The impact of water erosion and climate change on global cereal yields

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Declaration of ownership

I, Tony Carr, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Tony Carr

List of Publications

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Abstract

Water erosion can degrade soils and reduce agricultural productivity. Global modelling studies are increasingly used to explore the potential impacts of environmental change, especially climate change, on crop yields. Despite its impact on crops and its direct link to the climate system, water erosion has not previously been considered in projections of the impacts of climate change on global crop yields. Similarly, global water erosion assessments have not considered how water erosion affects crops, and vice versa. This thesis identifies a method to estimate global water erosion patterns and evaluates it using a global database of erosion measurements. It then examines the global potential impacts of erosion on maize and wheat yields, and explores how these might be affected by climate change in the future.

The Environmental Policy Integrated Climate (EPIC) crop model is used with global datasets on soil, topography, climate and field management to estimate erosion and its impacts on crop yields. Estimates using weather data for the years 1980–2010 suggest that water erosion reduced maize and wheat yields by 3% annually in around half of global arable land under current land management regimes. The estimated annual maize and wheat production losses due to water erosion accounted for less than 1% of the global production volume. However, water erosion in maize and wheat fields at low latitudes is likely to increase in the future due to the adverse effects of climate change on both crops.

Uncertainties remain about estimates of water erosion that need to be addressed through better integration of models and observations. Nevertheless, the integrated biophysical modelling framework developed in this study can provide a link between robust estimates of water erosion, economics, and policy making that have so far been lacking in global agricultural assessments.

Impact statement

It is necessary to improve the quality of indicators on the health of soil resources and to quantify the current and future impacts of water erosion in agriculture in physical and economic terms (Montanarella, 2007; Montanarella et al., 2016; Nkonya et al., 2011). Although water erosion is considered in numerous agricultural and environmental policy programs (Alewell et al., 2019), soil information available for policy formulation is frequently based on studies from the 1990s based on observations made in the 1980s or earlier (Montanarella et al., 2016).

Global gridded crop models (GGCMs), typically combinations of crop or ecosystem models and global gridded input data infrastructures, have become essential tools for analysing global phenomena, most notably climate change, that affect agriculture and ecosystems (Mueller et al., 2017). GGCMs have the capacity to develop large-scale indicators and to inform about agricultural productivity in a transparent and consistent way across large areas (Mueller et al., 2017). Although water erosion plays an important part in the productivity of cropland and the impact of agriculture on the environment, it is frequently neglected in commonly used GGCMs. Moreover, integrated assessment modelling studies that aim to assess environmental problems in a holistic way by linking social, economic, and environmental considerations (Laniak et al., 2013) require data on water erosion impacts on agricultural production (Porwollik et al., 2019).

The GGCM EPIC-IIASA is used to address the gaps in the literature regarding the links between water erosion and crop cultivation in various large-scale and global modelling studies to provide insights into the impact of water erosion in current and future agricultural environments. EPIC-IIASA has been confirmed as a reliable tool for global crop yield projections and stands out against comparable global crop models due to its detailed representation of soil processes including water erosion (Folberth et al., 2019; Balkovič et al., 2014).

By simulating the interactions between crops and water erosion on a global scale, EPIC-IIASA can provide much-needed indicators on the effects of water erosion on soil quality and productivity, and analyse patterns of water erosion in response to field management and environmental drivers. Moreover, by analysing the robustness of global water erosion estimates across different environments, this study addresses concerns about the uncertainty of large-scale and global water erosion estimates (Evans and Boardman, 2016b,a). Transparency of the robustness and uncertainty of model outputs is especially important if they are intended to inform policy programs (Panagos et al., 2016).

Finally, this study contributes to a better understanding of potential future pathways of global cereal production by analysing the combined impact of water erosion and climate change on maize and wheat yields. Although climate change and water erosion may affect farmers simultaneously, and in combination can multiply pressures on crops, they are often studied separately (Webb et al., 2017). Both climate change and water erosion impacts on crop production are spread unevenly around the globe. Therefore, research on both environmental change topics together will help identify hotspots where maize and wheat production are at risk from both climate change and water erosion, and thus increase knowledge of regional differences in the resilience of future crop production.

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List of Abbreviations

- AGMIP: Agricultural Model Intercomparison and Improvement Project
- C: Carbon
- CAP: Common Agricultural Policy
- CN: Curve Number
- DEM: Digital Elevation Model
- EPIC: Environmental Policy Integrated Climate Model
- FAO: Food and Agriculture Organization of the United Nations
- GCM: General Circulation Model
- GGCM: Global Gridded Crop Model
- GLADIS: Global Land Degradation Information System
- GLASOD: Global Assessment of Human-induced Soil Degradation
- IIASA: International Institute for Applied Systems Analysis
- IPBES: Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
- IPCC: Intergovernmental Panel on Climate Change
- ISI-MIP: Inter-Sectoral Impact Model Intercomparison Project
- ISRIC: World Soil Information Center
- ITPS: Intergovernmental Technical Panel on Soils
- LDN: Land Degradation Neutrality
- MUSLE: Modified Universal Soil Loss Equation
- N: Nitrogen
- P: Phosphorous

- RCP: Representative Concentration Pathway
- RUSLE: Revised Universal Soil Loss Equation
- SDG: Sustainable Development Goals
- SOM: Soil Organic Matter
- UNCCD: United Nations Convention to Combat Desertification
- UNEP: United Nations Environment Programme
- USDA: United States Department of Agriculture
- USLE: Universal Soil Loss Equation

Chapter 1

Introduction

1.1 The pressure on soil resources through the intensification of agriculture

Soil is one of the most important natural resources and essential for agriculture. A healthy soil is crucial for providing nutrients and water to crops. However, soil resources have become increasingly under pressure by the intensification of agriculture. The overuse of soil or land can lead to its degradation and reduces its value for agriculture. Between the 1960s and 2010s, global cereal production nearly tripled (Figure 1.1a). To sustain the productivity of soil during the ongoing intensification of grain cultivation, fertiliser use increased in a similar rate in the second half of the 20th century (Figure 1.1b). The intensification of cereal production in past decades triggered by improved crop varieties, irrigation technology, heavy machinery and increasing use of fertiliser, herbicides and pesticides resulted in major environmental impacts negatively affecting biodiversity, water and soil resources (Tilman et al., 2001; Vitousek et al., 1997).

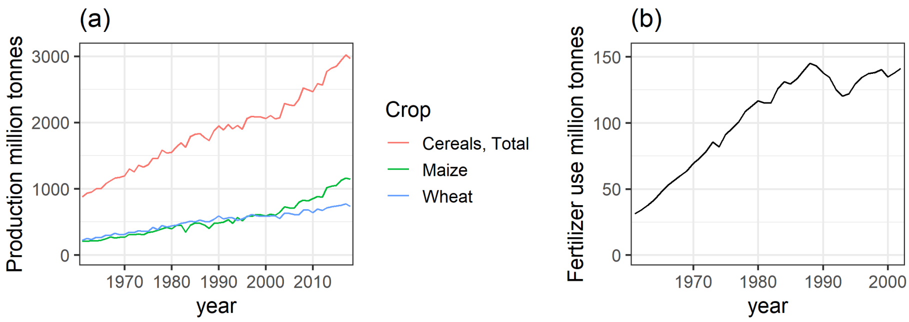

Figure 1.1: (a) Increase in global maize, wheat and total cereal production between the years 1961–2018 (FAO, 2020). (b) Increase in global fertiliser use between the years 1961-2002 (FAO, 2020).

The intensification of agriculture allowed for an enormous growth in global population, which increased from 2.5 billion in 1950 to 7.8 billion in 2020 (UN, 2020). The raising population in turn resulted in a raising demand in food and forage leading to further intensification of agriculture and pressure on soil resources. This development was accompanied by economic growth leading to a rise in per capita food consumption. Forecasts for the year 2050 predict that the global population will grow to 9.7 billion, the world GDP will be 2.5-fold and per capita income 1.8-fold compared to the year 2012 (Melorose et al., 2015; Alexandratos and Bruinsma, 2012). The *United Nations Food and Agriculture Organization* (FAO) estimates an increase in food production of about 40 - 53% by 2050 compared to 2012, with major differences across regions (FAO, 2018). Whilst future agricultural supply is driven by many factors such as consumer preferences, intensification of agricultural production, expansion of agricultural land, food loss and waste; regional differences are largely driven by the uneven spread of population growth (Valin et al., 2014). Consequently, the increasing pressure on agriculture and soil will vary strongly around the world. Most of the regions where population growth continues to be fast are those with inadequate food consumption and high levels of undernourishment (Gerland et al., 2014). Parts of the regions with a projected high growth in food demand already have low levels of agricultural productivity due to infertile soils (Montanarella et al., 2016).

1.2 Land degradation

Although soil degradation is estimated to have been ongoing for at least 12,000 years, it increased exponentially in the last 200 years (Sanderman et al., 2017). Before the invention of synthetic fertiliser in the early 20th century, it was common practice among farmers to maintain the fertility of soils by returning nutrients through crop residues and manure and preventing soil erosion. Traces of ancient farming systems, which were sustainable for hundreds and even thousands of years, can be found on all continents (Olsson et al., 2019). In modern agriculture, farming practices to maintain the natural fertility of soils have become less common as the increasing availability of artificial fertiliser allows to replenish depleted soil nutrients (Erisman et al., 2008). However, availability of fertiliser is spread unevenly around the globe. The depletion of soil nutrients in sub-Saharan Africa due to decades of farming without adequate fertiliser and manure is a primary factor limiting current food production (Sánchez, 2010; Folberth et al., 2013). Whilst access to fertiliser is an important requirement for the intensification of agriculture, leaching and runoff of excess fertiliser cause various negative impacts around cropland, which is a common cause of deteriorating environmental quality in developed regions (Montanarella et al., 2016). Moreover, despite the possibilities to replenish soil nutrients, increasing field management intensity is associated with deterioration in important soil properties and supporting ecosystem services (Squire et al., 2015).

The threat of land degradation for both humans and the environment has been recognised by many governments and international organizations. According to the *Science-Policy Platform on Biodiversity and Ecosystem Services* (IPBES) land degradation has negative impacts on at least 3.2 billion people worldwide leading to various socio-economic implications, such as migration, and the situation is expected to worsen due to climate change (Montanarella et al., 2018). Land degradation is addressed in the *Sustainable Development Goals* (SDGs), which is a roadmap by the *United Nations* (UN) to move towards a more sustainable use of the planet's resources (Keesstra et al., 2018). Goal 15 is of direct relevance to land degradation, with the objective to protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification and halt and reverse land degradation and halt biodiversity loss (Olsson et al., 2019). SDG 15.3 addresses *Land Degradation Neutrality* (LDN), which is related to land restoration and halting land degradation. The concept of LDN was introduced by the *United Nations Convention to Combat Desertification* (UNCCD) and is defined as '*a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems*' (Cowie et al., 2018). Pursuit of LDN requires effort to avoid further net loss of the land-based natural capital relative to a reference state, or baseline (Olsson et al., 2019). To reduce land degradation on arable land, several policy programs encourage sustainable land management practices. The EU's *Common Agricultural Policy* (CAP) ties agricultural subsidies to implementation of best management practices and environmental protection, for example, by providing crop insurance for lower fertiliser application rates (Smith et al., 2016). The post-2020 CAP includes as one of its main objectives efficient soil management, combined with measures to reduce soil erosion and increase soil organic carbon in European agricultural soils (Sartori et al., 2019). In the USA, the Farm Bill extends soil conservation compliance requirements in order to qualify for crop insurance subsidy (Islam and Reeder, 2014). Other examples include the USA's *Conservation Reserve Program* (set aside marginal lands, steep slopes); China's *Conservation Tillage Program*; and several policies in Africa for integrated land management to help protect vulnerable soils (Smith et al., 2016).

1.3 Land degradation by water erosion

Whilst many land degradation processes influence agriculture, water erosion is widely considered as the most serious threat to global soil resources on arable land and agricultural productivity (Den Biggelaar et al., 2004a; FAO and ITPS, 2015; Kaiser, 2004; Panagos et al., 2018; UNCCD, 2017).

Water erosion and wind erosion are combined under the term soil erosion, which describes the removal, transport and deposition of soil particles by water or wind from their original location to another site. As such, soil erosion impacts the residence time, flux rates, storage and distribution of important elements in soils that sustain the life-support system of the Earth, including carbon (C), nitrogen (N) and phosphorus (P) (Cherlet et al., 2018). The removal of topsoil can reduce crop yields due to the loss of nutrients in the topsoil, degradation of the soil structure, and decreasing plant-available water capacity (Våje et al., 2005). Soil erosion does not only affect the productivity of agriculture but also leads to negative off-site effects. The runoff of nutrients, pesticides and organic carbon, which are included in the topsoil, leads to the pollution of surface waters, eutrophication and the emission of greenhouse gases (Chappell et al., 2016; Ravishankara et al., 2009; Tilman et al., 2001; Vitousek et al., 1997). Other off-site effects caused by sediment runoff are the increased sedimentation of lakes and rivers affecting fisheries, wildlife habitats and biodiversity, increased risk of flooding, damage of recreational activities, and destruction of infrastructure such as roads, railways, waterways and harbours (Clark, 1985; Pimentel et al., 1995; Telles et al., 2011).

The soil degradation assessment in the GLASOD project showed that the vast majority of global soil degradation originated from soil erosion through wind and water (Oldeman et al., 1991). The latter has been shown to be responsible for more than half of the world's soil degradation. In the report on the *Status of the World's Soil Resources*, water erosion was named along the loss of organic carbon and nutrient imbalances as the most severe threat to soil resources (FAO and ITPS, 2015). In the *Guidelines for Sustainable Soil Management*, soil erosion is named as the most significant threat to global soils and the ecosystems services they provide (FAO, 2017). The threat of soil erosion for society has been recognised by many policy-makers and thus soil erosion is specifically addressed in several environmental and agricultural policy programs addressing land degradation (Alewell et al., 2019; Panagos et al., 2018; Sartori et al., 2019).

Regions most vulnerable to water erosion are mountain regions, due to steep slopes, the tropics and subtropics, due to abundant high energy precipitation, and arid regions, where precipitation events are rare but often intense and the vegetation cover is sparse. Due to their environmental characteristics, South America, sub-Saharan Africa, South and East Asia have been identified as the most vulnerable regions to erosion on agricultural land by several prior studies (Borrelli et al., 2017; Pimentel et al., 1995).

Water erosion is a natural process, but agricultural intensification and expansion accelerates water erosion dramatically. It has been estimated that agricultural activities are responsible for 75% of global soil erosion (Pimentel, 2006). In several regions worldwide, agricultural expansion due to population pressures and increasing demands for food and fodder led to the cultivation of marginal land susceptible to water erosion (Turkelboom et al., 2008; Willcocks and Twomlow, 1993) or soils prone to degradation (Wildemeersch et al., 2015). Although regional examples have also shown that increases in crop production due to rising population do not necessarily lead to more soil erosion if the land is managed sustainably (Tiffen et al., 1994), recent estimates suggest that the area of water erosion has increased due to deforestation and expansion of cropland (Borrelli et al., 2017). However, its actual extent and impact on crop production and environmental quality is highly uncertain.

1.4 Processes leading to water erosion

Water erosion is controlled by factors influencing the detachment and the transport of soil particles including rainfall and water runoff, soil properties, topography and land use. Soil runoff due to water erosion is initiated as soon as the velocity of water flow is big enough to reach the energy for the detachment of soil material. Subsequently, the dislodged material is transported to another location. During strong rainfall events the detachment of soil material through the energy of raindrops and the dispersion of disintegrated soil particles can also cause sealing and crusting of the topsoil (Oldeman, 1994).

