-0,09	0,84	-0,04	0,1	0,04
Norway	10	-8	6	-37	17	-10	71	-7	2	-6	10	-42	0,57	0,67	0,59	0,86	0,83	0,75	0,04
Albania	1	-1	31	-26	4	-10	38	-23	13	-4	26	-18	0,98	0,84	0,96	0,83	0,95	0,9	0,04
Estonia	2	-1	22	-9	3	-1	9	-16	0	-3	18	-10	0,96	0,93	0,99	0,93	0,97	0,9	0,06
Sudan	48	-39	59	-45	167	-38	59	-7	154	-55	172	-58	0,68	0,55	0,23	0,83	-0,15	-0,1	0,06
Kenya	0	-1	5	-12	258	30	13	-5	-22	-72	-27	-70	1	0,95	0,41	0,94	0,35	0,44	0,06
Mongolia	4	-6	11	-17	1093	-12	17	-6	14	-89	16	-89	0,73	0,64	-0,21	0,8	0,27	-0,12	0,06
New Zealand	3	-1	52	-27	18	-36	43	-32	66	-13	72	-22	0,99	0,65	0,14	0,62	0,07	-0,07	0,06
Switzerland	0	0	18	-11	25	-4	13	-14	5	-19	7	-22	1	0,86	0,74	0,85	0,74	0,7	0,08
Ireland	0	0	3	-3	5	-5	4	-3	6	-5	6	-6	1	0,98	0,95	0,97	0,97	0,87	0,1
Japan	7	-4	7	-2	10	-4	3	-9	12	-10	22	-5	0,79	0,79	0,56	0,76	0,74	0,66	0,11
Moldova	2	-1	3	-2	0	-23	4	-3	45	0	52	-2	0,99	1	0,85	0,99	0,86	0,85	0,11

Kyrgyzstan	3	-19	16	-27	25	-8	14	-13	11	-35	22	-39	0,9	0,78	0,87	0,92	0,64	0,65	0,12
Finland	15	-43	62	-4	31	-35	15	-43	3	-17	58	-11	0,68	0,91	0,86	0,67	0,92	0,83	0,13
Croatia	6	-6	2	-7	8	-10	8	-6	9	-6	3	-6	0,87	0,96	0,9	0,88	0,88	0,94	0,13
Tajikistan	1	-4	14	-23	63	-5	26	-13	5	-40	17	-53	0,97	0,94	0,51	0,94	0,43	0,44	0,13
Bangladesh	0	-2	1	-10	37	-8	9	-1	9	-27	10	-29	0,98	0,98	0,8	0,98	0,77	0,77	0,15
Saudi Arabia	8	-35	26	-39	4	-36	34	-22	10	-3	49	-23	0,19	0,17	0,57	0,55	0,57	0,71	0,15
Latvia	0	0	2	-10	11	-11	11	-1	12	-10	3	-11	1	0,97	0,96	0,97	0,96	0,95	0,17
Netherlands	2	-2	18	-15	6	-5	19	-15	3	-5	14	-19	0,99	0,88	0,98	0,88	0,99	0,88	0,19
Tunisia	0	-1	19	-21	2	-9	27	-14	10	-1	16	-18	1	0,86	0,98	0,86	0,98	0,88	0,19
Paraguay	10	-5	19	-16	-9	-38	14	-7	63	8	56	6	0,98	0,91	0,55	0,94	0,44	0,65	0,2
Chile	7	-9	0	-39	0	-45	48	-6	87	-4	43	-13	0,32	0,39	0,12	0,58	0,52	0,62	0,2
Slovakia	0	0	4	-6	5	-3	6	-3	3	-5	3	-5	1	0,96	0,99	0,96	0,99	0,98	0,21
Uruguay	2	-1	9	-4	14	-9	5	-8	10	-13	6	-11	0,99	0,98	0,95	0,97	0,96	0,96	0,22
Austria	0	-9	18	-24	2	-14	20	-15	6	-3	16	-17	0,98	0,83	0,91	0,76	0,81	0,81	0,23
Turkmenistan	8	-3	17	-26	68	1	35	-8	2	-41	1	-50	0,82	0,84	0,47	0,79	0,39	0,21	0,23
Nepal	14	-6	4	-13	6	-5	17	-8	14	-7	3	-10	0,91	0,92	0,93	0,91	0,92	0,93	0,24
Greece	97	-24	34	-7	11	-7	45	-19	78	-22	21	-4	0,21	0,92	0,95	0,58	0,29	0,95	0,24
Azerbaijan	2	-1	3	-9	19	-2	9	-3	3	-17	1	-23	0,99	0,96	0,73	0,94	0,68	0,56	0,25
South Africa	16	-31	28	-22	25	-13	6	-25	2	-23	12	-13	0,71	0,72	0,6	0,94	0,94	0,92	0,27
Belgium	2	-3	8	-9	7	-1	13	-8	2	-4	9	-15	0,96	0,93	0,98	0,92	0,94	0,86	0,27
Serbia	16	-6	5	-1	4	-5	15	-5	11	-4	10	-3	0,56	1	0,99	0,56	0,53	0,99	0,3
Belarus	2	-3	6	-2	16	0	1	-8	0	-15	1	-8	0,98	0,99	0,93	0,96	0,9	0,96	0,31
Sweden	2	-1	5	-10	5	-3	12	-4	5	-4	7	-11	0,98	0,92	0,99	0,91	0,98	0,91	0,32
Lithuania	1	-1	4	-7	12	-2	7	-4	2	-11	6	-17	1	0,96	0,97	0,97	0,97	0,92	0,34
Iraq	157	-5	156	-34	97	-31	59	-10	74	2	98	-16	0,08	0,05	0,06	0,11	0,69	0,22	0,38
Algeria	1	0	-3	-20	10	-43	25	4	75	-8	67	-24	1	0,88	0,73	0,88	0,68	0,77	0,43
Ethiopia	0	0	8	-8	43	-28	9	-7	40	-30	42	-25	1	0,97	0,63	0,97	0,53	0,61	0,48
Syria	0	-4	-3	-22	5	-15	24	3	18	-5	5	-19	1	0,91	0,73	0,93	0,72	0,61	0,51
Mexico	75	-1	68	-20	50	-19	25	-20	52	-6	91	-14	0,09	0,63	0,36	0,3	-0,08	-0,28	0,53
Hungary	1	-1	2	-3	12	-2	3	-2	3	-10	1	-11	1	0,99	0,96	0,99	0,95	0,96	0,62
Czech Republic	1	0	5	-3	3	-2	3	-5	3	-3	3	-1	0,99	0,94	0,98	0,96	0,98	0,97	0,63
Bulgaria	2	-2	3	-7	1	-10	7	-4	13	-1	12	-6	0,98	0,97	0,85	0,96	0,83	0,85	0,65
Afghanistan	1	-6	7	-3	42	-16	3	-7	21	-32	22	-31	0,98	0,35	0,47	0,33	0,33	0,41	0,68
Denmark	0	0	49	-8	14	-3	9	-33	3	-12	32	-9	1	0,97	0,98	0,97	0,98	0,97	0,72
Brazil	0	-11	1	-9	2	-1	7	-7	-1	-13	1	-11	0,76	0,97	0,99	0,79	0,76	0,96	0,79
Morocco	0	0	0	-11	-1	-29	12	0	42	2	39	-2	1	0,91	0,81	0,89	0,78	0,89	0,82
Spain	1	-1	3	-5	5	-7	7	-3	8	-3	9	-8	0,99	0,98	0,9	0,96	0,94	0,84	0,87
Romania	1	0	18	-6	1	-55	6	-14	201	-1	206	-2	0,99	0,97	0	0,97	0,04	0,06	0,9
Uzbekistan	0	0	-2	-18	86	3	22	2	-2	-46	-4	-56	1	0,88	0,6	0,86	0,54	0,47	0,97
Italy	60	-10	25	-9	-1	-24	33	-9	114	-6	66	2	0,64	0,97	0,9	0,73	0,49	0,85	1,02
Egypt	4	-2	148	-8	53	-26	9	-50	35	-27	62	-6	1	0,72	-0,4	0,77	-0,43	-0,37	1,24
Poland	4	-1	2	-1	4	-18	4	-2	25	-1	27	-4	0,99	1	0,6	0,99	0,64	0,61	1,37
Argentina	12	-6	6	-4	9	-5	17	-11	12	-12	3	-9	0,89	0,94	0,97	0,83	0,83	0,92	1,63
Iran	1	-3	0	-7	0	-8	8	-2	10	0	5	-3	0,97	0,98	0,85	0,96	0,9	0,92	1,96
United Kingdom	1	-2	4	-4	3	-1	2	-3	2	-3	1	-3	0,98	0,97	0,94	0,95	0,91	0,97	2,03
Kazakhstan	22	-10	0	-25	16	-18	50	-1	56	-16	4	-20	0,91	0,88	0,69	0,86	0,74	0,6	2,14
Ukraine	0	0	1	-3	1	-3	3	-1	3	-1	1	-3	1	0,97	0,96	0,97	0,96	0,97	2,88
Turkey	0	-3	1	-5	15	-6	5	-2	4	-14	3	-17	0,72	0,83	0,86	0,98	0,97	0,95	3,05
Germany	2	-2	2	-4	2	-4	5	-1	2	-1	0	-3	0,94	0,99	1	0,95	0,95	0,99	3,5

Pakistan	41	-7	43	-7	37	-19	2	-2	19	-2	19	-1	0,92	0,91	0,79	0,98	0,87	0,88	3,52
Australia	4	-4	5	-11	16	-1	14	-6	2	-11	6	-21	0,97	0,95	0,96	0,95	0,95	0,87	3,62
Canada	0	-1	2	-4	41	-7	5	-3	7	-28	4	-28	1	0,96	0,42	0,95	0,44	0,41	4,09
France	1	-1	5	-3	2	0	6	-5	1	-2	4	-5	0,99	0,93	0,98	0,85	0,99	0,9	5,6
Russia	0	-1	4	-4	3	-3	4	-4	3	-3	6	-6	1	0,98	0,16	0,98	0,05	0,1	7,29
United States	3	-1	0	-8	2	-3	7	1	4	-1	0	-5	0,96	0,92	0,96	0,8	0,96	0,77	8,61
India	14	-5	12	-1	6	-16	6	-8	28	1	33	-1	0,94	0,94	0,93	0,97	0,93	0,89	12,77
China	10	-9	10	-5	12	-19	3	-6	12	-3	19	-6	0,89	0,97	0,82	0,89	0,85	0,84	17,26
global	1	-8	0	-11	0	-17	6	-1	10	0	7	-3	0,85	0,98	0,95	0,86	0,86	0,97	100

Table D.3: The table of the country data for rice shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of detrended yield (t/ha) time series calculated from one of the 11 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks). Countries are in ascending order according to their share on global production based on FAOSTAT (FAO, 2014) average production for the period 2009-2013.

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Albania	140	-50	233	-70	1	-95	74	-28	949	12	1107	7	0,31	-0,26	-1	-0,3	0,25	-1	0
New Zealand	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Puerto Rico	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Saint Vincent and the Grenadines	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Saudi Arabia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Syria	24	-43	6	-83	-67	-96	457	-4	2408	186	1407	43	0,46	0	-0,33	0	-0,28	-0,64	0
Swaziland	36	-14	21	-9	6	-12	12	-7	28	-10	15	-9	0,32	0,68	0,56	0,89	0,24	0,4	0
Micronesia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Jamaica	0	0	NA	NA	63	-9	NA	NA	10	-39	NA	NA	1	NA	0,88	NA	0,87	NA	0
Reunion	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Algeria	0	0	11	-24	9	-17	986	-9	479	-8	18	-16	1	0,22	-0,13	0,21	-0,14	0,8	0
Mauritius	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Zimbabwe	21	-22	19	-20	43	-38	8	-5	63	-19	68	-16	0,39	0,63	-0,13	0,51	0,62	0,48	0
Papua New Guinea	0	0	8	-28	19	-11	42	-8	12	-15	7	-39	1	0,81	0,56	0,82	0,58	0,23	0
Brunei	63	-39	37	-30	9	-34	19	-13	85	-37	56	-28	0,37	0,44	0,23	0,9	0,53	0,62	0
Gabon	60	-28	89	-18	3	-5	6	-23	58	-29	87	-17	0,11	0,18	0,99	0,5	0,11	0,18	0
Trinidad and Tobago	13	-21	3	-16	264	1	11	-19	0	-78	2	-73	0,93	0,92	0,45	0,95	0,11	0,29	0
South Africa	237	-16	234	-21	95	-51	5	-3	195	-16	197	-15	0,2	0,13	-0,4	0,9	-0,17	-0,17	0
Solomon Islands	NA	NA	7	-3	4	-9	NA	NA	NA	NA	7	-3	NA	0,99	0,99	NA	NA	0,99	0
French Guiana	6	-29	10	-44	28	-21	29	-10	7	-19	13	-27	0,77	0,57	0,32	0,87	0,63	0,71	0
Azerbaijan	54	-13	9	-30	13	-9	76	-9	51	-15	21	-38	-0,48	0,66	0,87	-0,57	-0,53	0,55	0
Somalia	34	-67	5	-69	36	-44	46	-6	89	-69	89	-69	0,18	-0,07	0,64	0,73	0,09	-0,01	0
Fiji	0	0	12	-13	2	-3	16	-10	3	-2	14	-15	1	0,85	0,98	0,84	0,98	0,81	0
Hungary	0	-4	0	-17	-12	-93	15	0	1353	19	1143	16	0,96	0,88	0,06	0,88	0,1	0,2	0
Belize	2	-3	10	-18	17	-17	24	-11	23	-17	8	-15	0,97	0,91	0,79	0,87	0,74	0,82	0
Kyrgyzstan	4	-9	1	-37	4	-28	56	-1	45	-10	9	-30	0,48	0,79	0,88	0,38	0,38	0,75	0
Angola	84	-38	62	-35	33	-58	13	-8	60	-9	77	-9	0,03	0,06	0,23	0,19	0,6	0,41	0
Sudan	38	-71	43	-71	70	-82	2	-2	59	-34	60	-36	0,43	0,36	-0,06	0,98	0,39	0,33	0

Comoros	0	0	0	0	NA	NA	0	0	NA	NA	NA	NA	1	1	NA	1	NA	NA	0
Guatemala	47	-37	20	-35	19	-53	22	-4	41	-11	42	-13	0,29	0,46	-0,14	0,1	0,06	0,76	0
Niger	54	-22	35	-29	34	-62	67	-13	181	-11	97	-23	0,13	0,86	0,56	0,18	0,02	0,73	0
El Salvador	6	-7	0	-18	13	-33	19	-4	39	-6	23	-21	0,31	0,47	0,07	-0,03	0,37	0,44	0
Central African Republic	4	-4	8	-3	82	-12	2	-7	15	-44	13	-41	0,38	0,81	0,36	0,35	0,53	0,6	0,01
Morocco	85	-29	41	-32	41	-96	33	-6	2428	-17	2320	-18	-0,46	-0,48	-0,06	0,87	-0,23	-0,08	0,01
Zambia	8	-14	4	-22	20	-17	18	-7	32	-18	13	-21	0,56	0,47	0,12	0,88	0,18	0,1	0,01
Honduras	63	-33	48	-33	31	-27	11	0	25	-8	17	-8	0,1	0,43	0,4	0,76	0,71	0,82	0,01
Bulgaria	10	-4	10	-28	10	-11	51	-9	15	-6	20	-26	0,46	0,63	0,73	0,36	0,52	0,27	0,01
Romania	1	-4	1	-47	-6	-89	90	-1	874	9	415	10	0,5	0,46	-0,15	0,3	-0,02	0,15	0,01
Gambia	5	-5	12	-12	91	-2	8	-6	7	-50	14	-54	0,93	0,97	0,98	0,92	0,93	0,97	0,01
Burundi	6	-9	14	-16	46	-20	9	-10	29	-37	21	-36	0,61	0,64	-0,12	0,74	-0,3	0,06	0,01
Bhutan	15	-11	30	-24	12	-14	17	-12	5	0	16	-11	0,91	0,69	0,92	0,74	0,9	0,78	0,01
Tajikistan	10	-19	8	-27	11	-14	21	-2	21	-24	19	-33	0,62	0,34	0,79	0,51	0,54	0,33	0,01
Rwanda	3	-19	12	-23	13	-26	34	-26	41	-28	10	-10	0,53	0,85	0,77	0,48	0,36	0,76	0,01
Kenya	18	-44	29	-51	46	-21	16	-35	-2	-48	33	-55	0,13	0,18	0,69	0,63	0,31	0,3	0,01
East Timor	10	-13	16	-15	25	-2	29	-25	0	-27	5	-25	0,95	0,91	0,93	0,79	0,87	0,81	0,02
France	15	-4	49	-13	-13	-97	15	-30	3237	21	2750	50	0,52	0,53	-0,17	0,72	-0,19	-0,24	0,02
Ethiopia	7	-44	-9	-54	6	-72	28	-21	198	-33	255	-24	-0,66	-0,09	-0,44	-0,13	-0,54	-0,19	0,02
Malawi	3	-2	5	-4	4	-13	5	-4	17	-6	17	-8	0,99	0,93	0,83	0,93	0,78	0,78	0,02
Chile	31	-17	3	-10	33	-33	29	-16	34	-1	50	-23	0,49	-0,42	0,45	0,76	0,8	0,44	0,02
Togo	1	-2	3	-3	7	-4	3	-3	5	-7	7	-6	0,97	0,98	0,92	0,97	0,89	0,91	0,02
Turkmenistan	6	-14	3	-29	2	-66	25	-4	203	3	189	1	0,83	0,61	-0,21	0,66	-0,04	0,12	0,02
Haiti	4	-27	0	-27	35	-6	6	-3	11	-46	5	-46	0,75	0,81	0,52	0,65	0,15	0,38	0,02
Uzbekistan	5	-9	23	-15	14	-23	10	-20	38	-16	31	-18	0,98	0,85	0,76	0,83	0,82	0,72	0,02
Ukraine	11	-34	9	-31	9	-19	2	-3	2	-18	3	-15	0,81	0,81	0,74	1	0,9	0,88	0,02
Mauritania	7	-17	15	-31	18	-15	24	-22	4	-27	37	-39	0,71	0,57	0,75	0,54	0,6	0,23	0,02
Cameroon	26	-36	20	-36	21	-19	9	-19	27	-43	29	-47	0,64	0,57	0,66	0,53	0,23	0,61	0,02
Portugal	63	-37	60	-34	65	-32	20	-6	10	-8	5	-9	0,08	-0,01	-0,08	0,95	0,92	0,95	0,02
Benin	4	-6	25	-5	10	-10	2	-17	6	-8	14	-6	0,09	0,83	0,84	0,21	0,17	0,88	0,02
Iraq	14	-45	8	-49	-3	-56	11	1	52	-23	44	-24	0,44	0,5	0,12	0,8	0,07	0,34	0,03
Guinea-Bissau	0	-3	59	-19	29	-27	19	-37	34	-22	23	-4	0,97	0,95	0,96	0,96	0,95	0,97	0,03
Mexico	63	-31	78	-43	46	-17	22	-22	18	-41	34	-51	0,01	-0,5	0,14	0,2	0,14	0,3	0,03
Uganda	24	-5	10	-9	57	-5	16	-9	6	-23	2	-31	0,85	0,7	0,43	0,7	0,24	0,43	0,03
Chad	17	-54	19	-48	16	-30	9	-27	26	-40	28	-33	0,45	0,62	0,64	0,75	0,15	0,6	0,03
Greece	22	-19	19	-9	17	-14	20	-26	34	-31	22	-10	-0,19	0,72	0,65	-0,17	-0,13	0,38	0,03
Suriname	3	-38	4	-47	0	-33	64	-17	6	-8	17	-36	-0,17	0,04	-0,1	0,25	0,49	0,58	0,03
Costa Rica	13	-22	4	-22	44	-12	14	-4	10	-46	8	-46	0,88	0,93	0,26	0,96	-0,04	0,09	0,03
Panama	4	-3	15	-10	37	-14	8	-10	12	-24	10	-16	0,97	0,91	0,94	0,86	0,94	0,89	0,04
Mozambique	3	-1	12	-22	18	1	32	-12	8	-16	-1	-19	0,91	0,89	0,3	0,92	0,38	0,49	0,04
Burkina Faso	1	-11	13	-6	78	-3	8	-21	1	-48	-3	-44	0,93	0,89	-0,59	0,85	-0,61	-0,65	0,04
Liberia	4	-3	9	-18	12	-6	18	-8	7	-7	10	-12	0,8	0,92	0,91	0,77	0,78	0,94	0,04
Democratic Republic of the Congo	6	-7	7	-17	35	-53	23	-5	133	-25	123	-21	0,94	0,95	0,36	0,89	0,4	0,29	0,05
Kazakhstan	48	-55	11	-52	3	-24	72	-8	63	-47	21	-48	0,29	-0,1	0,47	0,51	0,44	0,23	0,05
Paraguay	3	-11	1	-18	54	-4	24	0	2	-35	2	-46	0,85	0,88	0,82	0,84	0,61	0,62	0,05
Nicaragua	1	-10	2	-5	133	-11	6	-6	13	-61	10	-58	0,99	0,98	0,48	0,98	0,49	0,48	0,06
Bolivia	21	-1	19	0	21	-12	2	-3	23	-17	19	-16	0,83	0,82	0,12	0,97	0,34	0,33	0,06
Ghana	2	-1	2	-3	8	-9	5	-3	10	-8	8	-9	0,98	0,99	0,86	0,98	0,82	0,86	0,07
Senegal	13	-52	14	-38	28	-25	10	-39	1	-50	3	-51	0,73	0,78	0,42	0,86	0,44	0,22	0,07

Cuba	0	0	6	-4	763	1	5	-5	-1	-88	4	-88	1	0,92	0,77	0,92	0,82	0,77	0,08
Afghanistan	26	-12	30	-20	48	-14	10	-5	16	-26	14	-30	0,82	0,85	0,58	0,98	0,58	0,56	0,08
Australia	11	-49	11	-53	28	-15	16	-2	2	-43	3	-47	0,3	0,19	0,74	0,95	0,29	0,17	0,09
Guyana	3	-10	8	-25	23	-21	22	-5	15	-14	6	-16	0,94	0,73	0,86	0,83	0,91	0,84	0,09
Dominican Republic	1	-20	19	-21	17	-4	6	-15	5	-31	23	-33	0,8	0,9	0,82	0,95	0,54	0,61	0,12
Turkey	72	-7	52	-13	30	-97	16	-18	3174	6	2834	4	0,74	0,72	-0,2	0,88	-0,15	-0,25	0,12
Spain	87	-18	88	-17	92	-27	9	-2	13	-3	14	-9	0,51	0,57	0,47	0,78	0,84	0,8	0,13
Venezuela	6	-14	5	-11	7	-21	2	-6	11	-3	15	-4	0,25	0,65	0,06	0,42	0,02	0,64	0,13
Russia	16	-41	-1	-45	17	-7	30	-3	0	-45	-4	-53	0,19	0,31	0,66	0,43	0,19	0,27	0,14
Sierra Leone	2	-2	7	-6	7	-12	9	-8	13	-5	16	-9	1	0,96	0,64	0,97	0,64	0,65	0,15
Côte d'Ivoire	3	-1	5	-2	12	-9	2	-5	10	-12	8	-7	0,98	0,99	0,93	0,95	0,83	0,94	0,17
Uruguay	8	-2	5	-2	7	-6	3	-2	5	-3	8	-3	0,98	0,99	0,98	0,98	0,98	0,98	0,19
Argentina	15	-3	18	-6	16	-2	8	-3	2	-10	3	-9	0,69	0,96	0,8	0,69	0,79	0,83	0,21
Italy	32	-20	5	-12	14	-20	27	-18	64	-18	30	-14	0,52	0,46	0,83	0,16	0,51	0,46	0,21
Ecuador	7	-12	4	-17	2	-22	30	-12	18	-2	32	-7	0,75	0,82	0,51	0,53	0,75	0,25	0,22
Taiwan	NA	NA	13	-14	15	-8	NA	NA	NA	NA	17	-20	NA	0,52	0,64	NA	NA	-0,13	0,23
Guinea	1	-1	8	-3	25	-4	4	-6	3	-19	6	-14	0,99	0,91	0,89	0,93	0,92	0,93	0,24
Mali	14	-26	21	-20	74	-16	14	-13	28	-58	12	-51	0,92	0,92	0,61	0,93	0,49	0,65	0,28
Tanzania	4	-25	2	-24	8	-27	9	-3	6	-6	5	-6	0,77	0,74	0,82	0,97	0,95	0,93	0,28
Colombia	14	-17	11	-24	25	-11	21	-16	6	-34	23	-39	0,71	0,36	0,73	-0,1	0,5	0,07	0,32
North Korea	1	0	2	-6	29	-9	6	-1	9	-22	10	-24	1	0,97	0,93	0,97	0,94	0,85	0,36
Malaysia	7	-8	6	-10	23	-10	9	-4	13	-25	12	-25	0,91	0,93	0,73	0,9	0,57	0,64	0,36
Iran	62	-53	58	-53	51	-21	36	-11	57	-40	69	-40	0,21	0,42	0,34	0,52	0,35	0,46	0,36
Peru	27	-26	6	-16	39	-30	25	-14	15	-11	33	-27	0,54	0,65	0,46	0,55	0,67	0,45	0,4
Laos	3	-2	3	-6	13	-6	5	-3	5	-12	5	-10	0,99	0,89	0,9	0,9	0,91	0,92	0,45
Sri Lanka	2	-3	3	-12	5	-1	10	-3	4	-5	3	-13	0,95	0,95	0,93	0,93	0,92	0,91	0,56
Madagascar	5	-9	10	-16	3	-4	9	-8	6	-7	10	-12	0,89	0,84	0,98	0,98	0,9	0,79	0,6
Nigeria	10	-9	19	-9	20	-6	22	-17	2	-13	24	-19	0,87	0,78	0,61	0,56	0,81	0,08	0,61
Nepal	1	-1	2	-5	14	-3	5	-2	3	-12	3	-10	0,98	0,95	0,99	0,94	0,98	0,95	0,63
Egypt	51	-5	483	-13	5	-27	30	-71	124	-3	654	-1	0,35	0,48	0,61	-0,12	0,08	0,09	0,78
South Korea	5	-1	2	-7	54	0	10	-1	0	-32	-1	-38	0,99	0,95	0,21	0,95	0,23	0,5	0,85
Cambodia	16	-2	2	-4	17	-3	14	-3	11	-5	1	-13	0,96	0,88	0,96	0,87	0,93	0,93	1,2
Pakistan	13	0	13	-6	1	-10	6	-4	22	2	19	-1	0,98	0,98	0,96	0,98	0,95	0,96	1,28
United States	8	-1	9	-11	6	-3	17	-2	12	-4	12	-16	0,93	0,69	0,99	0,5	0,92	0,64	1,31
Japan	19	-6	51	-11	7	-10	7	-18	11	-7	40	-8	0,79	0,93	0,9	0,92	0,84	0,94	1,48
Brazil	3	-6	4	-5	2	-4	3	-9	2	-4	8	-4	0,32	0,98	0,98	0,39	0,45	0,97	1,69
Philippines	2	-1	2	-7	38	-3	10	-3	3	-26	4	-33	0,99	0,98	0,8	0,98	0,77	0,8	2,37
Myanmar	4	0	8	-3	10	-9	6	-8	10	-6	10	-11	1	0,97	0,92	0,97	0,94	0,94	4,18
Thailand	20	-7	3	-6	35	-2	27	-8	11	-11	1	-29	0,82	0,96	0,89	0,86	0,78	0,86	4,97
Vietnam	8	-2	7	-5	42	-2	14	-6	1	-23	6	-33	0,94	0,96	0,13	0,83	0,29	0,15	5,81
Bangladesh	2	0	1	-1	17	-1	3	-2	1	-12	2	-15	1	0,99	0,97	0,99	0,98	0,98	6,97
Indonesia	3	-2	3	-5	4	-2	4	-2	4	-2	3	-4	0,98	0,96	0,97	0,95	0,97	0,95	9,36
India	5	-1	8	-3	13	-1	3	-3	1	-7	2	-10	0,88	0,89	0,9	0,94	0,93	0,95	20,97
China	12	-23	9	-25	14	-20	3	-1	5	-18	3	-20	0,71	0,9	0,82	0,82	0,83	0,85	27,99
global	3	-7	2	-7	11	-7	5	0	2	-10	2	-14	0,64	0,93	0,94	0,65	0,65	0,96	100

Table D.4: The table of the country data for soybeans shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of detrended yield (t/ha) time series calculated from one of the 13 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks). Countries are ordered increasing according to their share on global production based on FAOSTAT (FAO, 2014) average production for the period 2009-2013.