Soil runoff due to water erosion can be divided into different stages depending on its severity, according to Roose (1996): The initial phase of water erosion is called sheet erosion, which describes the evenly distributed removal of thin layers of the topsoil by overland flow or raindrop impact. However, sheet erosion is hardly detectable on a yearly basis, since other processes such as the respiration of swelling clay soil from rewetting or land management practices like tillage can have a higher impact on annual variability of topsoil depth. Nevertheless, annual repetition of sheet erosion can contribute to the removal of most of the surface horizon in a few decades. With ongoing runoff, sheet erosion can combine with more concentrated water flow along rills and grooves and lead to linear erosion of the topsoil, which results into the removal of several cm of the topsoil. The formation of rills is controlled by the cohesive strength of the soil and the shear forces exerted on the soil (Merritt et al., 2003). If the shear stress in a rill is high enough water flow within a rill may detach significant amounts of soil. Concentrated linear water erosion can lead to the formation of gullies, which increase the loss of soil up to more than 50 cm. In contrast to rill erosion, the deep channels caused by gully erosion cannot be obliterated by cultivation (Merritt et al., 2003).

The properties of the soil material determine the susceptibility of the soil to water erosion. The different sizes and weight of soil particles lead to a selective removal of soil material through water (Roose, 1996). As a result, erosion can lead to skeletonization of the soil surface as light material such as organic matter is removed, whereas heavier material such as sand and gravel is left behind. The selection process by water flow was described by Hjulstrom (1935), who studied the impact of water flow velocity and soil grain diameter on deposition, transport and erosion of soil material. With increasing diameter of the soil particle its weight increases, and thus more water flow velocity is necessary to gain the energy for the deposition and transport of the soil particle. Hence, coarse material such as gravel is less fragile to erosion than lighter material like fine sand. However, some material even lighter than sand such as clay is less susceptible to removal through water and erosion due to its cohesive forces. Cohesive soil materials have the properties to stick together and thus more energy is needed to detach them from the surface.

Another important property of soils is their infiltration capacity, which is determined by the density of soil particles and the available pore space. With increasing infiltration, the amount of water on the soil surface will be reduced resulting into less runoff. Thus, runoff will increase on soils, which are very dense on the surface and subsequently more erosion can occur (Favis-Mortlock and Mullan, 2011). The density of the soil surface can be modified by unsustainable land management with the use of heavy machinery or high livestock density.

The slope gradient of a field is a key driver for the transformation of rainfall into runoff and thus water erosion (García-Ruiz et al., 2015). With increasing slope steepness, the infiltration rate of the soil decreases, which increases the amount of water runoff. In addition, increasing slope steepness increases the volume and speed of water runoff. Similarly, the length of a slope determines volume and speed of water runoff, but relationships between slope length and runoff energy and capacity can be variable. Although common empirical erosion models suggest an increase in erosion with increasing slope length (Liu et al., 2000), experiments found that shortening slope length does not always reduce soil loss as soil properties and field management can alter the length effect on soil loss (Bagarello and Ferro, 2010; Loch, 1996).

Soil surface roughness and soil cover through vegetation and organic matter have a strong impact on water erosion. A protective layer of plants and organic matter can protect bare soils from incoming rainfall and thus reduce erosion. Moreover, a dense vegetation cover can reduce water erosion by increasing the soils' infiltration capacity (Istanbulluoglu and Bras, 2006). In addition, soil coverage increases the surface roughness and thus reduces water runoff. The latter can be also influenced through tillage management. Generally, the impact of soil roughness and cover on water erosion on cropland is largely determined by field management.

1.5 The impact of agriculture on water erosion

Naturally, the susceptibility of soil to water erosion depends on the degree of its exposure to water energy. Agriculture commonly increases the exposure of soil to water energy due to a decline in the natural vegetation cover. Other forms of land degradation caused by agriculture, such as soil compaction due to intensive land use by heavy machinery or high livestock density, can exacerbate the erosion process (Fleige and Horn, 2000). Due to the influence of humans on vegetation cover, soil roughness and soil permeability, the exposure of soil to water energy has increased in many areas. A review of soil removal rates from different landscapes illustrates that highest erosion rates are found on arable land (Montgomery, 2007). The same study also found substantially lower erosion rates in fields where soil conservation methods are applied in comparison to conventionally managed fields.

Land use decisions by farmers can both increase and decrease the degree of water erosion. More specifically, the control of soil cover and topsoil characteristics through crop, residue and tillage management enables farmers to influence the exposure of soil to water erosion. Usually, when growing row crops such as maize and soybeans, the soil surface between the crop rows is bare, which increases the vulnerability of soil to water energy (Kort et al., 1998). Monocultures often leave the soil bare during fallow periods in the winter or in the spring before the vegetation cover of crops is dense enough to protect the soil from incoming rain. Moreover, organic matter, which stabilises the soil structure, is usually low in intensive cultivated fields as heavy fertiliser use reduces its significance to sustain soil fertility (Corsi et al., 2012). Bare soils in general are very susceptible to water energy and should be avoided on croplands vulnerable to water erosion. During the fallow period cover crops such as grasses or legumes can be planted to add protection to the soil, and to fixate nutrients and sequester carbon (Alvarez et al., 2017; Corsi et al., 2012; Poeplau and Don, 2015). Furthermore, row crops can be combined with strips of other crops or weeds in order to increase the density of the vegetation cover and thus prevent erosion (Claassen et al., 2018).

Tillage refers to the mechanical treatment of the soil in order to prepare the land for growing crops, which affects the soil characteristics such as soil moisture, soil temperature, infiltration and evapotranspiration processes (Busari et al., 2015). Tillage can be performed in different ways depending on how intensive the topsoil is manipulated. Conventional tillage is the most intensive form of soil disturbance using agricultural machinery such as harrows and ploughs in order to mix harvest residues, organic matter and nutrients in the topsoil and break down soil aggregates to prepare the seedbed for crop planting (Claassen et al., 2018). Intensive tillage can accelerate erosion by breaking down soil aggregates through heavy machinery, which decreases the robustness of the soil (Zheng et al., 2018). In the mid-20th century, awareness that conventional tillage methods accelerate erosion increased and thus reduced tillage and no-tillage methods were tested in agriculture (Montgomery, 2007). With reduced tillage strategies, often more harvest residues are left on the field, which increases the surface roughness and thus slows water flow and soil erosion. The lower exposure of soils, as a result of more residues left on the field, reduces the susceptibility of the topsoil to erosion (Sharratt et al., 2015). In addition, retention of crop residue protects the soil from direct impact of raindrops and sunlight (Busari et al., 2015). Furthermore, the lower the depth of tillage the less the soil becomes disturbed, which can help to preserve and enhance the soils productivity or even restore previously lost productivity of the soil (Corsi et al., 2012). Moreover, the minimisation of soil disturbance enhances soil biological activities, soil air and water movement (Busari et al., 2015).

As outlined in the previous chapter, environmental characteristics of a field such as soil properties and topography are important factors for the susceptibility of arable land to water erosion. Farmers can alter relevant field characteristics and thus influence water erosion. In hilly landscapes, adaptation measures to reduce the effect of slopes steepness on water erosion can be critical to maintain agricultural productivity. The most effective anti-erosion measure on slopes is terrace farming, which is the practice of creating steps of flat areas in hilly landscapes in order to prevent water runoff (Chen et al., 2020). Another often used anti-erosion measure on hilly cropland is ploughing along the contours of the slope to break the water flow and thus decrease erosion (Zhang et al., 2004).

1.6 The impact of water erosion on crop productivity

Water erosion affects a variety of soil functions relevant for crop growth such as nutrient levels, pH, water-holding capacity, texture, infiltration rates and soil organic matter (den Biggelaar et al., 2001). The most frequently reported causes of yield reductions as a result of water erosion are (i) nutrient deficit, (ii) water deficit, and (iii) the reduction of soil depth leading to a limitation of root growth by a clayey subsoil or by a pan or bedrock (Bakker et al., 2004).

The impact of erosion on root growth and crop yields increases with progressing erosion as root growth becomes increasingly more difficult for the plant. Thus, erosion may not affect crop yields until an advanced degradation of the soil layer, when continuous soil loss has reduced the soil depth to such an extent that the development of the root system becomes restricted. Therefore, in some cases the impact of erosion on crop yields may increase over time with equal erosion rates (Bakker et al., 2004).

Water deficits due to erosion are most likely during droughts. Water availability for crops is affected by (i) reduced soil water storage capacity due to decreased soil depth, (ii) reduced soil water holding capacity due to loss of soil organic matter and soil structure, and (iii) reduced soil moisture availability due to the transport of clayey soil material to the surface (Bakker et al., 2004).

Important plant nutrients such as nitrogen, phosphorus and potassium are most abundant in the topsoil and thus are susceptible to surface runoff. Organic matter is an important natural component for soil fertility, which can be found in a high concentration near the soil surface in form of decaying leaves and stems. The high susceptibility of soil organic matter availability by soil erosion is demonstrated by studies, which show that removed soil through wind and water is richer in organic matter than the soil left behind (Pimentel et al., 1995; Lal, 2002). As eroded soil is often deposited at another field site, soil is often not lost but moved from one part of the landscape to another (Duan et al., 2016). However, the deposition of clay on the topsoil due to erosion can also lead to a reduced nutrient availability as clay particles absorb nutrients (Bakker et al., 2004).

Soil nutrients lost through erosion can be replaced by nutrients from synthetic or organic fertiliser. Thus, the amount of fertiliser applied to a field influences the impact of water erosion on crop yields. One study demonstrates that soils with severe erosion may produce 15-30% lower maize yields than uneroded soils, whereas the reduction ranges from 13 to 19% with fertilisation (Pimentel et al., 1995). Moreover, the timing of fertiliser application in respect to plant growth stages or rainfall events can be important in the reduction of water erosion impacts (Luo et al., 2020). The replacement of soil nutrients with fertiliser can lead to significant economic and environmental costs.

1.7 The impact of climate change on water erosion

Whilst many studies focus on the impact of climate change on crops, the impacts of climate change on soil resources are hardly explored (Montanarella et al., 2016). In a recent special report on *Climate Change and Land* by *The Intergovernmental Panel on Climate Change* (IPCC), the authors stated that "*climate change exacerbates the rate and magnitude of several ongoing land degradation processes and introduces new degradation patterns (high confidence)*" (Olsson et al., 2019). Water erosion was named as one of the land degradation processes most directly linked to climate change due to a projected increased frequency, intensity and/or amount of heavy precipitation. In addition, changes in vegetation cover and soil properties due to climate change may increase the risk of water erosion (Li and Fang, 2016). Consequently, the loss of soil productivity through water erosion and other land degradation processes in combination with climate change can multiply threats for natural resource-based livelihoods (Webb et al., 2017).

The impact of climate change on water erosion is the result of a complex web of relationships between climate, biomass, soil resources and the way farmers manage their fields (Figure 1.2). Direct climate change impacts on water erosion are mainly determined by changes in precipitation amount and intensity (Li and Fang, 2016; Nearing et al., 2004). Increasing rainfall amounts can lead to an increase in soil moisture and saturation of the soil generating more water runoff and soil loss. Excess runoff due to soil saturation is common after a long period of low-intensity rainfall, which is often the case in

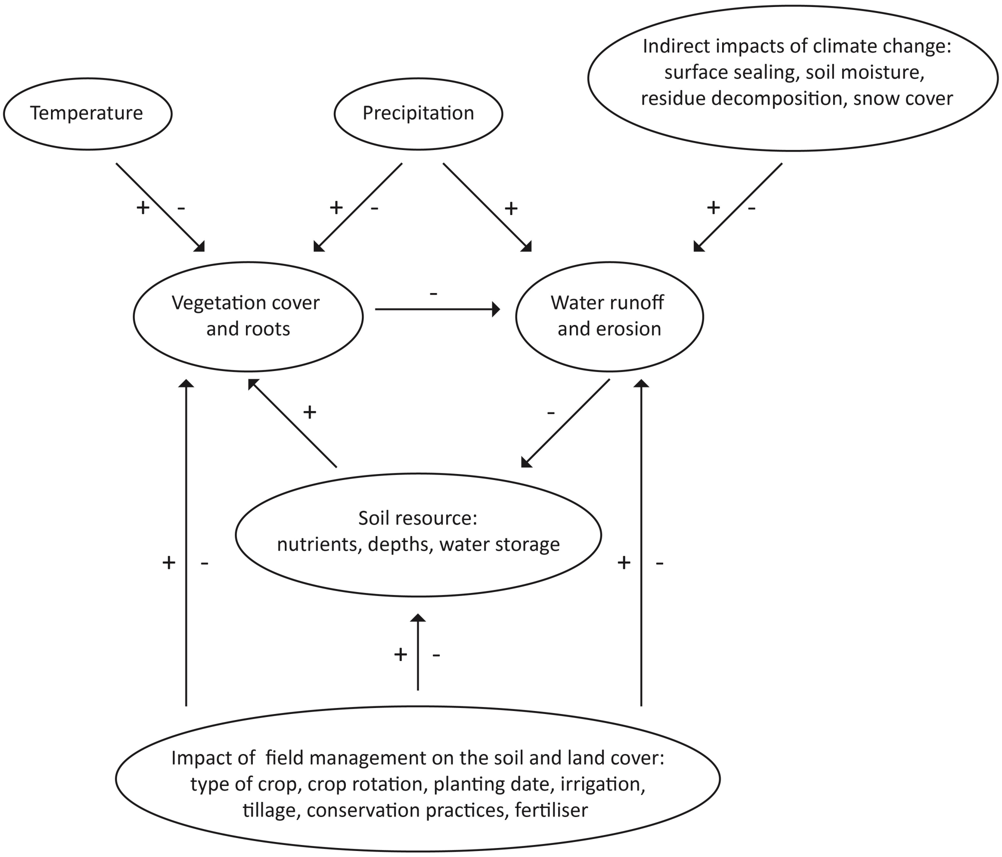

Figure 1.2: The main links between climate change, erosion, crops and field management. The diagram illustrates how climate change affects the interactions between crops and water erosion, and what opportunities farmers have to influence these relationships. The plus and minus signs indicate a positive or negative correlation between the respective components.

humid areas (Smith and Goodrich, 2006). Additional soil removal in saturated soils can be caused by subsurface runoff transporting soil particles underground (Li and Fang, 2016).

Changes in rainfall intensity generally affect rainfall energy during storm events, which directly affects the detachment of soil particles via the impact of raindrops (Van Dijk et al., 2002). Moreover, highly intense rainfall often exceeds the soils infiltration capacity and thus can cause excess runoff and a much greater transport of suspended sediment load (Mohamadi and Kavian, 2015). These events are most common in semi-arid and sub-humid zones and were observed in Beijing, the Mediterranean, Iran, France, and Western USA (Li and Fang, 2016). As changes in rainfall amount and rainfall intensity have different effects on soils, changes in the degree of both parameters together are likely to have a greater impact than changes in both separately (Nearing et al., 2004).

Rainfall also influences water erosion indirectly by controlling the availability of water supply for plants and thus the development and distribution of the soil's vegetation cover. Other indirect impacts of precipitation on water erosion are linked to the impact of land use on water erosion, which can be affected through spatio-temporal shifts in precipitation, which may influence planting dates and the length of the growing season. The timing of rainfall events also may have significant impacts on changes in wetting and drying of soils and thus their infiltration capacity affecting water erosion (Lado et al., 2004). Shifts in precipitation patterns can also directly affect water erosion if stronger precipitation is occurring at the beginning of the growing season or winter season, in which soils are less protected by dense vegetation covers (O'Neal et al., 2005; Leek and Olsen, 2000; Mullan et al., 2012).

The indirect impact of climate change on water erosion through changes in the protective vegetation cover are strongly influenced by temperature changes and water availability for plants. Projected temperature changes can both increase and decrease the vegetation cover and thus influence water erosion rates positively and negatively (O'Neal et al., 2005). Moreover, higher temperature can also reduce the time soils are protected through crop residues, by increasing microbial activity and their decomposition rates, which can be further accelerated by increases in soil moisture (Nearing et al., 2004). Higher temperatures can reduce soil protection through snow cover and increase the ratio of rain to snow and snowmelt (Li and Fang, 2016). Changes in temperature affect evapotranspiration, which influences soil moisture and infiltration capacity and thus the partitioning of water into surface and subsurface runoff (Nearing et al., 2004). Changes in solar radiation have similar indirect effects on water erosion as temperature changes, since solar radiation also affects plant growth, evapotranspiration, soil moisture and other parameters influenced by surface temperature.

Climate change can reduce water erosion most directly through decreasing precipitation amounts and intensity (Pruski and Nearing, 2002a). In addition, increased vegetation growth due to changing precipitation, temperature, solar radiation and CO_2 fertilisation can reduce water erosion (Chaplot, 2007; Olsson et al., 2019). Moreover, temperature increases can decrease soil moisture and thus increase the soil's water infiltration capacity.

Simultaneous positive and negative impacts of climate change on water erosion complicate research on climate change impacts on water erosion. For example, increases in temperature and soil moisture can lead to increased plant growth and thus soil cover, but also faster rates of residue decomposition due to an increased microbial activity and thus reduced soil cover (Nearing et al., 2004). Decreasing precipitation amounts can lead to lower water runoff but may also decrease the soils vegetation cover and thus the protection against water erosion (Pruski and Nearing, 2002a). Anthropogenic or socio-economic factors add further complexity to climate change impacts on water erosion. Climate change may alter field management such as planting and harvesting dates, type of cultivars, crop rotation and tillage techniques, which can have a significant impact on soil cover and thus water erosion (Nearing et al., 2004). Although climate change impacts on water erosion can be very variable, numerous studies agreed that increasing precipitation leads to increasing water erosion (Li and Fang, 2016). Where precipitation decreases, changes in interactions of plant biomass, runoff, and water erosion are more complex (Pruski and Nearing, 2002a).

Due to their complexity, the consequences of climate change on water erosion have not been investigated in depth. Thus, the impact of climate change on soil functions has been considered to be the largest source of uncertainty in any projections of the trends in key ecosystem services provided by the soil (Montanarella et al., 2016). As the quality of soil resources is one of the main determinants for agricultural productivity, further research on the links between climate change and soil degradation processes such as water erosion is necessary to improve the understanding of climate change impacts on agriculture.

1.8 The impact of climate change on crops

As the indirect effects of climate change on water erosion through changes in land use and vegetation cover are of great importance, the effects of climate change on crops are relevant for future water erosion.

Observed climate change is already affecting crop production through increasing temperatures, changing precipitation patterns, and greater frequency of some extreme events (Mbow et al., 2019). Regional effects of climate change are spread unevenly. Observations and projections of climate change impacts on the most important staple crops show that yields in many lower-latitude regions are affected negatively by climate changes, while in many higher-latitude regions, yields are affected positively (Mbow et al., 2019; Rosenzweig et al., 2014).

Increasing temperature can both increase and decrease crop yields, as these are determined by a minimum and maximum temperature within which the phenological development of a plant takes place, as well as by an optimum temperature at which the phenological phases are accelerated. The development of plants slows as temperature increases above the optimum and ceases when plants are exposed to their maximum temperature (Hatfield et al., 2011). As average temperatures in many tropical agricultural regions are already close to the high-temperature thresholds for suitable production of major staple crops, even moderate temperature increases in lower latitudes can have negative impacts on crop yields (Rosenzweig et al., 2014). Additionally, air temperature has an important impact on the amount of suitable days for a crop to grow. The time period of crop growth can be described in thermal time, which defines the time until a crop reaches maturity after a specific number of 'growing degree days' expressed by the sum of daily temperature values (Su et al., 2013). When daily temperatures increase, the rate of phenological development increases and the plant reaches maturity earlier, which results into less days where the plant can intercept light for biomass accumulation and thus yields will decrease (Ritchie and Nesmith, 1991). The definition of 'growing degree days' includes a base temperature below which crop growth does not continue. Consequently, temperature increase can lead to more days suitable for crop growth and thus create new potential regions where certain crops can grow (Zabel et al., 2014).

Crop cultivation systems are closely linked to hydrological systems through the availability of water resources, which are strongly dependent on precipitation and evapotranspiration patterns controlled by the climate system. It is rare that crop growth is limited solely based on heat stress due to high temperature. Crop damage due to increased temperature is rather connected to water stress for crops caused by increased evapotranspiration, which leads to a reduced availability of soil moisture (Carter et al., 2016). In addition, too much water as a result of increasing extreme rainfall events can also prevent or decrease crop growth. Increasing strong rainfall can wash away important nutrients from the topsoil for the crop, which limits its growth (Burt et al., 2016). Furthermore, increasing rainfall intensity can lead to waterlogging or flooding of the soil, which can damage crops due to a lack of oxygen and salinisation (Saraphirom et al., 2013; Rosenzweig et al., 2002). Therefore, changes in precipitation amounts, intensity and patterns can affect crops both positively and negatively.

Water availability for a crop can be also influenced through the impact of solar radiation on evapotranspiration and thus, changes in the degree of solar radiation affect crop growth (Carter et al., 2016). An increase in solar radiation will increase the amount of energy to vaporize water, which results into a loss of water for the plant. Furthermore, the degree of solar radiation influences crop growth through the availability of light, which is an important component for the plant to gain energy during photosynthesis. Therefore, increasing cloud cover will decrease the amount of solar radiation and thus decrease the productivity of the plant.

The effect of increasing atmospheric CO_2 on crop growth is largely positive. As crops use CO_2 as an input to gain energy during photosynthesis, an increase in the concentration of CO_2 in the atmosphere results in an increase of photosynthesis when other growth factors such as water and light are not limited. Thus, atmospheric CO_2 can have a fertilising effect for crops. Importantly, this effect is different in plants that differ in their method of carbon fixation during photosynthesis. Experiments have shown that C3 crops such as wheat increased significantly with increasing CO_2 due to increasing photosynthetic activity (Slingo et al., 2005). Crop growth of C4 crops such as maize may not response directly to increasing atmospheric CO_2, but yields might increase indirectly through increasing water use efficiency via reduction in stomatal conductance (Long et al., 2006b). However, recent studies highlight that although increasing CO_2 affects crop growth positively, it may lower concentrations of important nutrients in crops (Myers et al., 2014). More research is needed to fully understand the effect of increasing atmospheric CO_2 on crops and the impact on human nutrition.

Whilst changes in temperature, precipitation, solar radiation and atmospheric CO_2 mainly determine the impact of climate change on crops, changes in other climate parameters such as wind speed, relative humidity, and atmospheric ozone also influence crops, but are less explored (White et al., 2011). Moreover, climate change impact on crops are usually complex and are often the result of a combination of several stress factors. For example, in Malawi, crops drying before maturity and damage due to floods and watershortages led to food shortages in the 1990s and early 2000s (Mkwambisi et al., 2010). In Swaziland, changing rainfall patterns led to the spread of the parasitic weed *Striga asiatica*, which reduced maize production (Stringer et al., 2007). Excessively wet soil can reduce crop yields through an increased risk of plant disease and insect infestation or by delaying planting or harvesting due to inability to operate machinery (Rosenzweig et al., 2002).

1.9 The use of crop models in impact assessments

Given that humans have depended on agriculture for more than 10,000 years, the impact of environmental change and land management on agricultural production have long been a focus of science. Since the

1960s, numerical crop models have been used to simulate the complex biological and physical interactions in agricultural systems to understand the impact of environmental drivers and farming techniques on crop yields (De Wit, 1965; Monteith, 1965). With the emergence of global-scale phenomena that affect agricultural productivity (most prominently climate change), crop models are increasingly being applied at the global scale to explore regional variabilities of crop yield changes in response to environmental factors and field management (Mueller et al., 2017). In addition, crop model outputs frequently contribute to integrated assessment modelling studies. In these studies, models from different disciplines are combined to address complex global problems, such as the growing population and its demands for more food, water, and energy in the face of climate change, the limited arable land for expanding food production, and increasing pressures on natural resources and biodiversity (Jones et al., 2016). Moreover, crop models are a transparent and consistent tool to inform agricultural and environmental policies, which rely on large-scale indicators to represent administrative units ranging from regional to national scale.

As such, crop models are an important tool for researching complex global problems. However, not all biophysical interactions in crop cultivation systems are understood and thus not all processes relevant for crops are considered in crop models. Moreover, the complexity of modelling crop cultivation systems increases with the spatial focus of a study. Crop modelling studies that assess the impact of environmental change or management scenarios on agricultural productivity at the regional or global scale often neglect land degradation processes (Balkovič et al., 2018). Thus, such studies neglect a crucial driver of long-term agronomic trends. In addition, there is a growing need for large-scale indicators on land degradation impacts and patterns to inform policy programs (Montanarella et al., 2016). As water erosion can produce high costs for farmers and negatively affect infrastructure and environmental quality, many agricultural and environmental policy programs aim to reduce water erosion (Alewell et al., 2019). Models can help to analyse the effectiveness of field management scenarios to reduce water erosion and to project future water erosion rates and impacts under land use and climate change scenarios (Borrelli et al., 2020). Whilst there are currently efforts to improve models to monitor water erosion rates over large scales (Borrelli et al., 2021), more research is necessary to understand interactions between agriculture and water erosion and their impact on current and future crop production in different global regions. As agriculture influences human well-being and interacts with environmental quality, understanding these relationships and how they are influenced by regional characteristics, will be crucial to solve many current and future global challenges.

1.10 Thesis aims and objectives

The aim of this thesis is to better understand the effects of water erosion on current and future grain yields. In addition, this thesis aims to improve the representation of the interactions between water erosion and crops in large-scale crop modelling studies to improve crop yield projections and water erosion assessments. The global gridded crop model (GGCM) EPIC-IIASA is used for the analysis.

This model is used to generate large-scale and global crop yield projections to assess the impact of field management and climate change scenarios on crop production. Maize and wheat are used to represent cereal crops affected by water erosion.

The three main objectives of this thesis are to:

1. Analyse the robustness of water erosion rates simulated with EPIC-IIASA on global maize and wheat croplands.

2. Explore the impact of water erosion on global maize and wheat yields.

3. Explore the combined effects of climate change and water erosion on global maize and wheat yields.

The first objective aims to develop and test a modelling approach for estimating water erosion rates on global maize and wheat cultivation areas based on various field management scenarios. This includes identifying the most sensitive model input parameters controlling the simulation of water erosion, quantifying the uncertainty of simulated water erosion rates stemming from different field management scenarios and water erosion estimation methods, and evaluating the agreement of simulated water erosion rates with field data across different environments. The modelling approach evaluated in the first part of this thesis will be used for the second objective to simulate the impact of water erosion on global maize and wheat yields using historic climate data. The model outputs will be analysed to explore global differences in water erosion impacts on maize and wheat yields due to different environmental characteristics and field management. To address the third objective, the previous modelling approach will be applied with contrasting climate change scenarios. Based on the model outputs, regions where maize and wheat yields are susceptible to both climate change and water erosion will be identified, and the impact of climate change on water erosion will be analysed.

1.11 Thesis overview

The thesis is structured as follows. Chapter 2 reviews the literature on water erosion assessments. It highlights the advantages and disadvantages of common methods to assess water erosion patterns and impacts. It identifies simple water erosion models as the most suitable method for large-scale water erosion assessments. Further, it describes knowledge gaps on current and future water erosion patterns and impacts that can be addressed using the biophysical crop modelling framework developed in this study.

Chapter 3 reviews the literature on crop models. It provides an overview of the types of crop models and their applications, and presents the results of previous modelling studies on the impacts of climate change on crops, including their uncertainties. It finds that soil processes are often neglected in crop yield projections, although they can significantly influence the impact of climate change on crops and the effectiveness of climate change adaptation strategies.

Chapter 4 introduces the modelling framework of this study. It describes the relevant equations used in the EPIC model to simulate the interactions between crops and water erosion. Further, it lists the model inputs used in this thesis and the methods for aggregating, analysing and evaluating the model outputs.

Chapter 5 - 7 present and discuss the results of this thesis. In Chapter 5 the modelling framework of this thesis is evaluated by presenting and discussing the uncertainties, sensitivities and robustness of the simulated water erosion rates using EPIC-IIASA. Chapter 6 looks at the model results on the impact of water erosion on global maize and wheat yields. It analyses the major determinants influencing water erosion impacts on maize and wheat yields and draws conclusions on the role of water erosion impacts for the global production of both crops. Chapter 7 analyses the combined effects of climate change and water erosion on global maize and wheat yields. It identifies regions where maize and wheat production is susceptible to both climate change and water erosion and analyses potential changes in future water erosion due to climate change.

Chapter 8 summarises the thesis results and draws conclusions on the contributions of this thesis to global water erosion assessments and crop yield projections. It also considers the future research needs to improve estimates of large-scale water erosion and to account for soil degradation in global crop yield projections.

Chapter 2

Literature review of water erosion assessments

2.1 Introduction

Information on the state of soils is necessary to inform agricultural and environmental policy programs, such as the European Unions's Common Agricultural Policy (CAP) (Keesstra et al., 2016; Panagos et al., 2016). In addition, reducing soil erosion is an important matter for achieving several SDGs (Keesstra et al., 2016). However, Humphries and Brazier (2018) believe that soil-related policies are currently secondary, being the result of other environmental objectives. One important reason for this is the difficulty of assessing the state of soils on a scale that is relevant to policy. The difficulty of this task is shown by the various attempts to map global land degradation, which led to very different results.

Among the many land degradation processes that are commonly assessed, recent efforts have been made to improve the assessment of water erosion at regional and global scales using models (Borrelli et al., 2021). The recent studies have shown that modelling tools can provide information on the status of soil under different land use and can test the impacts of external factors such as climate and management on soils on policy-relevant spatial and temporal scales. According to Alewell et al. (2019), the recent modelling efforts have shown that large-scale modelling is inevitable to increase the social and political visibility of soil resource issues.

Despite the recent improvements, large-scale assessments on water erosion rates on arable land are still rare or do not provide detailed information on varying water erosion rates for different crops and field management strategies. This lack of information on water erosion also makes it difficult to quantify its impact on crop yields and pollution around croplands on a large scale, and how this might change in the future due to climate change. There is also a need for large-scale estimates of water erosion in other soil-related research areas. For example, earth science system models, climate change and carbon mitigation scenarios, and hydrology and flood forecasting models could be improved if soil erosion were considered (Alewell et al., 2019).

This literature review presents existing global assessments of land degradation to illustrate the complexity of evaluating the current state of soil resources on a large scale. Moreover, these assessments highlight the role of water erosion in global soil degradation. Subsequently, this literature review will present the latest regional and global water erosion assessments and the advantages and disadvantages of different methods to explore water erosion rates and impacts. Finally, this literature review presents the current state of knowledge as well as knowledge gaps regarding the impacts of climate change on water erosion.

2.2 Global land degradation assessments

Several global assessments suggest that large parts of the earth surface are already affected by land degradation. However, the degree of global land degradation named by a study strongly depends on the indicators used to describe land degradation. Commonly used methods to analyse global land degradation are remote sensing, biophysical models, inventories of land use/condition and expert opinions (Gibbs and Salmon, 2015). Due to the complexity of land degradation a complete assessment cannot be performed with a single method, but a combination of studies and methods can give an approximation (Vogt et al., 2011). Various indicators exist to measure the state of soil, vegetation and biomass or potential land degradation under specific land use and field management (Olsson et al., 2019). It is important to distinguish between studies monitoring the current state of land degradation and studies analysing potential land degradation. Studies focusing on land degradation processes often focus on their extent rather than quantifying their impact, e.g. changes in crop yields due to land degradation.