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Chile	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Costa Rica	25	-16	194	-33	113	-16	85	-70	10	-41	27	-68	0,05	0,5	0,11	0,18	-0,07	0,01	0
French Guiana	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Guyana	305	-25	NA	NA	903	-28	NA	NA	17	-60	NA	NA	0,03	NA	-0,25	NA	-0,13	NA	0
Jordan	0	0	5	-17	NA	NA	15	-4	NA	NA	NA	NA	1	0,11	NA	-0,55	NA	NA	0
Latvia	2	-27	55	-18	NA	NA	14	-51	NA	NA	NA	NA	0,11	0,91	NA	0,12	NA	NA	0
Malaysia	58	-49	12	-10	69	-15	46	-43	31	-37	10	-32	0,23	0,28	0,22	-0,09	0,12	0,14	0
Netherlands	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
New Zealand	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Senegal	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Azerbaijan	20	-26	45	-60	85	-86	96	-25	1015	-39	505	-21	0,14	0,53	0,05	0,14	-0,17	0,24	0
Suriname	0	0	37	-35	18	-8	54	-23	9	-13	16	-29	1	0,78	0,93	0,8	0,93	0,81	0
Tajikistan	40	-30	10	-22	12	-91	43	-12	988	-6	1031	-19	0,09	0,74	-0,19	0,16	-0,48	-0,15	0
Madagascar	0	0	NA	NA	187	-43	NA	NA	117	-64	NA	NA	1	NA	0,1	NA	0,06	NA	0
Iraq	43	-32	14	-44	19	-87	135	-52	813	-42	478	-3	0,32	0,35	-0,26	-0,21	-0,43	-0,22	0
Pakistan	60	-10	19	-5	592	-2	64	-7	24	-80	24	-85	0,25	0,92	-0,03	0,25	-0,15	0	0
Panama	0	0	44	-21	23	-5	27	-31	6	-18	24	-17	1	0,61	0,95	0,67	0,94	0,57	0
Kyrgyzstan	7	-20	2	-25	8	-89	25	-7	1716	-8	1356	-5	0,61	0,17	-0,32	0,48	-0,38	-0,32	0
Taiwan	NA	NA	23	-7	29	-70	NA	NA	NA	NA	308	-19	NA	0,89	0,32	NA	NA	0,38	0
Slovenia	17	-28	23	-16	26	-18	9	-31	14	-41	21	-16	0,52	0,58	0,68	0,2	0,3	0,45	0
Albania	24	-25	31	-18	38	-49	21	-39	54	-20	146	-33	0,38	0,84	0,3	0,34	0,36	0,22	0
Poland	3	-14	98	-19	98	-19	18	-46	26	-47	86	-24	0,56	0,29	0,29	0,21	0,02	0,55	0
Bhutan	40	-29	33	-11	99	-64	36	-20	98	-44	151	-46	0,17	0,9	0,26	0,19	0,04	0,12	0
Bulgaria	7	-7	11	-27	148	-21	52	-13	26	-54	45	-68	0,37	0,76	-0,01	0,34	0,02	-0,08	0
Philippines	20	-11	17	-8	39	-13	12	-11	12	-13	25	-16	0,52	0,75	0,43	0,83	0,66	0,65	0
Côte d’Ivoire	0	-2	4	-1	10	-18	1	-4	19	-9	24	-8	0,97	0,99	0,73	0,97	0,76	0,78	0
Morocco	0	0	12	-7	31	-17	7	-10	37	-22	53	-28	1	0,9	0,6	0,79	0,62	0,43	0
Togo	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
East Timor	6	-2	11	-9	22	-2	13	-6	1	-14	7	-11	0,99	0,92	0,91	0,92	0,95	0,86	0
Belize	0	0	25	-5	3	-8	4	-20	11	-3	37	-8	1	0,81	0,92	0,74	0,9	0,74	0
Georgia	0	-1	29	-15	51	-50	17	-22	119	-33	108	-28	0,97	0,87	0,37	0,81	0,4	0,34	0
Germany	30	2	9	-6	31	-18	40	-1	61	-18	19	-16	0,51	0,9	0,64	0,3	0,1	0,54	0
Syria	22	-3	193	-9	70	-47	27	-56	147	-25	133	-33	0,35	0,53	0,69	0,13	0,26	0,42	0
Spain	31	-30	82	-37	-42	-85	58	-59	722	67	449	49	-0,01	0,26	-0,16	0,03	-0,1	0	0
Mali	22	-4	23	-16	43	0	26	-9	11	-21	4	-21	0,21	0,63	0,53	0,11	-0,02	0,66	0
Honduras	3	-4	3	-9	7	-18	7	-4	19	-4	14	-7	0,42	0,98	0,8	0,39	0,44	0,78	0
Kenya	13	-16	34	-30	60	-44	69	-25	119	-37	60	-38	0,6	0,62	0,37	0,44	0,36	0,29	0
Peru	16	-4	4	-10	39	-64	21	-2	202	-27	173	-31	0,09	0,93	0,21	0,02	-0,03	0,14	0

Burundi	4	-3	10	-41	7	-13	66	-7	12	-4	4	-32	0,99	0,78	0,97	0,69	0,95	0,87	0
Liberia	0	0	15	-3	26	-5	3	-13	5	-18	17	-13	1	0,97	0,83	0,97	0,84	0,78	0
Switzerland	8	-7	26	-15	98	-10	20	-22	22	-46	20	-32	0,21	0,74	0,73	0,22	0,07	0,78	0
Tanzania	3	-4	23	4	9	-20	-4	-22	28	-9	50	1	0,99	0,63	0,4	0,63	0,33	0,37	0
Gabon	21	-6	24	-7	22	-21	26	-8	51	-13	19	-9	0,22	0,81	0,57	0,19	-0,21	0,56	0
Greece	400	-83	5	-13	34	-38	433	-83	703	-83	78	-34	-0,29	0,87	0,58	-0,37	-0,3	0,31	0
El Salvador	0	-1	12	-10	5	-14	11	-10	17	-4	20	-3	0,97	0,92	0,92	0,88	0,87	0,9	0
Nicaragua	3	-1	2	-3	23	-40	4	-2	87	-16	78	-16	0,39	0,99	0,61	0,39	0,21	0,65	0
Sri Lanka	0	0	10	-14	15	-28	16	-9	39	-13	38	-9	1	0,95	0,87	0,95	0,82	0,85	0
Angola	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Bosnia and Herzegovina	3	-5	11	-19	54	-21	20	-8	35	-33	28	-31	0,64	0,46	0,65	0,4	0,5	0,5	0
Laos	14	-8	35	-20	26	-13	43	-31	11	-12	47	-36	0,27	0,77	0,88	0,19	0,27	0,78	0
Cameroon	1	-5	7	-22	16	-20	23	-9	24	-15	18	-21	0,78	0,93	0,67	0,73	0,52	0,79	0
Benin	1	-1	6	-10	8	-14	12	-6	16	-7	14	-4	0,6	0,98	0,9	0,58	0,53	0,96	0,01
Czech Republic	7	-2	5	-5	22	-12	8	-3	19	-16	15	-14	0,53	0,89	0,82	0,4	0,37	0,93	0,01
Democratic Republic of the Congo	14	-2	24	-3	65	-16	4	-12	22	-30	17	-24	0,72	0,8	0,43	0,57	0,53	0,28	0,01
Burkina Faso	19	-5	3	-3	38	-4	17	-3	7	-19	2	-25	0,77	0,97	0,61	0,76	0,51	0,67	0,01
Nepal	5	-3	9	-13	12	-4	17	-6	3	-7	10	-16	0,89	0,91	0,94	0,86	0,76	0,85	0,01
Egypt	7	-8	6	-19	-41	-97	33	-2	3474	129	3230	122	0,98	0,61	-0,27	0,63	-0,29	-0,3	0,01
Slovakia	17	-10	19	-9	2	-34	6	-22	62	-6	63	-5	0,48	0,93	0,56	0,52	0,45	0,71	0,01
Ethiopia	5	-30	-1	-18	41	-31	6	-18	29	-38	40	-35	-0,07	0,9	0,13	0,12	0,03	0,21	0,01
Guatemala	2	-3	6	-8	3	-30	10	-8	41	-3	47	-9	0,53	0,97	0,81	0,5	0,46	0,82	0,01
Rwanda	11	-5	6	-19	5	-3	35	-11	11	-2	9	-18	0,98	0,96	0,96	0,9	0,97	0,93	0,02
Venezuela	87	-8	0	-8	39	-10	88	-7	42	-21	10	-29	-0,28	0,96	0,57	-0,3	-0,38	0,53	0,02
Bangladesh	51	-14	74	-34	63	-55	31	-16	92	-20	46	-20	-0,02	0,41	0,07	-0,01	-0,16	0,01	0,03
Australia	3	-4	3	-15	36	-53	55	-1	135	-20	117	-26	0,89	0,49	0,36	0,41	0,37	0,05	0,03
Moldova	3	-2	3	-3	6	-6	3	-3	6	-3	6	-3	0,89	1	0,96	0,9	0,89	0,97	0,03
Colombia	103	-9	10	-3	8	-31	84	-10	110	-14	61	-3	0,08	0,05	0,78	-0,12	0,19	0,02	0,03
Ecuador	67	-12	128	-12	52	-8	43	-44	12	-5	134	-28	0,64	0,4	0,72	-0,05	0,91	0,1	0,03
Hungary	0	-10	20	-4	8	-17	5	-16	13	-9	26	-7	0,97	0,95	0,95	0,94	0,92	0,96	0,03
Zimbabwe	8	-20	4	-18	6	-71	4	-4	210	-8	212	-7	0,94	0,94	0,06	0,93	0,19	0,23	0,03
Malawi	3	0	106	-24	118	-40	34	-47	84	-49	34	-5	0,07	0,19	0,11	0,12	0,06	0,81	0,04
Austria	15	-18	20	-24	25	-17	52	-20	6	-21	26	-31	0,1	0,79	0,74	0,03	0,17	0,6	0,04
Turkey	51	-3	77	-17	73	-27	52	-41	49	-40	24	-11	-0,03	0,17	-0,25	0,16	0,42	0,61	0,04
France	5	-2	7	-8	-1	-45	9	-2	95	1	95	-1	0,95	0,88	0,84	0,9	0,82	0,7	0,05
Croatia	7	-20	10	-9	16	-14	17	-27	2	-27	18	-20	0,48	0,89	0,89	0,47	0,39	0,85	0,05
Romania	2	-3	8	-10	25	0	14	-6	0	-18	2	-27	0,86	0,93	0,95	0,82	0,79	0,83	0,05
South Korea	5	-41	10	-7	0	-47	4	-38	16	-26	108	-3	-0,07	0,96	0,05	0,03	0,64	0,14	0,05
Cambodia	9	-3	43	-11	29	-37	21	-24	113	-21	81	-21	0,42	0,87	-0,12	0,4	0,16	-0,56	0,05
Kazakhstan	4	-24	3	-27	3	-37	20	-2	21	-4	16	-8	0,6	0,29	0,79	0,55	0,74	0,54	0,06
Zambia	0	0	4	-4	3	-15	4	-4	17	-2	13	-4	1	0,97	0,92	0,97	0,92	0,97	0,06
Thailand	86	-20	12	-4	12	-3	86	-17	83	-28	4	-14	0,12	0,96	0,97	0,11	0,02	0,91	0,07
Iran	26	-36	1	-14	20	-90	30	-32	964	6	1012	-18	0,02	0,91	-0,52	0	-0,34	-0,44	0,07
Uganda	6	-4	20	-17	31	-38	18	-12	76	-23	85	-35	0,96	0,84	0,52	0,79	0,48	0,46	0,07
Mexico	28	-58	66	-44	11	-70	10	-30	137	5	152	5	-0,24	0,27	-0,28	-0,15	-0,07	0,26	0,08
Japan	14	-1	17	0	8	-23	6	-3	47	-7	52	-4	0,95	0,96	0,89	0,96	0,84	0,85	0,09
Vietnam	2	-13	15	-4	167	-18	3	-20	12	-60	40	-60	0,82	0,93	0,63	0,82	0,6	0,67	0,09
Myanmar	12	-9	13	-5	1	-34	18	-15	45	-7	66	0	0,61	0,98	0,9	0,54	0,61	0,9	0,09
North Korea	1	-1	11	-3	6	-2	3	-10	4	-5	14	-7	1	0,94	0,91	0,94	0,91	0,91	0,14

Serbia	22	-21	4	-2	14	-31	22	-21	36	-8	62	-13	0,6	0,99	0,92	0,58	0,61	0,86	0,16
Nigeria	2	-8	3	-8	20	-13	3	-1	17	-23	18	-23	0,98	0,98	0,79	0,98	0,73	0,68	0,19
Italy	16	-31	12	-21	8	-44	31	-13	61	-15	61	-3	0,74	0,89	0,86	0,7	0,48	0,87	0,2
South Africa	61	1	10	-8	42	-4	47	3	42	-13	-1	-23	0,55	0,98	0,75	0,61	0,74	0,82	0,25
Indonesia	2	-5	1	-7	10	-6	8	-4	8	-10	8	-15	0,65	0,91	0,75	0,79	0,83	0,83	0,34
Russia	2	-1	23	-4	72	-36	3	-18	63	-39	60	-34	0,7	0,84	0,21	0,81	0,25	0,34	0,58
Bolivia	1	-7	6	-5	12	-68	2	-6	427	-8	401	-10	0,99	0,98	0,46	0,97	0,45	0,53	0,78
Ukraine	9	-3	1	-6	3	-9	12	-1	12	-5	4	-4	0,83	0,99	0,87	0,83	0,82	0,87	0,8
Uruguay	8	-5	19	-5	16	-16	4	-10	23	-16	27	-12	0,13	0,79	0,75	0,21	-0,01	0,7	0,88
Canada	4	-3	2	-3	15	-16	5	-2	20	-7	18	-2	0,94	0,74	0,29	0,52	0,46	-0,23	1,77
Paraguay	3	-1	6	-10	5	-41	15	-4	80	-2	82	-11	0,94	0,95	0,83	0,92	0,83	0,83	2,61
India	29	-7	6	-1	6	-13	30	-8	48	-12	20	-4	-0,08	0,95	0,95	-0,04	-0,04	0,87	4,85
China	4	-5	5	-1	5	-8	3	-5	13	-3	14	-5	0,84	0,99	0,86	0,84	0,83	0,84	5,53
Argentina	3	-4	25	-5	1	-3	6	-22	4	-5	23	-4	0,85	0,95	0,99	0,8	0,85	0,95	17,51
Brazil	13	-6	3	-8	6	-6	23	-5	21	-8	4	-7	0,42	0,97	0,13	0,62	0,07	0,2	27,48
United States	9	-3	6	-2	7	-2	3	-2	3	-4	1	-2	0,92	0,98	0,96	0,93	0,91	0,99	34,52
global	4	0	4	-3	3	-6	5	-1	10	-4	5	-4	0,39	1	0,97	0,39	0,28	0,96	100

Table D.5: The table of the country data for maize shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of the time series of total production (t) calculated from one of the 14 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks).

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Guadeloupe	NA	NA	-94	-95	NA	NA	NA	NA	NA	NA	NA	NA	NA	0,79	NA	NA	NA	NA	0
United Kingdom	NA	NA	-100	-100	NA	NA	NA	NA	NA	NA	NA	NA	NA	0,33	NA	NA	NA	NA	0
Djibouti	452	61	3437	1194	76	-84	-66	-95	3509	355	19991	2661	-0,1	0,04	-0,27	0,09	-0,62	-0,47	0
Suriname	104	75	1523	620	167	94	-74	-87	5	-32	738	187	0,01	0,3	0,38	-0,19	-0,08	0,68	0
Guam	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Micronesia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
French Guiana	17	-30	24	0	38	-48	-1	-43	39	-51	132	-16	-0,74	0,84	0,75	-0,71	-0,7	0,52	0
Antigua and Barbuda	NA	NA	-74	-74	-17	-17	NA	NA	NA	NA	-69	-69	NA	0,9	0,98	NA	NA	0,98	0
Montserrat	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Micronesia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Japan	-100	-100	-100	-100	-100	-100	941	9	824	371	369	-31	-0,73	-0,13	0,16	-0,76	-0,35	-0,29	0
Dominica	NA	NA	NA	NA	NA	NA	164	163	9	8	-59	-59	NA	NA	NA	0,54	0,54	1	0
Barbados	191	191	-84	-84	-42	-42	1667	1667	396	396	-72	-72	0,77	1	0,99	0,76	0,79	0,98	0
Grenada	-3	-3	-83	-83	-5	-5	479	479	2	2	-82	-82	-0,06	1	1	-0,06	-0,06	1	0
Mauritius	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Puerto Rico	-25	-32	-57	-64	-28	-82	93	59	376	4	125	-40	-0,03	0,68	-0,77	-0,03	-0,47	-0,66	0
Bahamas	14	14	-27	-44	NA	NA	107	58	NA	NA	NA	NA	-0,96	0,95	NA	-0,96	NA	NA	0
Saint Vincent and the Grenadines	4	4	-84	-84	-87	-87	535	535	674	674	22	22	-0,3	1	1	-0,3	-0,3	1	0
Vanuatu	-6	-7	-36	-41	17	8	57	45	-14	-21	-44	-49	0,09	0,99	0,99	0,11	0,07	0,98	0
Fiji	6	5	-29	-41	-22	-26	78	49	43	36	-6	-21	-0,06	0,86	0,94	-0,07	-0,03	0,83	0
Algeria	-90	-99	-91	-99	-85	-98	47	-69	365	-80	262	-59	-0,34	-0,04	-0,08	-0,65	-0,35	-0,23	0

Sao Tome and Principe	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Qatar	NA	NA	-52	-95	-40	-91	NA	NA	NA	NA	21	-92	NA	-0,05	-0,18	NA	NA	-0,12	0
Luxembourg	-98	-98	-87	-87	-94	-94	-84	-84	-65	-65	115	115	-0,25	1	1	-0,25	-0,25	1	0
Jamaica	29	28	-53	-64	-2	-27	259	174	76	32	-49	-54	0,17	0,83	0,97	0,11	0,17	0,92	0
Libya	5	-6	72	0	100	15	-4	-41	-18	-46	-3	-16	0,08	0,49	0,54	-0,15	-0,15	0,65	0
New Caledonia	-32	-33	-27	-32	40	32	-1	-6	-49	-52	-46	-51	-0,4	0,97	0,97	-0,48	-0,38	0,94	0
Trinidad and Tobago	5	5	-17	-35	13	7	62	25	-3	-7	-25	-39	-0,27	0,55	0,99	-0,19	-0,27	0,5	0
Lebanon	-5	-45	100	-5	672	-28	4	-53	32	-87	179	-87	0,02	0,29	-0,02	-0,05	-0,37	-0,19	0
Guyana	-4	-7	43	9	93	9	-13	-33	-13	-50	0	-26	-0,55	0,92	0,54	-0,55	-0,51	0,67	0
United Arab Emirates	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Comoros	59	51	-56	-56	NA	NA	260	243	NA	NA	NA	NA	0,11	1	NA	0,11	NA	NA	0
Niger	31	-18	138	63	2	-27	-28	-63	64	10	218	103	0,08	0,92	0,88	-0,15	0,27	0,78	0
Montenegro	-41	-51	3	-50	-95	-98	5	-48	2855	1005	3615	1748	0,06	0,85	0,55	0,03	-0,02	0,66	0
Guinea-Bissau	-2	-4	18	-23	9	-18	25	-17	18	-10	13	-14	-0,24	0,94	0,9	-0,26	-0,25	0,94	0
Papua New Guinea	-10	-11	11	3	38	8	-14	-19	-15	-35	4	-22	-0,71	0,77	0,4	-0,71	-0,73	0,22	0
Reunion	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Mauritania	6	3	-1	-19	116	22	27	8	-10	-51	-18	-57	-0,1	0,88	0,8	-0,23	-0,21	0,71	0
Botswana	42	10	103	54	347	-29	-8	-44	69	-67	155	-30	0,51	0,7	0,25	0,55	0,15	0,01	0
Kuwait	134	16	8373	216	935	12	-28	-98	120	-88	387	65	-0,13	0,51	0,06	-0,16	-0,17	-0,17	0
Armenia	-24	-33	1234	258	272	29	-80	-95	-35	-79	573	25	0,24	0,05	0,15	0,01	0,04	-0,16	0
Turkmenistan	-62	-79	-78	-88	-78	-84	119	26	76	26	20	-36	-0,18	0,15	0,75	-0,2	-0,23	0,33	0
Costa Rica	404	390	124	64	38	18	206	121	321	254	88	33	-0,54	0,81	0,44	-0,55	-0,38	0,68	0
Jordan	-8	-78	348	137	-68	-99	-70	-93	3312	-19	36566	1129	-0,31	0,72	-0,4	-0,33	-0,3	-0,51	0
Eritrea	-28	-32	8	-24	114	-5	-5	-35	-22	-68	-19	-50	0,04	0,77	0,68	-0,02	0,03	0,58	0
Dominican Republic	6	0	-46	-64	166	-50	181	96	106	-60	-22	-83	0,45	0,79	0,52	0,4	0,42	0,52	0
Sierra Leone	90	88	19	-15	530	470	120	64	-67	-70	-79	-86	-0,52	0,92	0,97	-0,51	-0,52	0,85	0
Gambia	26	26	110	108	356	274	-39	-40	-66	-72	-44	-54	-0,45	1	0,98	-0,45	-0,43	0,98	0
Gabon	-13	-17	-17	-51	61	-5	73	-1	-9	-48	-39	-48	-0,7	0,72	0,7	-0,74	-0,79	0,59	0
Sudan	20	-75	18	-79	-73	-96	32	1	623	126	558	101	-0,13	0,03	-0,13	-0,09	-0,01	0,25	0,01
Denmark	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0,01
Malaysia	-22	-25	-6	-12	1	-4	-13	-20	-18	-25	-2	-10	-0,24	0,9	0,98	-0,27	-0,24	0,91	0,01
Belize	-5	-6	10	-25	-14	-28	27	-13	32	10	51	-6	-0,1	0,7	0,95	-0,08	-0,13	0,54	0,01
Namibia	40	-57	54	-57	92	-44	1	-24	121	-59	149	-46	0,26	0,63	0,39	0,42	0,23	0,23	0,01
Lesotho	22	17	9	-26	46	7	64	7	16	-20	7	-42	0,71	0,83	0,55	0,58	0,48	0,48	0,01
Lithuania	-98	-98	-96	-99	-87	-91	141	-34	-75	-85	-72	-90	-0,19	0,32	0,81	-0,2	-0,15	0,03	0,01
Bhutan	14	-1	-10	-44	-38	-45	110	25	106	60	56	-1	0,12	0,67	0,89	0,08	0,12	0,45	0,01
Yemen	49	-24	16	-17	81	-19	31	-19	21	-19	14	-36	-0,3	0,7	0,37	-0,31	-0,38	0,42	0,01
Swaziland	-2	-5	-8	-17	-37	-42	16	4	68	54	54	32	0,45	0,96	0,63	0,43	0,42	0,8	0,01
South Korea	25	9	161	129	1	-22	-45	-58	40	27	234	139	0,18	0,92	0,64	0,2	0,21	0,64	0,01
Israel	-51	-90	-64	-74	-4	-98	89	-68	981	-62	1246	-66	-0,28	0,36	-0,35	-0,24	-0,36	-0,5	0,01
Panama	17	16	-13	-31	24	-22	67	34	50	-6	-2	-37	-0,3	0,81	0,8	-0,36	-0,34	0,92	0,01
Saudi Arabia	204	-22	189	6	830	71	5	-27	-36	-75	-38	-71	-0,2	0,1	-0,05	-0,43	-0,4	0,27	0,01
East Timor	5	-10	46	-25	35	6	40	-38	-2	-34	8	-29	-0,08	0,63	0,94	0,04	-0,07	0,36	0,01
Taiwan	NA	NA	27	-25	-50	-69	NA	NA	NA	NA	309	56	NA	0,81	0,84	NA	NA	0,59	0,01
Somalia	21	-54	23	-48	-21	-63	53	-15	200	10	99	13	-0,16	0,22	0,28	0,14	0,05	-0,2	0,01
Burundi	8	2	-20	-35	31	-2	66	27	11	-19	-30	-51	0,73	0,94	0,87	0,72	0,68	0,91	0,02
Switzerland	-66	-68	72	21	-62	-75	-73	-81	29	-13	452	334	0,54	0,75	0,81	0,46	0,46	0,84	0,02
Central African Republic	3	3	42	9	91	11	-5	-27	-7	-45	5	-25	-0,37	0,97	0,58	-0,39	-0,45	0,64	0,02
Tajikistan	-39	-67	-36	-67	-16	-73	18	-23	39	-51	30	-44	-0,12	0,47	0,02	-0,2	-0,16	0,08	0,02

Azerbaijan	-17	-39	62	-9	3	-34	-29	-51	7	-38	87	6	-0,57	0,69	0,49	-0,41	-0,39	0,6	0,02
Sri Lanka	20	5	6	-9	10	-41	30	0	89	4	63	-10	-0,14	0,88	0,64	-0,05	-0,05	0,51	0,02
Morocco	44	-45	-18	-65	8	-64	86	33	68	16	23	-37	-0,07	0,64	0,29	0,28	0,02	0,55	0,02
New Zealand	60	2	14	-43	107	-28	124	42	56	-18	-3	-49	0,02	0,17	0,33	-0,09	-0,16	0,26	0,02
Netherlands	-93	-95	-94	-95	-93	-95	19	-3	3	-10	-7	-26	0,16	0,63	0,38	-0,02	0,11	0,64	0,02
Senegal	39	37	37	-13	130	80	59	1	-22	-40	-40	-55	-0,11	0,96	0,97	-0,17	-0,15	0,96	0,02
Syria	-16	-41	45	-12	-29	-61	-27	-43	60	-4	165	31	0,23	0,39	0,48	0,22	0,25	0,5	0,03
Uzbekistan	-64	-74	-80	-87	-83	-86	101	65	109	70	19	-11	-0,35	0,62	0,86	-0,15	-0,18	0,48	0,03
Georgia	-33	-33	-30	-47	31	-23	26	-4	-12	-48	-31	-57	-0,3	0,88	0,8	-0,18	-0,39	0,68	0,03
Chad	49	-14	92	28	160	26	-23	-42	-19	-64	4	-43	-0,14	0,89	0,53	-0,24	-0,33	0,66	0,03
Iraq	15	-7	-3	-28	141	10	43	5	-2	-59	-21	-62	-0,36	0,87	0,58	-0,39	-0,51	0,43	0,03
Slovenia	-58	-60	2	-18	-20	-38	-51	-61	-35	-48	60	20	-0,15	0,7	0,68	-0,22	-0,17	0,52	0,03
Afghanistan	41	-23	-38	-68	28	-32	157	126	55	3	-36	-55	-0,63	0,39	0,48	-0,46	-0,51	0,55	0,03
Haiti	-10	-11	12	-29	21	-17	26	-20	8	-26	15	-21	0,33	0,85	0,97	0,15	0,27	0,89	0,03
Albania	-10	-15	65	-1	-38	-50	-8	-48	79	42	187	79	0,06	0,72	0,69	0,01	0,02	0,29	0,04
Cuba	-29	-37	-28	-38	-5	-70	8	-12	143	-27	129	-30	-0,55	0,91	-0,05	-0,55	-0,54	0,18	0,04
Australia	2	-50	8	-46	17	-16	-2	-11	-13	-52	-7	-48	0,19	0,48	0,53	0,37	0,16	0,32	0,05
Madagascar	49	46	3	-11	112	62	63	44	-9	-30	-38	-52	-0,59	0,91	0,87	-0,59	-0,62	0,9	0,05
Uruguay	54	23	4	-10	30	-5	61	26	35	3	1	-19	0,14	0,96	0,9	0,15	0,07	0,83	0,05
Rwanda	16	10	-5	-26	39	27	57	17	-11	-21	-25	-47	-0,39	0,97	0,98	-0,4	-0,38	0,96	0,06
Kazakhstan	-65	-80	-62	-85	-65	-76	47	-16	25	-19	51	-42	-0,15	0,47	0,79	-0,31	-0,11	0,64	0,06
Nicaragua	-6	-8	5	-2	27	17	-6	-12	-21	-26	-14	-21	-0,5	0,98	0,96	-0,49	-0,51	0,96	0,06
Kyrgyzstan	-23	-62	-17	-66	-44	-55	13	-7	51	-29	62	-37	-0,08	0,58	0,84	-0,07	-0,18	0,46	0,06
Honduras	71	67	86	52	64	39	11	-8	23	3	34	-4	-0,02	0,96	0,92	-0,06	-0,03	0,86	0,06
Guinea	126	117	106	57	347	220	45	6	-31	-51	-43	-59	-0,78	0,83	0,56	-0,8	-0,83	0,41	0,07
Côte d’Ivoire	-32	-35	-3	-7	-58	-76	-27	-32	175	62	298	126	-0,06	0,99	0,64	-0,06	-0,08	0,61	0,07
Togo	-10	-18	-31	-40	30	3	44	25	-16	-37	-41	-50	-0,74	0,97	0,95	-0,69	-0,71	0,98	0,08
Portugal	-18	-40	-44	-49	-52	-57	48	14	73	27	21	10	-0,24	0,97	0,88	-0,18	-0,23	0,88	0,08
Bosnia and Herzegovina	-13	-14	45	22	-11	-39	-30	-39	27	-2	160	50	0,38	0,91	0,3	0,4	0,25	-0,14	0,09
Belgium	-83	-85	-81	-85	-29	-66	5	-17	-55	-74	-48	-72	-0,04	0,95	0,56	-0,04	-0,07	0,59	0,09
Czech Republic	-74	-78	-71	-76	-55	-68	1	-20	-22	-47	-10	-41	-0,02	0,94	0,81	0,04	-0,23	0,71	0,09
El Salvador	-2	-3	-9	-23	5	-13	27	8	13	-8	0	-18	0,2	0,98	0,97	0,21	0,2	0,98	0,09
Cambodia	294	85	68	45	41	13	156	20	239	40	54	4	0,13	0,86	0,63	0,15	0,12	0,68	0,1
Belarus	-96	-96	-97	-98	-91	-92	67	53	-48	-56	-69	-72	-0,29	0,98	0,93	-0,28	-0,31	0,94	0,1
Zimbabwe	29	28	-13	-18	71	36	55	48	-5	-25	-39	-50	0,66	0,98	0,8	0,66	0,62	0,9	0,11
Bolivia	9	-5	7	-10	30	-1	12	-11	2	-20	8	-25	0,46	0,91	0,32	0,43	0,32	0,41	0,12
Angola	14	6	9	-9	263	26	19	-2	-15	-66	-17	-68	-0,11	0,94	0,35	-0,14	-0,07	0,16	0,12
Laos	4	1	104	82	136	85	-43	-51	-43	-57	11	-21	-0,25	0,9	0,81	-0,3	-0,23	0,92	0,12
Ecuador	1	-46	1	-15	-4	-38	5	-36	42	-26	67	2	-0,36	0,9	0,62	-0,35	-0,46	0,61	0,13
Slovakia	-38	-44	-62	-67	-34	-38	72	47	-5	-10	-39	-47	0,79	0,93	0,99	0,8	0,8	0,88	0,13
Benin	21	19	-7	-12	55	-4	38	28	32	-23	0	-43	-0,33	0,98	0,87	-0,29	-0,3	0,87	0,13
Democratic Republic of the Congo	-13	-15	-6	-20	15	-5	6	-9	-11	-26	-5	-25	-0,68	0,91	0,21	-0,68	-0,76	0,16	0,13
Moldova	-26	-27	-14	-19	10	-37	-10	-14	23	-29	44	-19	0,4	1	0,9	0,39	0,32	0,93	0,14
Bangladesh	206	181	857	650	1033	824	-58	-68	-67	-74	-4	-22	-0,39	0,71	0,9	-0,5	-0,49	0,79	0,14
Burkina Faso	16	15	-5	-11	125	93	30	23	-40	-49	-52	-59	-0,35	0,99	0,86	-0,35	-0,5	0,82	0,14
Chile	11	-14	-30	-43	41	-30	78	38	28	-19	-11	-52	0	0,89	0,51	-0,06	0,05	0,61	0,16
Myanmar	-2	-10	16	-1	82	-15	-3	-21	8	-44	35	-36	-0,27	0,41	0,71	-0,19	-0,35	0,75	0,16
Mali	40	36	11	5	182	143	32	23	-44	-52	-55	-63	-0,58	0,99	0,96	-0,6	-0,53	0,96	0,17
Peru	0	-21	5	-16	52	-30	10	-12	32	-34	21	-35	-0,14	0,71	-0,16	-0,19	-0,38	-0,37	0,18

Cameroon	20	14	79	18	121	37	-1	-35	-15	-42	4	-20	-0,44	0,95	0,79	-0,47	-0,39	0,91	0,19
Colombia	26	3	12	-11	20	-19	30	-2	27	1	30	-20	-0,12	0,88	0,4	-0,06	-0,14	0,56	0,19
Guatemala	11	8	-3	-14	26	2	29	13	9	-13	-4	-29	-0,13	0,92	0,69	-0,15	-0,15	0,86	0,19
Mozambique	23	19	44	16	101	60	4	-16	-23	-40	-15	-31	0,21	0,84	0,88	0,04	0,15	0,59	0,2
Ghana	-14	-16	8	4	9	-3	-19	-21	-13	-22	9	-2	-0,73	1	0,94	-0,73	-0,74	0,96	0,2
Croatia	-42	-44	-2	-14	3	-20	-33	-43	-28	-45	13	-9	0	0,97	0,85	0,01	0,03	0,94	0,21
North Korea	10	8	-11	-19	13	-38	33	22	81	14	46	-12	0,18	0,98	0,32	0,11	0,34	0,31	0,21
Bulgaria	4	-17	61	36	24	-18	-28	-44	17	-30	96	15	0,5	0,8	0,9	0,44	0,52	0,48	0,22
Venezuela	12	-1	3	-27	67	-31	37	9	46	-31	7	-38	-0,38	0,87	0,88	-0,38	-0,31	0,88	0,22
Nepal	-6	-9	-26	-35	130	-7	45	25	2	-59	-28	-71	-0,3	0,94	0,05	-0,22	-0,42	-0,01	0,23
Greece	5	-24	3	-9	41	14	7	-21	-16	-39	-15	-30	-0,46	0,9	0,8	-0,38	-0,47	0,71	0,23
Austria	-29	-32	-34	-53	-24	-33	59	7	8	-8	-5	-37	0,77	0,56	0,78	0,22	0,6	0,56	0,24
Iran	-35	-56	11	-18	131	28	-24	-51	-56	-72	-21	-62	-0,47	0,86	0,24	-0,47	-0,62	0,09	0,26
Uganda	-15	-16	-7	-15	53	8	0	-9	-22	-45	-21	-39	-0,74	0,95	0,68	-0,71	-0,77	0,62	0,29
Zambia	22	19	-6	-14	19	11	39	28	9	1	-16	-24	0,27	0,99	0,71	0,26	0,28	0,63	0,29
Poland	-64	-67	-56	-59	1	-8	-15	-21	-63	-66	-54	-59	-0,17	0,93	0,97	-0,25	-0,24	0,91	0,31
Paraguay	-28	-40	78	52	55	-10	-55	-61	-32	-54	73	8	0,12	0,93	0,88	0,1	0,12	0,91	0,35
Kenya	-6	-7	5	-15	131	-28	8	-11	29	-60	19	-54	0,32	0,95	0,18	0,22	-0,33	0,27	0,37
Malawi	94	88	-7	-29	242	92	167	104	-1	-36	-56	-72	0,41	0,93	0,88	0,38	0,38	0,88	0,4
Spain	-21	-30	-3	-23	13	-25	-5	-19	4	-36	29	-32	0,11	0,9	0,59	0,21	-0,08	0,57	0,45
Pakistan	1	-5	-4	-13	68	4	9	1	-9	-40	-12	-44	0,5	0,9	0,49	0,57	0,31	0,46	0,46
Tanzania	30	23	7	-7	135	76	36	20	-30	-46	-41	-60	0,03	0,97	0,88	0,02	0,04	0,82	0,51
Germany	-73	-77	-66	-74	-62	-71	-10	-22	-6	-38	20	-31	-0,27	0,9	0,95	-0,21	-0,31	0,86	0,52
Turkey	0	-11	8	-22	30	-26	24	-16	35	-31	21	-17	0,18	0,53	0,09	0,27	0,13	0,72	0,52
Vietnam	-5	-9	4	-13	61	40	8	-12	-35	-43	-26	-45	-0,28	0,97	0,89	-0,28	-0,29	0,89	0,54
Thailand	31	-7	-6	-16	-5	-23	58	0	76	3	10	-2	0,29	0,99	0,95	0,21	0,05	0,97	0,55
Ethiopia	39	-2	23	-5	92	-19	17	-19	83	-41	55	-45	-0,34	0,9	0,59	-0,36	-0,51	0,56	0,62
Serbia	-50	-51	5	-3	-60	-67	-49	-53	52	23	224	141	-0,29	0,99	0,93	-0,27	-0,19	0,93	0,66
Russia	-78	-78	-82	-85	-70	-88	44	28	88	-25	31	-45	0,2	0,92	-0,12	0,2	0,11	-0,1	0,76
Hungary	-8	-10	-34	-40	0	-9	49	36	0	-10	-32	-38	0,94	0,99	0,92	0,93	0,91	0,96	0,76
Philippines	19	8	-16	-18	-2	-9	42	31	23	19	-9	-14	-0,17	0,97	0,99	-0,11	-0,18	0,96	0,79
Egypt	0	-3	282	6	9	-19	-7	-72	22	-11	346	3	0,4	0,65	0,5	0,05	0,25	0,51	0,81
Italy	-23	-34	-23	-37	-13	-31	14	-6	3	-17	-6	-16	0,1	0,9	0,83	-0,01	-0,05	0,88	0,92
Nigeria	1	-9	0	-10	31	-6	2	-6	-3	-22	-2	-23	-0,57	0,97	0,94	-0,57	-0,58	0,92	0,99
Romania	-6	-7	-5	-15	-4	-12	11	-1	7	-2	4	-8	0,62	0,98	0,99	0,59	0,6	0,98	1,03
Canada	13	-26	-4	-40	1	-29	27	16	16	-8	-2	-24	0,61	0,8	0,21	0,64	-0,04	0,3	1,33
South Africa	33	5	10	0	6	-41	22	6	83	25	78	5	0,51	0,78	0,75	0,44	0,57	0,85	1,34
France	-44	-45	-39	-42	-34	-50	-4	-8	10	-13	18	-10	0,61	0,95	0,95	0,57	0,6	0,95	1,7
Indonesia	-1	-11	-14	-24	6	-4	18	12	-3	-10	-15	-23	-0,24	0,96	0,91	-0,24	-0,25	0,85	2,06
Ukraine	-46	-53	-57	-65	-41	-48	40	18	3	-14	-27	-36	0,18	0,96	0,99	0,18	0,18	0,96	2,18
India	7	-4	1	-6	23	-7	14	-5	15	-22	1	-18	-0,09	0,99	0,91	-0,07	-0,09	0,93	2,38
Mexico	0	-7	-1	-8	-4	-16	5	-2	17	0	15	-1	0,41	0,97	0,85	0,41	0,34	0,82	2,38
Argentina	-18	-22	-5	-18	-23	-30	-2	-16	15	5	27	16	0,52	0,97	0,99	0,46	0,49	0,97	2,54
Brazil	7	3	-4	-9	12	-3	15	9	6	-6	-6	-16	0,64	0,99	0,98	0,67	0,69	0,99	7,04
China	-8	-12	1	-9	7	-6	-2	-8	-6	-14	-4	-11	-0,21	0,98	0,97	-0,19	-0,21	0,97	21,54
United States	-10	-13	-6	-9	-6	-10	-3	-5	-3	-5	2	-2	0,72	0,98	1	0,73	0,72	0,99	35,74

Table D.6: The table of the country data for wheat shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of the time series of total production (t) calculated from one of the 14 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks).