The *Global Assessment of Human-induced Soil Degradation* (GLASOD) carried out by the *World Soil Information Center* (ISRIC) and the *United Nations Environment Program* (UNEP) from 1987-1990 was the first major global assessment of land degradation focusing on soil resources (Oldeman et al., 1991). As that study focused on soil degradation, the loss of vegetation and biodiversity were neglected in GLASOD. In that project, the degree of soil erosion by wind and water, chemical soil deterioration, and physical soil deterioration was assessed based on expert judgement by soil scientists on loosely defined physiographic units on a global scale. The outcome of that study estimated that 38% of global land was lightly affected by land degradation made by humans, 46% moderately and 15% of global land was affected in a high degree. The most important degradation process was erosion by water and wind, which accounted for 84% of degradation. The most degraded area was Europe (25%), followed by Asia (18%) and Africa (18%) (Nkonya et al., 2011).

The most comprehensive assessment of global land degradation was conducted by the *Food and Agriculture Organization of the United Nations* (FAO) in collaboration with the *International Institute for Applied Systems Analysis* (IIASA) presented in the *Global Land Degradation Information System* (GLADIS). GLADIS gives insights into the global status of land resources and degradation pressures acting on them derived from a combination of biophysical and socioeconomic determinants (Nachtergaele et al., 2011). GLADIS provides classes of land degradation based solely on biophysical indicators, which assess the status and degradation of soil, water, biomass and biodiversity. Moreover, the assessment includes past and present trends and thus recognises causes and impacts due to biophysical and socio-economic factors, and includes a prognosis of future land degradation trends. The results show that 32% of global land is in areas with high provision of biophysical goods and services, but with medium to strong degradation processes. Further, 27% of the global population live in areas with a low provision of biophysical goods and services and a medium to strong degradation (Nachtergaele et al., 2011). The special definition of the land degradation index adding social and economic indicators to biophysical factors gives a more comprehensive insight into the impact of land degradation in certain regions and thus provides a wide range of information. As such, the assessment also indicates that 42% of the very poor live in degraded areas, as compared with 32% of the moderately poor and 15% of the non-poor (Nkonya et al., 2011).

In the report on the *Status of the World's Soil Resources* by *The Intergovernmental Technical Panel on Soils* (ITPS) about 200 soil scientists reviewed the scientific knowledge from more than 2000 peer-reviewed scientific publications to provide a global perspective on the current state of the soil, its role in providing ecosystem services, and the threats to its continued contribution to these services (FAO and ITPS, 2015). The land degradation processes considered in the report are erosion, compaction, acidification, contamination, sealing, salinisation, waterlogging, nutrient imbalance (i.e., both nutrient deficiency and nutrient excess), and losses of soil organic carbon and of biodiversity. Soil erosion has been identified as the most severe land degradation process leading to deteriorating water quality in developed regions and to lowering of crop yields in many developing regions (Montanarella et al., 2016). The authors concluded that nitrogen and phosphorus fertiliser use in infertile tropical and semi-tropical soils – the regions where the most food insecurity among us are found – needs to be increased, while global use of these products needs to be reduced.

The most recent assessment of global land degradation was carried out by Pravalie et al. (2021) based on a collection of geospatial data from previous studies on aridity, water erosion, vegetation decline, soil salinisation and soil organic carbon decline. The authors concluded that aridity is by far the largest singular pressure for agricultural systems, affecting 40% of the arable lands' area, and that water erosion is the second major degradation process, affecting 20% of global arable systems. However, Pravalie et al. (2021) only considered water erosion rates larger than 10 tha^{-1}, which have been considered as not sustainable to maintain agricultural productivity. Moreover, aridity is usually not considered in land degradation assessments, as dryness is a climatic impact rather than a land degradation process. Pravalie et al. (2021) concluded that simultaneous pressure of multiple land degradation processes is rare. According to their study, the most common combination of aridity and water erosion affect 7% of cropland.

Despite several attempts at mapping the spatial and temporal scale of degraded land, it remains a challenging task due to the difficulty of defining land degradation, determining baselines or measuring relevant processes (Herrick et al., 2019). Therefore, views on assessing land degradation are diverging and thus no reliable global maps of the extent and severity of land degradation exist. The most prominent estimates of the global extent of land degradation are very variable, ranging from 1–6 billion ha of ice-free land surface (up to 66%) (Gibbs and Salmon, 2015). To support the goal of governments and international organisations of reducing land degradation, it is necessary to improve indicators and baseline datasets of land degradation at global scale to better monitor progress (Pravalie et al., 2021).

2.3 Water erosion assessments

2.3.1 Large-scale water erosion assessments

First attempts to address water erosion at the global scale were made in the 1930s (Jacks and Whyte, 1939). Since then, many studies estimated the amount of soil loss due to water erosion worldwide (García-Ruiz et al., 2015). The majority of erosion studies is concentrated in North America and Europe. The earliest estimates of global soil loss are based on extrapolation of erosion plot data to the global scale or they are derived from sediment yields from rivers (Myers, 1993; Pimentel et al., 1995; Walling and Webb, 1983). More recent global estimates are derived from models (Borrelli et al., 2017; Doetterl et al., 2012; Van Oost et al., 2007). Doetterl et al. (2012) summarised existing estimated agricultural soil loss amounts on a global scale based on both field measurements and model outputs, which range between 24 and 120 Pg yr^{-1}. The wide range of estimates indicates considerable uncertainty in global water erosion estimates.

Large-scale water erosion assessments based on field experiments

As models have only recently become the preferred method for large-scale water erosion assessments, most earlier assessments have been based on extrapolation from field experiments, contributing to the majority of available regional and global water erosion estimates. The most cited value of global soil loss on arable land is 75 Pg yr^{-1}, which was estimated by Pimentel et al. (1995) based on plot measurements, but has been criticised repeatedly due to the uncertainty of extrapolating plot measurements to larger scales (Crosson, 1995). Cerdan et al. (2010) reviewed erosion rates from 81 experimental sites in 19 European countries and estimated a mean annual erosion rate on arable land in Europe of 3.6 t ha^{-1}, although aggregation of the data by land use showed large variations. Boardman (1998) questioned the usefulness of an average rate of soil erosion for Europe or other continents as the rates vary too much in time and space. Further, he suggested that plot experiments are a poor basis for regional generalisation as they only represent data from a very small area.

Although the usefulness of field data for large-scale water erosion assessments has been criticised, they are often used to assess the severity of regional soil erosion problems. Several previous researchers used a collection of field measurements of soil erosion rates to compare them to tolerable soil erosion rates (Verheijen et al., 2009; Benaud et al., 2020; Montgomery, 2007). Montgomery (2007) collected field data worldwide derived from various field measurement methods and estimated median and average water erosion rates of 1.5 and 3.9 mm yr^{-1} on cropland under conventional agriculture. Assuming a soil bulk density of 1200 kg m^{-3} these values equal to median and average water erosion rates of

18 and 47 t ha^{-1}. These rates exceed suggested tolerable rates of 1 t ha^{-1} (Benaud et al., 2020) and previous estimates of average annual soil formation rates of 0.3 t ha^{-1} – 1.4 t ha^{-1} (Evans et al., 2019; Montgomery, 2007; Verheijen et al., 2009). Even the more generous tolerable soil loss rates defined by the U.S. Department of Agriculture (USDA) of up to 11 t ha^{-1} (Schertz and Nearing, 2006) are below the values derived by Montgomery (2007).

Benaud et al. (2020) collected soil erosion measurements across the UK derived from different field experiment methods and concluded that mean erosion rates are low, while 16% of observations exceed soil loss rates of 1 t ha^{-1}. Although Benaud et al. (2020) collected a large amount of data from across the UK, they concluded that understanding whether or not the UK has a soil erosion problem remains unclear as i) existing studies are skewed towards locations with a known erosion likelihood and ii) the definition of a tolerable erosion rate remains problematic in the absence of a comprehensive and methodological consistent national-scale study of historic and current soil erosion rates.

A meta-analysis of more than 4000 erosion measurement sites by García-Ruiz et al. (2015) showed an extraordinarily high variability in erosion rates, with almost any rate possible irrespective of slope, climate, scale, land use/land cover and other environmental characteristics. Despite a slight positive correlation between erosion rates and slope and annual precipitation, there is much variability in erosion measurements that is at least partially related to the experimental conditions. In addition, Cerdan et al. (2006) noted that large-scale studies based on data from experimental plots tend to estimate higher amounts of soil loss because the locations of erosion measurements are often biased towards bare soil cover, steep slopes or extreme precipitation events.

As such, the usefulness of field data to derive conclusions on large-scale erosion rates is questionable due to their uneven distribution and variable quality. Boardman (2006) concluded that '*for most areas in the world the erosion data is woefully inadequate*'. Stroosnijder (2005) challenged the adequacy of erosion measurements and warned of a scientific and technical crisis because '*there are insufficient empirical data of adequate quality, a lack of funds to improve that situation, a lack of development of new technologies and equipment, and a lack of skilled personnel*'. Benaud et al. (2020) concluded that '*existing monitoring approaches have been resource intensive in nature and/or biased towards a single erosion process, hindering their suitability for future, holistic national-scale monitoring programs.*' The uneven distribution of erosion measurements for different global regions reduces their usefulness for robust global erosion estimates.

Large-scale water erosion assessments based on models

Models can be used as a tool to overcome the lack of data coverage to estimate erosion rates and account for the variability of soil, topography, climate and field management around the world. Model outputs overcome the lack of homogeneity in available data and thus can be useful to identify soil erosion hotspots determined by the combination of erosion controlling factors in a more transparent way.

The Universal Soil Loss Equation (USLE) and its modification have been used with high-resolution global input data to estimate water erosion (Borrelli et al., 2017; Doetterl et al., 2012; Van Oost et al., 2007). These studies resulted in a range of annual global soil removal estimates and water erosion rates on cropland of between 13 – 22 Gt and 11 - 13 t ha^{-1}. These estimates are less variable and more closely compared to field measurements from various sources than earlier estimates, which suggests a higher robustness.

However, the use of models in large-scale erosion assessments has been criticised heavily (Evans and Boardman, 2016b). The most commonly used models for large-scale assessments are USLE-type models due to their simplicity. However, their use is criticised as they are based on plot data and thus not suitable for extrapolation to large fields. In addition, they were not developed for environmental conditions different than the United States' Midwest.

Nevertheless, due to their simplicity and the growing availability of global environmental datasets that can be used as sources for model input data, USLE-type models are widely seen as the most reliable tools to derive erosion estimates on large and global scales (Alewell et al., 2019). Moreover, unlike field observations, models can provide predictive estimates of water erosion and are therefore useful in land use and climate change impact assessments and scenario analysis.

2.3.2 Common water erosion modelling techniques

Common factors in models used to determine water erosion are land use, slope, precipitation amount and intensity, runoff and peak runoff rates, runoff shear stress, soil cohesion, and surface roughness (de Vente and Poesen, 2005). Most models focus on plot to catchment scale and simulate only a selection of erosion processes (sheet-, till-, ephemeral gully erosion), whereas permanent gullies, mass movements and riverbank erosion are most often not considered (De Vente et al., 2013). Furthermore, models focus either on simulating single erosion events or on assessing average erosion in hourly, daily, monthly or annual time-steps (Karydas et al., 2014). As such, water erosion models differ in complexity, data requirements and equations used to formalise processes and the outputs they provide (Abdelwahab et al., 2018). Therefore, the choice of model strongly depends on the data and calibration requirements, temporal and spatial scale and the erosion process considered (De Vente et al., 2013).

Most reviews classify water erosion models into empirical, conceptual and physics-based models (Merritt et al., 2003; de Vente and Poesen, 2005). Empirical water erosion models delineate a mathematical algorithm out of the relationship between the confounding measurable parameters, which control water erosion, and measured eroded sediments (Alewell et al., 2019). Empirical models are the simplest type of model and thus their computational and data requirements are usually less than for conceptual and physics-based models (Merritt et al., 2003). However, empirical models are often criticised for ignoring the inherent non-linearities in the catchment system (Wheater et al., 1993). The most widespread empirical water erosion model is the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978).

Conceptual models typically represent a catchment as a series of internal storages and usually incorporate the underlying transfer mechanisms of sediment and runoff generation in their structure through defined flow paths (Merritt et al., 2003). Thus, conceptual models include a general description of catchment processes, which distinguishes them from empirical models (Sorooshian, 1991). Often used conceptual models are SWAT (Neitsch et al., 2011) or ANSWERS (Beasley et al., 1980).

Physics-based models such as the WEPP (Lane et al., 1992) and the EUROSEM (Morgan et al., 1998) include physical equations describing streamflow and sediment and associated nutrient generation in a catchment (Merritt et al., 2003). Although parameters used in physical-based models are measurable, they usually need to be calibrated against observed data due to their large number and the heterogeneity of important catchment characteristics (Merritt et al., 2003). Although most reviews on water erosion models classify models into physics-based models, conceptual models, and empirical models, most models do not fall strictly into one category, as even the physics-based models retain some empirical elements in the model algorithms (de Vente and Poesen, 2005).

The complexity of a model can be further distinguished between spatially distributed models and lumped models. Spatially distributed models reflect the spatial variability of processes and outputs and thus are capable to produce erosion patterns in a single run, whereas lumped models only produce a single value in a single run (Karydas et al., 2014). The WEPP and EUROSEM models are polygon-based models adapted to catchment scale and include special elements such as channels and ponds, which allows to identify potential sources and sinks of water, sediments and associated chemicals within a catchment (Jetten et al., 2003). USLE-type models are lumped models assuming a spatially homogenous uniform hillslope, although it is possible to apply them to more complex terrain using a raster approach to generate spatially distributed outputs (Jetten et al., 2003). Thus, spatially distributed models can be further distinguished between models based on independent raster, where soil loss is estimated at a specific location without contribution from a neighbouring location, and pathway type models, where topological relations are considered (Karydas et al., 2014).

2.3.3 The Universal Soil Loss Equation

The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and its modifications are the most widely known modelling approach to assess soil erosion and have been applied in more than 100 countries (Alewell et al., 2019). USLE was developed with an empirical approach based on a statistical analysis of more than 10,000 plot-years of soil loss data (Wischmeier and Smith, 1978). USLE simulates mean annual soil loss due to sheet and rill erosion on hillslopes determined by rainfall erosivity, soil erodibility, topography, crop system and management practice.

In the 1990s, the USLE was further developed to the Revised Universal Soil Loss Equation (RUSLE), by updating the main components of the USLE (Renard et al., 1997). A detailed description of the components of the USLE and its modification is included in Chapter 4.2.5. The RUSLE was further developed to the RUSLE2, which used process-based equations to simulate the detachment, transport and depositions of soil particles (USDA-ARC, 2013). As USLE and RUSLE were designed to predict long-term average annual soil loss and do not consider runoff explicitly, its ability to predict event soil losses is limited (Kinnell, 2010). In a modified version of the USLE (Modified USLE, MUSLE), the erosivity factor based on rainfall energy was replaced with an erosivity factor based on runoff energy, which improves the equations applicability to individual storm events (Williams, 1975).

Alewell et al. (2019) states that the main reasons USLE type modelling is so widely used throughout the world are i) its high degree of flexibility and data accessibility, ii) a parsimonious parametrisation, iii) extensive scientific literature and iv) comparability of results allowing to adapt the model to nearly every kind of condition and region of the world. According to Risse et al. (1993), '*USLE has been used throughout the world for a variety of purposes and under many different conditions simply because it seems to meet the need better than any other tool available*'. In addition, Renard et al. (1997) stated that more than four decades of using the USLE has proven that it is valuable as a conservation-planning guide in the USA, providing farmers and conservation planners with a tool to estimate rates of soil erosion for different cropping systems and land managements.

2.3.4 Uncertainties in water erosion models

The main causes of uncertainty in water erosion models are: i) low input data quality, ii) incomplete description of erosion, sediment transport and deposition processes or model structure, and iii) errors in measured erosion rates for model calibration and evaluation (De Vente et al., 2013).

The significance of uncertain input data for simulating water erosion varies with the model and study location as they influence the sensitivity and importance of factors describing water erosion. In most models and locations, slope steepness and length are important factors for determining water erosion. Thus, the spatial resolution of Digital Elevation Models (DEMs), which are often used to derive slope information for model inputs, has a strong impact on simulated erosion (Mondal et al., 2017; Liu et al., 2011). Also, the temporal resolution of climate data such as rainfall intensity, duration and seasonality, is often named as important input data for the robustness of water erosion estimates (Shen et al., 2012).

Land use information for simulating water erosion can be both difficult to obtain without on-site observations and difficult to simulate. Although some models simulate crop growth and seasonal differences in vegetation cover, several erosion models assume constant land use throughout the simulation period (De Vente et al., 2013; Borrelli et al., 2017). If constant land use is assumed, feedbacks of climate change to soil cover cannot be considered in water erosion models. In addition, land cover data is often obtained from regional land use maps, which is not always a good indicator of the soil's protection from raindrop impact and surface runoff, which is mainly determined by the percentage soil cover and root density (De Vente et al., 2013).

Furthermore, data on soil conservation measures and other field management techniques that influence the soil's protection are often not readily available. Even if detailed data on farming techniques is available, explaining the effectiveness of soil conservation measures in reducing soil runoff remains difficult (Chen et al., 2020).

The requirement for detailed input data is usually highest for process-based models due to their complexity, which may increase the negative impact of uncertain input data on the robustness of model results. Moreover, it can be challenging to obtain detailed input data in data scarce study regions or over large scales (Panagos et al., 2016). For example, polygon-based models such as the WEPP and

EUROSEM models require detailed data to include special elements such as channels and ponds to identify potential sources and sinks of water sediments and associated chemicals within a catchment (Jetten et al., 2003). In addition, detailed field data is needed to evaluate spatial soil erosion and soil deposition patterns. The evaluation of spatial patterns in models is important for the evaluation of their robustness. For example, previous studies predicted acceptable soil loss rates but an incorrect pattern of the source and sink areas and thus they 'predicted the correct result for the wrong reasons' (Jetten et al., 2003). However, even when spatial datasets are available, simulated spatial heterogeneity is difficult to evaluate as the available field data does not always provide the necessary detail and thus spatial relationships in model structure may increase modelling uncertainty (Brazier et al., 2007).

If all the necessary input data is available, process-based models may simulate a more robust estimate of water erosion than less complex model. However, some water erosion processes are hardly understood and thus their representation in models may reduce the robustness of model outputs (Parsons, 2019). Therefore, complex models are exposed to more potential error sources due to their model structure than simpler models (Brazier et al., 2000).

According to Alewell et al. (2019), the two main problems with complex models are i) the unavailability of the complex set of input parameters especially at large temporal and spatial scales and ii) over-parametrisation which results in a non-uniqueness of fit and/or insensitivity of model output to some of the input parameters. Moreover, several studies concluded that more complex models do not perform better than the USLE (Alewell et al., 2019; Jetten et al., 2003; Kinnell, 2010). Nevertheless, as the robustness of complex models is largely determined by the availability of input data, their applicability may improve in the future due to increasing availability of high-resolution data through improving remote sensing techniques (de Vente and Poesen, 2005).

Although USLE is a simple model it also suffers from errors due to the lack of input data or errors due to unknown water erosion processes. For example, the robustness of the topographic factor of the USLE has been questioned as the relationship between slope length and soil erosion is not clear (Bagarello and Ferro, 2010). Also the simplicity of the USLE is repeatedly criticised. Although there is a lack of measured rainfall intensity and sub-hourly data over long-periods, the simple empirical equation implemented in USLE, which correlates the rainfall erosivity factor with available daily/monthly/annualy rainfall, is often criticised (Oliveira et al., 2013). In addition, USLE-type models are often criticised that they do not include gully erosion, bank erosion and mass movements, despite a potentially large contribution to total sediment yield by these processes (De Vente et al., 2013). Evans and Boardman (2016b) criticised that USLE is mainly driven by rainfall and slope factors whereas in Britain the occurrence of erosion is largely determined by soil type and land use. Parsons (2019) mentioned that USLE does not account for interactions between each factor, although previous observations show that soil erodibility is not independent of rainfall intensity. He further points out that USLE is developed from plot data characterised by slopes between 2 – 18 % and fields between 30 to 300 ft (9 – 90 m) long and thus its application on fields with different characteristics is uncertain. As USLE is based on data from small plots, several authors criticised the use of USLE on large scales (Evans, 2013; Evans and Boardman, 2016b). However, this criticism disregards the suggested application of USLE for large-scale applications by its developers, who proposed to '*break down the drainage area into a series of tracts having relatively homogeneous land use and treatment. The erosion equation is then used to approximate the average annual rate of soil movement from each tract*' (Wischmeier and Smith, 1965). However, using a raster scheme assumes that cells are independent from each other and thus neglects possible sediment redistribution.

Apart from the RUSLE2 modification, sediment deposition is not considered in USLE-type equations (Kinnell, 2010). Models that do explicitly simulate sediment transport and deposition are based on complex interactions between erosion, deposition and topography and thus require very detailed input data (De Vente et al., 2013). Moreover, modelling sediment redistribution is further complicated as the process is not fully understood (Trimble and Crosson, 2000). In some cases environmental change is primarily reflected in reorganisation within the basin rather than in a direct change in sediment yield at the basin outlet (de Vente and Poesen, 2005). Several studies showed that changes in land use or climate may alter erosion rates in upslope areas but did not significantly change sediment export at the basin outlet (Trimble, 1999; Walling, 1999; Prosser et al., 2001). As USLE-type equations do not consider sediment deposition, they provide gross erosion rates and thus may overestimate the impact of environmental changes on erosion. Furthermore, this hampers the evaluation of model outputs with field measurements, which mostly provide net erosion rates.

As measured water erosion rates are usually used for model calibration and evaluation, their robustness can be crucial for the quality of model outputs. Due to the high heterogeneity of the water erosion process and experimental setups to measure water erosion, measurements are very prone to errors and some methods are more uncertain than others (García-Ruiz et al., 2015; Rüttimann et al., 1995; Parsons, 2019). Furthermore, the observed data needs to be appropriate for the setup of the modelling study. Water erosion measurements at specific temporal and spatial scales might not be representative for other scales. Scaling soil erosion rates up or down may lead to errors as soil erosion processes vary with scale (Prasuhn et al., 2013). For example, Parsons et al. (2004) argues that the quantity of soil eroded is not directly proportional to the area over which erosion is measured. The consideration of temporal scales in measured erosion rates is important as water erosion can be very variable between days, seasons and years and thus event-based or seasonal measurements are not representative of mean annual water erosion (De Vente et al., 2013). Therefore, it is crucial to select data for model calibration and validation that correspond to the spatial and temporal scale at which the model is applied (de Vente and Poesen, 2005). Moreover, a direct comparison between simulated erosion rates on fields or larger scales against erosion assessments based on field studies is difficult as erosion measurements have been often reported to be skewed to higher risk sites and thus field studies often do not include all erosion risk sites equally (Benaud et al., 2020; Cerdan et al., 2010).

In general, the large spatial and temporal variability of soil erosion and the uncertainty of input parameters used in models to predict soil erosion hampers the calibration and validation of soil erosion models, which will not be solved by constructing even more complete, and therefore more complex, models (Jetten et al., 2003). The simplicity of USLE has the advantage of increasing transparency and objectiveness of model evaluation and thus facilitates the interpretation of model results by policy makers (Alewell et al., 2019; Panagos et al., 2016). Moreover, modelling studies usually do not focus on accurately predicting absolute erosion values, but rather to predict relative differences, trends over times and systems reactions to processes and management practices (Alewell et al., 2019). Despite the existing uncertainties, models are a useful tool to test hypotheses on process understanding, relative spatial and temporal variations, scenario development and controlling factors (Oreskes et al., 1994).

2.3.5 Common methods for measuring water erosion based on field experiments

As modelling water erosion can be challenging and includes numerous sources of uncertainty, several authors prefer field-based water erosion assessment methods over modelling (Evans and Boardman, 2016b,a). However, different methods to measure erosion in the field have advantages and disadvantages, including many different uncertainties. In other words, all water erosion assessment methods are subject to criticism (Parsons, 2019; Trimble and Crosson, 2000; Parsons and Foster, 2011). Similar to the varying water erosion estimates generated by different types of models, also the approach chosen to measure water erosion influences the measurement results strongly. For example, Brazier (2004) observed that different methods to measure erosion yielded different erosion rates at a location. Due to the complexity of measuring water erosion there is often only a weak correlation between environmental factors and erosion rates, which hampers the use of observed data in parametrisation and validation of models (García-Ruiz et al., 2015).

The most common methods to measure erosion on cropland are plot experiments, radioisotopic tracer experiments and volumetric surveys. Other methods such as topographic surveys (e.g. laser scanning) are used less frequently to assess erosion on arable land as their resolution capability raises questions about their accuracy to detect finer traces of erosion and erosion on vegetation-covered land (Hsieh et al., 2009). In addition, this method does not distinguish between ground surface lowering due to erosion and other potential reasons on cropland such as soil compaction (Parsons, 2019). Other common methods such as suspended sediment yield measurements and bathymetry do not represent spatially explicit observations of on-site erosion and may include sediments from various sources such as bank erosion or road erosion. Thus, they are of limited value for water erosion assessments focusing only on agricultural land.

Most erosion measurements come from plot experiments introduced in the USA in the 1920s (Hudson, 1993). An overview of this method is provided by Cerdan et al. (2010), Hudson (1993), Mutchler et al. (1994), De Ploey and Gabriels (1980) and Zachar (1982). Soil loss due to water erosion can be quantified from sediment runoff collected from plots varying in sizes and in experimental design (total collection of sediment, fractioned collection of sediments using multislott divisors, measurement of discharge and sediment concentration by tipping buckets and Coshocton wheels). Plot scale studies are useful to build an empirical understanding of soil erosion under different environmental conditions and land use. As such, measurements of soil runoff from plots are useful to compare the relative changes in erosion under different topographic, climate and controlled field management conditions (Auerswald et al., 2009; Cerdan et al., 2010). Plot experiments were used for the development of the USLE model (Brazier, 2004).

However, the accuracy of erosion measurements derived from runoff plots has been questioned due to the complexity in designing plot experiments and collecting soil runoff data. In addition, the spatial extent of plot scale studies has a strong impact on measured erosion rates and thus may create bias (Parsons et al., 2006). In small plots, sediment mobilisation is dominated by rain splash, rill, and interrill erosion and thus sediment yield is relatively low. On larger areas sediment yields are expected to increase due to an increase in active erosion processes and flow shear stress due to concentration of flow (Vandekerckhove et al., 2000). However, with increasing basin areas also sediment storage, e.g. at footslopes, is expected to increase (de Vente et al., 2007). Cerdan et al. (2010) point out that plot erosion rates cannot be directly extrapolated to larger areas as plots do not entirely capture the spatial variability of erosion processes and rates as they occur in the landscape scale. Although the experimental settings of plots are often very resource intensive, erosion plots can only imitate natural conditions (Boix-Fayos et al., 2006).

Radioisotopic tracer experiments use the caesium radionuclide (^{137}Cs) released from nuclear weapon tests and nuclear power plant accidents as a tracer to measure long-term mean soil erosion rates in the period since the time of ^{137}Cs fallout (mainly in 1960s) until the time of soil sampling for ^{137}Cs determination (Fulajtar et al., 2017; Mabit et al., 2014b; Zapata, 2002). ^{137}Cs radionuclides from nuclear fallout are deposited in the topsoil and bind to soil colloids, so that they are only moved with the soil particles by mechanical processes such as soil erosion. Its chemical mobility and uptake by plants is negligible (Mabit et al., 2014a; Zapata, 2002). If part of the topsoil contaminated by ^{137}Cs is removed by erosion, the ^{137}Cs concentrations in soil profiles can be used to trace soil movements (Walling et al., 2014).

The use of radionuclides to assess soil erosion patterns is based on the four main assumptions that i) the fallout is locally, spatially uniform, ii) the fallout is rapidly and irreversibly fixed onto soil particles; iii) the subsequent redistribution of fallout is due to the movement of soil particles; and iv) estimates of soil erosion can be derived from measurements of ^{137}Cs inventories (Walling and Quine, 1992). However, the validity of all four of these assumptions has been questioned (Parsons and Foster, 2011). The objections of Parsons and Foster (2011) were discussed by Mabit et al. (2013). One of the most important confirmation of the usefulness of the ^{137}Cs method given by Mabit et al. (2013) are the positive results of a comparison between erosion values obtained with various measurement methods and erosion values obtained by ^{137}Cs method. Mabit et al. (2013) conclude that the ^{137}Cs method is based on a set of presumptions, which should be met to produce useful results, and careful interpretation of the obtained values is needed. If the basic assumptions are met and the methodological recommendations are followed the ^{137}Cs method is useful to assess erosion on agricultural fields.

A major advantage of the ^{137}Cs method is that it provides long term mean erosion rates (representing the period since ^{137}Cs fallout in the 1960s until the time of sampling) and overcomes the problem of high temporal variability of erosion. Erosion rates from short-term field experiments are stronger influenced by the high interannual variability of erosion, which can lead to unreliable estimates of erosion rates (García-Ruiz et al., 2015). Furthermore, the erosion rates are determined for a grid of ^{137}Cs sampling points, which can provide valuable information on the spatial distribution of erosion.

Volumetric measurements of rill erosion are used since approximately the 1940s in the USA (Kaiser, 1978) and the 1950s in Europe (Lobotka, 1955), usually at field scale (Boardman, 1990, 2003; Boardman and Evans, 2020; Brazier, 2004; Evans, 2002, 2013; Herweg, 1988; Zachar, 1982). The volume of erosion rills is calculated by multiplying their lengths and profile cross-sectional areas, which are usually measured along several traverses or estimated from terrestrial and aerial photos (Evans, 1986; Watson and Evans, 1991). The erosion volume is expressed in volume units (m^3 ha^{-1}) but can be converted to weight units (t ha^{-1}) by multiplying the volume with the soil bulk density. Volumetric measurements of rill erosion have been considered as a good method to monitor erosion in large fields (Boardman and Evans, 2020).

The most common criticism against volumetric measurements is that it neglects splash and sheet-wash erosion as it assumes that rills and gullies are mainly causing soil redistribution within fields (Parsons, 2019). Neglecting sheet erosion in volumetric surveys likely leads to an underestimation of erosion in a field (Parsons, 2019). Erosion rates obtained with ^{137}Cs have been observed to be significantly higher than erosion rates derived from volumetric surveys, which highlight the significance of quantifying less-visible erosion processes, such as sheet wash (Benaud et al., 2020). Volumetric surveys have been also criticised due to their high degree of subjectivity (Panagos et al., 2016). For example, Casali et al. (2006) reported that the error in measurements of the rill length can be ca. +/- 50 % due to their random irregularity. Boardman and Evans (2020) reported the difference in rill volumes ranging from -18% to +50% resulting from different numbers of traverses used for rill cross section measurements. In addition, a large difference between rill volumes derived from field measurements and rill volumes derived from photos has been reported (Watson and Evans, 1991). Therefore, volumetric measurements require careful planning and skilled surveyors to reduce the subjectivity and ensure consistency in obtained erosion estimates. If the robustness of obtained erosion volumes can be ensured, volumetric surveys can be very useful to monitor erosion over large areas on arable land.

2.4 Studies on the impact of water erosion on crop yields

While there are many studies that look at water erosion rates, there are few studies on the effects of water erosion on crops. A major reason is that assessing the erosion–productivity relationship is difficult due to the slow reduction in soil productivity, which may not be recognised until crop production is no longer economically viable (Bakker et al., 2004). Moreover, improved technology often masks erosion impacts (Littleboy et al., 1996), which hampers the observation of a decline in soil productivity over multiple years.