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Izumi-Mirca (%)	min. rel.diff. Izumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Izumi (%)	min. rel. diff. Ray-Izumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Izumi-Spam (%)	min. rel. diff. Izumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Izumi	min. r Mirca-Spam	min. r Ray-Izumi	min. r Ray-Spam	min. r Izumi-Spam	Share on global production (%)
Angola	57	20	6	-13	167	1	62	36	51	-34	25	-61	-0,37	0,77	0,38	-0,37	-0,39	0,45	0
Bhutan	37	13	282	52	27	-28	-26	-64	90	-8	426	35	-0,3	0,4	0,47	-0,27	-0,27	-0,1	0
Botswana	61	-54	22	-83	-41	-94	188	32	1276	181	899	80	-0,15	-0,06	-0,47	0,02	-0,1	0,03	0
Burundi	8	2	-36	-47	36	-12	93	66	18	-25	-35	-61	0,01	0,9	0,89	0,01	-0,02	0,89	0
Cameroon	75	-66	73	-60	239	71	3	-31	-47	-84	-42	-77	-0,49	0,18	0,81	-0,61	-0,47	0,31	0
Chad	341	-72	238	-78	-2	-37	32	12	464	-63	351	-71	-0,18	-0,24	-0,05	-0,12	-0,2	-0,34	0
Colombia	264	143	112	78	92	-35	92	14	284	66	239	-7	-0,65	0,96	0,4	-0,65	-0,4	0,44	0
Cyprus	NA	NA	1394	986	850	200	NA	NA	NA	NA	307	34	NA	0,37	-0,41	NA	NA	-0,14	0
Democratic Republic of the Congo	52	36	90	57	237	39	-7	-28	10	-58	23	-43	0,22	0,81	0,5	0,23	-0,01	0,62	0
Ecuador	203	10	48	-13	155	-27	108	2	76	-26	52	-50	-0,63	0,12	-0,21	-0,63	-0,49	0,23	0
Eritrea	-26	-32	-7	-31	109	-19	6	-22	-8	-68	-11	-59	-0,19	0,88	0,42	-0,17	-0,2	0,74	0
Guatemala	124	71	-26	-44	-3	-59	225	172	329	92	41	-30	-0,57	0,81	0,6	-0,65	-0,41	0,6	0
Honduras	39	31	57	25	92	53	8	-12	-10	-32	2	-31	-0,41	0,96	0,92	-0,42	-0,45	0,91	0
Jordan	224	150	585	189	29	-47	-5	-57	450	140	1065	242	-0,38	0,42	0,29	-0,13	-0,24	-0,11	0
Kuwait	-40	-62	178	88	184	30	-71	-86	-65	-84	95	-23	-0,65	0,39	-0,16	-0,61	-0,67	-0,04	0
Lesotho	71	64	116	79	35	4	-5	-21	60	26	105	34	0,45	0,96	0,9	0,45	0,39	0,84	0
Madagascar	-21	-24	23	-7	331	-39	-16	-37	26	-81	70	-71	-0,74	0,95	0,33	-0,75	-0,55	0,35	0
Malawi	-5	-15	12	-33	-2	-55	33	-13	92	0	103	-5	-0,13	0,78	0,67	-0,01	-0,12	0,53	0
Mali	-26	-88	-22	-88	78	-76	65	-65	-8	-73	-23	-67	-0,19	-0,02	-0,12	-0,5	-0,54	0,15	0
Malta	-27	-27	-84	-84	-4	-4	352	352	-24	-25	-83	-83	0,67	1	1	0,77	0,67	1	0
Mauritania	35	14	-17	-30	-7	-27	86	56	107	12	10	-22	-0,12	0,93	0,82	-0,15	-0,18	0,78	0
Montenegro	-42	-49	14	-47	-94	-99	2	-49	3847	864	4668	1715	-0,23	0,79	0,3	-0,22	-0,21	0,4	0
Mozambique	115	50	319	122	289	179	-30	-50	-29	-58	25	-40	0,02	0,61	0,44	0,05	0,08	0,8	0
Namibia	138	-37	70	-49	316	-36	51	8	226	-41	121	-52	-0,31	-0,32	-0,37	-0,25	-0,19	0,44	0
New Caledonia	1100	1036	NA	NA	-18	-25	NA	NA	1502	1301	NA	NA	-0,16	NA	0,95	NA	-0,11	NA	0
Niger	77	-46	80	-41	301	-11	2	-26	14	-59	38	-56	-0,42	0,29	0,22	-0,32	-0,39	-0,15	0
Oman	19	-36	18	-26	-15	-46	45	-46	79	-23	68	7	-0,42	0,55	0,48	-0,5	-0,37	0,12	0
Qatar	NA	NA	19660	5584	-61	-73	NA	NA	NA	NA	99374	17084	NA	-0,11	0,4	NA	NA	-0,38	0
Somalia	28	-45	784	142	719	-31	-72	-93	93	-90	754	-3	0,11	-0,13	-0,01	0,07	-0,06	-0,02	0
South Korea	132	72	241	140	65	15	-4	-41	103	20	114	50	-0,33	0,88	0,85	-0,25	-0,38	0,71	0
Swaziland	92	65	228	173	-35	-43	-39	-44	233	153	473	319	0,14	0,93	0,99	0,14	0,36	0,89	0
Taiwan	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Thailand	-3	-17	281	120	56	-21	-61	-74	15	-37	210	108	-0,24	0,61	0,1	-0,23	-0,1	0,2	0
Uganda	27	15	54	26	78	-18	0	-21	55	-29	79	-21	-0,38	0,94	-0,02	-0,4	-0,42	-0,01	0
United Arab Emirates	933	702	45	-3	-61	-76	971	451	4066	1946	455	204	-0,34	0,83	0,21	-0,2	-0,47	0,28	0
Venezuela	-17	-19	39	1	405	-36	-18	-40	37	-83	81	-72	0,02	0,86	-0,25	-0,02	-0,07	-0,24	0
Zimbabwe	-12	-39	-14	-42	47	7	7	-3	-36	-45	-37	-47	0,02	0,47	0,79	0,06	0,22	0,84	0
Georgia	-21	-24	3	-21	-3	-33	-1	-24	17	-20	25	-8	-0,14	0,89	0,54	-0,03	-0,06	0,66	0,01

Luxembourg	12	4	14	14	165	165	-1	-9	-58	-61	-57	-57	-0,21	1	1	-0,21	-0,21	1	0,01
Portugal	15	9	56	25	-26	-34	-8	-29	74	50	129	77	-0,45	0,94	0,72	-0,5	-0,56	0,53	0,01
Rwanda	114	99	36	-15	330	282	131	50	-48	-53	-68	-80	-0,57	0,73	0,93	-0,55	-0,58	0,78	0,01
Tanzania	-20	-22	25	-12	1	-57	-12	-36	83	-18	136	18	0,21	0,97	0,86	0,21	0,11	0,88	0,01
Israel	-27	-41	-60	-74	39	-6	169	46	-21	-58	-67	-78	0,44	0,51	0,73	0,2	0,3	0,7	0,02
Lebanon	-28	-31	139	-7	287	43	-24	-60	-51	-80	8	-52	0,36	0,64	0,31	0,3	-0,03	0,42	0,02
Libya	28	-2	177	57	37	-22	-27	-59	86	-23	151	41	-0,41	0,23	0,48	-0,43	-0,49	0,38	0,02
Nigeria	41	-20	13	-32	146	28	31	11	18	-58	-7	-64	-0,17	0,56	0,46	-0,07	-0,3	0,13	0,02
North Korea	20	-29	-16	-55	8	-28	69	43	35	-12	-15	-42	0,04	0,88	0,88	0,05	0,03	0,82	0,02
Slovenia	-32	-36	-33	-42	4	-12	15	-4	-24	-37	-26	-39	-0,33	0,86	0,66	-0,33	-0,33	0,84	0,02
Armenia	-20	-22	15	-4	15	-5	-18	-32	-16	-32	18	0	0,39	0,93	0,93	0,38	0,4	0,95	0,03
Bolivia	-3	-17	9	3	40	-25	-9	-22	16	-31	44	-23	-0,03	0,92	0,64	-0,03	-0,06	0,42	0,03
Bosnia and Herzegovina	-10	-11	47	32	-12	-24	-32	-39	18	1	86	50	0,16	0,98	0,98	0,17	0,16	0,96	0,03
Myanmar	13	8	37	2	107	-18	11	-20	34	-47	59	-33	0,15	0,87	0,25	0,2	0,14	0,46	0,03
Peru	99	44	89	73	205	88	15	-19	-19	-35	-3	-40	-0,25	0,93	0,7	-0,21	-0,44	0,63	0,03
Zambia	4	-41	-8	-38	119	26	19	-14	-16	-69	-30	-67	-0,79	0,87	0,1	-0,79	-0,82	0,09	0,03
Albania	25	22	19	-33	-32	-41	87	5	110	82	74	13	-0,32	0,84	0,96	-0,32	-0,32	0,9	0,04
Norway	29	7	-24	-55	109	61	190	54	-34	-38	-56	-77	-0,16	0,67	0,59	-0,13	-0,01	0,75	0,04
Yemen	-3	-30	13	-30	34	-41	4	-31	22	-39	21	-16	0,23	0,76	-0,09	0,19	0,07	0,1	0,04
Estonia	-21	-27	-14	-36	33	28	17	-14	-35	-44	-35	-51	-0,23	0,93	0,99	-0,24	-0,2	0,9	0,06
Kenya	-2	-2	1	-16	315	51	16	-2	-34	-76	-39	-76	0,2	0,95	0,41	0,28	0,27	0,44	0,06
Mongolia	55	5	59	18	636	-46	17	-15	163	-69	169	-73	-0,36	0,64	-0,21	-0,36	-0,29	-0,12	0,06
New Zealand	17	12	74	-16	0	-46	42	-33	118	16	133	6	-0,01	0,65	0,14	-0,02	-0,06	-0,07	0,06
Sudan	134	-3	46	-49	303	-6	175	59	164	-48	66	-74	-0,02	0,55	0,23	-0,01	-0,29	-0,1	0,06
Switzerland	-2	-2	66	24	17	-10	-21	-40	10	-16	59	17	0,73	0,86	0,74	0,65	0,63	0,7	0,08
Ireland	-9	-12	-24	-29	14	3	27	16	-13	-21	-28	-36	0,06	0,98	0,95	0,04	0,07	0,87	0,1
Japan	19	7	-11	-18	24	8	37	22	10	-11	-10	-30	-0,14	0,79	0,56	-0,21	-0,07	0,66	0,11
Moldova	-10	-12	3	-2	-9	-30	-8	-14	45	-3	66	7	0,45	1	0,85	0,45	0,42	0,85	0,11
Kyrgyzstan	-28	-43	30	-17	18	-13	-30	-46	-17	-51	45	-27	-0,39	0,78	0,87	-0,36	-0,55	0,65	0,12
Croatia	-37	-41	-5	-14	-13	-28	-30	-37	-15	-32	19	9	-0,23	0,96	0,9	-0,22	-0,22	0,94	0,13
Finland	4	-48	44	-14	74	-13	17	-41	-29	-41	6	-40	0,38	0,91	0,86	0,39	0,3	0,83	0,13
Tajikistan	-25	-29	72	16	101	17	-38	-57	-36	-64	44	-42	0,12	0,94	0,51	0,13	0,05	0,44	0,13
Bangladesh	-20	-23	10	-1	-6	-37	-22	-29	25	-17	76	14	0,16	0,98	0,8	0,14	0,23	0,77	0,15
Saudi Arabia	28	-29	41	-32	17	-29	31	-35	11	-6	48	-23	0,1	0,17	0,57	0,1	0,1	0,71	0,15
Latvia	-8	-9	-27	-36	16	-6	42	26	-3	-22	-30	-39	0,08	0,97	0,96	0,01	0,14	0,95	0,17
Netherlands	8	4	-31	-51	24	12	117	55	-7	-14	-43	-60	0,38	0,88	0,98	0,33	0,39	0,88	0,19
Tunisia	35	34	29	-14	63	45	57	6	-7	-17	-21	-44	0,31	0,86	0,98	0,21	0,35	0,88	0,19
Chile	61	38	-14	-48	36	-25	165	68	114	7	-10	-45	-0,03	0,39	0,12	-0,05	-0,21	0,62	0,2
Paraguay	37	17	66	17	87	27	0	-17	-2	-35	6	-28	-0,54	0,91	0,55	-0,4	-0,18	0,65	0,2
Slovakia	2	1	-5	-14	4	-4	18	7	5	-3	-5	-12	0,39	0,96	0,99	0,38	0,38	0,98	0,21
Uruguay	25	21	-27	-36	21	-4	92	68	28	0	-33	-44	-0,37	0,98	0,95	-0,35	-0,36	0,96	0,22
Austria	5	-5	67	9	2	-13	-11	-37	10	1	64	17	0,52	0,83	0,91	0,5	0,51	0,81	0,23
Turkmenistan	-32	-36	29	-18	154	53	-20	-48	-56	-75	-26	-63	-0,13	0,84	0,47	-0,14	-0,34	0,21	0,23
Greece	112	-18	40	-3	14	-4	50	-16	85	-18	23	-3	0,2	0,92	0,95	0,55	0,28	0,95	0,24
Nepal	13	-7	34	12	14	3	-10	-29	4	-15	22	7	-0,38	0,92	0,93	-0,36	-0,38	0,93	0,24
Azerbaijan	-19	-22	-11	-21	29	7	0	-11	-25	-39	-19	-39	-0,11	0,96	0,73	-0,02	-0,2	0,56	0,25
Belgium	70	61	13	-5	73	62	79	46	4	-2	-30	-45	0,63	0,93	0,98	0,68	0,62	0,86	0,27
South Africa	84	8	36	-17	23	-14	57	11	64	24	22	-5	-0,17	0,72	0,6	0,05	-0,01	0,92	0,27
Serbia	-45	-49	13	6	-65	-68	-50	-54	71	49	250	207	-0,21	1	0,99	-0,23	-0,22	0,99	0,3

Belarus	-28	-30	11	3	11	-4	-31	-37	-26	-37	10	1	-0,01	0,99	0,93	-0,01	0,01	0,96	0,31
Sweden	-6	-9	-8	-21	12	4	18	1	-10	-17	-13	-28	0,44	0,92	0,99	0,42	0,44	0,91	0,32
Lithuania	-9	-10	-3	-14	19	4	4	-7	-14	-24	-7	-27	0,38	0,96	0,97	0,42	0,34	0,92	0,34
Iraq	367	73	50	-62	376	67	396	180	32	-24	-52	-80	0,14	0,05	0,06	-0,09	0,03	0,22	0,38
Algeria	7	6	7	-12	37	-29	21	0	49	-21	48	-33	0,22	0,88	0,73	0,24	0,32	0,77	0,43
Ethiopia	18	17	9	-7	148	25	25	6	-3	-53	-17	-56	-0,55	0,97	0,63	-0,53	-0,47	0,61	0,48
Syria	-11	-14	9	-12	11	-10	-2	-19	0	-20	11	-14	0,15	0,91	0,73	0,16	0,18	0,61	0,51
Mexico	117	22	52	-28	25	-33	68	9	125	40	107	-7	0,26	0,63	0,36	0,23	-0,32	-0,28	0,53
Hungary	10	9	-5	-9	17	2	22	15	8	-6	-10	-21	0,55	0,99	0,96	0,55	0,55	0,96	0,62
Czech Republic	12	11	4	-4	16	11	16	6	2	-5	-10	-14	0,26	0,94	0,98	0,29	0,25	0,97	0,63
Bulgaria	-2	-5	13	2	-10	-19	-6	-15	22	6	36	15	0,52	0,97	0,85	0,54	0,46	0,85	0,65
Afghanistan	-4	-11	12	2	51	-10	-7	-16	9	-39	21	-32	0,34	0,35	0,47	0,27	0,07	0,41	0,68
Denmark	-22	-24	15	-29	14	-2	10	-32	-20	-32	1	-30	-0,16	0,97	0,98	-0,24	-0,26	0,97	0,72
Brazil	45	26	-1	-11	55	50	58	34	-5	-18	-34	-42	-0,07	0,97	0,99	-0,11	-0,07	0,96	0,79
Morocco	0	-2	-6	-17	17	-15	19	4	17	-16	9	-23	0,09	0,91	0,81	0,13	0,07	0,89	0,82
Spain	0	-2	-2	-10	-1	-12	12	1	13	1	10	-8	0,63	0,98	0,9	0,63	0,61	0,84	0,87
Romania	9	7	16	-8	12	-50	17	-6	192	-4	170	-14	0,65	0,97	0	0,7	0,03	0,06	0,9
Uzbekistan	-29	-31	-24	-36	100	10	9	-8	-36	-65	-31	-68	0,01	0,88	0,6	0,02	-0,08	0,47	0,97
Italy	134	34	10	-20	21	-7	121	53	154	15	19	-27	-0,28	0,97	0,9	-0,33	-0,35	0,85	1,02
Egypt	-12	-17	166	-2	80	-12	-13	-65	-3	-50	48	-15	-0,38	0,72	-0,4	-0,38	-0,42	-0,37	1,24
Poland	-8	-13	-3	-6	-7	-27	-2	-9	24	-3	34	1	0,35	1	0,6	0,36	0,34	0,61	1,37
Argentina	5	-12	9	-2	2	-12	7	-19	12	-11	14	1	0,33	0,94	0,97	0,33	0,34	0,92	1,63
Iran	11	7	0	-7	18	8	19	8	3	-7	-11	-18	0,56	0,98	0,85	0,54	0,54	0,92	1,96
United Kingdom	3	0	13	5	6	1	-4	-10	2	-3	8	3	0,13	0,97	0,94	0,19	0,27	0,97	2,03
Kazakhstan	69	27	17	-13	44	1	77	21	76	-5	-3	-25	0,53	0,88	0,69	0,5	0,52	0,6	2,14
Ukraine	8	7	-7	-11	5	1	22	16	7	3	-11	-14	0,48	0,97	0,96	0,49	0,48	0,97	2,88
Turkey	3	0	-7	-12	17	-4	17	10	5	-13	-7	-25	0,73	0,83	0,86	0,9	0,89	0,95	3,05
Germany	9	5	-1	-6	27	20	14	7	-13	-16	-21	-24	0,31	0,99	1	0,28	0,31	0,99	3,5
Pakistan	36	-10	29	-16	40	-18	9	4	13	-7	5	-12	0,71	0,91	0,79	0,75	0,6	0,88	3,52
Australia	-4	-11	5	-10	24	6	5	-14	-12	-22	-1	-25	0,42	0,95	0,96	0,41	0,4	0,87	3,62
Canada	10	9	-9	-15	26	-16	29	20	32	-11	4	-28	0,49	0,96	0,42	0,49	0	0,41	4,09
France	4	1	10	1	11	8	3	-7	-4	-7	0	-8	0,8	0,93	0,98	0,71	0,8	0,9	5,6
Russia	25	23	-5	-12	25	17	40	31	6	-1	-20	-29	0,42	0,98	0,16	0,47	-0,11	0,1	7,29
United States	11	6	5	-3	-10	-14	10	3	26	19	18	12	0,54	0,92	0,96	0,54	0,55	0,77	8,61
India	48	23	56	38	47	16	-2	-15	20	-5	35	1	0,43	0,94	0,93	0,43	0,52	0,89	12,77
China	-3	-19	-8	-21	-19	-41	9	0	38	19	38	9	0,04	0,97	0,82	0,06	0,08	0,84	17,26

Table D.7: The table of the country data for rice shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of the time series of total production (t) calculated from one of the 11 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for –NA and NA values for calculation where no harvested area is reported by at least one of the masks).

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Afghanistan	55	8	32	-18	76	3	34	16	20	-24	-3	-40	0,22	0,85	0,58	0,19	0,16	0,56	0,08
Albania	452	85	30718	2682	256	-83	-93	-97	977	-8	31519	2699	-0,1	-0,26	-1	-0,3	-0,1	-1	0

Algeria	97	0	37	-6	5	-20	1291	-19	604	2	51	8	-0,02	0,22	-0,13	-0,13	-0,07	0,8	0
Angola	51	-48	158	4	89	-40	-41	-52	-6	-47	98	2	-0,04	0,06	0,23	-0,53	-0,11	0,41	0
Argentina	-23	-35	58	25	6	-11	-46	-51	-25	-34	50	32	-0,08	0,96	0,8	-0,05	-0,1	0,83	0,21
Australia	-13	-61	11	-53	-33	-55	-11	-25	51	-16	97	1	0,13	0,19	0,74	0,19	0,1	0,17	0,09
Azerbaijan	-41	-57	37	-13	-10	-28	-45	-65	-27	-47	90	-3	-0,58	0,66	0,87	-0,6	-0,55	0,55	0
Bangladesh	27	23	22	18	44	22	6	2	1	-12	-1	-17	0,82	0,99	0,97	0,83	0,79	0,98	6,97
Belize	38	31	-2	-27	-2	-30	87	34	98	34	15	-10	-0,19	0,91	0,79	-0,25	-0,11	0,82	0
Benin	-32	-39	68	28	53	25	-52	-60	-50	-57	10	-10	-0,8	0,83	0,84	-0,81	-0,81	0,88	0,02
Bhutan	5	-19	167	57	8	-18	-48	-61	0	-5	148	90	0,4	0,69	0,92	0,28	0,34	0,78	0,01
Bolivia	5	-16	13	-5	37	-1	-8	-14	-8	-38	1	-29	-0,71	0,82	0,12	-0,74	-0,8	0,33	0,06
Brazil	46	31	-2	-10	18	10	54	34	25	16	-11	-21	-0,42	0,98	0,98	-0,39	-0,39	0,97	1,69
Brunei	50	-44	162	34	628	340	-42	-58	-74	-91	-56	-79	-0,28	0,44	0,23	-0,17	-0,17	0,62	0
Bulgaria	118	79	33	-13	82	47	141	42	29	13	-12	-46	-0,2	0,63	0,73	-0,27	-0,35	0,27	0,01
Burkina Faso	11	-1	70	41	207	67	-21	-42	-35	-67	-15	-51	-0,33	0,89	-0,59	-0,28	-0,35	-0,65	0,04
Burundi	81	53	140	77	158	42	-13	-25	18	-39	45	-23	-0,83	0,64	-0,12	-0,85	-0,86	0,06	0,01
Côte d’Ivoire	-3	-7	-5	-11	-19	-34	6	-2	44	14	36	17	-0,04	0,99	0,93	-0,04	-0,09	0,94	0,17
Cambodia	24	5	21	14	46	21	3	-11	-5	-18	-4	-17	0,2	0,88	0,96	0,18	0,16	0,93	1,2
Cameroon	62	-20	368	150	123	51	-65	-74	-12	-60	174	12	-0,63	0,57	0,66	-0,59	-0,49	0,61	0,02
Central African Republic	16	9	99	79	181	36	-38	-42	-16	-60	35	-30	-0,39	0,81	0,36	-0,34	-0,45	0,6	0,01
Chad	132	-12	18	-49	278	128	110	44	-26	-65	-61	-80	-0,71	0,62	0,64	-0,72	-0,7	0,6	0,03
Chile	55	-1	-13	-24	36	-31	82	19	57	15	23	-37	-0,3	-0,42	0,45	-0,28	-0,28	0,44	0,02
China	22	-16	12	-23	14	-20	9	5	15	-10	6	-18	0,22	0,9	0,82	0,19	0,2	0,85	27,99
Colombia	14	-17	16	-20	26	-10	15	-19	5	-35	27	-37	-0,15	0,36	0,73	-0,09	0,04	0,07	0,32
Comoros	30	29	-56	-56	NA	NA	196	194	NA	NA	NA	NA	0,21	1	NA	0,21	NA	NA	0
Costa Rica	112	47	28	-4	154	55	74	47	18	-42	-24	-62	0,26	0,93	0,26	0,2	-0,58	0,09	0,03
Cuba	2	2	0	-10	665	-11	14	3	14	-86	10	-87	0,28	0,92	0,77	0,3	0,22	0,77	0,08
Democratic Republic of the Congo	71	51	36	6	117	-24	55	20	130	-24	77	-37	-0,36	0,95	0,36	-0,23	0,05	0,29	0,05
Dominican Republic	84	46	89	25	162	116	21	-3	-15	-44	-13	-52	0,21	0,9	0,82	0,2	-0,11	0,61	0,12
East Timor	163	108	2	-25	185	123	252	104	5	-23	-59	-71	-0,04	0,91	0,93	-0,09	-0,08	0,81	0,02
Ecuador	-2	-18	-2	-23	22	-7	26	-12	-9	-24	3	-27	0,22	0,82	0,51	0,28	0,12	0,25	0,22
Egypt	30	-21	459	-16	4	-27	12	-75	98	-20	628	-4	-0,37	0,48	0,61	-0,35	-0,27	0,09	0,78
El Salvador	100	75	41	16	-17	-51	60	27	256	141	135	51	-0,67	0,47	0,07	-0,71	-0,75	0,44	0
Ethiopia	18	-48	0	-49	114	-44	20	2	94	-54	94	-59	-0,84	-0,09	-0,44	-0,73	-0,49	-0,19	0,02
Fiji	42	42	-20	-38	3	-2	130	78	45	38	-19	-40	-0,19	0,85	0,98	-0,18	-0,18	0,81	0
France	0	-17	24	-28	-17	-97	21	-26	2997	11	2397	32	0,11	0,53	-0,17	0,12	-0,24	-0,24	0,02
French Guiana	-16	-48	-1	-50	53	-5	8	-24	-29	-51	-16	-45	-0,14	0,57	0,32	-0,39	-0,18	0,71	0
Gabon	-71	-87	-68	-86	-77	-79	16	-16	31	-41	44	-36	-0,28	0,18	0,99	-0,5	-0,29	0,18	0
Gambia	108	88	34	5	135	20	78	55	72	-20	11	-55	-0,18	0,97	0,98	-0,15	-0,18	0,97	0,01
Ghana	7	4	31	25	38	17	-15	-20	-10	-24	9	-9	0,02	0,99	0,86	0,03	0,01	0,86	0,07
Greece	21	-19	38	5	15	-16	2	-37	36	-29	44	7	-0,12	0,72	0,65	-0,04	0,03	0,38	0,03
Guatemala	163	13	111	14	39	-45	25	-3	117	37	113	30	-0,11	0,46	-0,14	-0,64	-0,62	0,76	0
Guinea	19	16	-3	-14	100	54	37	23	-24	-40	-41	-52	-0,53	0,91	0,89	-0,57	-0,58	0,93	0,24
Guinea-Bissau	39	33	89	-4	45	-18	37	-27	63	-5	30	1	-0,14	0,95	0,96	-0,15	-0,19	0,97	0,03
Guyana	45	25	99	39	77	15	-8	-28	11	-16	36	8	0,18	0,73	0,86	-0,06	0,06	0,84	0,09
Haiti	76	23	88	37	137	65	-5	-13	7	-48	12	-42	-0,2	0,81	0,52	-0,08	0,17	0,38	0,02
Honduras	21	-50	-12	-60	-54	-74	39	25	164	95	99	56	-0,66	0,43	0,4	-0,64	-0,65	0,82	0,01
Hungary	184	159	-35	-46	-3	-92	412	321	3772	202	626	-32	-0,52	0,88	0,06	-0,52	-0,43	0,2	0
India	38	30	40	27	51	32	5	-2	-1	-9	-1	-13	0,49	0,89	0,9	0,62	0,64	0,95	20,97
Indonesia	16	9	7	-2	27	19	11	6	-5	-11	-12	-19	-0,33	0,96	0,97	-0,41	-0,2	0,95	9,36

Iran	54	-55	43	-57	60	-16	42	-6	41	-45	44	-49	-0,21	0,42	0,34	0,09	-0,24	0,46	0,36
Iraq	-20	-63	-36	-70	-16	-62	31	21	23	-39	-2	-48	0,01	0,5	0,12	0,01	-0,18	0,34	0,03
Italy	26	-24	7	-10	16	-18	17	-24	52	-24	30	-13	0,47	0,46	0,83	0,01	0,27	0,46	0,21
Jamaica	3446	3446	NA	NA	-46	-70	NA	NA	11668	6626	NA	NA	-0,41	NA	0,88	NA	-0,49	NA	0
Japan	96	55	99	17	50	25	33	2	31	10	32	-13	-0,08	0,93	0,9	0,02	-0,1	0,94	1,48
Kazakhstan	35	-57	-28	-69	-26	-45	145	31	108	-31	10	-53	-0,3	-0,1	0,47	-0,1	-0,42	0,23	0,05
Kenya	29	-39	143	-8	92	5	-34	-63	-19	-57	90	-36	-0,36	0,18	0,69	-0,39	-0,26	0,3	0,01
Kyrgyzstan	-48	-54	43	-10	-41	-59	-44	-64	26	-19	171	72	0,29	0,79	0,88	-0,01	0,31	0,75	0
Laos	22	17	119	99	48	23	-41	-46	-4	-20	71	47	-0,04	0,89	0,9	0,02	-0,01	0,92	0,45
Liberia	38	35	15	-13	36	15	54	18	19	2	-4	-24	-0,35	0,92	0,91	-0,35	-0,34	0,94	0,04
Madagascar	136	104	89	43	141	125	42	20	1	-11	-20	-36	0,41	0,84	0,98	0,55	0,45	0,79	0,6
Malawi	51	42	-14	-22	121	85	86	69	-19	-36	-55	-64	0,02	0,93	0,83	-0,01	-0,05	0,78	0,02
Malaysia	77	53	42	21	64	20	35	19	41	-6	13	-24	0,77	0,93	0,73	0,75	0,4	0,64	0,36
Mali	48	-5	59	6	248	68	12	-14	-17	-72	-26	-67	0,2	0,92	0,61	0,24	-0,17	0,65	0,28
Mauritania	25	-4	71	3	99	43	-5	-40	-28	-50	20	-47	-0,48	0,57	0,75	-0,19	-0,8	0,23	0,02
Mauritius	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Mexico	122	-6	91	-39	29	-27	56	-4	73	-8	63	-40	-0,5	-0,5	0,14	-0,36	-0,32	0,3	0,03
Micronesia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Morocco	61	-41	38	-34	19	-97	16	-18	2763	-17	2698	-6	-0,35	-0,48	-0,06	-0,05	-0,6	-0,08	0,01
Mozambique	65	57	19	-18	44	24	100	33	41	10	-14	-30	-0,03	0,89	0,3	0,05	-0,14	0,49	0,04
Myanmar	13	8	20	7	52	26	4	-10	-13	-26	-12	-29	-0,37	0,97	0,92	-0,4	-0,38	0,94	4,18
Nepal	0	-1	-2	-9	22	4	8	2	-4	-18	-7	-19	0,6	0,95	0,99	0,62	0,62	0,95	0,63
New Zealand	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Nicaragua	-5	-16	25	16	199	14	-19	-29	-17	-72	5	-60	-0,6	0,98	0,48	-0,64	-0,64	0,48	0,06
Niger	35	-31	178	46	35	-61	-29	-63	142	-22	300	56	0,01	0,86	0,56	0,26	0,23	0,73	0
Nigeria	-15	-29	10	-16	45	14	2	-31	-35	-45	-5	-38	-0,65	0,78	0,61	-0,76	-0,51	0,08	0,61
North Korea	1	0	-18	-25	25	-11	34	24	13	-20	-9	-37	0,63	0,97	0,93	0,58	0,63	0,85	0,36
Pakistan	-14	-24	-17	-31	-9	-19	10	-1	3	-14	-3	-20	0,41	0,98	0,96	0,42	0,38	0,96	1,28
Panama	59	48	24	-3	146	55	53	28	-4	-35	-34	-49	-0,13	0,91	0,94	-0,17	-0,22	0,89	0,04
Papua New Guinea	5	4	322	179	38	4	-62	-75	0	-25	259	106	-0,47	0,81	0,56	-0,4	-0,49	0,23	0
Paraguay	28	10	12	-9	95	21	39	12	1	-36	-11	-53	0,21	0,88	0,82	0,23	0,14	0,62	0,05
Peru	16	-33	20	-4	73	-13	0	-31	-16	-33	22	-33	-0,13	0,65	0,46	-0,33	-0,51	0,45	0,4
Philippines	29	25	15	4	96	38	24	9	-8	-34	-18	-47	-0,16	0,98	0,8	-0,13	-0,1	0,8	2,37
Portugal	68	-35	66	-32	60	-34	19	-7	16	-3	13	-2	-0,04	-0,01	-0,08	-0,04	0,04	0,95	0,02
Puerto Rico	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Reunion	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Romania	947	896	84	-3	97	-78	1015	451	4872	411	351	-4	-0,4	0,46	-0,15	-0,6	-0,42	0,15	0,01
Russia	40	-28	3	-43	2	-19	54	14	38	-24	15	-44	-0,53	0,31	0,66	-0,2	-0,52	0,27	0,14
Rwanda	98	62	387	234	180	83	-42	-66	5	-41	92	57	-0,71	0,85	0,77	-0,73	-0,69	0,76	0,01
Saint Vincent and the Grenadines	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Saudi Arabia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Senegal	88	-19	54	-17	168	58	35	-24	-20	-60	-34	-68	0,03	0,78	0,42	0,23	-0,11	0,22	0,07
Sierra Leone	115	105	17	3	280	213	108	76	-34	-44	-64	-72	-0,24	0,96	0,64	-0,25	-0,22	0,65	0,15
Solomon Islands	NA	NA	54	40	123	95	NA	NA	NA	NA	-28	-35	NA	0,99	0,99	NA	NA	0,99	0
Somalia	-29	-83	-65	-89	-32	-72	128	48	96	-67	27	-79	-0,21	-0,07	0,64	-0,18	-0,19	-0,01	0
South Africa	239	-15	231	-21	71	-57	8	-1	239	-3	236	-3	-0,08	0,13	-0,4	0,42	-0,29	-0,17	0
South Korea	7	1	-9	-16	37	-11	25	12	15	-22	0	-37	-0,05	0,95	0,21	-0,08	-0,15	0,5	0,85
Spain	44	-37	69	-25	90	-28	-7	-16	-12	-24	4	-17	0,05	0,57	0,47	0,03	0,02	0,8	0,13
Sri Lanka	67	58	68	43	78	68	10	-3	0	-8	-1	-17	0,07	0,95	0,93	0,04	0,07	0,91	0,56

Sudan	-14	-82	6	-79	-64	-96	-11	-15	389	97	463	125	-0,32	0,36	-0,06	-0,3	-0,33	0,33	0
Suriname	32	-20	-39	-69	2	-32	263	82	34	18	-33	-63	-0,64	0,04	-0,1	-0,43	-0,48	0,58	0,03
Swaziland	470	211	-32	-49	-19	-33	833	504	681	307	-15	-33	-0,37	0,68	0,56	-0,36	-0,25	0,4	0
Syria	455	154	5577	810	5661	603	-54	-92	-32	-92	366	-56	-0,13	0	-0,33	0,06	-0,39	-0,64	0
Taiwan	NA	NA	36	3	37	10	NA	NA	NA	NA	17	-19	NA	0,52	0,64	NA	NA	-0,13	0,23
Tajikistan	-2	-30	107	40	92	49	-45	-56	-38	-62	32	-26	-0,06	0,34	0,79	0,23	-0,41	0,33	0,01
Tanzania	92	41	30	-3	206	108	58	42	-31	-39	-53	-58	-0,42	0,74	0,82	-0,32	-0,28	0,93	0,28
Thailand	27	-1	22	12	80	30	14	-18	-11	-29	-10	-37	0,13	0,96	0,89	0,19	0,1	0,86	4,97
Togo	-10	-12	-6	-11	-16	-25	0	-5	19	6	24	10	-0,4	0,98	0,92	-0,37	-0,36	0,91	0,02
Trinidad and Tobago	125	58	-10	-27	466	56	152	85	31	-72	-43	-85	-0,3	0,92	0,45	-0,28	-0,29	0,29	0
Turkey	86	-1	50	-14	94	-95	26	-10	2248	-25	1831	-31	-0,25	0,72	-0,2	-0,2	-0,26	-0,25	0,12
Turkmenistan	-16	-31	26	-14	29	-58	-18	-38	89	-35	179	-2	-0,24	0,61	-0,21	-0,39	-0,17	0,12	0,02
Uganda	23	-3	106	71	183	71	-38	-51	-39	-57	6	-28	-0,73	0,7	0,43	-0,76	-0,84	0,43	0,03
Ukraine	51	-9	-1	-38	5	-22	54	46	47	17	-3	-20	-0,12	0,81	0,74	-0,24	-0,2	0,88	0,02
United States	-3	-11	5	-14	2	-7	9	-9	4	-10	13	-16	0,17	0,69	0,99	0,1	0,19	0,64	1,31
Uruguay	-27	-34	5	-2	12	-1	-31	-34	-32	-38	3	-8	0,15	0,99	0,98	0,16	0,19	0,98	0,19
Uzbekistan	-17	-27	-31	-52	-57	-71	56	10	192	77	98	23	-0,5	0,85	0,76	-0,57	-0,57	0,72	0,02
Venezuela	14	-8	6	-11	48	9	9	1	-13	-24	-16	-30	-0,07	0,65	0,06	-0,12	-0,12	0,64	0,13
Vietnam	48	34	37	21	116	50	23	1	-9	-31	-11	-44	0,16	0,96	0,13	0,11	0,18	0,15	5,81
Zambia	16	-8	6	-21	55	7	22	-3	9	-31	-11	-38	-0,42	0,47	0,12	-0,39	-0,54	0,1	0,01
Zimbabwe	-4	-38	51	2	94	-16	-32	-41	-6	-53	57	-21	0,08	0,63	-0,13	0,27	0,22	0,48	0

Table D.8: The table of the country data for soybeans shows the lowest and highest values of mean relative difference (%) and the lowest correlation coefficient (r) of the time series of total production (t) calculated from one of the 13 modeled yields, aggregated with one of the four masks, in relation to the aggregation with each of the other masks (NA is set for -Inf and Inf values for calculation where no harvested area is reported by at least one of the masks).

aggregation unit	max. rel. diff. Ray-Mirca (%)	min. rel. Diff. Ray-Mirca (%)	max. rel.diff. Iizumi-Mirca (%)	min. rel.diff. Iizumi-Mirca (%)	max. rel. diff. Spam-Mirca (%)	min. rel.diff. Spam-Mirca (%)	max. rel. Diff. Ray-Iizumi (%)	min. rel. diff. Ray-Iizumi (%)	max. rel. Diff. Ray-Spam (%)	min. rel. Diff. Ray-Spam (%)	max. rel. diff. Iizumi-Spam (%)	min. rel. diff. Iizumi-Spam (%)	min. r Mirca-Ray	min. r Mirca-Iizumi	min. r Mirca-Spam	min. r Ray-Iizumi	min. r Ray-Spam	min. r Iizumi-Spam	Share on global production (%)
Albania	360	70	748	428	-56	-84	-41	-77	1207	696	4927	1274	-0,25	0,84	0,3	-0,27	-0,2	0,22	0
Angola	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Azerbaijan	-31	-59	195	-19	-29	-95	-47	-79	1552	-11	3127	321	0,22	0,53	0,05	-0,09	-0,19	0,24	0
Belize	-46	-48	-18	-37	-58	-63	-17	-35	50	25	122	50	-0,35	0,81	0,92	-0,37	-0,35	0,74	0
Bhutan	144	67	118	46	48	-73	44	-7	511	40	452	19	-0,23	0,9	0,26	-0,24	-0,27	0,12	0
Bosnia and Herzegovina	0	-8	213	128	44	-26	-58	-68	39	-30	286	109	0,11	0,46	0,65	-0,14	-0,07	0,5	0
Bulgaria	399	254	408	235	201	-4	28	-17	426	39	445	19	-0,28	0,76	-0,01	-0,29	-0,41	-0,08	0
Burundi	3	-4	58	-16	26	1	15	-34	-5	-18	27	-17	-0,59	0,78	0,97	-0,57	-0,59	0,87	0
Côte d’Ivoire	-19	-21	-8	-12	-57	-68	-8	-13	148	86	179	106	-0,01	0,99	0,73	-0,01	0,06	0,78	0
Cameroon	-24	-26	185	108	23	-15	-64	-75	-9	-40	197	99	-0,9	0,93	0,67	-0,92	-0,93	0,79	0
Chile	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Costa Rica	1177	625	11484	2557	-92	-97	-59	-91	40312	9270	139073	34631	-0,33	0,5	0,11	-0,2	-0,48	0,01	0
East Timor	15	6	-35	-47	16	-7	113	75	16	-3	-34	-45	0	0,92	0,91	0,01	-0,02	0,86	0
El Salvador	-2	-3	55	26	42	16	-22	-37	-17	-31	24	0	-0,43	0,92	0,92	-0,4	-0,44	0,9	0
French Guiana	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Gabon	-4	-7	-20	-40	44	-7	61	20	5	-33	-35	-50	-0,58	0,81	0,57	-0,53	-0,5	0,56	0
Georgia	181	179	12	-26	53	-50	272	142	516	75	79	-38	-0,3	0,87	0,37	-0,37	-0,18	0,34	0

Germany	-21	-41	8	-6	158	63	-14	-42	-49	-76	-40	-58	0,09	0,9	0,64	0,07	-0,01	0,54	0
Greece	-88	-100	-7	-23	39	-35	-86	-100	-82	-100	52	-43	-0,38	0,87	0,58	-0,35	-0,37	0,31	0
Guyana	207212	29254	NA	NA	2063940	147847	NA	NA	-75	-90	NA	NA	-0,3	NA	-0,25	NA	-0,27	NA	0
Honduras	-26	-27	24	11	-24	-42	-33	-42	25	-2	95	58	-0,53	0,98	0,8	-0,55	-0,47	0,78	0
Iraq	19	-50	250	73	-93	-99	-36	-86	10526	579	28503	4689	0,03	0,35	-0,26	-0,28	-0,06	-0,22	0
Jordan	52	-61	23456	18595	NA	NA	-99	-100	NA	NA	NA	NA	-1	0,11	NA	-1	NA	NA	0
Kenya	455	226	11140	5777	1990	635	-93	-96	-35	-81	923	295	-0,68	0,62	0,37	-0,78	-0,92	0,29	0
Kyrgyzstan	118	62	-16	-38	40	-86	185	138	2843	36	822	-40	-0,32	0,17	-0,32	-0,26	-0,33	-0,32	0
Laos	17	-6	255	110	175	91	-44	-73	-48	-59	77	-23	-0,32	0,77	0,88	-0,36	-0,4	0,78	0
Latvia	78	39	25	-34	NA	NA	151	16	NA	NA	NA	NA	-0,16	0,91	NA	-0,11	NA	NA	0
Liberia	5	5	-22	-34	84	40	59	34	-25	-42	-46	-60	-0,33	0,97	0,83	-0,34	-0,3	0,78	0
Madagascar	30	29	NA	NA	394	-3	NA	NA	64	-73	NA	NA	-0,22	NA	0,1	NA	-0,2	NA	0
Malaysia	432	75	467	355	-68	-84	0	-62	2286	1018	2828	1717	-0,22	0,28	0,22	-0,27	-0,17	0,14	0
Mali	19	-7	1259	824	4255	2957	-89	-93	-96	-98	-62	-72	-0,45	0,63	0,53	-0,37	-0,55	0,66	0
Morocco	82	69	8	-11	15	-27	103	63	151	63	66	-21	-0,02	0,9	0,6	-0,07	-0,29	0,43	0
Netherlands	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
New Zealand	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Nicaragua	-22	-26	-13	-17	-60	-81	-9	-14	339	97	372	122	-0,25	0,99	0,61	-0,3	-0,31	0,65	0
Pakistan	22	-36	8	-14	-75	-96	37	-27	2289	320	2968	281	-0,03	0,92	-0,03	-0,04	-0,28	0	0
Panama	30	27	140	32	103	57	-5	-47	-19	-37	26	-16	-0,71	0,61	0,95	-0,84	-0,78	0,57	0
Peru	16	-17	6	-8	13	-71	19	-10	245	-15	242	-14	-0,2	0,93	0,21	-0,11	-0,13	0,14	0
Philippines	419	285	4	-18	18	-26	443	323	463	340	31	-12	-0,67	0,75	0,43	-0,69	-0,75	0,65	0
Poland	83	63	518	154	337	79	-31	-70	-6	-58	163	7	-0,06	0,29	0,29	0,08	-0,07	0,55	0
Senegal	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Slovenia	-41	-64	1333	879	24	-19	-95	-97	-40	-70	1341	901	-0,44	0,58	0,68	-0,36	-0,46	0,45	0
Spain	30	-39	312	43	-90	-97	-32	-84	5222	890	7422	1943	-0,41	0,26	-0,16	-0,32	-0,25	0	0
Sri Lanka	212	204	10	-14	175	72	256	176	74	10	-42	-62	-0,33	0,95	0,87	-0,33	-0,32	0,85	0
Suriname	-15	-19	33	-37	-48	-59	31	-36	104	63	154	55	-0,15	0,78	0,93	-0,08	-0,14	0,81	0
Switzerland	-16	-40	124	51	54	-30	-55	-69	9	-52	174	56	-0,31	0,74	0,73	-0,38	-0,35	0,78	0
Syria	30	-8	559	105	-42	-82	-42	-83	847	89	1431	339	-0,1	0,53	0,69	-0,23	-0,3	0,42	0
Taiwan	NA	NA	27	-4	-24	-82	NA	NA	NA	NA	618	43	NA	0,89	0,32	NA	NA	0,38	0
Tajikistan	-45	-69	-8	-35	-92	-99	-24	-56	10836	348	13283	853	-0,45	0,74	-0,19	-0,41	-0,37	-0,15	0
Tanzania	0	-7	87	58	-32	-51	-38	-50	98	45	267	147	-0,36	0,63	0,4	-0,26	-0,44	0,37	0
Togo	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0
Benin	7	-4	-42	-51	60	28	99	85	-21	-34	-58	-65	-0,8	0,98	0,9	-0,81	-0,8	0,96	0,01
Burkina Faso	58	28	4	-2	95	36	53	29	1	-25	-28	-47	-0,41	0,97	0,61	-0,43	-0,54	0,67	0,01
Czech Republic	80	47	-12	-20	413	270	106	70	-59	-66	-77	-83	-0,02	0,89	0,82	-0,02	-0,03	0,93	0,01
Democratic Republic of the Congo	-14	-23	19	-6	156	31	-15	-29	-38	-67	-27	-53	-0,72	0,8	0,43	-0,82	-0,86	0,28	0,01
Egypt	229	47	22	-8	-18	-95	254	29	6598	414	2633	82	-0,39	0,61	-0,27	-0,39	-0,48	-0,3	0,01
Ethiopia	-14	-46	-3	-19	-20	-61	-10	-35	81	-17	142	11	-0,5	0,9	0,13	-0,48	-0,47	0,21	0,01
Guatemala	-1	-11	-11	-23	10	-24	18	1	19	-19	15	-29	-0,8	0,97	0,81	-0,77	-0,75	0,82	0,01
Nepal	-11	-18	4	-16	20	3	3	-17	-18	-26	-1	-24	-0,33	0,91	0,94	-0,34	-0,34	0,85	0,01
Slovakia	-26	-34	-33	-49	61	4	29	5	-22	-58	-42	-67	-0,18	0,93	0,56	-0,14	-0,2	0,71	0,01
Rwanda	5	-10	-29	-46	107	91	89	27	-47	-53	-63	-72	-0,68	0,96	0,96	-0,7	-0,69	0,93	0,02
Venezuela	188	176	-2	-10	341	185	208	183	4	-32	-66	-78	-0,61	0,96	0,57	-0,59	-0,54	0,53	0,02
Australia	13	3	4	-14	-2	-66	87	5	244	21	205	4	0,29	0,49	0,36	0,06	0,18	0,05	0,03
Bangladesh	2846	983	2655	948	17577	4807	115	-8	-66	-85	-79	-88	-0,62	0,41	0,07	-0,48	-0,46	0,01	0,03
Colombia	286	41	11	-2	37	-13	247	47	214	11	28	-23	-0,32	0,05	0,78	-0,42	-0,32	0,02	0,03
Ecuador	98	6	126	-13	39	-16	72	-36	47	26	154	-22	-0,1	0,4	0,72	-0,15	-0,21	0,1	0,03

Hungary	17	5	-17	-34	83	41	79	40	-23	-38	-49	-62	0,05	0,95	0,95	0,09	0,05	0,96	0,03
Moldova	94	89	-5	-11	325	276	116	100	-49	-54	-75	-78	0,02	1	0,96	0,03	0,1	0,97	0,03
Zimbabwe	3	-24	-2	-22	-23	-79	5	-3	307	20	303	20	0,27	0,94	0,06	0,31	-0,09	0,23	0,03
Austria	-8	-29	-9	-42	40	-8	61	-10	-18	-45	-14	-53	-0,36	0,79	0,74	-0,45	-0,27	0,6	0,04
Malawi	18	13	1900	639	104471	28945	-84	-94	-100	-100	-97	-98	-0,31	0,19	0,11	-0,16	-0,25	0,81	0,04
Turkey	133	22	74	-18	5	-56	153	0	290	71	102	44	-0,71	0,17	-0,25	-0,53	-0,12	0,61	0,04
Cambodia	-18	-24	45	-10	170	33	-11	-44	-25	-70	-13	-62	-0,67	0,87	-0,12	-0,7	-0,73	-0,56	0,05
Croatia	-38	-44	8	-10	25	-8	-32	-48	-37	-51	8	-26	-0,03	0,89	0,89	-0,07	-0,08	0,85	0,05
France	-28	-32	11	-5	-43	-69	-27	-35	151	24	252	79	-0,27	0,88	0,84	-0,24	-0,3	0,7	0,05
Romania	101	86	-1	-17	76	40	143	101	39	13	-34	-53	-0,23	0,93	0,95	-0,27	-0,22	0,83	0,05
South Korea	-91	-95	27	7	4	-45	-92	-95	-90	-94	132	8	-0,12	0,96	0,05	-0,01	0,55	0,14	0,05
Kazakhstan	109	48	166	90	235	107	-12	-24	-25	-41	-8	-27	0,07	0,29	0,79	0,09	0,01	0,54	0,06
Zambia	28	21	-8	-15	287	220	47	31	-61	-68	-73	-77	-0,16	0,97	0,92	-0,18	-0,23	0,97	0,06
Iran	9	-46	-3	-17	22	-90	17	-39	828	-11	952	-23	-0,47	0,91	-0,52	-0,57	-0,43	-0,44	0,07
Thailand	120	-7	6	-9	-19	-30	133	2	201	16	36	13	-0,34	0,96	0,97	-0,37	-0,36	0,91	0,07
Uganda	-37	-43	4	-28	63	-22	-21	-39	-7	-66	29	-54	-0,61	0,84	0,52	-0,58	-0,73	0,46	0,07
Mexico	150	8	36	-54	-10	-75	214	59	579	169	153	6	-0,51	0,27	-0,28	-0,29	-0,32	0,26	0,08
Japan	16	1	5	-10	18	-15	21	10	37	-14	25	-22	0,2	0,96	0,89	0,19	0,2	0,85	0,09
Myanmar	-23	-38	10	-8	39	-10	-18	-40	-29	-52	17	-30	-0,94	0,98	0,9	-0,94	-0,94	0,9	0,09
Vietnam	-4	-17	22	2	315	28	-8	-29	-32	-74	-5	-73	-0,29	0,93	0,63	-0,31	-0,55	0,67	0,09
North Korea	-1	-2	-6	-18	-2	-10	20	5	10	1	4	-15	0,68	0,94	0,91	0,55	0,6	0,91	0,14
Serbia	-13	-59	0	-5	-29	-57	-10	-57	3	-37	151	34	-0,1	0,99	0,92	-0,08	-0,07	0,86	0,16
Nigeria	-7	-15	-2	-13	38	1	-1	-5	-8	-39	-3	-37	-0,49	0,98	0,79	-0,49	-0,37	0,68	0,19
Italy	3	-39	-5	-33	-28	-63	39	-9	109	14	106	24	-0,15	0,89	0,86	-0,06	-0,17	0,87	0,2
South Africa	22	-24	2	-15	123	50	31	-16	-26	-58	-42	-55	0,08	0,98	0,75	0,05	-0,44	0,82	0,25
Indonesia	20	11	-13	-20	-23	-35	49	30	83	49	33	5	-0,13	0,91	0,75	-0,22	-0,15	0,83	0,34
Russia	67	64	35	6	219	18	56	24	43	-46	-5	-61	0,11	0,84	0,21	-0,02	-0,17	0,34	0,58
Bolivia	-31	-42	0	-10	69	-51	-25	-36	69	-62	214	-43	-0,55	0,98	0,46	-0,6	-0,73	0,53	0,78
Ukraine	61	55	3	-4	534	465	64	51	-72	-75	-83	-84	-0,33	0,99	0,87	-0,31	-0,31	0,87	0,8
Uruguay	252	222	63	30	1342	947	163	81	-68	-76	-86	-90	-0,32	0,79	0,75	-0,38	-0,33	0,7	0,88
Canada	-27	-31	-25	-28	24	-10	0	-7	-23	-42	-20	-33	-0,12	0,74	0,29	-0,2	-0,15	-0,23	1,77
Paraguay	-2	-9	27	7	75	-3	-13	-26	2	-45	31	-36	-0,41	0,95	0,83	-0,4	-0,45	0,83	2,61
India	-16	-41	6	-1	34	10	-15	-41	-23	-54	-5	-24	-0,31	0,95	0,95	-0,33	-0,34	0,87	4,85
China	-4	-12	-1	-7	10	-4	0	-8	0	-14	3	-14	0,2	0,99	0,86	0,19	0,36	0,84	5,53
Argentina	-17	-21	30	-1	60	54	-20	-38	-47	-51	-19	-37	-0,12	0,95	0,99	-0,11	-0,11	0,95	17,51
Brazil	0	-12	-3	-14	73	52	15	-6	-34	-47	-40	-46	-0,68	0,97	0,13	-0,66	-0,69	0,2	27,48
United States	-2	-13	6	-2	7	-1	-8	-12	-8	-14	1	-2	0,35	0,98	0,96	0,35	0,35	0,99	34,52

E Egypt case showing sensitivity to spatial distribution of harvested area per mask and model

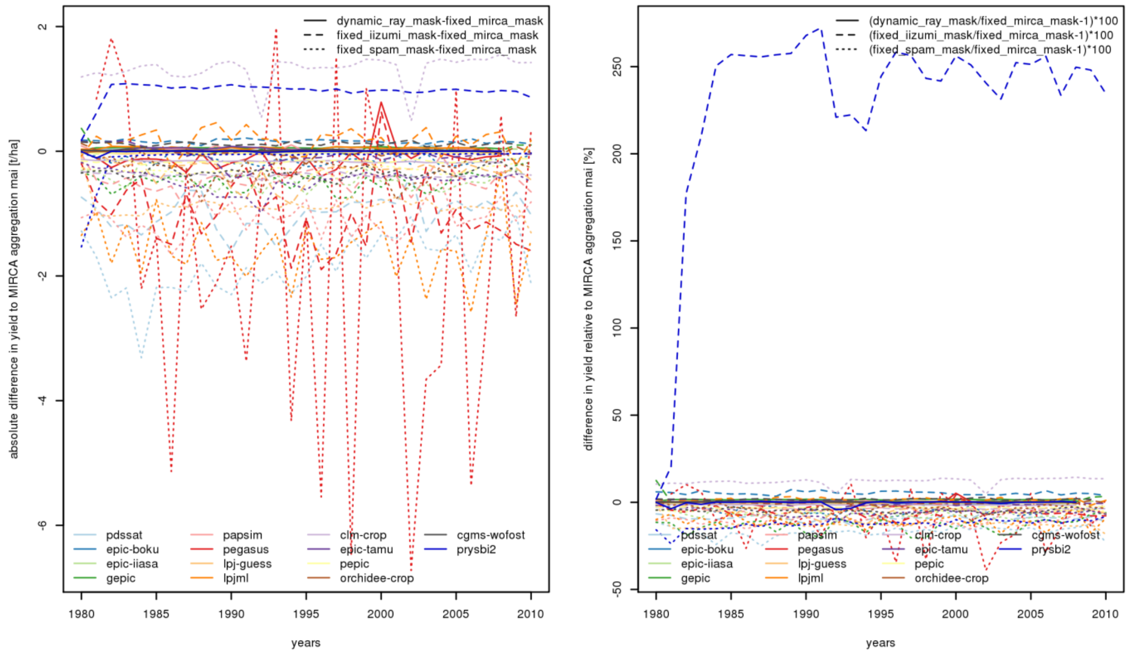

Fig. E.1: (Left panel) Absolute (t/ha) and (right panel) relative (%) differences between maize yield time series aggregated with MIRCA2000 in comparison to aggregations with Ray, Iizumi, and SPAM2005 for Egypt over the time period of the AgMERRA climate data set.

F Aggregation of grid cell yield to Food production unit (FPU – river catchment area crossed with country information) and country scale for the USA

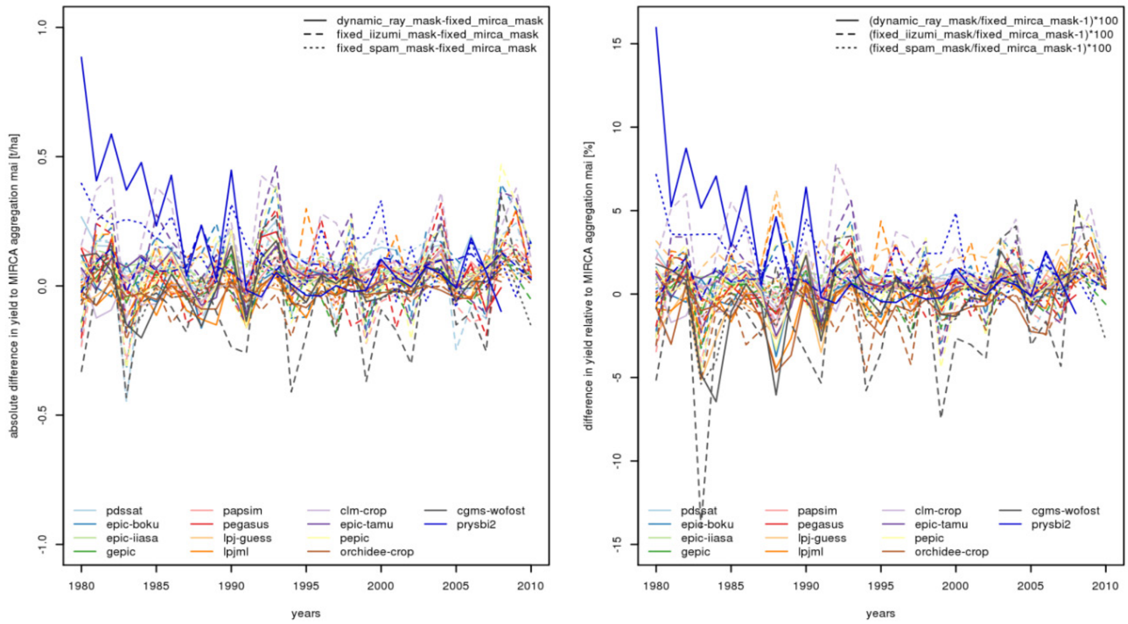

Fig. F.1: Aggregated maize yields per model and mask for the food production unit Mississippi river catchment in the USA. (Left panel) Absolute (t/ha) and (right panel) relative difference (%) between MIRCA2000 based aggregation of modeled yields in comparison to the other three aggregations with Ray, Iizumi, and SPAM2005.