2.4.1 Methods to quantify the impact of water erosion on crop yields

The impact of soil loss on crop yields can be measured experimentally in the field. Water erosion impacts on crops are usually reported as absolute or relative reduction of crop yields per soil lost. Common methods are to artificially remove or add topsoil, comparison of yields in different landscape positions with different soil depths and comparison of yields in different plots with different degrees of water erosion (Bakker et al., 2004).

However, by reviewing studies about the relationships between crop productivity and erosion, Bakker et al. (2004) found a significant variability of the crop productivity response to erosion due to the choice of experimental methodology. Although many factors affect crop yields significantly, the most important factor explaining the observed variations between the studies reviewed is the experimental method used to assess the erosion–productivity relationship. Bakker et al. (2004) identified several sources of methodological uncertainties in existing studies, which may explain the variability in study results: Artificial changes in soil depth have a stronger impact on soil properties in comparison to a slow gradual runoff of soil, which is more common under natural conditions. Moreover, it is challenging to ensure homogenous conditions in different plots and transects in a comparison of crop yields influenced by different degrees of water erosion and thus the impact of other factors on crop growth and development cannot be excluded easily. In addition, soil depth change in natural environments can be also caused by other processes and thus it cannot be that easily related to water erosion alone. Bakker et al. (2004) suggested that the conclusions of past research investigating the relationship between erosion and crop productivity appear to be inconsistent.

2.4.2 Large-scale assessments of the impact of water erosion on crop yields

Panagos et al. (2018) summarised numerous studies analysing the impact of water erosion on crop productivity losses (Bakker et al., 2004, 2007; Den Biggelaar et al., 2004a; van den Born et al., 2000; De la Rosa et al., 2000; Lal, 1995; Larney et al., 2009; Oyedele and Aina, 1998). Most of these studies are focused on Northern America and Europe. Although the outcomes of existing studies are very variable, Panagos et al. (2018) estimated a crop productivity loss of 8% in intensively cultivated agricultural fields with annual erosion rates higher than 11 t ha^{-1}. Panagos et al. (2018) assumes that impacts of water erosion below a rate of 11 t ha^{-1} will be compensated with fertiliser application in Europe based on the tolerant soil erosion rate suggested by the USDA.

The most comprehensive study on the impact of water erosion on crop productivity was conducted by Den Biggelaar et al. (2004a). Based on a review of field studies of water erosion impacts on various crops in 37 countries, from which half the studies were conducted in North America. Den Biggelaar et al. (2004a) found only minor differences of absolute crop yield declines due to water erosion between continents. However, in relative terms crop yield declines in Africa, Asia, Australia and Latin America were two to six times higher compared to Europe and North America. The high average yields in the most productive regions where mainly responsible for the low impact of water erosion on crops in relative terms.

Den Biggelaar et al. (2004b) extrapolated the collected plot data across global soil types and estimated an average global annual reduction of 0.3% of yields from maize, millet, potatoes, sorghum, soybeans and wheat corresponding to an estimated annual loss of USD 523.1 million. However, due to missing data this estimate does not cover the entire globe. Due to a lack of data and the large variation of erosion impacts by soil order and crops, Den Biggelaar et al. (2004b) concluded that in general, little is known about these losses for many important crops in many developing countries. In summary, studies are too limited to generate a global picture of water erosion impacts on crops and to compare water erosion impacts across different regions and crops.

2.5 Studies on the impact of climate change on water erosion

Research on the impacts of climate change on water erosion has a long history, dating back to the 1940s, due to the close link of both processes (Li and Fang, 2016). Earlier research was focused on observed impacts of changing weather parameters (primarily precipitation) on water erosion (Leopold, 1951; Langbein and Schumm, 1958). In the 1990s several studies emerged, in which hypothetical climate change scenarios are used to simulate the impact of artificially modified climate parameters on water erosion (Favis-Mortlock et al., 1991; Favis-Mortlock and Boardman, 1995; Lee et al., 1996). With increasing development of climate and erosion models, the number of studies on the impact of climate change on water erosion substantially increased since the year 2000 (Li and Fang, 2016). The studies are primarily focused on the United States, Europe and China.

The most recent research on climate change impacts on water erosion is commonly based on a modelling approach linking water erosion models (e.g., USLE-based models, WEPP), hydrological models (e.g., SWAT) or crop models (e.g., EPIC) with General Circulation Models (GCMs) (Li and Fang, 2016). Another common approach is to focus on erosion changes caused by land use changes due to different driving forces including climate change (Maeda et al., 2010; Paroissien et al., 2015).

In a review of recent assessments of climate change impacts on water erosion, Li and Fang (2016) concluded that water erosion may both increase or decrease under climate change, depending on geographic locations, climate scenarios, precipitation patterns, topographic conditions, and land management practices. Although, this review found that changes in future water erosion vary widely around the world, in 136 records collected by Li and Fang (2016) erosion rates increased under future climate scenarios, while only 55 records showed a decreasing trend and 14 records indicated no change.

Pruski and Nearing (2002a) compared changes of water erosion, simulated with the WEPP model, with changes in relevant climate parameters at eight locations across the United States. They observed significant direct impacts of precipitation changes on water erosion, but often the key factor affecting water erosion were changes in biomass production induced by soil moisture, atmospheric CO_2, temperature, and solar radiation. Overall, they concluded that water erosion can be expected to increase where precipitation increases are significant, but if precipitation decreases, water erosion may both increase or decrease depending on the complex interactions between plant biomass, runoff, and erosion. In a separate study, the same authors simulated the responses of water erosion to precipitation changes using the WEPP model at three locations across the United States, which suggested that each +1% change in precipitation can effect a +2% change in runoff and a +1.7% change in erosion, if other factors stay equal (e.g., temperature, CO_2 levels, and solar radiation) (Pruski and Nearing, 2002b). In another study in the U.S. Midwest, Lee et al. (1996) estimated a similar relative response of water erosion to increasing precipitation. Their outputs from the EPIC model suggested a relative increase in erosion rates twice that of precipitation (e.g. 37 % increase in water erosion for 20% in precipitation) for current temperature and CO_2. Using EPIC as well, Favis-Mortlock and Boardman (1995) simulated the impact of precipitation changes on water erosion in the UK and found an average increase of annual water erosion by about 12% due to an increase of precipitation of 10% and 2°C warming. In a separate study at the same locations, mean annual water erosion simulated with the EPIC model increased up to 30% under a similar climate change scenario (Favis-Mortlock et al., 1991). The differences to the prior study are likely due to changes of hydrological parameters and a different version of EPIC (Favis-Mortlock and Boardman, 1995), which indicates the difficulty of comparing case studies examining water erosion changes due to climate change.

Several studies have addressed the nonlinearity of changes in surface runoff and water erosion in response to changing climate parameters when accounting for the interactions of precipitation, temperature, and CO_2 concentrations with biomass (e.g., Gautam et al., 2015; Pruski and Nearing, 2002a). This complexity was comprehensively addressed by Nunes et al. (2013), who used a sequential modelling approach linking a storm-based erosion model and a regional climate change model with SWAT, to analyse the impact of projected lower rainfall amounts and higher storm intensities in Mediterranean watersheds with changing vegetation covers. Their results suggest that in many cases an increase in vegetation cover on cropland through warmer temperatures and CO_2 fertilisation is expected to mitigate the impacts of increased storm rainfall. The significant impact of biomass on water erosion changes was also considered by O'Neal et al. (2005), who accounted for the role of different field management practices on climate change impacts on water erosion in the United States. In 10 out of 11 locations water erosion simulated with the WEPP model under climate change scenarios increased by average 95% due to average precipitation change of +7%. In comparison to similar studies soil loss changes were greater and very variable due to the variation in management and planting dates in addition to changing climate parameters. Increased water erosion was caused sometimes by increased precipitation and sometimes by decreased crop cover from lowered maize yields due to extreme heat or drought. In other studies based on the WEPP model, water erosion rates increased even when precipitation decreased due to a drop in maize yields and soil residue cover caused by climate change (Southworth et al., 2000, 2002b,a). Hence, reduced rainfall does not necessarily lead to reduced water erosion. On the contrary, adaptation of soil conservation farming techniques can lead to reduced water erosion even when precipitation increases. For example, Klik and Eitzinger (2010) used the WEPP model to demonstrate the effectiveness of no-tillage and grass cover to decrease future water erosion under climate change projections in Austria.

Mullan et al. (2012) point out that the biggest limitations of studies on climate change impacts on water erosion are the lack of considering land use and field management, next to the coarse temporal and spatial scale of climate change data. To address the significance of these limitations, the authors created different land use, management and rainfall intensity scenarios and simulated water erosion in Northern Ireland using the WEPP model and sub-daily and spatially downscaled rainfall projections. Model outputs suggested both a dramatic increase and decrease in future water erosion rates, depending on the specific scenario. Neglecting sub-daily rainfall and land use management scenarios would lead to a projected decrease in water erosion rates and thus hide the potential for increased water erosion under climate change in the study area. Due to the importance of sub-daily rainfall in their analysis, Mullan et al. (2012) stressed the need to look beyond average annual precipitation amounts to analyse future rates of soil erosion. Other studies underline this conclusions. For example, Routschek et al. (2014) suggest that projected changes in precipitation patterns including increasing rainfall intensities will lead to a significant increase in water erosion by 2050 in Saxony, Germany. Additionally, Zhang and Nearing (2005) attributed increased soil loss simulated with the WEPP model under selected climate scenarios in central Oklahoma in the United States to increased frequency of large storms represented by an increased variability in monthly precipitation. Further, Pruski and Nearing (2002b) addressed the different impacts of annual precipitation amounts and daily precipitation amounts (representing precipitation intensity) and suggested that changes in the latter had stronger impacts on water erosion changes. Although changes in precipitation intensity have been identified as highly relevant for climate change impact studies on water erosion, few studies include sub-daily rainfall data due to the coarse temporal resolution of projected climate parameters (Li and Fang, 2016).

In summary, model outputs about interactions between climate change and water erosion are highly variable between studies. The strongest agreement appears to be on a predicted increase in water erosion rates when precipitation increases significantly. However, the rate of increase varies between studies. Due to the many interactions between biomass and water erosion under changing climate parameters, general conclusions on the impact of climate change on water erosion are challenging to draw from present modelling studies. In addition, some interactions are neglected due to missing input data or lack of process representation in the model structure. Common addressed shortcomings are the lack of accounting for gully erosion in models, sub-daily rainfall or for changing rain to snow ratios with changing temperatures (Li and Fang, 2016). The latter can have a strong impact on the distribution of seasonal precipitation patterns and thus water erosion rates (Mukundan et al., 2013). In addition, most studies are based on field management scenarios, which do not account for farmers responses to a changing climate. As changes in crop cover are often decisive in climate change impacts on water erosion, this leads to a major uncertainty in predicted water erosion rates. In addition, shortcomings of models to simulate climate change impacts on crops, including crop responses to extreme heat or rainfall events and CO_2 fertilisation, add uncertainty to modelled water erosion rates. General conclusions about climate change impacts on water erosion are also hampered by the difficulty of comparing study results as often different models or model parameters are used. Furthermore, conclusions derived from modelled water erosion changes under climate change are linked to model inputs from a specific location describing environmental characteristics and land use. Transferring findings from one study locations to different locations with different circumstances is difficult as water erosion does not response linear to changing climate parameters. Therefore, extrapolating model outputs from field studies to larger scales is uncertain as well. As most studies were conducted in Europe, China and North America, little is known about climate change impacts on water erosion outside these regions.

2.6 Discussion

2.6.1 Models are the preferred method for assessing water erosion at large scales

Models are necessary to provide much needed large-scale indicators of water erosion using increasingly available datasets on topography, soils, climate and land use. Although empirical water erosion models such as USLE are often criticised as oversimplified models (e.g., Trimble and Crosson, 2000), its simplicity facilitates the application on large scales and data-scarce regions and improves the transparency of model outputs. Several authors agree that the simplicity of USLE-type models makes them most suitable for global water erosion assessments (Borrelli et al., 2017; Doetterl et al., 2012; Van Oost et al., 2007; Alewell et al., 2019).

More complex water erosion models demand detailed input data and calibration of model parameters, which becomes increasingly challenging with increasing scale of a study. This complexity is a major disadvantage for regional or global studies. Furthermore, even complex models with detailed data cannot fully simulate the real world as some water erosion processes are not fully understood.

Some authors criticise the use of water erosion models on large scales and prefer to use field experiments instead (Evans and Boardman, 2016b). Although field studies have many shortcomings as well, they may be more reliable to monitor erosion at specific locations if enough resources are available. However, major drawbacks of field experiments are their subjectivity as field methods are not fully standardised, as well as their high resource intensity as they demand a large amount of time and knowledge. Thus, they are not suitable to acquire the large amount of data necessary for large-scale and global assessments (Panagos et al., 2016). Moreover, water erosion models are needed to run scenarios (e.g. climate change impacts) and can be linked with other models (e.g. crop models) to quantify impacts of water erosion; thus, they are essential to address many pressing research objectives.

2.6.2 A better evaluation of the modelled water erosion estimates is needed

As USLE-type models are empirical models based on observations from the Midwest United States global water erosion estimates need to be evaluated. The robustness of USLE-type models decreases with increasing deviation of environmental characteristics that shaped the data used to develop the model. Previous studies evaluated their global estimates by comparing it to similar modelling studies or to a collection of field data derived from a mix of methods. However, previous studies neglected the varying quality of water erosion estimates for different environments in their evaluations. Therefore, there is a need for a more detailed robustness analysis of global water erosion estimates, which accounts for the impact of different environmental characteristics on model outputs.

Furthermore, model outputs vary between different models as they differ in complexity, structure and parametrisation. Even the different models from the USLE-family generate different water erosion estimates. Model intercomparison projects, which have been very useful for the crop and climate modelling community (Rosenzweig et al., 2013, 2014; Mueller et al., 2017), may help to further address and quantify the uncertainties of water erosion models.

2.6.3 The impact of water erosion on crops is not adequately quantified

Whilst previous studies have focused on improving the spatial and temporal resolution of input data such as topography or precipitation (Naipal et al., 2015; Panagos et al., 2017), the important impact of farming techniques and different crops on water erosion rates has been neglected. One reason is that previous studies used static input data, which does not account for the daily interactions between climate, soil, crops and their management.

As common modelling methods used in large-scale water erosion assessments do not account for the daily interactions between crops and water erosion or different field management intensities (e.g. fertiliser use), they are of limited value to assess water erosion impacts on crop yields. Whilst some field studies exist, which quantify water erosion impacts on crop yields, large-scale assessments are rare. The few attempts to estimate water erosion impacts on crops on a continental scale are based on a limited amount of field experiments (Den Biggelaar et al., 2004a; Panagos et al., 2018).

Field experiments to assess water erosion impacts on crops are highly complex due to the slow reduction in soil productivity. Furthermore, they are highly subjective as no standardised way exists to measure this process. As the method used to measure water erosion impacts on crops can be the strongest driver influencing study results (Bakker et al., 2004), comparing the conclusions of different field studies or collating data from field studies to generate conclusions on larger scales is highly uncertain. Due to a lack of data, previous assessments on large-scale water erosion impacts on crops relied on the limited and very heterogeneous data currently available. However, the importance of the setup of field experiments can mask the impact of different environmental and management characteristics on water erosion rates. Moreover, the available data only represents a limited amount of environments, crops and field management conditions.

As a result, little is known about the effects of water erosion on crop production and its economic consequences. In addition, sound conclusions on geographically varying water erosion impacts cannot be drawn from existing studies and thus large-scale indicators to highlight regions most susceptible to water erosion impacts are lacking. To assess water erosion impacts on crops on a large or global scale a consistent method is needed to capture the effects of varying site characteristics on water erosion impacts.