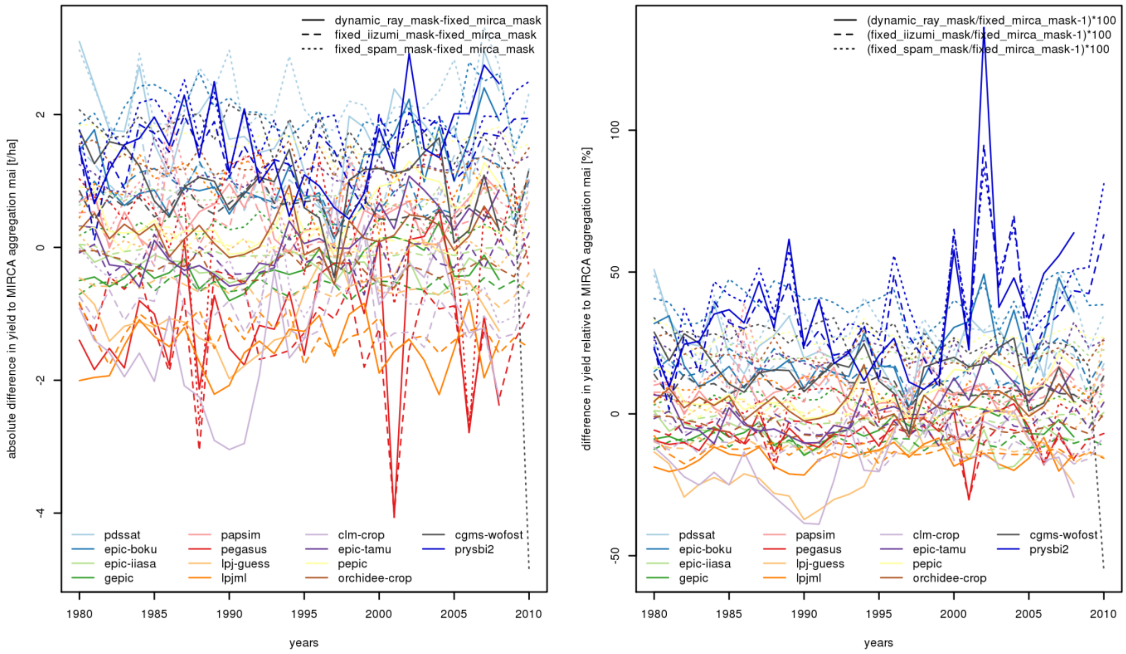

Fig. F.2: As Fig. F.1 but for the food production unit Colorado River catchment in the USA**.**

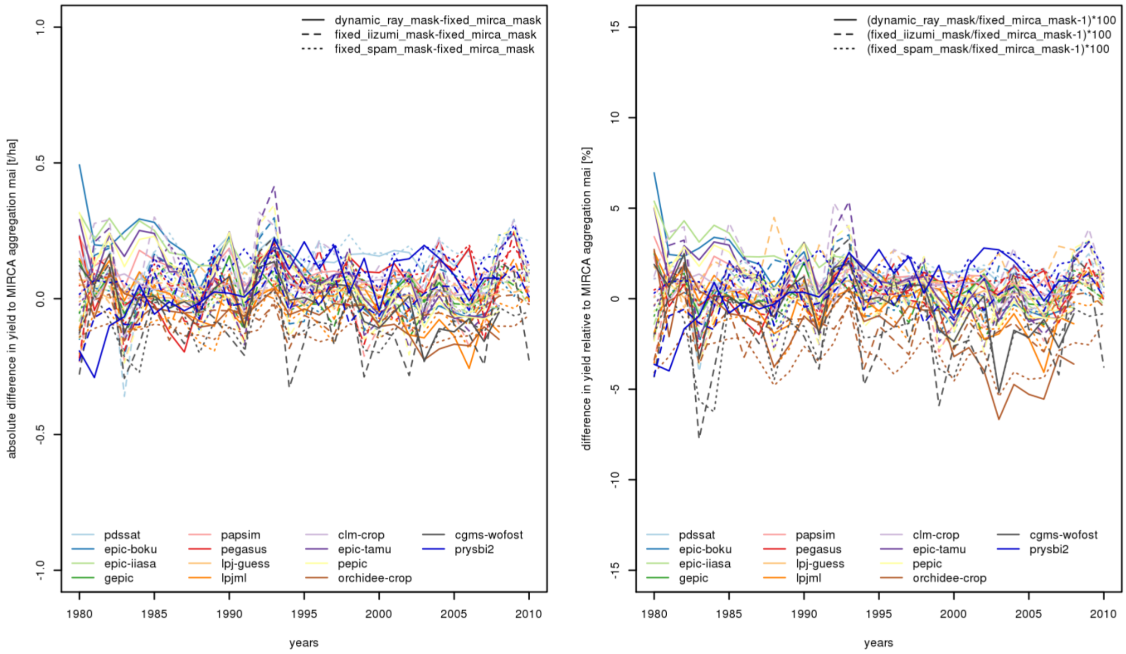

Fig. F.3: As Fig. F.1 but for the country USA, which at national aggregation scale does not show any sensitivity to the crop masks

Table G.1: Harvested areas per crop mask for maize, wheat, rice, soybeans at country scale as reported by MIRCA2000 (Portmann et al., 2010) for MIRCA, Ray (Ray et al., 2012), Iizumi (Iizumi et al., 2014), and SPAM2005 (You et al., 2014) for SPAM.

	Maize harvested area (ha)				Wheat harvested area (ha)				Rice harvested area (ha)				Soybeans harvested area (ha)			
country	**MIRCA**	**Ray**	**Iizumi**	**SPAM**	**MIRCA**	**Ray**	**Iizumi**	**SPAM**	**MIRCA**	**Ray**	**Iizumi**	**SPAM**	**MIRCA**	**Ray**	**Iizumi**	**SPAM**
Afghanistan	240398	97461	102700	207102	2074704	2091234	2175853	2200733	134058	135044	136211	160162	33	565	1692	18
Albania	71782	53242	93056	42511	107585	106420	97150	70574	3	10	231	9	982	830	5382	264
Algeria	6307	430	893	399	1502241	862162	1652588	1866316	196	196	241	188	1	1	0	0
Angola	728142	688012	744998	1094324	2668	2411	2681	4046	7767	4135	12353	11065	232	231	1481	5741
Antigua and Barbuda	46	0	12	38	0	0	0	0	0	0	0	0	0	0	0	0
Argentina	3529272	3170263	3111010	2601894	6042771	6497558	6198313	5627313	264192	220371	352107	240873	8705280	9167113	9541941	14516155
Armenia	2550	3000	30131	3405	121888	111922	139094	122165	2708	120	170	56	2	909	429	0
Australia	68740	82262	67533	72834	11798968	12141002	11818890	12551100	137478	133300	137524	72205	56000	35787	36315	25827
Austria	283232	198355	167342	190819	290982	318841	413378	293181	4	0	172	0	14381	16909	12888	18924
Azerbaijan	37934	34236	47819	32487	533438	472112	461423	579646	3502	4242	4382	2786	445	900	1829	343
Bahamas	277	151	173	0	0	0	0	0	0	0	0	0	0	0	0	0
Bahrain	0	0	6	0	0	0	1125	0	0	0	0	0	0	0	0	0
Bangladesh	7293	7353	64264	74569	764008	807407	837261	524535	7971883	10197295	9555742	9838158	1448	172	2728	18673
Barbados	164	115	27	96	0	0	0	0	0	0	0	0	0	0	0	0
Belarus	354172	13578	8504	28560	376548	452384	395155	362280	32	52	141	86	450	503	1292	153
Belgium	147335	37441	25437	62860	143028	252468	149689	232587	1	0	0	0	1	2	0	0
Belize	9589	9919	9706	7251	0	0	82	0	2152	2660	1918	1810	158	342	226	139
Benin	396681	557097	363407	589449	15	47	54	4	27427	24220	36919	38271	8594	7159	3895	10665
Bhutan	20616	15872	15201	11762	5623	5363	15928	5848	56133	49592	115006	53816	1800	1004	1645	748
Bolivia	289314	305770	275957	326585	127401	118163	133633	120162	148466	156694	141316	167488	608181	596369	565522	901374
Bosnia and Herzegovina	187573	183988	244472	153066	87422	93382	124151	70026	0	0	0	0	6067	4925	13920	4618
Botswana	46378	97054	81891	58841	916	1393	1183	477	2	7	30	91	916	1070	2353	979
Brazil	11345600	11531945	10747503	12132375	1455338	1052959	1429403	2205227	2965996	3616224	2806183	3424611	13585403	13658443	12796169	22219381
Brunei	41	43	135	160	0	0	0	0	735	460	1401	4921	0	0	0	0
Bulgaria	500703	483628	774817	409523	1145717	980862	1255815	1027863	3650	3803	4407	6012	4304	4763	21779	5777
Burkina Faso	206541	221480	191300	419808	111	6	30	28	31834	38438	48060	55100	5250	2924	2954	4148
Burundi	129438	128461	90522	140295	10830	9730	6331	11183	13775	26882	29149	24343	9516	7276	10419	8507
Cambodia	71571	158551	109112	87825	11	13	85	0	1897053	2072048	2248078	2366359	32156	35753	36166	75117
Cameroon	338720	316388	506091	529526	739	334	589	1472	28993	45122	113420	53600	11233	11632	30993	12337
Canada	1422886	1100237	915956	1068785	10616147	10843505	9493285	9487314	0	0	0	0	1050303	1079745	794686	1163456
Cape Verde	21269	30626	9414	0	0	0	0	0	0	0	0	0	0	0	0	0
Caspian Sea	3256	1245	3366	3065	41356	37116	93454	43317	5930	19442	31599	33688	4475	329	952	4441
Central African Republic	93499	94374	116268	130964	20	38	201	2	13510	18115	24918	20879	47	46	586	44
Chad	98982	85655	141236	162792	2003	1815	1917	1422	30634	86297	30430	100280	77	75	1106	17
Chile	110205	68447	76655	125244	264390	358943	225585	359291	25081	25631	21056	25758	0	0	0	0

China	24845121	23068966	23908921	26222268	31099229	26615313	26064057	22452623	28956984	30334055	29594545	28828128	9237975	9003812	8514836	9414771
Colombia	514567	567004	509536	590781	9359	21134	19021	12320	420532	467239	438622	425513	17240	27816	28041	35369
Comoros	1380	1611	610	0	0	0	0	0	11362	16266	4994	0	0	0	0	0
Costa Rica	5254	8855	11686	6947	0	0	0	0	29388	65271	36123	51665	0	3	110	0
Côte d'Ivoire	783740	320746	741427	289282	0	0	0	0	485219	358987	442108	351250	3398	2585	2301	1021
Croatia	500744	477878	467891	417403	265251	278843	246716	212813	1	0	53	10	52795	47196	46512	50547
Cuba	149649	126082	102354	140643	0	0	0	0	160759	199744	151046	142485	0	0	0	0
CuraÃ§ao	0	0	133	0	0	0	0	0	0	0	0	0	0	0	0	0
Cyprus	77	0	1373	0	600	0	7389	6033	0	0	88	0	0	0	96	0
Czech Republic	253505	54460	66097	88098	714693	948378	708305	808973	0	0	0	0	1976	2178	1828	9121
Democratic Republic of the Congo	1473148	1481425	1345991	1505896	4724	7299	7875	6815	253282	425951	324008	406776	23738	23962	23155	37183
Denmark	71490	0	31	0	656021	609897	506623	657810	0	0	0	0	0	0	0	0
Djibouti	1	6	30	6	0	0	24	0	0	0	0	0	0	0	15	0
Dominica	0	146	54	131	0	0	0	0	0	0	0	0	0	0	0	0
Dominican Republic	60505	57638	22885	54769	0	0	0	0	65317	123718	103973	146557	0	0	0	0
East Timor	59896	68625	56080	64790	0	0	0	0	17899	47773	15750	40703	958	964	566	916
Ecuador	456214	443579	429255	401592	24890	23371	24530	19121	324457	341670	303522	388663	55167	42007	41681	38359
Egypt	826926	843026	961030	806085	1029083	1034882	1103544	1212144	647204	659217	620731	643040	3867	8809	10062	12260
El Salvador	241275	225017	202560	218256	64	83	688	73	4769	6518	6716	3512	1031	1016	1412	1376
Equatorial Guinea	192	170	1834	0	0	0	0	0	0	5	243	0	24	23	147	0
Eritrea	18021	22507	18142	25698	21655	23516	17260	22662	1	32	134	0	19	18	212	0
Estonia	668	54	26	0	66013	69541	46428	84995	0	0	0	0	25	28	16	0
Ethiopia	1183086	1644427	1217006	1744791	759474	1060261	771624	1317338	3416	8217	3786	6913	7451	6864	6751	3927
Fiji	510	330	331	389	0	0	0	0	5937	5166	4234	5978	0	0	0	0
Finland	303	48	12	0	156520	144438	139367	207343	0	0	0	0	22	27	9	0
France	3155805	1738592	1824824	1617579	4849866	5220507	5085395	5242434	19224	19733	15993	18257	77854	94232	97066	53877
French Guiana	47	52	57	48	0	0	0	0	7242	8444	6504	8676	0	0	0	0
Gabon	17654	15677	10731	18679	0	0	0	0	2260	512	387	502	2191	2099	1353	2486
Gambia	2568	2634	5349	10288	0	0	0	0	7907	16002	9464	9718	0	0	0	0
Georgia	188556	172908	110019	165984	138774	105014	118084	107244	164	277	475	0	1428	1454	1267	1470
Germany	1447594	386192	383277	469790	2553234	3050672	2499634	3195198	34	0	0	0	256	846	841	1670
Ghana	732751	680416	779141	765553	0	0	0	0	91438	114986	117867	117356	29	22	169	176
Greece	212813	222896	212860	230651	807802	878522	844576	833376	24457	22116	28354	23886	4	1931	1707	2001
Grenada	328	237	55	312	0	0	0	0	0	0	3	0	0	0	0	0
Guadeloupe	55	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
Guam	13	16	3	0	0	0	0	0	0	0	0	0	0	0	0	0
Guatemala	597836	613516	570083	744808	7098	4424	4878	3545	9931	17244	17447	11631	9568	11644	9786	12478
Guernsey	0	0	577	0	0	0	3045	0	0	0	0	0	0	0	0	0
Guinea	80977	221097	146152	305548	0	0	0	0	427457	632492	380937	682345	149	110	466	157
Guinea-Bissau	14778	23303	15286	15059	0	0	0	0	51108	75966	60874	57692	0	0	0	0

Guyana	2548	3254	3070	3522	0	0	0	0	79585	121596	147122	114928	0	0	0	508
Haiti	246307	235571	236286	229544	0	0	0	0	29673	48353	55638	52070	0	0	0	0
Honduras	217985	373777	335162	325637	1087	1834	1489	1645	16475	3632	9812	5768	1535	1587	1919	1127
Hong Kong	56	0	215	0	0	0	114	0	494	0	12934	0	0	28	362	0
Hungary	1232366	1173236	769536	1178578	1078015	1049896	1001751	1126340	2384	3089	1537	2629	22713	21446	14765	36447
India	6613570	6693057	6627782	7756796	19249654	27577152	26895890	26557918	32544203	45272215	42346463	43659306	4588723	6235157	6225244	7874696
Indonesia	3359815	3410133	2754415	3375065	0	0	0	0	9653368	11702028	10001031	11791478	818710	825149	708552	574432
Iran	172420	183077	178723	276795	5503209	5042022	5492844	6482698	552507	513203	501018	585586	84524	76106	73088	77218
Iraq	76189	71877	73356	175310	787287	1222776	460713	1903091	126593	99750	74994	109454	85	694	2131	43
Ireland	76	0	0	0	87725	77546	64466	94745	0	0	0	0	0	0	0	0
Isle of Man	0	0	0	0	0	0	3898	0	0	0	0	0	0	0	0	0
Israel	8303	2250	2823	4427	91318	65845	31129	108976	2822	0	0	0	111	130	0	0
Italy	1313973	1063318	944497	1137536	1745458	2315209	1534091	2134122	221968	220545	227059	226648	252445	241265	204172	159952
Jamaica	1802	1540	700	1476	0	0	0	0	9	13	0	3	0	0	0	0
Japan	99325	75	300	62	190439	182560	158809	214795	1213737	1767845	1601257	1696565	122295	126087	112945	137608
Jersey	0	0	694	0	0	0	5368	0	0	0	0	0	0	0	0	0
Jordan	1210	1286	4759	1076	15305	18040	81465	22248	0	0	0	3	1	1	152	0
Kazakhstan	391623	82964	111893	114749	9364895	9999558	10894308	11623277	115967	74207	75514	83528	6963	12043	31290	39296
Kenya	1528836	1464453	1525811	1698647	135414	127124	129351	156650	14103	16718	26543	18554	1240	223	18669	2918
Kiribati	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kosovo	124127	115719	94998	2597	71355	67463	54524	3997	155	190	164	118	13388	9724	7432	12
Kuwait	26	22	149	60	288	178	727	717	58	0	145	7	0	0	22	0
Kyrgyzstan	109869	54386	54411	63422	473905	437480	534214	447322	14438	10041	20399	8229	96	352	290	458
Laos	54209	57907	107094	118549	1687	155	2077	201	520984	664288	1108033	679992	7236	6489	17077	14191
Latvia	2752	136	86	131	141867	142920	101220	149056	0	0	0	0	39	71	58	0
Lebanon	772	526	1542	663	24947	21826	38365	35621	0	0	0	0	0	0	54	0
Lesotho	123111	174137	114155	137643	19839	28873	37536	24680	1	8	41	0	202	732	2029	817
Liberia	2648	2659	29682	10225	0	0	0	0	125484	152560	132965	153454	7291	5340	3632	7824
Libya	909	2000	1376	1459	152366	157293	234292	164920	0	0	0	0	0	0	0	0
Lithuania	13731	287	381	1488	352600	368514	326397	374225	0	0	0	0	49	56	194	0
Luxembourg	5165	178	657	305	4582	8341	5209	12157	0	0	0	0	0	1	0	0
Macedonia	55227	53924	124631	30755	116332	120203	126756	102386	2793	3403	1704	2279	2311	1714	8358	364
Madagascar	123906	192065	118330	234280	3518	4041	3305	4294	531043	1208602	909755	1249361	71	50	0	86
Malawi	674970	1374130	593602	1533375	4401	5038	3348	2445	25714	44416	20975	54585	186	143	1386	68659
Malaysia	25485	27207	23322	24487	4	4	25	0	489546	839743	656210	649118	466	182	916	34
Mali	150932	153609	161695	403268	3517	2657	1836	2971	218969	346360	288464	438004	54	41	453	1252
Malta	0	0	0	0	2576	2381	414	2483	0	0	0	0	0	0	0	0
Martinique	0	0	54	0	0	0	0	0	0	0	0	0	0	0	0	0
Mauritania	8606	13090	7336	16416	366	296	282	285	12812	18822	19055	21622	0	0	0	0
Mauritius	57	70	10	59	0	0	0	0	0	0	0	0	0	0	0	0
Mexico	7474690	7137828	7071499	7229980	668670	695213	605117	557723	76486	84059	82265	67318	70174	98335	80536	79993
Moldova	512124	457463	432390	474964	368916	363131	368073	335896	31	89	454	95	11728	10856	9991	43312

Mongolia	2732	997	5602	4	244444	189769	350056	150755	102	91	275	0	592	414	3502	0
Montenegro	108504	100491	74734	2668	59249	55475	40945	1683	0	0	0	0	11582	8416	4893	17
Montserrat	25	20	4	21	0	0	0	0	0	0	0	0	0	0	0	0
Morocco	261818	237500	206677	244872	2559237	2901551	2391983	3030750	6181	5601	6050	5234	999	1130	1081	993
Mozambique	935424	1297674	1193597	1615590	1585	1534	5312	5425	75137	184308	79716	92106	1501	1072	8429	2818
Myanmar	227406	220655	254793	322623	94794	82431	102375	98629	5355848	6429812	5954453	7407768	107487	106665	103051	146570
Namibia	27471	43517	26733	26680	793	1050	1099	2307	26	3	21	144	0	0	6	2
Nepal	703899	719460	509696	734757	576264	634093	740776	623531	1367297	1461206	1314485	1460102	16859	19305	18521	20629
Netherlands	190602	19156	10770	11819	96303	103932	56006	112633	0	0	0	0	0	2	4	0
New Caledonia	949	1178	672	1287	10	5	0	8	0	0	0	0	0	0	0	0
New Zealand	23635	48805	18422	17943	45804	39415	52563	38761	0	0	0	0	0	0	0	0
Nicaragua	286185	334780	295025	348892	50	80	296	28	67156	94999	82127	85934	3267	7787	6654	2504
Niger	35105	36413	80158	28874	4566	5992	4356	6612	33274	32523	68277	33541	861	2162	3001	2683
Nigeria	3667350	3229282	3514361	3725793	31728	59700	31795	58366	2054280	2161682	1905132	2487532	510548	519723	494421	600988
North Korea	541219	479294	460473	490360	75297	56327	48088	69188	585736	524131	470467	570435	304674	309610	261839	286200
Norway	0	0	0	0	47030	67335	33503	83887	0	0	0	0	0	0	0	0
Oman	0	0	46	0	407	424	404	292	0	0	0	0	0	0	21	0
Pakistan	953074	971615	896093	1026982	8200112	8439522	7398165	8341140	2931677	2391445	2146832	2632389	7853	7591	6882	277
Palestina	1586	0	1274	34	16020	0	11540	581	0	0	0	0	0	0	0	0
Panama	57846	61889	43371	61392	0	0	0	0	63280	85641	68523	113776	141	134	224	222
Papua New Guinea	1293	1292	1397	1455	0	0	0	0	303	273	1178	352	0	0	366	0
Paraguay	365655	331996	600772	525848	166467	157868	231303	340507	32138	30205	35570	40615	1162210	1145915	1373178	1905068
Peru	448328	513123	445476	461082	69021	146426	129010	132461	260645	283732	296306	324550	2117	2161	2201	1763
Philippines	2545027	2484654	2122989	2452850	0	0	0	0	2883830	3996720	3241167	4080972	764	879	783	748
Poland	359121	150012	151170	348330	2533151	2654233	2396266	2260340	16	42	25	95	368	431	1345	953
Portugal	284172	147081	151249	121182	216789	232738	269576	149822	26494	24582	27477	25679	197	26	772	18
Puerto Rico	436	260	179	283	0	0	0	0	0	0	0	0	0	0	0	0
Qatar	123	0	7	74	24	0	4131	8	0	0	0	0	0	0	0	0
Republic of Congo	12066	11703	18337	14511	11	14	52	7	2004	3098	2992	1730	76	74	1168	631
Reunion	3004	0	1928	0	0	0	0	0	29	0	35	0	0	0	0	0
Romania	3015838	2991833	2694285	2667140	2013408	1951631	1970910	2236304	1695	1658	3094	3538	117063	96147	88002	135512
Russia	4242595	736522	671963	904089	19663228	21408807	18029568	23768625	184755	189898	192307	161526	404382	404990	444762	750270
Rwanda	72820	83364	65357	97751	4672	8636	5398	19651	3537	6036	15344	8778	21036	16395	10968	32199
Saint Kitts and Nevis	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
Saint Vincent and the Grenadines	348	200	57	47	0	0	0	0	0	0	0	0	0	0	0	0
Sao Tome and Principe	135	1000	22	1192	0	0	0	0	0	0	0	0	0	0	0	0
Saudi Arabia	4887	6254	6833	19501	439514	418881	490906	491290	0	0	0	0	0	0	19	0
Senegal	84418	84326	77919	157513	14	11	75	22	46691	85498	63072	98212	0	0	0	1
Serbia	958296	896657	956140	372628	520813	489460	561105	176858	2	0	414	5	103467	75374	72796	47019

Sierra Leone	8463	9901	7929	51529	0	0	0	0	181456	195829	198896	645694	55	41	798	89
Singapore	94	76	269	87	0	0	0	0	13	159	659	205	3	2	96	9
Slovakia	240396	146451	84789	155245	376055	392578	345399	374163	11	14	8	25	3687	5269	2940	8326
Slovenia	72245	47913	65366	51094	36816	39388	22112	35079	80	0	26	0	805	883	10305	869
Solomon Islands	0	0	0	0	0	0	0	0	418	0	603	898	0	0	0	0
Somalia	179856	186462	256038	153959	2403	2686	14522	4479	5339	1015	1794	2667	14	24	111	0
South Africa	3070615	3990587	3038929	2856237	811186	927608	866653	798243	1337	1286	1325	1169	92884	109987	101976	172880
South Korea	32410	28893	80556	28853	3109	2501	9048	4568	1107230	1077538	994291	981940	8294	98281	113155	101558
South Sudan	9734	31657	57567	60760	5764	11704	18366	1296	1562	2129	4674	8154	17	469	126	83
Spain	555472	438936	517724	409423	2229788	2346439	2118209	2112853	116192	116263	104431	114817	3012	4080	9244	675
Sri Lanka	27659	28648	27446	27940	0	0	0	0	499385	832000	813812	848477	690	1037	1034	2482
Sudan	80137	64904	53396	10412	114935	82608	106054	173193	4589	3733	3426	976	17	16	38	154
Suriname	40	34	346	100	0	0	0	0	36585	34219	21476	37195	34	53	51	23
Swaziland	59709	58604	53511	34939	175	210	488	113	48	41	27	37	191	70	1021	514
Sweden	48	0	0	0	348420	401935	305027	373739	0	0	0	0	0	0	0	0
Switzerland	46000	15129	63790	11825	70450	69616	98736	66096	10	0	37	0	639	1299	2303	1008
Syria	71386	51368	80946	49705	1509805	1515658	1696425	1597285	7	25	376	1218	2478	2936	6614	1007
Taiwan	40691	0	32037	19499	0	0	0	0	220053	0	264586	262795	0	151	156	89
Tajikistan	47423	14946	19316	28360	312392	344306	472396	384824	16282	21958	31128	28071	352	625	523	44
Tanzania	1384031	1005264	1407459	2891687	62487	69103	65785	38262	224545	411119	286640	636860	5962	5322	8070	3295
Thailand	1185713	1109954	1101420	1058200	1754	1795	4580	1703	7602731	8259319	9004295	10145473	207602	196352	185598	141590
Togo	375189	394503	241235	445835	0	0	0	0	34891	36384	31804	27339	157	77	292	802
Trinidad and Tobago	1094	427	823	1219	0	0	0	0	1218	2138	1067	1894	0	0	0	0
Tunisia	3	0	3	0	559632	682889	607340	892415	0	0	15	0	0	0	0	0
Turkey	565094	557393	531681	571527	8995123	9447767	8286158	9180469	56086	55176	55295	83988	15173	20640	20301	12515
Turkmenistan	97388	9713	17088	18044	598314	664253	659945	903378	38993	65521	47496	49139	336	3370	1306	0
Uganda	631328	634898	565692	794705	8620	10990	11683	10422	61088	76836	114796	110310	104727	115917	100461	143885
Ukraine	3380493	1313784	1328622	1950909	5636616	5187660	5184942	5875042	21509	25106	19498	20678	62333	74663	76234	461711
United Arab Emirates	0	0	132	0	56	75	76	20	0	0	0	0	0	0	60	0
United Kingdom	111511	0	42	0	1851492	2086455	2014200	1897721	0	0	0	0	0	0	0	0
United States	31997759	29315257	29579873	29597227	22404497	21484947	23481481	19858581	1334917	1229324	1291576	1282923	29307538	29618131	29629973	29664870
Uruguay	54382	44399	52927	53596	159685	122852	106835	168699	205681	193598	206251	216670	10750	21068	28918	261552
Uzbekistan	252558	49988	40430	41576	1271702	1299209	989735	1368871	157968	125082	88927	59054	45	299	150	8
Vanuatu	1401	1774	878	1582	0	0	0	0	0	0	0	0	0	0	0	0
Venezuela	449029	482982	429129	664913	1142	1401	1214	1171	157214	140656	158324	216717	1681	1738	1702	5505
Vietnam	666803	715544	588858	1006755	2861	4448	21751	3973	4846430	7688028	6189047	7390075	121717	130414	138559	202690
Yemen	34912	32440	37164	40358	102038	87738	101298	93868	0	0	0	0	0	0	0	0
Zambia	533051	613497	478382	630858	11961	10476	9122	20156	11730	14036	11921	15122	15396	10919	9678	41107
Zimbabwe	1061879	1421673	891586	1659773	47543	44232	41162	64864	648	637	823	881	62493	56817	53461	41422

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Appendix B

Supplementary Information to Chapter 3: Generating a rule-based global gridded tillage dataset

S1 Terms and definitions used

Arable cropland is the land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years). The abandoned land resulting from shifting cultivation is not included in this category (FAO, 2014).

Conservation Agriculture (CA) as reported by the FAO is a farming practice comprising minimum soil disturbance, the maintenance of a permanent vegetative cover of the soil (either by residue mulch layer and standing biomass) and diverse crop rotation (http://www.fao.org/conservation-agriculture/en/, accessed 08/31/2018). The no-tillage farm implements for seeding may range from disc like furrow openers but new developments of air-pressured seeding equipment embark even lesser soil disturbance. The use of no-tillage or minimum tillage practices (direct planting) mitigates some of the pressures on the soil and requires operational costs on farm. At the same time it enables the farmer for multiple cropping per year. Direct planting without proper soil cover may lead to increased herbicide requirements.

Cropland is considered as the sum of arable land cultivated with annual and perennial crops.

Perennial cropland is the land cultivated with long-term crops which do not have to be replanted for several years (such as cocoa and coffee); land under trees and shrubs producing flowers, such as roses and jasmine; and nurseries (except those for forest trees) (FAO, 2014).

Tillage is a means of soil management in order “To provide a favorable environment for crop growth and production, but still conserve soil and water resources” (FAO, 1984). The choice of tillage practice depends on soil, climatic, crop type, and socio-economic factors (Opara-Nadi, 1993). Conventional tillage practices are mostly perceived as the inversion and mixing of the soil layer with a plow after harvest in order to burry residues or for seedbed preparation. During the crop growing season cultivation as mechanical disturbance of the soil surface is practiced to loosen the soil, to manage weeds, to work in fertilizer, or other soil amendments. Tillage has a high altering effect on soil aggregates, and increases the decomposition of soil organic matter through aeration and exposure to microbial oxidation. This effect is approved off in conventional tillage, as with increased turnover times of soil organic matter, nutrients become available for promoting crop growth in case of timely seeding.

Alternative tillage practices as reduced tillage or no-tillage are holding promising potential to improve the water content and aggregate stability of the soil, protect from erosion, and to increase the soil organic matter pools in the soil. Literature findings of comparative site studies show different outcomes on the effect of reduced tillage on soil organic matter stocks exhibiting the fact that the outcome varies in time and space, due to cropping intensity, crop type, climate regime, soil type, and depth (Pittelkow et al., 2015b).

Table S2 List of crop types as in SPAM2005 (IFPRI/IIASA, 2017b), with indication of crop type grouping to annual or perennial, and whether considered as suitable for CA in this study.

Crop name long	Crop category	CA suitability
wheat	annual	included
rice	annual	excluded
maize	annual	included

Crop name long	Crop category	CA suitability
barley	annual	included
rest	annual	included
other oil crops	perennial	excluded
tobacco	annual	included
teas	perennial	excluded
cocoa	perennial	excluded
robusta coffee	perennial	excluded
arabica coffee	perennial	excluded
other fibre crops	perennial	excluded
cotton	annual	included
sugarbeet	annual	excluded
sugarrcane	perennial	excluded
oilpalm	perennial	excluded
vegetables	annual	included
temperate fruit	perennial	excluded
tropical fruit	perennial	excluded
plantain	perennial	excluded
banana	perennial	excluded
coconut	perennial	excluded
groundnut	annual	included
other roots	annual	excluded
cassava	annual	excluded
yams	annual	excluded
sweet potato	annual	excluded
potato	annual	excluded
sesameseed	annual	included
rapeseed	annual	included
sunflower	annual	included
soybean	annual	included
other pulses	annual	included
lentil	annual	included
pigeon pea	annual	included
cow pea	annual	included
chick pea	annual	included
beans	annual	included
other cereals	annual	included
sorghum	annual	included
small millet	annual	included
pearl millet	annual	included

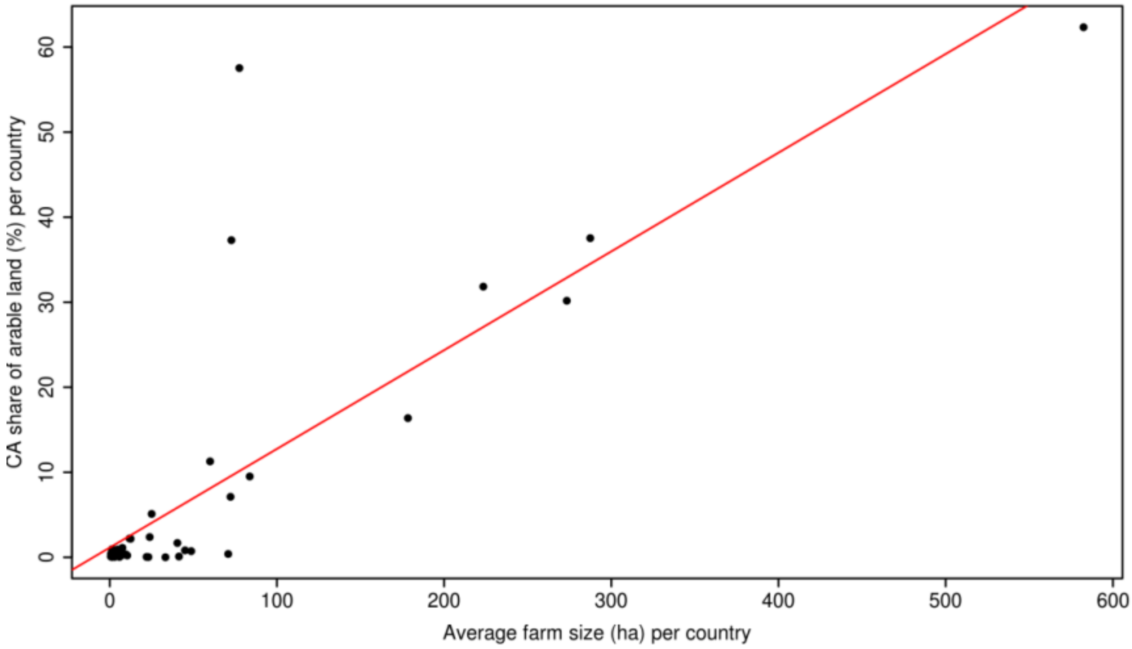

Figure S3 Relation between national average farm size (ha) (Lowder et al., 2014) and share (%) of Conservation Agricultural area on arable land (FAO, 2016). Black dots denote country values and the red line is the fitted regression line with the resulting coefficient of determination of r^2=0.66 ($p < 0.001$, slope of 0.116, n=41 excluding Australia, because of its very large average farm size of 3243 ha farm^{-1} but still with a CA adoption share of 20.4 % on their arable land).

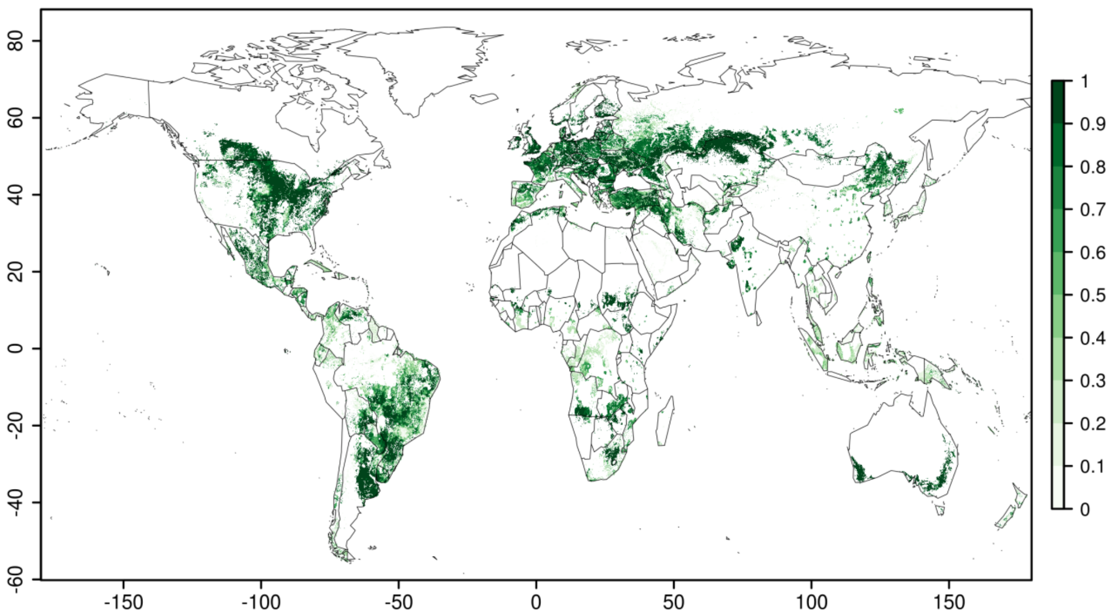

Figure S4.1 Crop mix as ratio, of cropland area of 22 annual rainfed considered CA-suitable crop types to total sum of cropland per grid cell on potential CA area (based on IFPRI/IIASA (2017b)) with values ranging between 0 and 1.

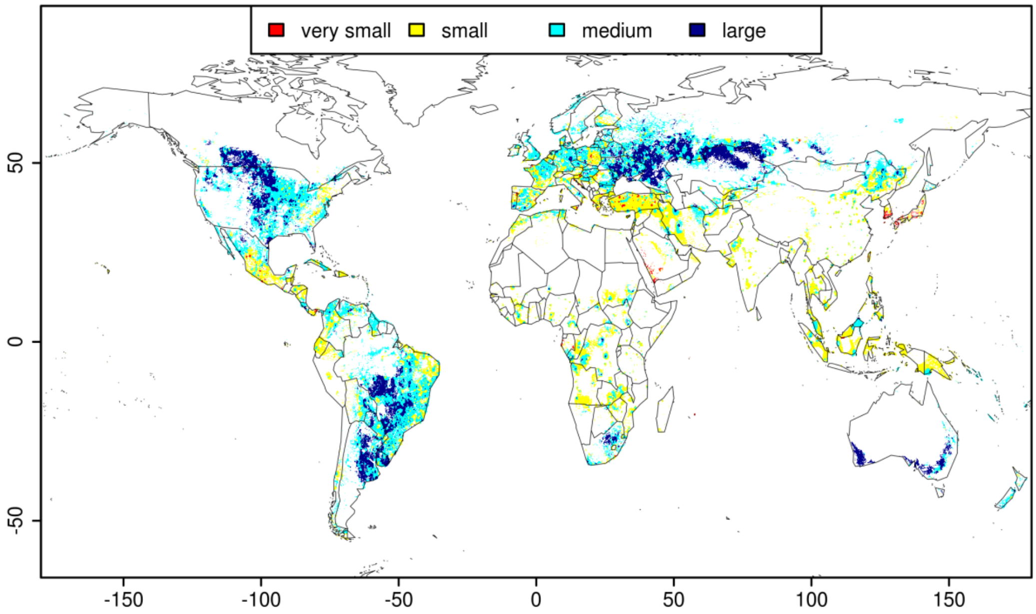

Figure S4.2 Field size on potential CA area (classes: very small (<0.5 ha), small (0.5-2 ha), medium (2-100 ha), large (>100 ha) as in (Herrero et al., 2017)) based on Fritz et al. (2015); with own modifications).

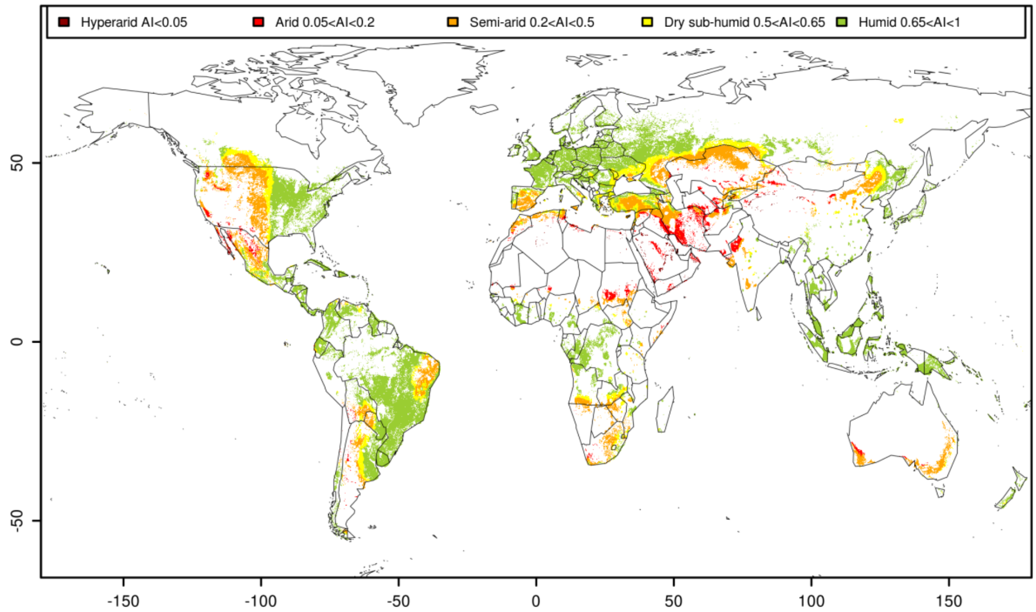

Figure S4.3 Aridity index as ratio of average yearly precipitation divided by average yearly potential evapotranspiration on potential CA area (based on data by FAO (2015), with own modifications).

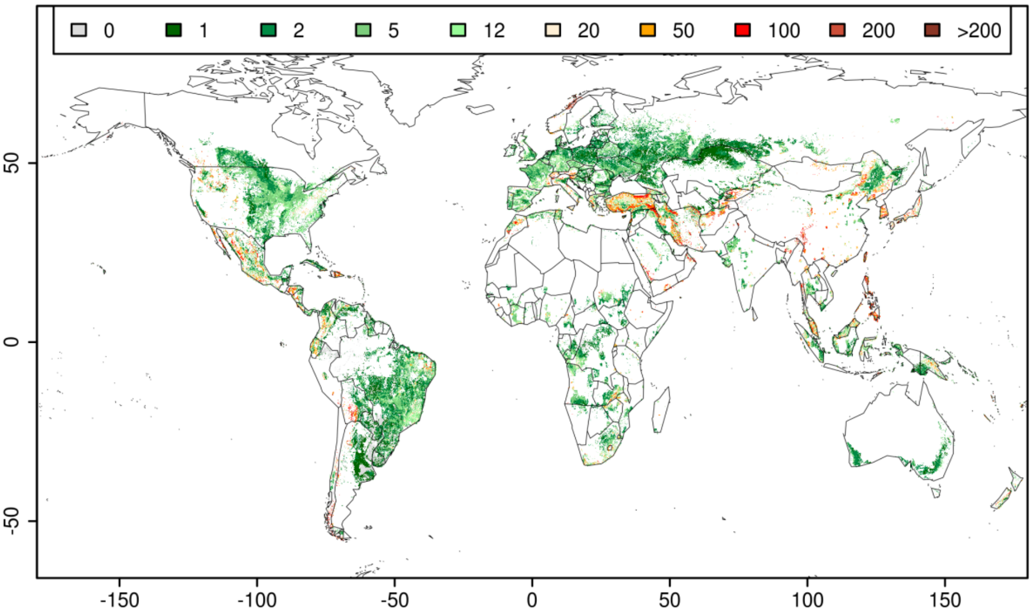

Figure S4.4 Water erosion in t ha^{-1} year^{-1} on potential CA area (based on GLADIS by Nachtergaele et al. (2011); with own modifications).

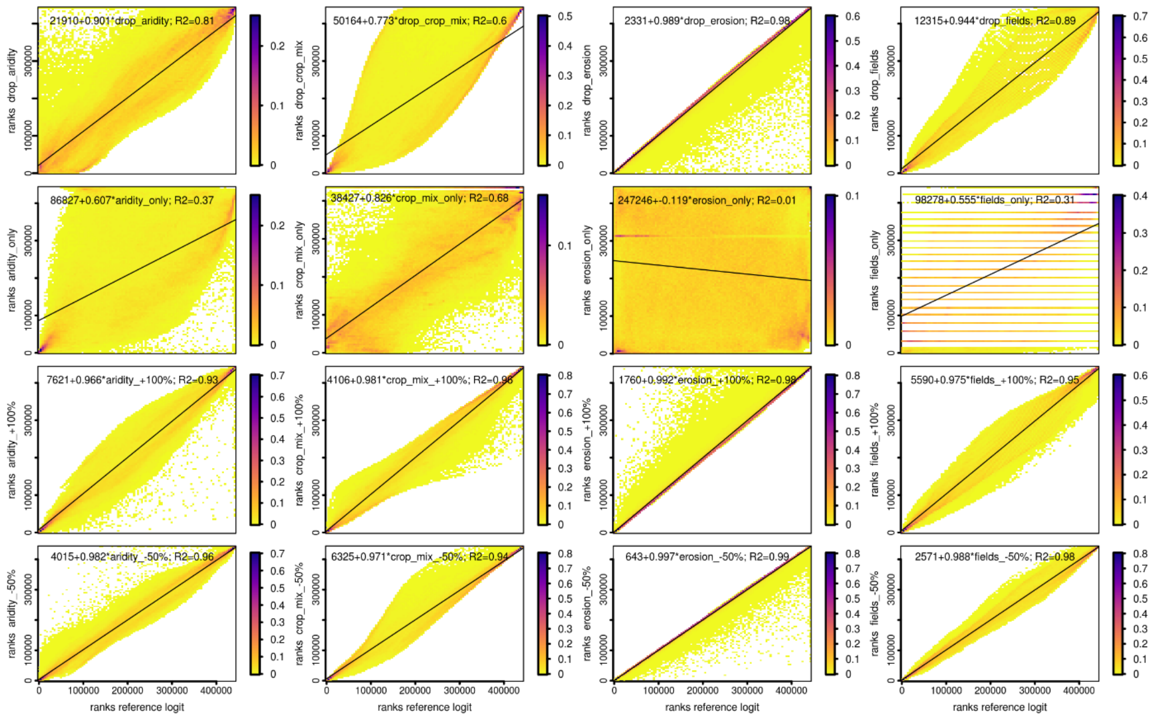

Figure S5 Density scatterplot per sensitivity combinations of our logit model with the four input variables (from left-right: aridity, crop mix, erosion, fields) per grid cell, when (first row) dropping one variable, (second row) taking one variable only, (third row) adding 100 % to slope, and (forth row) taking 50 % off of the original slope of a variable (note for settings in lines three and four, that the other three variable parameters remain unchanged respectively). The plots show that within the scope of our sensitivity analysis ranks of the alternative logit settings mostly show changed order close to the regression line (black line, p <0.001 for all combinations). The darker color pattern within the density plots shows that more grid cells in the lower and upper end of the rank numbers have more different ranks than in the center.

Table S6 Spearman rank correlation coefficient (r) of the reference logit model to each of sensitivity combination of variables and slopes in the logit model for each of the 54 CA area reporting countries. We aggregated values to country scale applying the accompanying grid cell allocation key by IFPRI/IIASA (2017a).

Country	Variable	Correlation (r) reference to drop one variable	Correlation (r) reference to one variable only	Correlation (r) reference to modified slope of one variable by plus 100 %	Correlation (r) reference to modified slope of one variable by minus 50 %
Argentina	field size	0.927	0.653	0.979	0.986
	erosion	0.990	0.085	0.991	0.996
	aridity	0.896	0.370	0.972	0.981
	crop mix	0.609	0.735	0.986	0.980
Australia	field size	0.912	0.744	0.982	0.987
	erosion	0.999	-0.064	0.998	1.000
	aridity	0.879	0.826	0.985	0.984
	crop mix	0.958	0.781	0.995	0.996
Azerbaijan	field size	0.919	0.246	0.971	0.985
	erosion	0.993	0.415	0.995	0.998
	aridity	0.961	-0.323	0.953	0.988
	crop mix	0.102	0.883	0.982	0.951
Belgium	field size	0.883	0.801	0.980	0.981
	erosion	0.998	0.394	0.998	0.999
	aridity	0.957	-0.245	0.930	0.985
	crop mix	0.613	0.868	0.973	0.961
Bolivia (Plurinational State of)	field size	0.905	0.509	0.972	0.982
	erosion	0.956	0.063	0.958	0.986
	aridity	0.962	0.740	0.981	0.992
	crop mix	0.839	0.866	0.982	0.975
Brazil	field size	0.947	0.351	0.960	0.987
	erosion	0.998	0.018	0.999	1.000
	aridity	0.878	0.395	0.940	0.971
	crop mix	0.614	0.870	0.978	0.961
Canada	field size	0.921	0.703	0.983	0.987
	erosion	0.994	-0.148	0.993	0.997
	aridity	0.849	0.627	0.976	0.984
	crop mix	0.772	0.595	0.985	0.981
Chile	field size	0.989	0.045	0.988	0.997
	erosion	0.896	0.076	0.957	0.979
	aridity	0.267	0.774	0.951	0.921
	crop mix	0.884	0.243	0.952	0.972
China	field size	0.931	0.472	0.972	0.986
	erosion	0.963	0.123	0.971	0.990
	aridity	0.937	0.034	0.957	0.984
	crop mix	0.414	0.860	0.974	0.947
Colombia	field size	0.977	0.285	0.981	0.994
	erosion	0.994	0.012	0.995	0.999
	aridity	0.655	0.835	0.969	0.956
	crop mix	0.881	0.629	0.963	0.977
Democratic People's Republic of Korea	field size	0.990	0.312	0.997	0.996
	erosion	0.672	0.853	0.984	0.957
	aridity	0.930	0.023	0.915	0.985
	crop mix	0.869	0.583	0.962	0.980
Finland	field size	0.488	0.778	0.968	0.939

Country	Variable	Correlation (r) reference to drop one variable	Correlation (r) reference to one variable only	Correlation (r) reference to modified slope of one variable by plus 100 %	Correlation (r) reference to modified slope of one variable by minus 50 %
	erosion	0.999	-0.155	0.999	1.000
	aridity	0.907	0.464	0.952	0.978
	crop mix	0.872	0.186	0.958	0.988
France	field size	0.872	0.696	0.973	0.979
	erosion	0.996	-0.243	0.996	0.998
	aridity	0.904	0.136	0.950	0.980
	crop mix	0.558	0.675	0.964	0.952
Germany	field size	0.890	0.770	0.973	0.978
	erosion	0.998	-0.169	0.996	0.999
	aridity	0.889	0.692	0.969	0.981
	crop mix	0.870	0.534	0.971	0.978
Ghana	field size	0.970	0.078	0.985	0.994
	erosion	0.995	-0.140	0.996	0.998
	aridity	0.978	0.722	0.987	0.993
	crop mix	0.649	0.968	0.993	0.989
Greece	field size	0.974	0.409	0.987	0.995
	erosion	0.991	-0.022	0.994	0.998
	aridity	0.952	0.272	0.981	0.991
	crop mix	0.485	0.909	0.989	0.982
Hungary	field size	0.466	0.884	0.975	0.936
	erosion	0.999	0.402	1.000	1.000
	aridity	0.947	-0.009	0.945	0.986
	crop mix	0.901	0.456	0.956	0.980
India	field size	0.980	0.349	0.990	0.996
	erosion	0.934	0.003	0.986	0.987
	aridity	0.906	0.610	0.979	0.987
	crop mix	0.772	0.897	0.988	0.988
Iraq	field size	0.931	0.125	0.962	0.985
	erosion	0.883	0.533	0.957	0.969
	aridity	0.956	-0.381	0.960	0.988
	crop mix	0.223	0.838	0.971	0.955
Ireland	field size	0.916	0.279	0.935	0.976
	erosion	0.998	-0.182	0.998	0.999
	aridity	0.280	0.895	0.972	0.929
	crop mix	0.989	0.016	0.992	0.998
Italy	field size	0.889	0.506	0.967	0.980
	erosion	0.966	0.244	0.969	0.988
	aridity	0.758	0.399	0.894	0.927
	crop mix	0.722	0.614	0.926	0.948
Kazakhstan	field size	0.716	0.815	0.980	0.967
	erosion	0.995	-0.298	0.994	0.999
	aridity	0.944	0.129	0.965	0.987
	crop mix	0.842	0.638	0.990	0.992
Kenya	field size	0.920	0.086	0.937	0.978
	erosion	0.961	0.328	0.991	0.994
	aridity	0.902	0.671	0.974	0.984
	crop mix	0.739	0.824	0.982	0.974
Kyrgyzstan	field size	0.967	0.002	0.975	0.993
	erosion	0.807	0.758	0.975	0.972
	aridity	0.982	-0.340	0.980	0.995
	crop mix	0.565	0.807	0.968	0.959
Lebanon	field size	0.857	0.336	0.956	0.975
	erosion	0.978	0.338	0.989	0.993
	aridity	0.991	-0.124	0.992	0.998
	crop mix	0.419	0.813	0.971	0.960

Country	Variable	Correlation (r) reference to drop one variable	Correlation (r) reference to one variable only	Correlation (r) reference to modified slope of one variable by plus 100 %	Correlation (r) reference to modified slope of one variable by minus 50 %
Lesotho	field size	0.888	-0.039	0.814	0.968
	erosion	0.891	0.289	0.959	0.974
	aridity	0.470	0.479	0.949	0.837
	crop mix	0.767	0.334	0.942	0.957
Madagascar	field size	0.960	0.253	0.982	0.992
	erosion	0.994	-0.008	0.983	0.998
	aridity	0.937	0.299	0.986	0.989
	crop mix	0.393	0.883	0.983	0.972
Malawi	field size	0.804	0.737	0.950	0.976
	erosion	0.957	-0.173	0.978	0.990
	aridity	0.962	0.663	0.972	0.991
	crop mix	0.837	0.743	0.981	0.954
Mexico	field size	0.940	0.492	0.971	0.988
	erosion	0.988	0.280	0.990	0.997
	aridity	0.935	0.445	0.971	0.987
	crop mix	0.626	0.788	0.968	0.946
Morocco	field size	0.931	0.292	0.970	0.984
	erosion	0.871	0.417	0.955	0.976
	aridity	0.962	-0.241	0.970	0.990
	crop mix	0.348	0.797	0.965	0.948
Mozambique	field size	0.907	0.104	0.934	0.976
	erosion	0.984	0.446	0.993	0.997
	aridity	0.919	0.247	0.944	0.980
	crop mix	0.472	0.860	0.970	0.941
Namibia	field size	0.931	-0.134	0.903	0.991
	erosion	0.996	-0.017	0.998	0.999
	aridity	0.989	0.034	0.992	0.997
	crop mix	-0.077	0.913	0.992	0.897
Netherlands	field size	0.862	0.346	0.955	0.971
	erosion	1.000	0.059	1.000	1.000
	aridity	0.984	0.011	0.987	0.996
	crop mix	0.467	0.900	0.981	0.973
New Zealand	field size	0.966	0.222	0.975	0.992
	erosion	0.952	0.147	0.974	0.985
	aridity	0.617	0.561	0.912	0.927
	crop mix	0.641	0.537	0.924	0.924
Paraguay	field size	0.896	0.616	0.978	0.983
	erosion	1.000	0.172	1.000	1.000
	aridity	0.752	0.467	0.894	0.951
	crop mix	0.633	0.465	0.923	0.918
Portugal	field size	0.958	0.875	0.989	0.992
	erosion	0.999	-0.265	0.999	1.000
	aridity	0.974	0.897	0.995	0.996
	crop mix	0.956	0.896	0.992	0.993
Republic of Moldova	field size	0.871	0.468	0.958	0.976
	erosion	0.998	0.144	0.998	0.999
	aridity	0.993	-0.089	0.993	0.998
	crop mix	0.483	0.868	0.976	0.958
Russian Federation	field size	0.949	0.595	0.984	0.990
	erosion	0.999	-0.303	0.999	1.000
	aridity	0.962	0.737	0.987	0.994
	crop mix	0.794	0.887	0.990	0.985
Slovakia	field size	0.676	0.822	0.967	0.950

Country	Variable	Correlation (r) reference to drop one variable	Correlation (r) reference to one variable only	Correlation (r) reference to modified slope of one variable by plus 100 %	Correlation (r) reference to modified slope of one variable by minus 50 %
	erosion	0.998	-0.226	0.998	0.999
	aridity	0.764	0.523	0.934	0.960
	crop mix	0.923	-0.182	0.961	0.980
South Africa	field size	0.947	0.693	0.984	0.991
	erosion	0.998	-0.565	0.997	0.999
	aridity	0.978	0.219	0.987	0.995
	crop mix	0.647	0.910	0.988	0.981
Spain	field size	0.920	0.525	0.960	0.982
	erosion	0.997	-0.075	0.997	0.999
	aridity	0.954	-0.028	0.967	0.989
	crop mix	0.408	0.836	0.966	0.930
Switzerland	field size	0.959	0.330	0.980	0.991
	erosion	0.770	0.162	0.908	0.915
	aridity	0.798	0.154	0.831	0.915
	crop mix	0.515	0.757	0.957	0.946
Syrian Arab Republic	field size	0.977	0.452	0.984	0.995
	erosion	0.997	0.021	0.997	0.999
	aridity	0.990	0.530	0.993	0.998
	crop mix	0.649	0.958	0.993	0.981
Tunisia	field size	0.960	0.027	0.965	0.990
	erosion	0.994	0.135	0.994	0.998
	aridity	0.967	0.197	0.969	0.992
	crop mix	0.222	0.956	0.989	0.964
Turkey	field size	0.896	0.348	0.958	0.978
	erosion	0.943	0.153	0.959	0.987
	aridity	0.929	0.308	0.961	0.983
	crop mix	0.576	0.798	0.970	0.953
Ukraine	field size	0.881	0.587	0.975	0.983
	erosion	0.999	0.107	0.999	1.000
	aridity	0.925	0.514	0.975	0.986
	crop mix	0.705	0.710	0.980	0.976
United Kingdom	field size	0.903	0.620	0.958	0.978
	erosion	0.996	-0.253	0.996	0.999
	aridity	0.521	0.873	0.970	0.935
	crop mix	0.976	0.051	0.978	0.993
United Republic of Tanzania	field size	0.966	0.204	0.974	0.992
	erosion	0.990	0.119	0.991	0.997
	aridity	0.969	0.476	0.984	0.993
	crop mix	0.565	0.942	0.988	0.974
United States of America	field size	0.942	0.592	0.981	0.990
	erosion	0.995	-0.073	0.997	0.999
	aridity	0.890	0.475	0.962	0.981
	crop mix	0.599	0.552	0.965	0.947
Uruguay	field size	0.824	0.142	0.950	0.956
	erosion	1.000	-0.291	1.000	1.000
	aridity	0.976	0.223	0.973	0.993
	crop mix	0.255	0.850	0.978	0.968
Uzbekistan	field size	0.762	0.483	0.939	0.966
	erosion	0.978	0.047	0.991	0.997
	aridity	0.933	0.119	0.952	0.984
	crop mix	0.519	0.606	0.963	0.910

Country	Variable	Correlation (r) reference to drop one variable	Correlation (r) reference to one variable only	Correlation (r) reference to modified slope of one variable by plus 100 %	Correlation (r) reference to modified slope of one variable by minus 50 %
Venezuela (Bolivarian Republic of)	field size	0.954	0.420	0.975	0.990
	erosion	0.995	-0.183	0.997	0.998
	aridity	0.928	0.325	0.971	0.987
	crop mix	0.479	0.859	0.977	0.957
Zambia	field size	0.825	0.396	0.931	0.962
	erosion	0.950	0.388	0.981	0.990
	aridity	0.918	0.377	0.957	0.981
	crop mix	0.696	0.721	0.961	0.962
Zimbabwe	field size	0.725	0.649	0.986	0.978
	erosion	0.958	0.085	0.969	0.988
	aridity	0.953	0.387	0.980	0.990
	crop mix	0.752	0.556	0.993	0.996

The logit model sensitivity results show differing patterns for each of the countries, where cell ranks change due to differing slopes and variable combinations in the logit model equation. For the setting of dropping a variable, most correlation to the reference logit model is lowest for dropping crop-mix (see Namibia, Azerbaijan, Iraq correlation values respectively) and highest mostly for dropping erosion. For the sensitivity setting of taking one variable only into the logit model, more than half of the correlation coefficients to the reference logit model are lower than r^2=0.5. For 32 out of 216 total country-variable combinations, we even find negative correlations mostly occurring when taking erosion only into the logit model. For South Africa we find the overall lowest correlation coefficient when taking erosion only (r^2=-0.565) but relatively high correlation when dropping erosion (r^2=0.998). Changing the slope of the functions results in very low changes of the rank order of grid cells and corresponding CA-suitable area, as can be interpreted from the fact that even the lowest correlations coefficients of slope settings to the reference logit model remain above r^2= 0.812 when manipulating the slopes of the input variable functions by +100 % or -50 %.

Table S7 Conservation Agriculture area for 54 reporting countries (FAO, 2016), as presented in this study and the difference between both values (note, that for New Zealand and North Korea not enough potential CA area could be detected in the SPAM2005 cropland dataset, so instead of 230 km^2 for Korea only 23.9 km^2, and for New Zealand instead of 1620 km^2 only 785.2 km^2 could be downscaled. Deviation between reported and downscaled CA area of the further countries are caused by our downscale algorithm, which tries to minimize deviation from reported national CA area value by in- or excluding potential CA area of a whole grid cell).

Country	Year of considered national reported CA value	National reported CA (km^2)	CA downscaled (km^2)	Difference CA downscaled to reported CA (km^2)
Argentina	2007	227080	227069.6	-10.4
Australia	2005	90000	90006.1	6.1
Azerbaijan	2013	13	12.3	-0.7
Belgium	2013	2.68	13.9	11.3
Bolivia (Plurinational State of)	2007	7060	7042.2	-17.8
Brazil	2006	255020	255024.5	4.5
Canada	2006	134790	134797.6	7.6
Chile	2005	1200	1196.1	-3.9
China	2005	1000	1016.8	16.8
Colombia	2005	1020	1021.2	1.2
Democratic People's Republic of Korea	2011	230	23.9	-206.1

Country	Year of considered national reported CA value	National reported CA (km^2)	CA downscaled (km^2)	Difference CA downscaled to reported CA (km^2)
Finland	2011	1600	1602.1	2.1
France	2005	1500	1510.2	10.2
Germany	2013	2000	2005.5	5.5
Ghana	2008	300	302.7	2.7
Greece	2013	240	231.9	-8.1
Hungary	2005	80	73.1	-6.9
India	2013	15000	15000.8	0.8
Iraq	2012	150	149.8	-0.2
Ireland	2005	1	18.4	17.4
Italy	2005	800	794.0	-6.0
Kazakhstan	2007	6000	5997.8	-2.2
Kenya	2004	150	165.2	15.2
Kyrgyzstan	2013	7	6.8	-0.2
Lebanon	2011	12	10.4	-1.6
Lesotho	2005	1.3	12.7	11.4
Madagascar	2011	60	60.1	0.1
Malawi	2011	160	129.9	-30.1
Mexico	2007	228	228.2	0.2
Morocco	2008	40	39.4	-0.6
Mozambique	2006	90	89.1	-0.9
Namibia	2011	3.4	5.2	1.8
Netherlands	2011	5	0.4	-4.6
New Zealand	2008	1620	785.2	-834.8
Paraguay	2007	20940	20941.5	1.5
Portugal	2006	250	245.3	-4.7
Republic of Moldova	2011	400	382.0	-18.0
Russian Federation	2011	45000	45011.3	11.3
Slovakia	2006	100	92.5	-7.5
South Africa	2005	3000	3005.0	5.0
Spain	2005	3000	3008.1	8.1
Switzerland	2005	90	86.9	-3.1
Syrian Arab Republic	2012	300	304.4	4.4
Tunisia	2007	60	61.7	1.7
Turkey	2013	450	446.7	-3.3
Ukraine	2011	6000	6015.5	15.5
United Kingdom	2005	240	234.0	-6.0
United Republic of Tanzania	2011	250	260.6	10.6
United States of America	2007	265000	264992.6	-7.4
Uruguay	2007	5539	5538.8	-0.2
Uzbekistan	2013	24.5	36.2	11.7
Venezuela (Bolivarian Republic of)	2005	3000	2999.8	-0.2
Zambia	2002	400	398.6	-1.4
Zimbabwe	2011	1393	1394.9	1.9
World		**1102899.9**	**1101899.2**	**-1000.7**

Table S8 Area weighted means of aridity, field size, crop mix, and water erosion over tillage system areas generated in this study.

Area type	Aridity index (P/PET)	Field size (10-40)	Crop mix (0-1)	Water erosion (t ha^{-1} $year^{-1}$)
Potential CA	0.734	31	0.87	10.8
CA	0.675	36	0.96	5.2
Traditional annual tillage	0.823	15	0.00	35.2

Area type	Aridity index (P/PET)	Field size (10-40)	Crop mix (0-1)	Water erosion (t ha^{-1} $year^{-1}$)
Traditional rotational tillage	1.106	15	0.00	46.7
Rotational tillage	1.007	26	0.34	24.6
Reduced tillage	0.607	16	0.03	33.8
Conventional annual tillage	0.755	29	0.72	13.0
Scenario CA	0.733	31	0.87	10.8
Total cropland	**0.806**	**23**	**0.41**	**23.1**

In the Table S8 we show area weighted means of our four logit model input variables aridity, field size, crop mix, and water erosion aggregated over each of tillage system areas mapped in this study. For aridity reduced tillage is the only area with dry sub-humid conditions, i.e. with an average aridity below the threshold of 0.65, all others are humid with values above 0.65. Traditional rotational and rotational tillage are on average more humid than the annually tilled areas. Potential CA area is more humid than downscaled CA area. Regarding field size we find, that downscaled CA area has the largest field size contrary to both traditional tillage system areas showing the smallest ones. Crop mix is calculated for cells with at least one of the 22 CA-suitable annual crop type areas in grid cells reporting large fields in low income or all field sizes in high income countries, so that none was derived for traditional tillage system areas. The highest crop mix ratio is found for the actually downscaled CA area. Regarding water erosion we find very low erosion levels under CA area which is either because we actually did hit the right cells where this practice is already protecting the soil or the general low impact of the variable in the logit equation. For downscaled, potential, and scenario CA area we calculated lower erosion levels than the T-value (12 t ha^{-1} $year^{-1}$ as erosion loss tolerance level) defined by USDA (Montgomery, 2007). Even for conventional annual tillage area the average erosion level of 13 t ha^{-1} $year^{-1}$ is only 1 t higher than the T-value. We find largest average water erosion levels for both types of traditionally tilled areas (in cells reporting small fields as dominant and in low income countries), which either might result from the climatic conditions in the tropics and sub-tropics with intensive rainfall events, increased slopes because of mountainous landscapes, deforestation, or nutrient mining resulting in degradation of the soil asset. As well does reduced tillage area have a quite high average water erosion rate, as it is mainly distributed within a narrow band of the tropical climate zone, this may also be because of climate conditions, where elevated weathering of soils results in shallow soil depths. Generally the averaged values of the four datasets across the potential and scenario CA data are similar or identical because of just few different amounts of grid cells considered.