2.6.4 The impact of climate change on water erosion is unclear

On smaller scales, process-based crop models are frequently used to analyse the relationship between climate change and water erosion on cropland. Whilst studies could demonstrate a close link between changing climate parameters and water erosion, projecting changes in water erosion rates and impacts is challenging due to many reasons. Some of the most import reasons are the uncertainty in projected precipitation changes and their low temporal resolution. Moreover, disentangling the impact of single climate parameters on water erosion is difficult due to the many complex interactions between climate, soil and land use. Numerous modelling studies have already addressed these complexities, which led to important insights on the significance of land use and climate change impacts on crops for projecting water erosion changes.

As climate change impacts on crops vary around the globe it can be expected that also climate change impacts on water erosion vary in different global regions. Thus, hotspots should be identified where the susceptibility of crop production to water erosion may potentially increase due to climate change to concentrate efforts and research on soil conservation strategies at locations where they are most needed in the future. However, the conclusions of existing studies are limited to single fields, mostly located in Europe, China and North America. Moreover, as their study design has an overwhelming effect on the model outputs (e.g. models used, climate and field management scenarios), the different studies cannot be directly compared with each other. Thus, using the outcomes of existing studies to project differences of changing water erosion rates in different regions is limited.

Application of the models used to analyse the links between climate change and water erosion on larger scales would generate model outputs that describe the impact of climate change on interactions between crops and water erosion for different regions in a consistent way. This could provide useful indicators on the geographic variations of climate change impacts on water erosion and their variability under different climate and management scenarios. In addition, the model outputs can provide another layer to climate change impact assessments on crops by accounting for water erosion impacts on crops. This will help to identify regions vulnerable to both climate change and water erosion.

2.7 Conclusion

This literature review addressed several knowledge gaps about i) the uncertainty of water erosion estimates, ii) the impacts of water erosion on crop production, and iii) the impact of climate change on water erosion and its consequences for crop production. As there is a need for large-scale indicators on water erosion rates and impacts, and on land degradation more generally, these knowledge gaps need to be addressed.

Process-based crop models coupled with water erosion models are useful tools to simulate links between crops and water erosion and thus can address many of the literature gaps. The simplicity of empirical equations such as USLE-type models facilitates their application on a global scale and their linkage to process-based crop models.

However, global water erosion estimates based on USLE-type models include many uncertainties, which need to be addressed more thoroughly. This is considered in the robustness analysis of EPIC-IIASA's water erosion estimates, which is carried out as part of the first research objective of this thesis.

Improving confidence in water erosion estimates simulated using USLE in conjunction with GGCMs will provide a tool for analysing plant-water erosion interactions on a global scale. This will enable the simulation of new large-scale water erosion indicators targeted under the second and third research objectives, including (i) estimates of the impact of water erosion on crops for different global regions; and (ii) insights into the impacts of climate change on water erosion in different global regions.

Chapter 3

Literature review of crop models

3.1 Introduction

Crop models are used to simulate crop yields as a function of genotype, soil, weather and management strategies. Climate change and water erosion have an impact on the interacting processes in crop production systems and thus influence crop growth, crop development and crop yields. Crop models are frequently used to investigate the impacts of climate change on potential crop productivity via perturbations in the mean and variability of climate variables such as temperature and precipitation, as well as through the impacts of increasing atmospheric CO_2 concentration (Ewert et al., 2015; White et al., 2011). In addition, crop models are used as a tool to explore field management strategies for improving the resilience of crop production systems to climate change (Matthews et al., 2013; Webber et al., 2014). As not all interacting processes between the soil, biomass and climate are understood, crop models differ in their structure and complexity. Uncertainties in crop response to changing temperature, precipitation and atmospheric CO_2 are often discussed in crop modelling studies because of their relevance in climate change impact studies (e.g., Deryng et al., 2014; Osborne et al., 2013). More complex crop models also simulate interactions between the plant-soil-system, which are very important for exploring field management strategies for adapting to climate change.

Given the global importance of climate change and the central interest in agriculture, crop models are increasingly applied at the global scale (using global gridded input data infrastructures) to assess the impact of climate change on global crop production (Mueller et al., 2017). In addition, global gridded crop models (GGCMs) are used to address a wide range of questions beyond the impact of climate change on annual crop yields. For example, they are frequently used to assess weather-induced crop-yield variability, the impact of extreme weather events on crops, or yield gaps due to water and nutrient deficiency (e.g., Balkovič et al., 2014; Frieler et al., 2017; Jägermeyr et al., 2016; Leng and Hall, 2019). Moreover, model outputs of GGCMs are frequently used as inputs for global economic models to explore wider questions of the impacts of changing crop production in the face of population growth and economic development (Nelson et al., 2014). As such, GGCMs are an essential tool for addressing many pressing research questions.

However, GGCMs are largely driven by variable information on weather and atmospheric CO_2 concentrations, whereas assumptions on soil properties and/or management systems are usually static; thus, models do not reproduce all temporal dynamics and spatial patterns of observed crops yields (Mueller et al., 2017). As the contribution of weather variability to crop variability is lower in low-input systems than in high-input systems (Ray et al., 2015), negligence of other processes influencing crop yields such as the impact of pests, diseases, changes in management and soil quality through land degradation, reduces the significance of model outputs in some global regions. Accounting for land degradation depend substantially on soil parameters and soil process parameterisation, i.e. hydrology and nutrient turnover, which are often neglected domains in GGCMs (Folberth et al., 2019).

This literature review provides an overview of the types and uses of crop models and discusses their uncertainties. It will outline the focus of the latest large-scale and global climate change impact studies based on crop models, highlighting frequently neglected topics that need further scrutiny.

3.2 Crop model types

Crop models are mostly deterministic models. They are used to estimate crop yields as a function of input parameters and initial conditions. Deterministic crop models can be further divided into statistical, process-based and empirical models.

Statistical models can be used as a simple form of crop model, which are often based on regression equations. With the help of statistical crop models, the past relationship between changes in crop yields and determining parameters such as climate conditions can be used to receive estimates for future yield trends (Lobell et al., 2011). The advantage of this method is that no extensive input data and field calibration data is required, which can be helpful in regions where data is scarce (Lobell and Burke, 2010). However, predictions from statistical models are limited to the locations the data was derived from to develop the model (Ritchie and Alagarswamy, 2002). Moreover, statistical models do not predict responses to nonlinearities and do not explain the reason for certain changes (Jones et al., 2016; Challinor et al., 2009). Thus, statistical models are restricted to the climates and atmospheric conditions of today, and generally do not take into account interactions between crop genotype and environmental and management factors (Rötter et al., 2011). As such, they are of limited use for generating crop yield projections under different climate change scenarios and for adaptation decisions.

Process-based (or mechanistic) models are the most complex type of model because it is assumed that the individual parts of a system and their connections are understood and thus they can simulate an approximation of the real system. In process-based modelling crop yields are determined by equations representing a crop's physiological response to environmental variables (Estes et al., 2013). Although process-based models can simulate processes very close to the real system, they suffer from the major drawback of requiring a high amount of input data.

Unlike process-based models, empirical models are not based on the assumption that all underlying biological, physical and chemical processes of a system are understood. Empirical models are based on observed relationships among experimental data, which are represented in a model. The simulated relationships fit the observed relationship and thus allow to predict what will happen in certain circumstances that fit the prior observed circumstances (Hudson, 1993). Due to the simulation of relationships with the help of empirical observations rather than mathematical descriptions, empirical models require less data to run and are thus easier to use on a wider scale. Common crop models often include both process-based and empirical elements.

3.3 Typical crop model routines to simulate crop growth

Common process-based crop models share the same fundamental approach of simulating the development of crops from germination to harvest as a response to climate, soil, phenological characteristics and field management. These determinants also influence the timing of different phenological stages such as flowering, grain-filling and the partitioning of the biomass into grain and other plant parts, which controls the amount of the yield. The many single factors used in the simulation of crop growth and yield can be divided into defining factors such as CO_2, radiation, temperature, and crop characteristics, which determine the potential crop production, and factors limiting or reducing crop growth such as nutrient and water deficiency and the exposure to pollutants, pests, diseases and weeds (Jones et al., 2016; Bouman et al., 1996; Rabbinge, 1993). The range of factors involved in the simulation of crop growth and yields varies between crop models.

The most common way of simulating the development of crops is by calculating the timing of key phenological stages in the plants life cycle as a function of temperature (degree-days) and daylength (Boote et al., 2013). The potential rate of development is usually modified by limiting and reducing factors, which play an important role in delaying or accelerating specific crop development phases (Boote et al., 2013). Next to capturing the development characteristics of a crop, the final yield also depends on the separately simulated daily growth rate (Dodds, 2010). A common method to predict biomass accumulation is based on the work by Monteith (1977), who found a linear relationship between seasonal aboveground biomass accumulation of C-3 crops grown without stress in Britain, and intercepted solar radiation. The slope of this relation is the radiation use efficiency (RUE) in gMJ^{-1}, which is used by crop models as a constant to link plant growth to solar radiation (Boote et al., 2013; Dodds, 2010). Some crop models alternatively or additionally link plant growth to crop water use by using transpiration use efficiency (TUE) as a constant, which is the ratio of biomass produced per unit of water transpired by a crop. This method is based on the work by De Wit (1958) who correlated water use with plant growth. This relationship has been frequently used and modified, most prominently by adding vapour pressure deficit (VPD) as an environmental variable, which is addressing the increase in transpiration of a plant as the vapour pressure deficit of its surrounding air increases (Tanner and Sinclair, 1983). With the latter modification TUE is measured in $gkg^{-1}kPa$. Best estimates for crop growth rates can be achieved by using a combination of both the RUE and TUE methods (Dodds, 2010). Leaf area expansion plays a crucial part in estimating the interception of solar radiation; thus, this process is an important component in the simulation of plant growth rates. However, it is a difficult process to simulate as it is highly sensitive to temperature, atmospheric CO_2 concentration and the availability of water and nutrients (Boote et al., 2013). Common methods implemented in crop models are to use empirical leaf area curves specifying the course of growth and senescence of the leaf area during the growing season, which are influenced by crop development stages and crop stress. The simulation of leaf expansion can be either independent from the plants growth rate or calculated as a function of biomass accumulation (Dodds, 2010). Once the end of the growing season is reached a typical method to determine final yield is to use a prior defined harvest index, which is the ratio of the grain yield to the total above-ground biomass. Some crop models also simulate individual grains during the growing season in order to determine the final yield.

More complex crop models also simulate soil processes such as carbon, nutrient and water dynamics in the plant-soil-system and thus can provide outputs of soil components next to crop yield estimates (Boote et al., 2013). Outputs of those sub-models are further used to derive limiting and reducing factors to adjust potential biomass to actual biomass. Modelling the outputs and inputs of the water balance between crops and the soil is necessary in order to calculate important processes for biomass accumulation and crop development such as time-varying availability of water and nutrients for the plant (Jones et al., 2016). Therefore, most crop models are able to simulate hydrological processes such as infiltration, percolation, runoff and evapotranspiration, as well as carbon and nitrogen dynamics. In order to represent these dynamics, the physical and chemical processes in the soil need to be simulated as well as field management interventions, which have an impact on those processes. The many factors influencing those dynamics complicate adequate representation of water, carbon and nitrogen flows and thus common crop models differ in the way they include those processes. Furthermore, some processes such as responses to phosphorus, potassium, or micronutrients in the plant-soil-system are even more complex and are thus hardly implemented in crop models. Similar to this, routines to simulate the reduction of actual biomass due to damages on plants by insects, diseases, weeds and pollutants are absent in most crop models due to their complexity (Jones et al., 2016).

3.4 Crop models and their applications

The earliest crop growth simulation models were developed in the 1960s (De Wit, 1965; Monteith, 1965). Today, numerous crop models exist. The selection of crop models for a study depends to a large degree on the emphasis on different research questions, crops and regions (Ewert et al., 2015). The latter can be decisive for choosing crop models as models often perform best in regions, where the data was collected to support the development of the model (Challinor et al., 2017). Some crop models may be more suitable for climate change impact studies, whereas other models might be a better fit for a study on the impact of management strategies on soil productivity. For example, the crop models STICS (Brisson et al., 1998) and HERMES (Kersebaum, 2007) are frequently used to simulate crop N stress. APSIM (Keating et al., 2003) and DSSAT crop models (Dzotsi et al., 2010) have been proposed as useful crop models to simulate the impact of P deficiency on crops (Ewert et al., 2015). The CROPGO model includes routines to account for soil salinity impacts on crops (Webber et al., 2010). CERES (Hoogenboom et al., 2019), EPIC (Sharpley and Williams, 1990) and APSIM (Keating et al., 2003) were the most frequently used crop models in a review of studies using crop simulation models to investigate different aspects of how climate change might affect agricultural systems. (White et al., 2011). Few crop models include sub-models to simulate water erosion and its impact on crops. The most prominent exceptions are EPIC and APSIM. Other crop models focusing on the sustainable use of soil resources are NRTM (Shaffer et al., 1983), CENTURY (Parton et al., 1987) and PERFECT (Littleboy et al., 1989), but they are limited in their ability to address crop management issues and accurate simulation of crop yields and are used less frequently in crop productivity studies (Keating et al., 2003; White et al., 2011).

Crop models are applied at field, regional and global scales. Most early crop models were developed for application at plot and field scale; thus, early applications of crop models in climate change impact studies were mainly site-based (Ewert et al., 2015). Recently, global gridded crop models (GGCMs) have been developed by combining crop or ecosystem models with global gridded input data infrastructures to directly use the outputs of global climate models to generate projections of future crop yields (Challinor et al., 2009). In addition, large-scale model outputs can easier be used as indicators for administrative units to inform environmental and agricultural policies (Ewert et al., 2011; Alewell et al., 2019). A major difference to field-scale model applications is that GGCMs cannot be calibrated and evaluated against field observations. Usually the evaluation of the performance of large- to global-scale models is based on a comparison to (sub-) national yield statistics, or to gridded yield data sets that are based on (sub-)national statistics (Mueller et al., 2017). Today, several prominent crop models are used next to ecosystems simulation models for climate change impact assessments at regional to global scales. Commonly used crop and ecosystems simulation models for large-scale climate change impact assessments include EPIC (Balkovič et al., 2014; Liu et al., 2007), DayCent (Stehfest et al., 2007), PEGASUS (Deryng et al., 2011), DSSAT (Deryng et al., 2014; Schauberger et al., 2017), GLAM (Osborne et al., 2007), LPJmL (Bondeau et al., 2007) and WOFOST (Boogaard et al., 2013).

Although crop models are now widely used to assess the impacts of climate change, most models were originally developed to support decisions about field management, such as choice of crop cultivar, irrigation timing and fertiliser application (Hertel and Lobell, 2014). Hence, crop models are often used for climate change adaptation studies. According to Matthews et al. (2013), crop models can contribute to i) determining where and how well crops of the future will grow; ii) crop improvement programmes; iii) identifying what future crop management practices will be appropriate and iv) assessing risk to crop production in the face of greater climate variability. The most frequently explored strategies in climate change adaptation studies based on crop models are changes in planting dates and cropping systems (cultivars or rotation), whereas new practices (e.g. type and distribution of fertilisers and tillage practices), interacting practices (e.g. planting dates and irrigation management) and improved crop characteristics are explored less frequently (White et al., 2011; Ewert et al., 2015). To thoroughly account for the impacts of different field management strategies on crop yields, models need to simulate the interactions between farming techniques, such as tillage, crop and residue management, and processes affecting soil quality.