Table S9 Sums of tillage systems areas per country (n=191) on physical cropland aggregated with grid cell allocation key for countries (IFPRI/IIASA, 2017a).

Country name	Cropland (km^2) (IFPRI/IIASA, 2017b)	Conventional annual tillage (km^2)	CA (km^2)	Reduced tillage (km^2)	Rota-tional tillage (km^2)	Tradi-tional rotational (km^2)	Tradi-tional annual tillage (km^2)	Scenario CA (km^2)
Afghanistan	28932	12139	0	0	337	1039	15417	6086
Ãland Islands	14	12	0	0	2	0	0	8
Albania	2918	26	0	0	5	770	2116	24
Algeria	39101	29981	0	0	6591	607	1922	26559
Andorra	13	6	0	0	7	0	0	3
Angola	29135	10473	0	0	614	731	17317	6285
Anguilla	10	3	0	0	7	0	0	2
Antigua & Barbuda	24	12	0	0	12	0	0	11
Argentina	248058	11329	227070	0	9659	0	0	231220
Armenia	2938	1343	0	0	306	172	1117	761
Australia	226123	129800	90006	0	6317	0	0	213540

Country name	Cropland (km^2) (IFPRI/IIASA, 2017b)	Conventional annual tillage (km^2)	CA (km^2)	Reduced tillage (km^2)	Rota-tional tillage (km^2)	Tradi-tional rotational (km^2)	Tradi-tional annual tillage (km^2)	Scenario CA (km^2)
Austria	10430	9435	0	0	995	0	0	8530
Azerbaijan	13112	10279	12	0	1084	221	1516	1744
Bahrain	22	5	0	0	17	0	0	0
Bangladesh	90550	6347	0	0	1025	8986	74191	1514
Barbados	53	11	0	0	41	0	0	10
Belarus	33239	30893	0	0	2305	3	38	25161
Belgium	6189	5670	14	0	505	0	0	3695
Belize	631	241	0	0	390	0	0	216
Benin	16824	522	0	379	34	741	15149	443
Bhutan	1788	0	0	0	0	290	1498	0
Bolivia	25098	11191	7042	0	1607	753	4505	15496
Bosnia & Herzegovina	5706	2504	0	0	534	405	2263	2317
Botswana	1554	1529	0	0	25	0	0	1383
Brazil	616114	223944	255024	0	119508	2030	15607	420609
Brunei	204	119	0	0	85	0	0	47
Bulgaria	26883	23998	0	0	1945	195	745	22911
Burkina Faso	51851	3555	0	1705	55	482	46053	3971
Burundi	12881	0	0	0	0	4566	8315	0
Cambodia	26899	9918	0	0	545	556	15880	1156
Cameroon	43770	3208	0	108	2543	10874	27037	2241
Canada	261638	118646	134798	0	8194	0	0	246921
Cape Verde	465	0	0	0	0	39	427	0
Central African Republic	9058	1557	0	0	281	1307	5914	999
Chad	29280	5273	0	0	92	717	23198	4951
Chile	12851	8133	1196	0	3521	0	0	5496
China	1335729	303891	1017	126	24144	133202	873348	183326
Colombia	40010	16093	1021	0	17738	3871	1287	8848
Congo	2917	1534	0	0	569	220	593	650
Congo, DRC	59365	16171	0	0	2955	5258	34981	7691
Costa Rica	4458	939	0	0	3519	0	0	312
Cote d'Ivory	67051	14954	0	0	16432	20751	14915	8928
Croatia	8518	7591	0	0	928	0	0	7034
Cuba	17550	9097	0	0	8254	94	104	5028
Cyprus	1125	769	0	0	356	0	0	544
Czech Republic	22675	21673	0	0	1001	0	0	20600
Denmark	16996	16940	0	0	57	0	0	14275
Djibouti	76	0	0	0	0	0	76	0
Dominica	107	38	0	0	70	0	0	9
Dominican Republic	8288	3104	0	0	4844	216	123	774
Ecuador	24591	10447	0	0	10894	1592	1658	4976
Egypt	47432	3231	0	0	669	6496	37036	219
El Salvador	6364	528	0	0	321	2036	3479	516
Equatorial Guinea	889	353	0	0	536	0	0	0
Eritrea	6759	510	0	1568	62	358	4260	440
Estonia	3688	3560	0	0	127	0	0	3408
Ethiopia	97701	2430	0	6797	514	10416	77544	2217
Fiji	1492	262	0	0	1230	0	0	47
Finland	12979	11311	1602	0	66	0	0	12257
France	134435	120717	1510	0	12208	0	0	104406
French Guiana	146	124	0	0	21	0	0	7
Gabon	2204	1440	0	0	764	0	0	601

Country name	Cropland (km^2) (IFPRI/IIASA, 2017b)	Conventional annual tillage (km^2)	CA (km^2)	Reduced tillage (km^2)	Rota-tional tillage (km^2)	Tradi-tional rotational (km^2)	Tradi-tional annual tillage (km^2)	Scenario CA (km^2)
Georgia	5819	4222	0	0	1314	64	218	2174
Germany	93173	89155	2005	0	2012	0	0	82287
Ghana	64610	1440	303	0	643	26024	36201	1061
Greece	28323	18190	232	0	9901	0	0	10321
Grenada	94	42	0	0	53	0	0	35
Guadeloupe	171	31	0	0	140	0	0	24
Guatemala	19721	2497	0	34	3074	3782	10334	1981
Guinea	29333	2288	0	112	327	6719	19887	1357
Guinea-Bissau	3365	14	0	191	1	325	2834	24
Guyana	1990	1246	0	0	744	0	0	125
Haiti	10702	1479	0	0	647	1964	6611	1081
Honduras	10106	3812	0	0	3379	1266	1649	3402
Hungary	40622	38383	73	0	2166	0	0	36471
India	1558662	181111	15001	107461	11018	126696	1117375	161503
Indonesia	270842	56095	0	0	48388	51416	114944	32279
Iran	136040	91162	0	0	13206	2996	28676	48739
Iraq	38137	29609	150	0	1912	309	6157	15546
Ireland	3358	3316	18	0	24	0	0	2984
Israel	3142	2108	0	0	1034	0	0	1019
Italy	53978	34986	794	0	18198	0	0	27214
Jamaica	1448	3	0	0	28	1140	276	2
Japan	28083	25134	0	0	2949	0	0	4849
Jordan	1661	194	0	0	112	645	711	70
Kazakhstan	148677	140046	5998	0	2633	0	0	134797
Kenya	44766	9449	165	0	1715	5094	28343	8953
Kiribati	272	18	0	0	253	0	0	7
Kosovo	57	0	0	0	0	8	49	0
Kuwait	70	48	0	0	22	0	0	38
Kyrgyzstan	8548	7300	7	0	736	76	430	1101
Laos	12334	1787	0	0	199	1070	9278	284
Latvia	7126	6912	0	0	214	0	0	6274
Lebanon	2505	1335	10	0	1160	0	0	619
Lesotho	2245	1933	13	0	34	2	263	1875
Liberia	4959	1602	0	0	337	796	2225	878
Libya	7005	4482	0	0	2523	0	0	2443
Liechtenstein	5	5	0	0	0	0	0	5
Lithuania	12256	11872	0	0	384	0	0	10914
Luxembourg	451	414	0	0	36	0	0	407
Macedonia	3609	939	0	0	141	442	2087	739
Madagascar	29263	435	60	0	52	4762	23955	105
Malawi	34520	5763	130	0	283	1193	27150	5159
Malaysia	57839	18173	0	0	39666	0	0	12890
Maldives	61	0	0	0	0	45	16	0
Mali	47428	6322	0	1189	239	1117	38560	5959
Malta	67	54	0	0	13	0	0	36
Martinique	191	37	0	0	153	0	0	31
Mauritania	3792	595	0	0	47	173	2976	445
Mauritius	741	39	0	0	703	0	0	34
Mexico	145349	111783	228	5791	27546	0	0	82423
Moldova, Republic of	17401	14529	382	0	2342	55	93	13888
Mongolia	1631	1525	0	0	4	0	102	1176
Montenegro	113	0	0	0	0	60	53	0
Montserrat	3	2	0	0	1	0	0	2
Morocco	72316	41365	39	0	5084	3156	22671	36777

Country name	Cropland (km^2) (IFPRI/IIASA, 2017b)	Conventional annual tillage (km^2)	CA (km^2)	Reduced tillage (km^2)	Rota-tional tillage (km^2)	Tradi-tional rotational (km^2)	Tradi-tional annual tillage (km^2)	Scenario CA (km^2)
Mozambique	55194	8366	89	0	887	3515	42336	6840
Myanmar	102876	6769	0	0	409	6237	89460	2706
Namibia	3597	3216	5	0	59	10	307	2910
Nepal	47046	2355	0	0	265	4299	40127	728
Netherlands	6512	6182	0	0	330	0	0	2831
New Caledonia	117	70	0	0	47	0	0	40
New Zealand	2264	904	785	0	575	0	0	785
Nicaragua	9878	5179	0	0	1287	784	2629	4294
Niger	73479	5919	0	0	38	615	66907	5910
Nigeria	410586	27641	0	22805	8253	50935	300952	13537
North Korea	25889	310	24	0	13	2026	23516	24
Norway	3526	3480	0	0	46	0	0	2887
Oman	443	129	0	0	314	0	0	24
Pakistan	201969	10841	0	0	1394	15288	174445	3827
Palestinian Territory, Occupied	85	0	0	0	0	32	53	0
Panama	3313	2101	0	0	1212	0	0	840
Papua New Guinea	9182	2692	0	0	6333	110	46	742
Paraguay	39442	16135	20941	0	1948	17	400	34687
Peru	27867	1566	0	0	1273	6436	18592	605
Philippines	105635	35751	0	0	28926	20350	20608	22169
Poland	103304	99157	0	0	4147	0	0	89970
Portugal	14498	6720	245	0	7533	0	0	3400
Puerto Rico	348	40	0	0	308	0	0	29
Qatar	51	31	0	0	20	0	0	24
Romania	78111	73946	0	0	4165	0	0	66381
Russia	549795	493599	45011	0	11185	0	0	484052
Rwanda	12128	206	0	0	248	2847	8827	199
San Marino	13	11	0	0	2	0	0	10
Sao Tome & Principe	355	0	0	0	0	298	57	0
Saudi Arabia	9822	7342	0	1	2479	0	0	1154
Senegal	23371	1906	0	40	63	529	20832	1608
Serbia	9767	5917	0	0	568	660	2623	5540
Seychelles	34	22	0	0	12	0	0	22
Sierra Leone	13960	950	0	0	32	1208	11770	197
Slovakia	11967	11429	92	0	446	0	0	10789
Slovenia	1412	1177	0	0	235	0	0	1036
Solomon Is.	836	170	0	0	666	0	0	40
Somalia	8385	4897	0	0	177	172	3139	4324
South Africa	55841	46397	3005	0	6439	0	0	44374
South Korea	14821	12666	0	0	2155	0	0	3488
Spain	132010	86117	3008	0	42884	0	0	69584
Sri Lanka	18798	586	0	0	424	6987	10802	376
St. Kitts & Nevis	18	3	0	0	14	0	0	2
St. Lucia	87	18	0	0	69	0	0	8
St. Vincent & the Grenadines	92	32	0	0	60	0	0	15
Sudan	125120	64140	0	6058	1711	1915	51296	64178
Suriname	545	472	0	0	73	0	0	13
Swaziland	1461	749	0	0	634	7	71	629
Sweden	12255	12175	0	0	81	0	0	11322

Country name	Cropland (km^2) (IFPRI/IIASA, 2017b)	Conventional annual tillage (km^2)	CA (km^2)	Reduced tillage (km^2)	Rota-tional tillage (km^2)	Tradi-tional rotational (km^2)	Tradi-tional annual tillage (km^2)	Scenario CA (km^2)
Switzerland	2322	2025	87	0	210	0	0	1694
Syria	44650	30387	304	0	5999	1342	6618	21820
Taiwan	4900	3121	0	0	1779	0	0	1943
Tajikistan	8687	5960	0	0	840	194	1692	1899
Tanzania	113154	11195	261	0	1440	16384	83874	8283
Thailand	168057	74221	0	0	17846	11239	64751	16952
The Gambia	2698	389	0	0	5	34	2271	357
Timor-Leste	1465	678	0	0	351	77	359	312
Togo	14656	243	0	25	48	1318	13022	199
Trinidad & Tobago	483	78	0	0	405	0	0	49
Tunisia	37116	17365	62	0	13872	4291	1527	14057
Turkey	204423	183746	447	0	20231	0	0	158681
Turkmenistan	17389	16593	0	0	642	18	136	1160
Uganda	43409	2431	0	0	2443	11068	27467	1884
Ukraine	220606	207247	6015	0	4706	54	2584	187922
United Arab Emirates	1936	115	0	0	1821	0	0	0
United Kingdom	41700	40761	234	0	705	0	0	37849
United States	955389	669911	264993	0	20485	0	0	792663
Uruguay	10232	4253	5539	0	440	0	0	7455
Uzbekistan	37354	32660	36	0	3041	63	1553	5439
Vanuatu	1026	99	0	0	928	0	0	45
Venezuela	20337	10920	3000	10	6407	0	0	9723
Vietnam	85611	24076	0	0	3634	11279	46622	1962
Yemen	10452	190	0	0	65	1162	9036	108
Zambia	13899	6510	399	0	335	182	6472	5531
Zimbabwe	30367	9371	1395	0	331	868	18403	10178

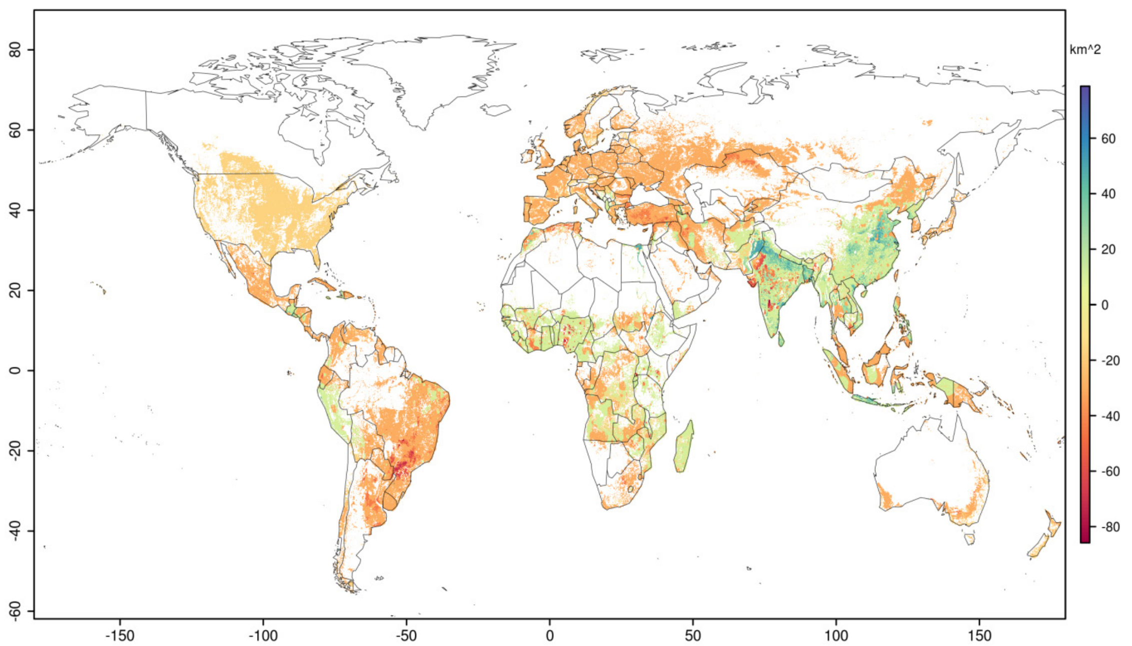

Figure S10 Area difference (km^2) map of the calculated sum of our mapped traditional annual and traditional rotational tillage system area and the sum of cropland under low input and subsistence farming (IFPRI/IIASA, 2017b). Reddish colors indicate less cropland in our traditional tillage dataset, mostly found in high income countries – larger discrepancy depicted in the South of Brazil. Blue colors show more area in our traditional tillage dataset in large parts of India, and South-East Asia.

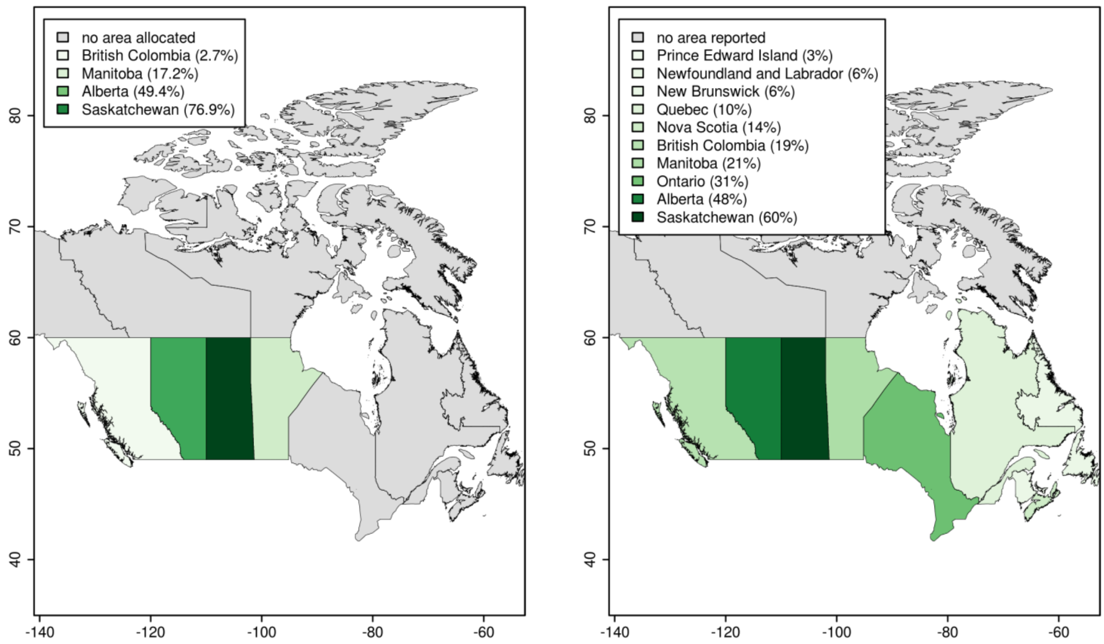

Figure S11.1.1 We aggregated mapped Conservation Agricultural area to state or provincial scale using the GADM-1 data (Global Administrative Areas, 2015). The map (left) shows the downscaled CA area share (%) on cropland (IFPRI/IIASA, 2017b) per Canadian province and territory. The other map (right) shows reported provincial no-tillage shares (%) on cropland by Statistics Canada (2007) for year 2006.

Table S11.1.2 Aggregated cropland, downscaled CA area, CA share on cropland as well as reported reference (Statistics Canada, 2007) cropland, no-tillage area values, and no-tillage shares on cropland for Canadian provinces and territories.

Province or Territory	Aggregated SPAM2005 cropland (km^2)	Downscaled CA (km2)	Downscaled CA share on cropland (%)	Reference cropland (km^2)	Reference no-tillage share (%)
Alberta	64179	31708	49	75782	48
British Columbia	1072	29	3	1985	19
Manitoba	32382	5563	17	38906	21
New Brunswick	614	0	0	657	6
Newfoundland and Labrador	12	0	0	24	6
Northwest Territories	0	0	0	0	0
Nova Scotia	280	0	0	267	14
Nunavut	0	0	0	0	0
Ontario	23876	0	0	26995	31
Prince Edward Island	969	0	0	1100	3
Quebec	9695	0	0	11291	10
Saskatchewan	124708	95933	77	133482	60
Yukon	0	0	0	0	0
Canada	**257786**	**133233**	**52**	**290488**	**46**

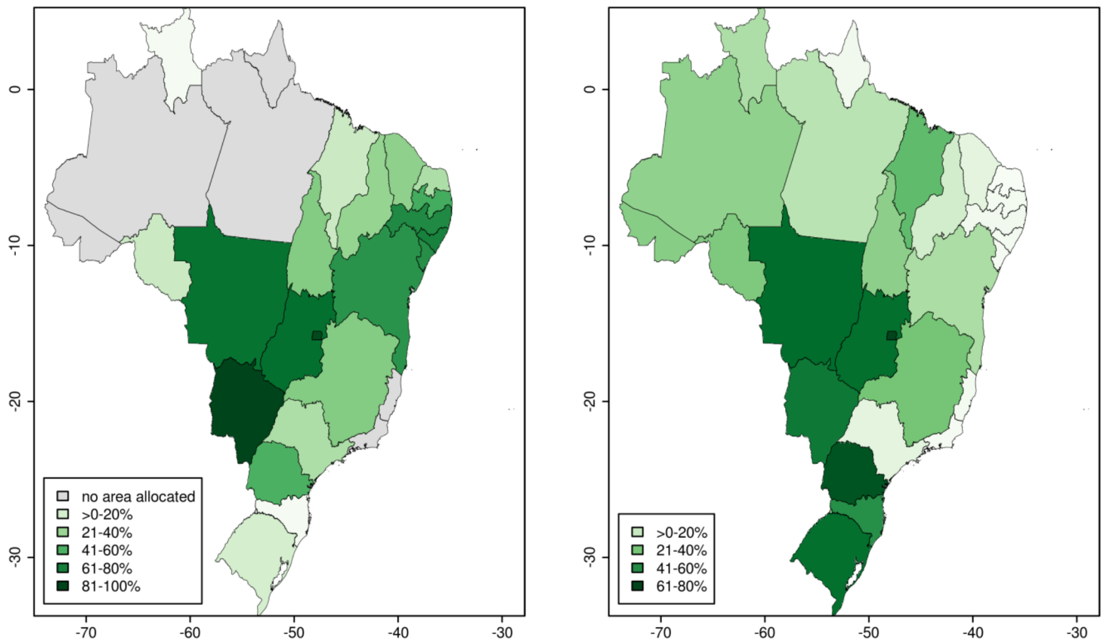

Figure S11.2.1 Aggregating tillage area for Brazilian states the map (left) shows the downscaled CA area share (%) on annuals cropland (IFPRI/IIASA, 2017b) and the other map (right) based on no-tillage share (%) on annuals cropland reported in the 2006 Agricultural Census by the Brazilian Institute of Geography and Statistics (IBGE) (Fuentes Llanillo et al., 2013) for the years 2007-08.

Table S11.2.2 Aggregated cropland, downscaled CA area, and CA share on cropland as well as reported reference (Fuentes Llanillo et al., 2013) annuals cropland, no-tillage area values, and no-tillage shares on annuals' cropland for Brazilian states.

State	Aggregated SPAM2005 annuals cropland (km2)	Downscaled CA (km2)	Downscaled CA share on annuals cropland (%)	Reference annuals cropland (km2)	Reference no-tillage share (%)
Acre	1118	0.0	0	59	35
Alagoas	2123	1576.2	74	161	3
Amapa	118	0.0	0	2	4
Amazonas	1417	0.0	0	99	33
Bahia	25685	17165.5	67	6363	27
Ceara	13716	5519.3	40	643	11
Distrito Federal	1312	1205.2	92	672	77
Espirito Santo	1041	0.0	0	32	3
Goias	41114	32952.8	80	19161	67
Maranhao	16807	3729.2	22	2982	42
Mato Grosso Do Sul	30223	28236.8	93	12531	68
Mato Grosso	79714	63493.8	80	32872	64
Minas Gerais	27490	11731.1	43	9280	39
Para	10212	0.4	0	477	23
Paraiba	4121	2404.1	58	89	3
Parana	90011	50639.4	56	37071	74
Pernambuco	6362	4524.0	71	333	4
Piaui	9940	3778.4	38	1091	16
Rio De Janeiro	437	0.0	0	35	2
Rio Grande Do Norte	1084	341.0	31	27	1
Rio Grande Do Sul	76516	14273.6	19	40853	66

Rondonia	3993	877.4	22	419	37
Roraima	545	11.7	2	77	27
Santa Catarina	15709	355.8	2	7579	57
Sao Paulo	24634	7744.2	31	4718	11
Sergipe	2329	1604.4	69	18	2
Tocantins	6727	2856.6	42	1073	33
Brazil	**494497**	**255020.8**	**52**	**178718**	**49**

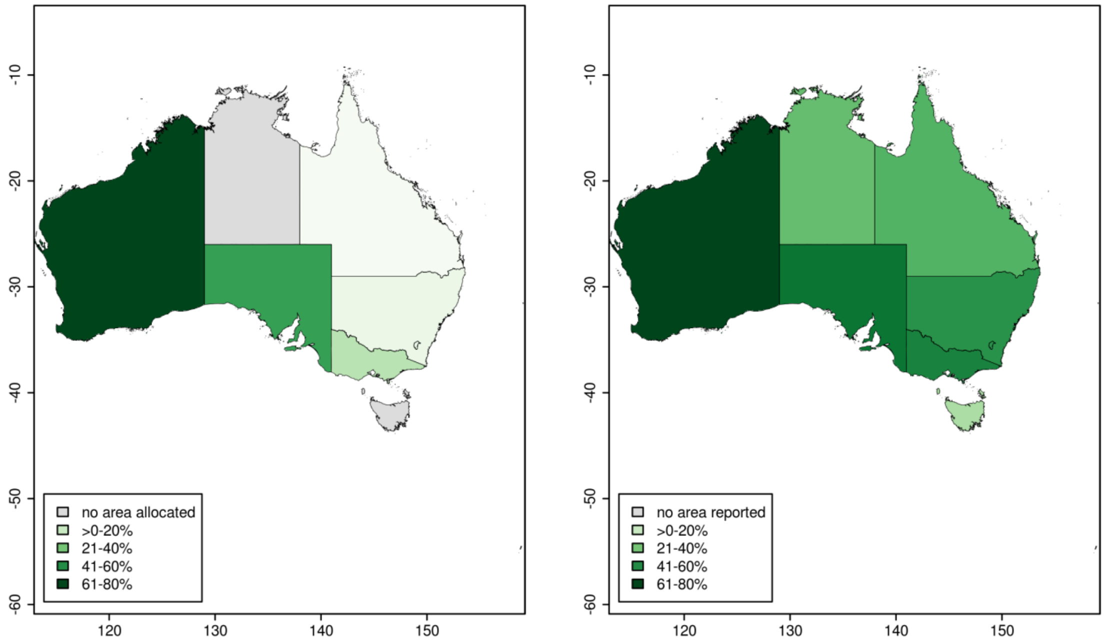

Figure S11.3.1 For the Australian states and territories the map (left) shows the downscaled CA area share (%) on cropland (IFPRI/IIASA, 2017b) and map (right) reported no-tillage share on land prepared for crops and pastures as collected in the 2007–08 Agricultural Resource Management Survey (ARMS) conducted and published by the Australian Bureau of Statistics (2009) for the year 2006.

Table S11.3.2 Aggregated cropland, downscaled CA area, and share as well as reported reference (Australian Bureau of Statistics, 2009) cropland, no-tillage area values, and no-tillage shares (%) on cropland per Australian state and territory.

State or Territory	**Aggregated SPAM2005 cropland (km^2)**	**Downscaled CA (km^2)**	**Downscaled CA share (%)**	**Reference cropland and pasture (km^2)**	**Reference no-tillage (km^2)**	**Reference no-tillage share (%)**
New South Wales & Australian Capital Territory	4357	64196	7	77889	44608	57
Northern Territory	0	35	0	187	80	43
Queensland	285	15755	2	26978	12576	47
South Australia	20059	38064	53	43462	28902	67
Tasmania	0	419	0	947	265	28
Victoria	7776	33616	23	40198	25233	63
Western Australia	57425	73819	78	79691	63137	79
Australia	**89903**	**225904**	**40**	**269352**	**174803**	**65**

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Appendix C

Supplementary Information to Chapter 4: The role of cover crops for cropland soil carbon, nitrogen leaching, and agricultural yields - A global simulation study with LPJmL (V. 5.0-tillage-cc)

Supplement content:

S1 Supplementary information to methods and data

S1.1 General model functions in LPJmL5.0-tillage-cc

In the model three litter layers and five hydrologically active soil layers of differing thickness to a total depth of three meter are distinguished. Each soil layer has its specific temperature and moisture levels, affecting the decomposition rates of soil organic matter, represented in the model by fast and slow decomposing (30 and 1000 years turnover time, respectively) C and N pools (Lutz et al., 2019; Schaphoff et al., 2018a). Carbon and N pools of represented vegetation, litter, and soil layers are updated daily. Biomass formation is represented by a simplified version of photosynthesis according to Farquhar et al. (1980). The phenology of tree and grass plant functional types (PFTs) of the represented natural vegetation are based on Jolly et al. (2005) with modification of the growing season index as described in Forkel et al. (2014). Crop functional types (CFTs, see Table S1.1) representing the vegetation on managed land are parameterized with specific temperature and phenological heat unit requirements for growth (Müller et al., 2017b). Cropland irrigation was mechanistically simulated by either surface flooding, sprinkler, or drip irrigation, here setting one type per country (Jägermeyr et al., 2015; Rohwer et al., 2007). We used the potential irrigation setting to simulate irrigated cropping systems (for cropland areas equipped for irrigation as informed by the input data, see Sect. S1.2) to account for missing representation of ground water sourcing, when this model version only considers surface water withdrawal amounts, in the case of alternatively setting to limited irrigation.

During simulated main crop growing seasons, manure (C to N ratio of applied manure was assumed to be 14.5 to 1) was applied at the first scheduled mineral N fertilization event of a growing crop (CFT). Half of the N contained in the manure was assumed as ammonium (NH_4) and added to the pool of the upper soil layer, whereas the entire C and the remaining N (assumed as organic share), were transferred to the respective litter pools. Conventional tillage was assumed as the default soil management on all cropland, applied when converting land to cropland, as well as at main crop seeding and harvest events. The tillage routine submerges and transfers 95 % of the surface biomass remaining on-site, to the incorporated soil litter pools. In the model, tillage mostly affects processes in the first soil layer up to 20 cm depth (Lutz et al., 2019). In the case of no-tillage, the remaining aboveground biomass of the main crops' residues left on the field after harvest are added to the surface soil litter pools, representing mulching practices.

Table S1.1 Crop functional types (CFTs) in LPJml5.0-tillage-cc and included in the study.

CFT	Simulated as
temperate cereals	wheat
rice	rice
tropical cereals	millet
pulses	field peas
temperate roots	sugar beet
tropical roots	cassava
maize	maize
sunflower	sunflower
soybean	soybean
groundnuts	groundnuts
rapeseed	rapeseed
sugarcane	sugarcane
others	maize in tropical and wheat in temperate regions

CFT	Simulated as
managed grass	managed temperate C3, polar C3, and tropical C4 grass (outputs not considered here)
bioenergy grass	not simulated here
bioenergy trees	not simulated here
cover crop	temperate C3, polar C3, and tropical C4 grass with daily allocation

S1.2 Model input data

For the simulations of this study, the model was driven with monthly mean temperature input data from the Climate Research Unit (CRU TS version 3.23, University of East Anglia Climate Research Unit, 2015; Harris et al. (2014)). Monthly precipitation and number of wet days data was from the Global Precipitation Climatology Centre (GPCC Full Data Reanalysis version 7.0; Becker et al. (2013)). The monthly radiation data (shortwave and net longwave downward) was taken from the ERA-Interim data set (Dee et al., 2011). Soil texture classes remained static over the simulation period and were based on the Harmonized World Soil Database (Nachtergaele et al., 2009) and soil-pH was taken from the WISE data set (Batjes, 2006). Annual atmospheric CO_2-concentration input data were based on the NOAA/ESRL Mauna Loa station (Tans and Keeling, 2015) reports, and natural N deposition data on the ACCMIP database (Lamarque et al., 2013).

Model input data on historical land use, distinguishing shares of irrigated and rainfed crop-group specific physical cropland (years 850-2015), as well as mineral N fertilizer application rates (years 1900-2015), were based on LUH2v2 data by Hurtt et al. (2020b). The original data per crop group were (dis-)aggregated and remapped, using the MADRaT tool (Dietrich et al., 2020), to match the CFTs of LPJmL (Table S1.1) and the here targeted simulation unit of 0.5 degree grid cell resolution (~50 km x 50 km at the equator). In the year 2010 there were 1,502,674,969 ha total physical cropland (Fig. S1.2 for maps of physical cropland and mineral N fertilizer application rates).

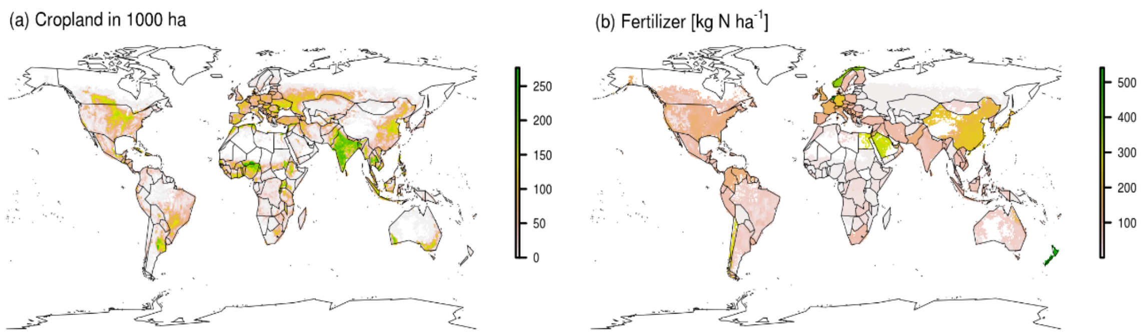

Figure S1.2 Maps depict the spatial pattern of the model input data used in the process based simulations and for post-processing model outputs: (a) Physical cropland in 1000 hectares per grid cell and (b) Mineral N fertilizer application rate in kg N ha^{-1} for the year 2010, based on LUH2v2 (Hurtt et al., 2020b) physical cropland distribution data.

Sowing date and phenological heat units were prescribed with a growing season input data set based on Portmann et al. (2010) and Sacks et al. (2010), described by Elliott et al. (2015). The historical manure input data (years 1860-2014) was based on the time series of N contained in manure applied on cropland by Zhang et al. (2017). The residue input data set (years 1850-2015) prescribed the fraction of residue biomass remaining on the field after harvest of the main crop. It was generated, by setting residue recycling shares to values per CFT-group (i.e., cereals, fibrous, non-fibrous, and others), which were obtained from (Dietrich et al., 2020) and based on national reported cropland data retrieved from FAOSTAT accounting for historical main crop residue removal rates associated to land management practices, as burning on field, as well as to secondary off-field usages, as household burning, and livestock fodder.

S1.3 Overview simulation setup for cover crop and tillage scenarios

Table S1.3 Spin-up and soil management scenario modeling protocol using LPJml5.0-tillage-cc.

Simulation step	Number of years	Start year	End year	Year restart writte n	Land use and other management	Tillage setting	Soil cover off-season cropland
1. Spin-up:							
1.1. Potential natural vegetation	7000	(-)5101	1900	1900	-	-	-
1.2. Land use	451	1511	1961	1961	static 2010	tillage	bare fallow
2. Management scenarios:							
2. 1. Baseline (REF)	50	1962	2011	-	static 2010	tillage	bare fallow
2.2. Cover crops (CC)	50	1962	2011	-	static 2010	tillage	cover crops
2.3. Cover crops with no-tillage (CCNT)	50	1962	2011	-	static 2010	no-tillage	cover crops
2.4. No-tillage (NT)	50	1962	2011	-	static 2010	no-tillage	bare fallow

S1.4 Conservation Agriculture cropland area time series data (1974-2010)

We applied a time series of the global annual CA cropland area per grid cell covering the years 1974-2010 (Fig. S1.4). This data set was obtained combining data of the historical land use and physical cropland used as model input (Sect. S1.2), field size (Fritz et al., 2015) (year ~2005), water erosion (Nachtergaele et al., 2011) (year 2000), aridity index (FAO, 2015) (averaged for years 1965-1990), Gross National Income time series (World Bank, 2017) (years 1987-2010), and national reported CA cropland area for the years 1974-2010 (FAO, 2016). Input data to this time series were recycled as static value per grid cell with considered cropland, if available only for one time slice or else adjusted for the coverage of the entire CA area reporting period, the physical cropland data, and resolution. In the case of missing national reported annual CA area values, these were interpreted as zero, if outside reporting periods, or gaps filled with the last reported value, if within. National reported Conservation Agriculture area data were downscaled to the grid scale physical cropland distribution following methods described in Porwollik et al. (2019). Historical annual shares of reported and mapped Conservation Agriculture area on global cropland rose from 0.02 % in the year 1974 to 10 % in 2010 (FAO, 2016). During this period largest increases of CA area were reported for cropland in Northern and South America, but also for Australia, New Zealand, and Kazakhstan. For Africa and Asia adoption rates of CA practices were rather low (Kassam et al., 2018; Porwollik et al., 2019; Prestele et al., 2018). This CA cropland time series data as well has been included in Herzfeld et al. (2021) and Karstens et al. (2020), quantifying soil C responses to historical land-use change dynamics and land management practices, including tillage practices and sensitivity to crop residue removal rates.

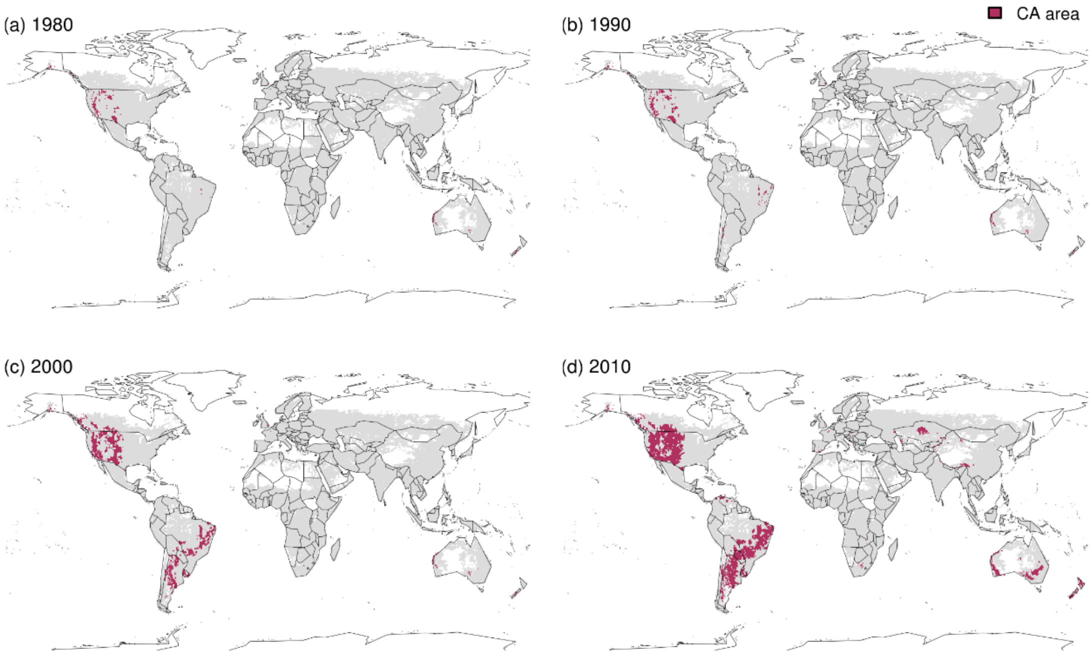

Figure S1.4 Maps (a-d) of global cropland mapped with Conservation Agriculture area (purple) and conventional tillage practices (grey) per grid cell showing time slices of the gridded time series data applied in this study for the years: 1980, 1990, 2000, and 2010, respectively, (white as no cropland).

S2 Supplementary information to management results

S2.1 Simulated responses to cover crop and tillage practices in comparison to values found in the literature

Table S2.1 Responses to cover crops (CC) in comparison to the control simulation with bare soil fallow (REF) on cropland during off-season between consecutive primary crop growing seasons, both with conventional tillage for soil C sequestration rate, as well as changes of N leaching rate and following main crop productivity in comparison to other studies' findings (see Sect. 2.3 for equations used). The time period indicated in the first column depicts the number of years since introduction of the cover crop practice as well as the management duration. The time period indicated for a value found in the literature correspond to the time frame of LPJml5.0-tillage-cc model outputs used to generate global area-weighted median (Q1, Q3) changes as provided in the second column of the table.

Time period (years)	Simulated ΔCC median (quartiles)	Literature estimate	Unit per hectare per year	Literature type	Literature source
Soil carbon sequestration rate (Eq. 1)					
12 - 50	0.55 (0.26, 0.88)	0.01-0.46	t C ha^{-1} yr^{-1}	Report	Paulsen (2020), range of annual soil C sequestration rates by CC citing Poeplau and Don (2015) and two other experimental studies' results, summarized as: 0.1 to 0.46 for topsoil (0-15 cm depth) and 0.01 to 0.32 t C ha^{-1} yr^{-1} subsoil (15-75 cm depth), originally report in kg C ha^{-1} yr^{-1}
20 - 50	0.53 (0.25, 0.84)	0.05-0.25	t C ha^{-1} yr^{-1}	Review	Lal (2004b), range of annual soil C sequestration rates by CC, value from their

Time period (years)	Simulated ΔCC median (quartiles)	Literature estimate	Unit per hectare per year	Literature type	Literature source
					Fig. 2, unit originally reported in kg C ha^{-1} yr^{-1}
25 - 50	0.52 (0.24, 0.82)	0.05-0.5	t C ha^{-1} yr^{-1}	Review	Stockmann et al. (2013), range of potential annual soil C sequestration rates by CC per climatic region based on Lal (2008), depth not indicated, also cited in Olin et al. (2015) cover crop simulation for 1.5 m soil depth stating maximum C sequestration rate in tropical humid region of 0.08 and over time diminishing to 0.01 kg C m^{-2} yr^{-1}
1 - 50	0.55 (0.22, 0.90)	0.125, 0.258, 0.515	t C ha^{-1} yr^{-1}	Simulation	Sommer and Bossio (2014), annual soil C sequestration rates for simulations of 'improved arable land management practices' for 0-25 cm depth, total potential 32-64 PgC soil C accumulation on agricultural land after 87 years of CC globally, 0.37 (0.74) PgC yr^{-1} C in their low (high) input scenarios as average annual C sequestration rates over the first 50 years, in their functions assuming 13.3 (26.2) Mg C ha^{-1} cumulative C sequestration after 87 years in their low (high) scenarios, respectively
1 - 50	0.55 (0.22, 0.90)	0.32±0.08	t C ha^{-1} yr^{-1}	Meta-analysis	Poeplau and Don (2015), value for mean ± SD annual C sequestration rate, mean total SOC stock change of 16.7 ± 1.5 Mg C ha^{-1} in the upper 22 cm soil depth for 1-54 years
1 - 50	0.55 (0.22, 0.90)	0.56	t C ha^{-1} yr^{-1}	Meta-analysis	Jian et al. (2020), value stated as mean rate of carbon sequestration from cover cropping across all studies reported originally in Mg C ha^{-1} yr^{-1}; based on 5,241 data entries from 281 published studies, no indication of duration
Change nitrogen leaching rates (Eq. 2)					
1 - 17	-46 (-68, -13)	-50 (-61, -37)	%	Meta-analysis	Thapa et al. (2018), value for CC grasses (99 % Confidence Interval (CI)), including data of Tonitto et al. (2006) below
2 - 7	-39 (-61, -8)	-50 (-60, -40)	%	Meta-analysis	Valkama et al. (2015), value as average reduced N leaching loss (95 % CI) for grasses as mainly non-leguminous CC, them also citing Quemada et al. (2013) for Southern European and USA studies meta-analysis for non-leguminous CC effect in irrigated systems as well reporting 50 % per year as annual average across experiments and durations

Time period (years)	Simulated ΔCC median (quartiles)	Literature estimate	Unit per hectare per year	Literature type	Literature source
2 - 3	-10 (-36, -1)	-70	%	Meta-analysis	Tonitto et al. (2006), values as mean, 95 % CI guessed from their Fig. 7 about -78 to -62 %
Change yield maize (Eq. 2)					
1 - 50	-0.9 (-11, 0.4)	1 (0.99, 1.02)	%	Meta-analysis	Marcillo and Miguez (2017), update of a former meta-analysis on corn yields with grass cover crops, for US and Canada, for publications on experiments between years 1965-2015 but no indication for duration found, these authors find neutral to positive effects but no significant differences, value as weighted mean (95 % CI) response ratio (yield with CC to yield without CC)
1 - 5	0 (-1, 0)	1.3-9.6	%	National statistic	SARE (2019), report with data from National Cover Crop surveys conducted annually for crop years 2012-2016 in USA, range of annual changes for corn yield with CC compared to without
Change yield soybean (Eq. 2)					
1 - 5	0 (0, 0.3)	2.8-11.6	%	National statistic	SARE (2019), report with data from National Cover Crop surveys conducted annually for crop years 2012-2016, range of annual changes for soybean yield with CC compared to without
Change average yield as mean across median changes of the four crops					
1 - 28	-2.1	-4	%	Meta-analysis	Abdalla et al. (2019), meta-analysis on CC for n=102 of total 158 for non-legumes effects
1 - 17	-2	not significantly different	%	Meta-analysis	Thapa et al. (2018), non-legumes CC effect on yields of different following main crop types, including data of Tonitto et al. (2006)
2 - 7	-1.5	-3	%	Meta-analysis	Valkama et al. (2015), for 'Nordic countries' as Denmark, Sweden Finland, Norway, on CC for spring cereals
2 - 3	-0.1	-3	%	Meta-analysis	Tonitto et al. (2006), non-legume CC effect on corn, sorghum, and vegetables experiments, USA and Canada, decline found not statistically significant

S2.2 Soil N immobilization rate and gross N mineralization rate with management duration

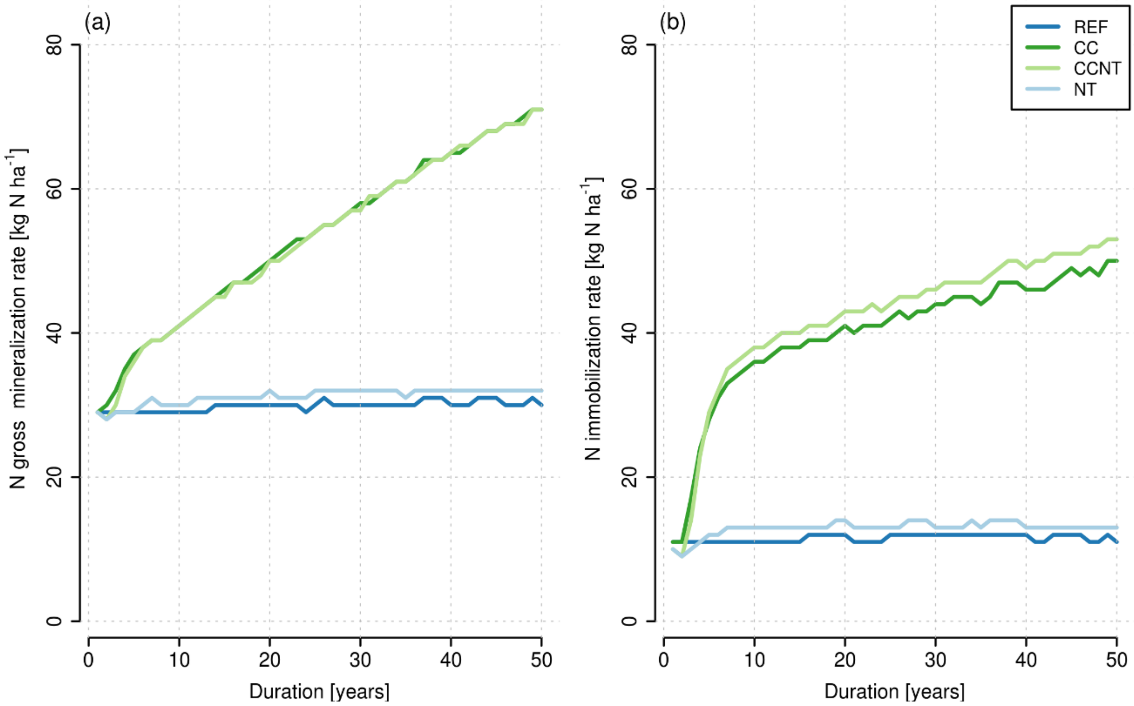

Figure SI2.2 Global annual spatial aggregated area-weighted median: (a) Gross N mineralization rates and b) N immobilization rates for global cropland soils during the 50 year simulation period as lines for each simulated management scenario (REF, CC, CCNT, and NT).

S2.3 Spatial pattern of changes in soil C and N leaching rate due to cover crop management

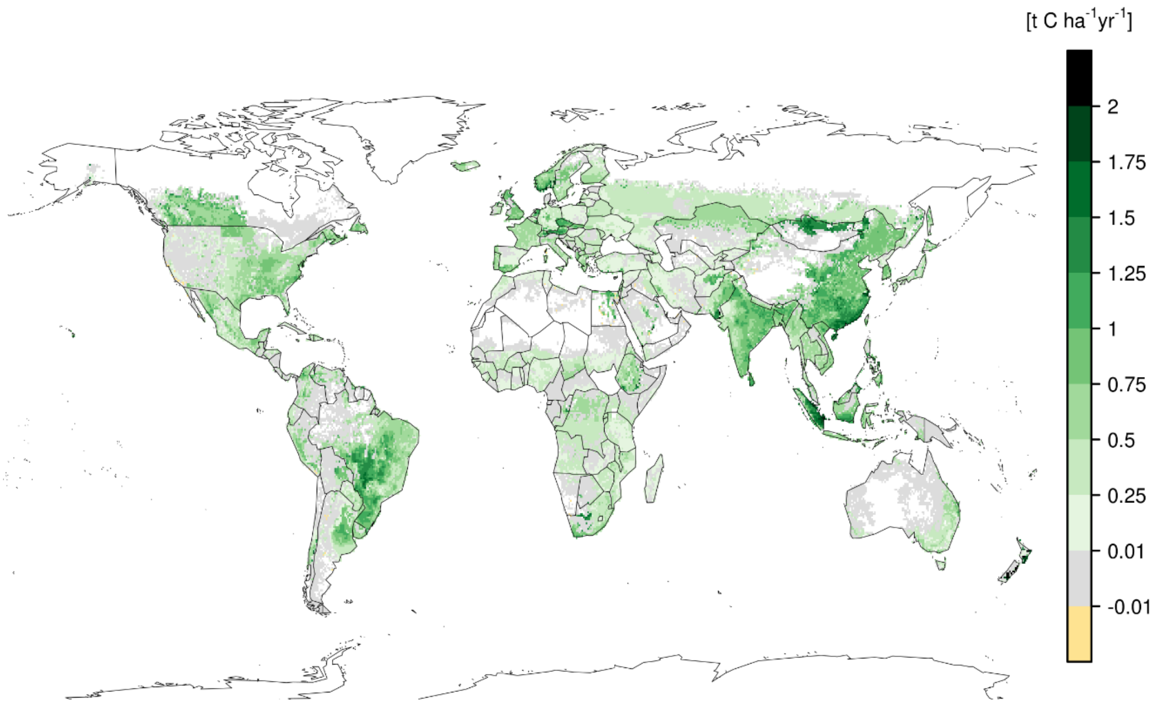

Figure S2.3.1 Map of average annual soil carbon sequestration rates in t C ha^{-1} yr^{-1} with cover crops (CC), as absolute difference to the soil carbon stock in the control with bare fallow (REF) divided by the management duration (Eq. 1), per cropland hectare and grid cell in the 50th year of the simulation period (white as no cropland).

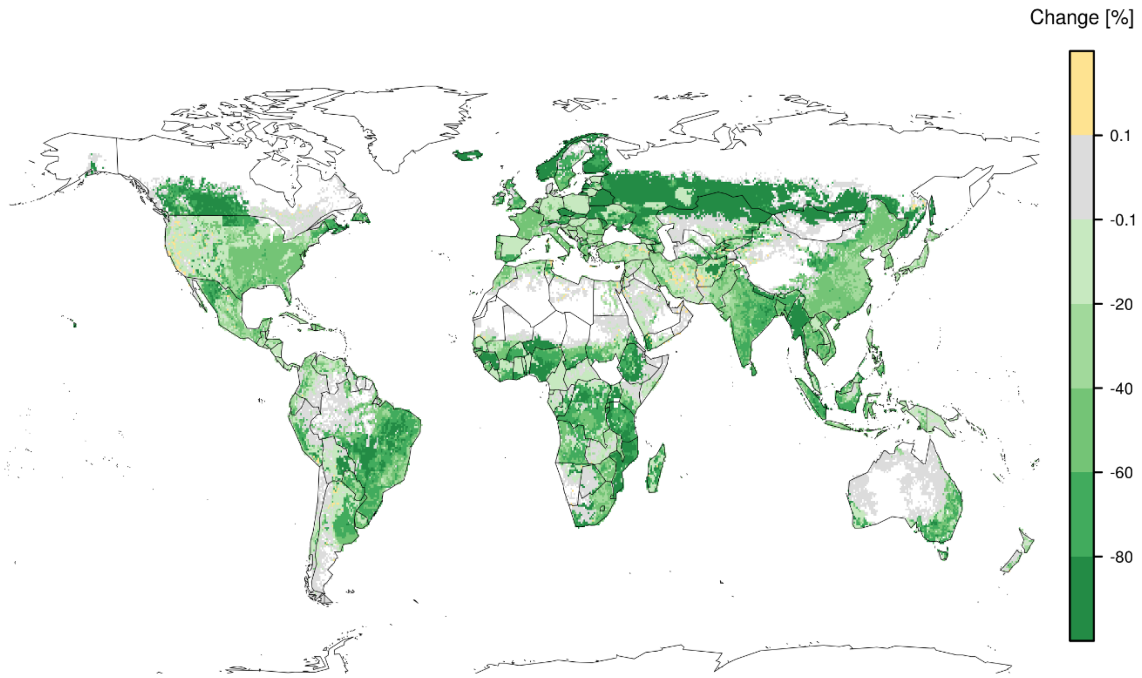

Figure S2.3.2 Map displays the changes of soil N leaching rates from cropland as annual median relative difference in percent (%) per hectare and grid cell due to cover crops (CC) relative to the control with bare fallow (REF) for the 50 year simulation period.

S2.4 Boxplots of changes for rainfed and irrigated crop productivity due to altered management

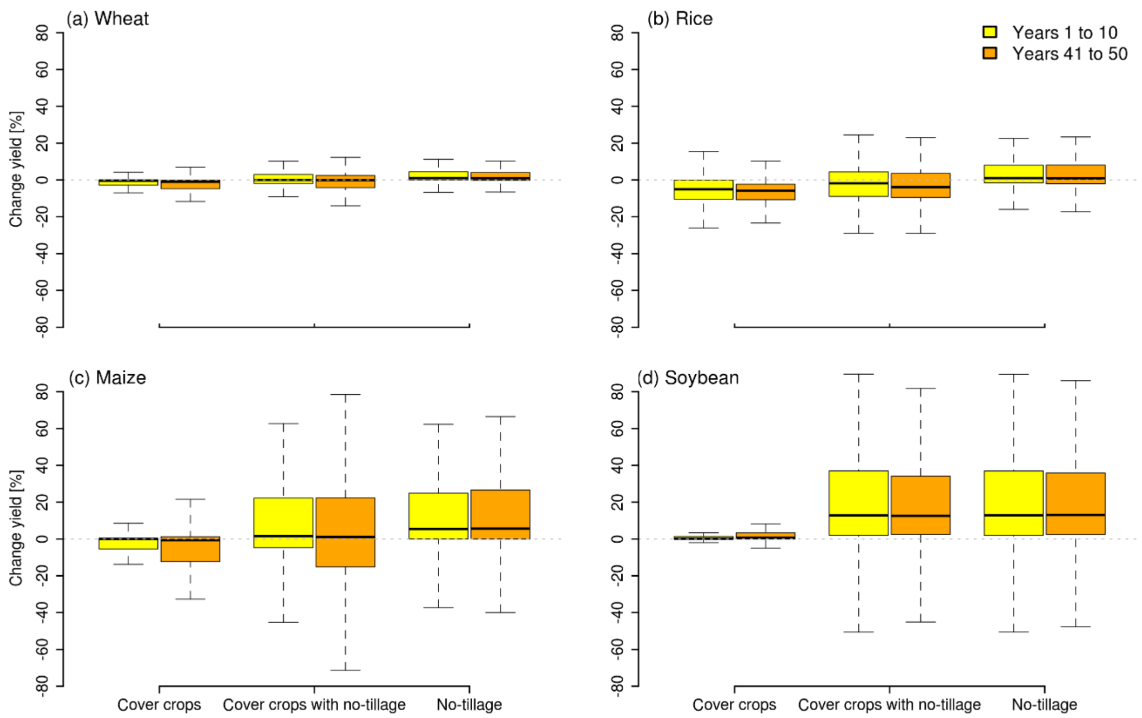

Figure S2.4.1 Panels (a-d) displaying changes in rainfed wheat, rice, maize, and soybean yield as boxplots of relative differences in percent (%) area-weighted by crop-specific physical cropland, due to alternative management practices (CC, CCNT, and NT) compared to the baseline (REF) for the first (left bars, yellow) and last decades (right bars, orange) of the 50 year simulation period. Boxes' black midlines indicate the spatial median across the distribution of responses, the lower and upper edges of the boxes the first and third quartiles, and whiskers extending both to the minimum and maximum values within 1.5 times the interquartile range, respectively from each Q1 and Q3 (outliers, defined as values outside this range are not shown here).

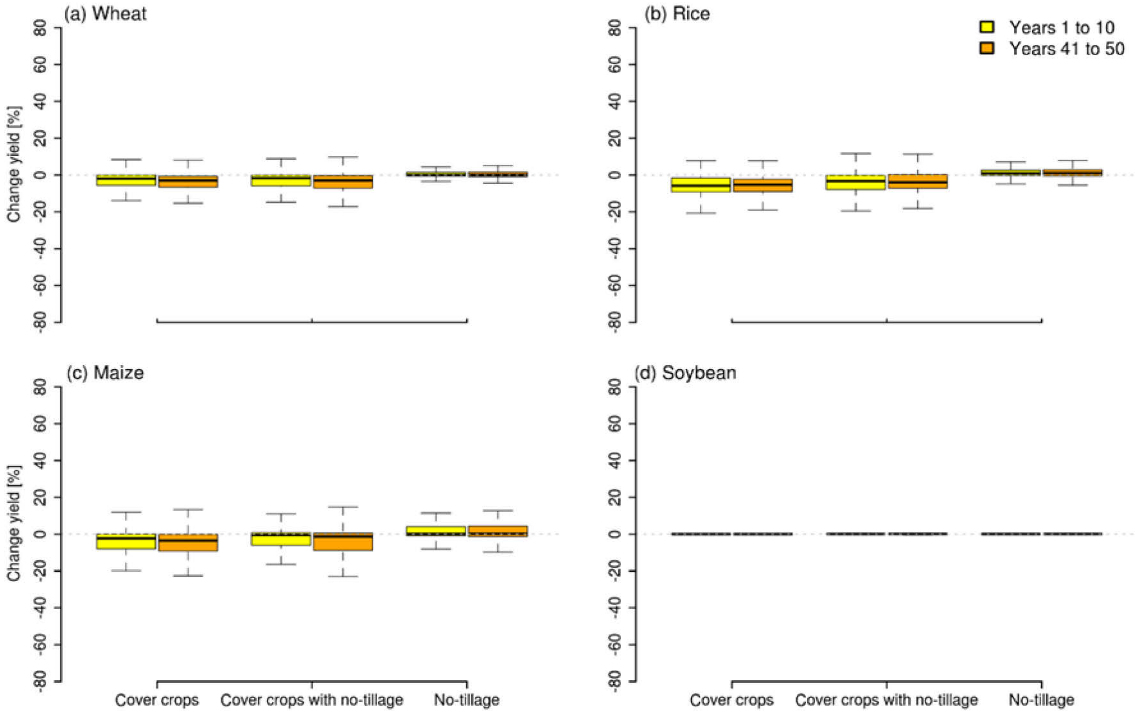

Figure S2.4.2 Panels (a-d) displaying changes in irrigated wheat, rice, maize, and soybean yield as boxplots of relative differences in percent (%) area-weighted by crop-specific physical cropland, due to alternative management practices (CC, CCNT, and NT) compared to the baseline (REF) for the first (left bars, yellow) and last decades (right bars, orange) of the 50 year simulation period. Boxes' black midlines indicate the spatial median across the distribution of responses, the lower and upper edges of the boxes the first and third quartiles, and whiskers extending both to the minimum and maximum values within 1.5 times the interquartile range, respectively from each Q1 and Q3 (outliers, defined as values outside this range are not shown here). Irrigated shares of total global crop type specific physical cropland area were 16 % for wheat, 12 % for maize, 35 % for rice, and 11 % for soybean based on land use model input data described in Sect. S1.2.

S2.5 Spatial pattern of productivity changes due to cover crop practices combined with no-tillage

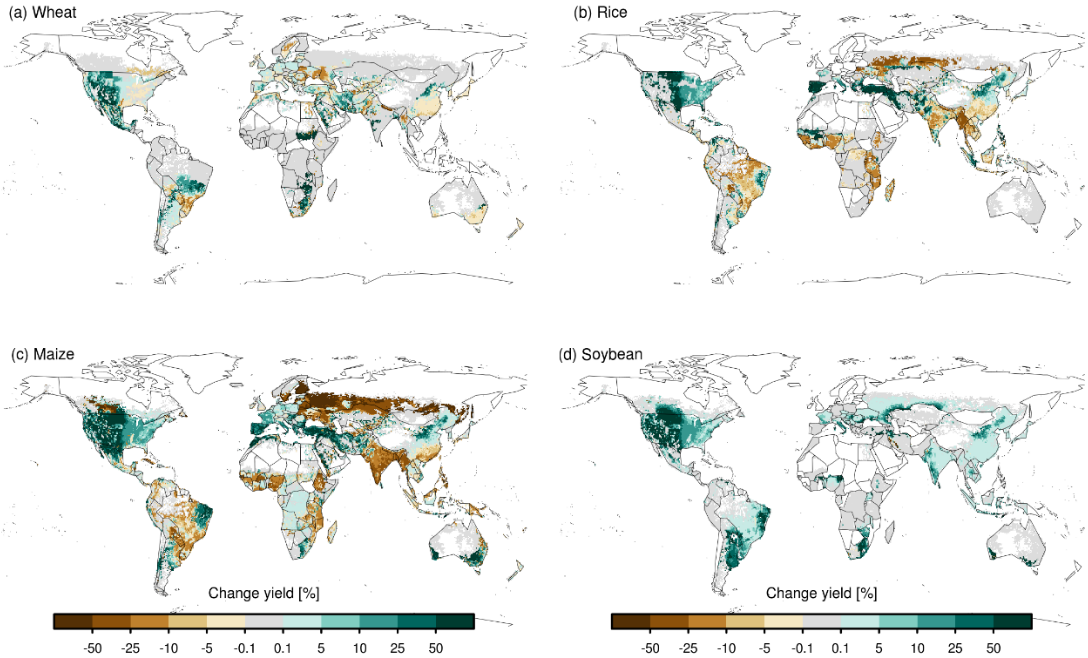

Figure S2.5 Maps showing changes of crop productivity in response to cover crop practices combined with no-tillage (CCNT) compared to the baseline with conventional tillage and bare fallow on cropland area during main crop off-season periods (REF) as annual median relative differences in percent (%) per hectare of crop-specific cropland area and grid cell of the year 2010 for: (a) Wheat, (b) rice, (c) maize, and (d) soybean for the 50 year simulation period.

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Declaration

I herewith confirm, myself to be the lead author of each of the chapters included in this thesis with details of contribution from myself and co-authors as formulated in the sections of the respective research articles of Chapter 2-4. Further I declare that I prepared the rest of the work independently by myself, using only the sources and materials as indicated in the thesis' text.

Berlin, Vera Porwollik