3.5 Global climate change impact assessments using crop models

Knowledge on the magnitude, rate, and pattern of climate change impacts on agricultural productivity are based on more than two decades of research (Rosenzweig et al., 2014). Common methods to analyse these impacts are based on GGCMs and statistical analysis of historical data. Studies comparing methods found that estimated climate change impacts using different methods yield similar results (Lobell and Asseng, 2017; Liu et al., 2016; Zhao et al., 2017). Crops most considered in climate change impact assessments are wheat, maize, soybean and rice and the dominant regions studied are the USA and Europe (White et al., 2011).

The results of GGCMs are compared in the *Agricultural Model Intercomparison and Improvement Project* (AgMIP) (Rosenzweig et al., 2013) and the *Inter-Sectoral Impact Model Intercomparison Project* (ISI-MIP) (Warszawski et al., 2014). Rosenzweig et al. (2014) summarised model outputs of seven GGCMs participating in AgMIP and indicated strong negative impacts of climate change on crop production, especially at low latitudes and at higher levels of warming. Model outputs under the RCP 8.5 scenario are summarised in Figure 3.1, which illustrates that highest negative yield changes for future maize, wheat, rice and soybean yields are at low latitudes. The contrast of climate change impacts between high-latitudes and low-latitudes is most pronounced for maize and wheat among the assessed crops with general agreement among models. Strong negative climate change impacts on crops at low latitudes can occur at moderate temperature increases (1 to 2 °C) due to the narrow gap between the high- temperature thresholds for suitable production of crops such as maize and wheat and the present temperature in tropical climates (Hatfield et al., 2011). This conclusion is confirmed by several other studies observing highest climate change impacts on major staple crops at low latitudes (e.g., Balkovič et al., 2014; Zhao et al., 2017). In addition, one study confirms these patterns by suggesting that areas in Russia, China, and Canada are projected to gain suitable plant growing days (Mora et al., 2015).

Most studies analysing projected climate change impacts on crop yields focus on the impact of temperature changes on crop yields. In addition, most studies account for future changes in field management by analysing climate change impacts under different fertilisation and irrigation management scenarios. Rosenzweig et al. (2014) summarised the simulated yield changes presented in Figure 3.1 based on model outputs with and without explicit nitrogen stress. The former considers current fertiliser application rates based on observational databases, whereas the latter scenario considers ideal fertiliser application that completely eliminates nitrogen stress for crops, which considerably reduces negative climate change impacts. Similarly, Balkovič et al. (2014) explored the impact of climate change on global wheat production under different irrigation and fertilisation intensification scenarios and concluded that the negative impacts of climate change can partly be offset by adequate intensification using nutrient additions and currently existing irrigation infrastructure. Some studies simulate climate change impacts

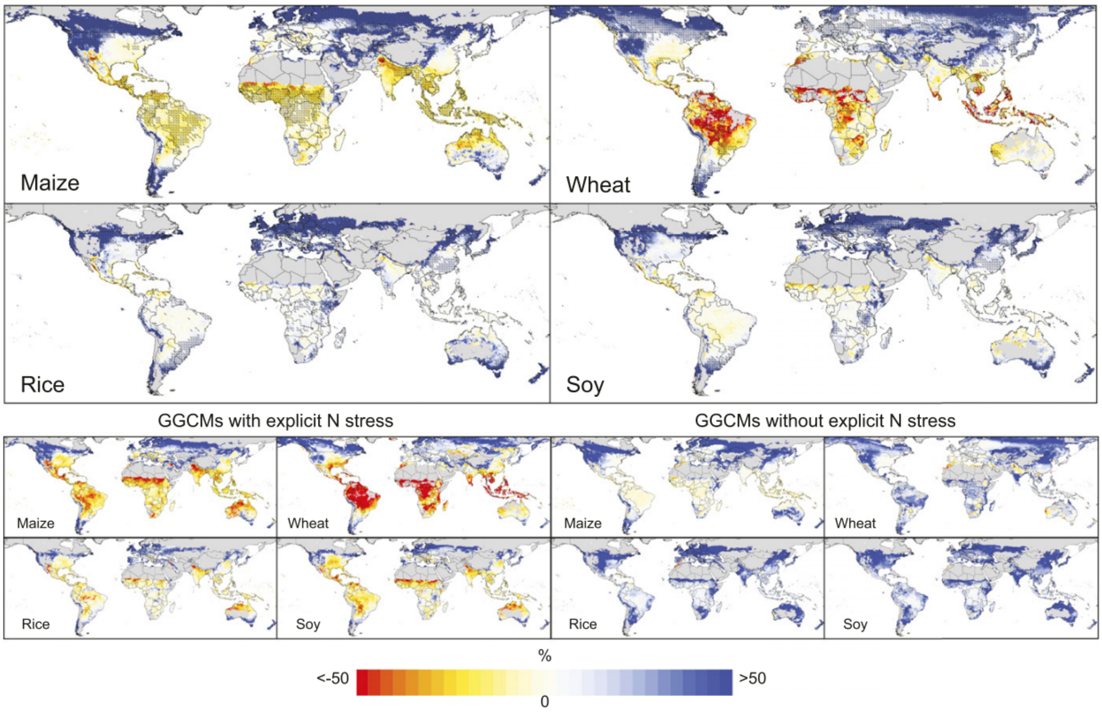

Figure 3.1: AgMIP median yield changes (%) for RCP8.5 (2070–2099 in comparison to 1980–2010 baseline) with CO_2 effects over all five GCMs x seven GGCMs (6 GGCMs for rice) for rainfed maize (35 ensemble members), wheat (35 ensemble members), rice (30 ensemble members), and soy (35 ensemble members). Hatching indicates areas where more than 70% of the ensemble members agree on the directionality of the impact factor. The bottom 8 panels show the corresponding yield change patterns over all five GCMs x four GGCMs with nitrogen stress (20 ensemble members from EPIC, GEPIC, pDSSAT, and PEGASUS; except for rice which has 15) (Left); and 3 GGCMs without nitrogen stress (15 ensemble members from GAEZ-IMAGE, LPJ-GUESS, and LPJmL) (Rosenzweig et al. 2014).

with more sophisticated field management scenarios. For example, Iizumi et al. (2017) addressed responds of crop yields to global temperature considering agronomic adjustments through socioeconomic changes by accounting for improved technologies, field management and historical patterns of fertiliser input in a GGCM. The model outputs show that global mean yields of maize and soybean will decrease with warming at the end of this century even when agronomic adjustments are considered, whereas those of rice and wheat increase with warming. However, complex future field management scenarios are usually highly uncertain. Therefore, some studies choose to present their results based on scenarios reflecting current conditions. For example, Zhao et al. (2017) used GGCMs, local point-based models, statistical regressions, and field-warming experiments to demonstrate that without CO_2 fertilisation, effective adaptation, and genetic improvement, each degree-Celsius increase in global mean temperature would, on average, reduce global yields of wheat by 6.0%, rice by 3.2%, maize by 7.4%, and soybean by 3.1%.

As indicated in the last example, atmospheric CO_2 fertilisation is regularly addressed in climate change impact studies and was found to be significant for crop yield projections (e.g., Levis et al., 2018; Ren et al., 2018; Tebaldi and Lobell, 2018). In a review about crop modelling studies that were conducted from 1995 to 2002, Tubiello and Ewert (2002) found that about half of the studies dealing with climate change considered responses to CO_2. A more recent review mentioned that most papers ignoring effects of CO_2 were published prior to the year 2000 suggesting an increasing consideration of CO_2 fertilisation in climate change impact studies (White et al., 2011). For example, Levis et al. (2018) analysed the effects of CO_2 fertilisation on C3 and C4 crops using a mechanistic model embedded in an earth system model, and found that CO_2 fertilisation can mitigate yield losses of C3 crops such as wheat, rice and soybean worldwide. This is in line with studies reviewed by the IPCC (IPCC, 2014) and confirmed in recent studies (e.g., Ren et al., 2018; Reyer et al., 2017; Tebaldi and Lobell, 2018). However, the mitigation effect of CO_2 fertilisation varies for crops and regions. For example, in a regional analysis in the Middle East and northern Africa, Waha et al. (2017) found a significant correlation between crop yield decrease (legumes and maize are worst affected) and temperature increase regardless of whether the effects of CO_2 fertilisation or adaptation measures are taken into account. Similarly, Iizumi et al. (2018) compared outputs from a GGCM running with a factual and a non-warming counterfactual climate scenario as input respectively and concluded that between 1981 - 2010 climate change has decreased global mean yields of maize, wheat and soybeans by 4.1, 1.8 and 4.5%, even when CO_2 fertilisation and agronomic adjustments are considered. Rosenzweig et al. (2014) mentioned that CO_2 fertilisation does not compensate for increases in water demand and shortening of already-short growing periods for annual C3 crops in the tropics. However, Rosenzweig et al. (2014) also mentioned that responses to climate change impacts between models are more similar and much more negative across tropical and midlatitude bands once CO_2 effects are removed. However, relative yield changes with and without CO_2 effects are much closer in C4 maize than in the C3 crops indicating the higher significance of CO_2 effects for certain crops. Conclusions from field experiments suggest that the direct fertilisation effect on crop yields in model projections is overestimated suggesting that crop model parametrisation of CO_2 effects remains a crucial area of research (e.g., Ainsworth et al., 2008; Long et al., 2006b). One study also highlighted that increasing CO_2 lowers concentrations of important nutrients in crops; thus, threatening human nutrition (Myers et al., 2014).

Whilst changes in precipitation intensity, amounts and patterns are often decisive for observed seasonal crop yield changes (Huntington et al., 2017), they are less suitable to explain projected yield trends. Often, studies analysing projected climate impacts focus on temperature, which is more important than precipitation for yield trends, whereas precipitation plays a more important role in year-to-year variability of crop production than temperature (Lobell and Burke, 2008; Lobell and Field, 2007). Moreover, climate models perform the simulation of large-scale patterns of precipitation less well than for surface temperature (IPCC, 2014). Nevertheless, some studies focus on projected rainfall-related impacts for agriculture due to crop damage through heavy precipitation and flooding, or due to droughts through lack of rainfall. The latter is very important on rainfed cropland and is among the most severe climate related risk for crops (FAO, 2018); thus, it is subject to most studies researching precipitation related climate change impacts. For example, projected changes in precipitation where used by Al-Bakri et al. (2010) to asses their impact on rainfed wheat and barley in the Yarmouk basin in Jordan using the crop simulation model DSSAT. Their model outputs suggested that a reduction of rainfall by 10–20% reduced the expected yield by 4–8% for barley and 10–20% for wheat, respectively. An increase in rainfall by 10–20% increased the expected yield by 3–5% for barley and 9–18% for wheat, respectively. The impact of projected precipitation changes on crop yields were analysed on a larger scale by Leng and Hall (2019) using a drought index and the outputs of 11 GGCMs participating in the AGMIP and ISI-MIP projects. They calculated an increase in yield loss risk by 9%–12%, 5.6%–6.3%, 18.1%–19.4% and 15.1%–16.1% for wheat, maize, rice and soybeans, respectively, in the ten largest producing countries by the end of the 21st century without considering the benefits of CO_2 fertilisation and adaptations. Whilst studies often highlight the positive effects of increasing precipitation on crop yields (e.g., Kang et al., 2009), few studies focus on the negative impacts of projected precipitation increases on crop yields. Often crop models fail to capture the negative impacts of heavy rain and extremely wet conditions (Balkovič et al., 2018). In one notable study based on the application of a modified version of the model CERES-Maize, Rosenzweig et al. (2002) estimated a doubling of crop damage within 30 years in the USA from increased heavy precipitation under climate change causing excess soil moisture and flooding. Rosenzweig et al. (2002) focused their discussion on crop losses through anoxic conditions, increased risk of plant disease and insect infestation, or delayed planting or harvesting due to inability to operate machinery caused by excess soil moisture and flooding. Water erosion impacts on crops are usually neglected in studies analysing yield changes due to precipitation changes. The relationships between crops, precipitation and water erosion in response to climate change are highly complex and are thus rather subject to field scale studies, which focus on disentangling these interactions to derive conclusions on potential changes in future water erosion rates (e.g., Mullan et al., 2012; Nunes et al., 2013; O'Neal et al., 2005).

In summary, most studies on projected climate change impacts focus on the impact of changes in temperature, precipitation and atmospheric CO_2 on crop yields. Although not all impacts of those changing climate parameters are considered or their effects are uncertain. Other important climate parameters are neglected in present studies such as solar radiation, wind speed, relative humidity, and atmospheric ozone (White et al., 2011). One important reason for their negligence is the low confidence in the projected changes of these climate parameters (IPCC, 2014).

3.6 Uncertainty and limitations of crop models

Due to uncertainty in certain model input data, model parameters and representation of biophysical processes, the robustness of model outputs varies for different locations, scales, environments, crops and scenarios. As all uncertainties cannot be addressed in a complex model study, it is common to identify and quantify the most important model uncertainties for a specific study (Gabbert et al., 2010). Uncertainty ranges are commonly determined by varying model outputs simulated with varying input values for the most sensitive parameters or through outputs simulated with different models. However, the latter can be challenging due to a wide variety of methodological approaches in different models (White et al., 2011; Asseng et al., 2013).

As crop model studies are based on numerous methods, model intercomparison projects (MIPs) have been established to compare model outputs from different sites, crops and spatial scales and to develop standard protocols for modelling impacts. Prominent MIPs are AgMIP (Rosenzweig et al., 2013), ISI-MIP (Warszawski et al., 2014) and *Modelling European Agriculture with Climate Change for Food Security* (MACSUR) (Bindi et al., 2015). Additionally, these comparison projects play an important role in identifying and assessing the most significant uncertainties in crop model outputs (Challinor et al., 2017; Mueller et al., 2017).

Commonly discussed uncertainties due to limitations of crop models result from the need to strengthen the physiological assumptions of models (e.g. plant response to temperature), responses to CO_2 and genetic diversity of crop cultivars (White et al., 2011; Boote et al., 2013). Lacking representation of extreme weather events in crop models, such as increased frequency and intensity of extreme heat, drought or heavy rains, could lead to an overestimation of positive climate change impacts (Balkovič et al., 2018). In addition, several non-weather related processes influencing crop yields are not considered in most crop models such as impacts of pests, diseases and weeds (White et al., 2011). Further, very few crop models include effects of frost, snow, hail, flood, wind, and ozone on crop growth (Ewert et al., 2015). Also, soil degradation and soil microbial processes influencing nutrient cycles and nutrient availability for plants are often not taken fully into account in most crop models (Folberth et al., 2014).

These limitation are often the result of a lack of field data to evaluate models. Model outputs are usually compared against data from field experiments reflecting a wide range of crops and growing conditions defined by varying CO_2 and ozone concentrations, drought effects and deficit irrigation (Ewert et al., 2015; Boote et al., 2013). Global coverage of data from long-term experiments and the representation of all growing conditions in field experiments need to be improved to comprehensively evaluate crop model outputs (Ewert et al., 2015; Boote et al., 2013). In addition, model outputs other than crop yields and biomass, such as the representation of nitrogen cycling or carbon cycling, have not been adequately evaluated due to a lack of field data (Ewert et al., 2015). This uncertainty results in differences in the representation of processes between crop models. Generally, the consensus on the nature and magnitude of essential processes simulated in crop models needs to be improved (Challinor et al., 2017).

Another important source of uncertainty is information on climate and soil, which are often not available in the necessary spatial detail and thus adds uncertainty to crop model studies at all scales (Nendel et al., 2013). Climate change impact studies at field scale usually use downscaled climate change projections (Mullan et al., 2012; Vanuytrecht et al., 2016), adding bias and a significant source of uncertainty (Challinor et al., 2017). However, Asseng et al. (2013) found a greater uncertainty in simulating wheat yields under climate change due to variations among crop models than to variations among downscaled climate models. In large-scale analysis, soil data needs to be aggregated, which also has a strong effect on model outputs (Hoffmann et al., 2016). Although uncertainty of climate projections is often described as the major uncertainty in climate change impact studies, Folberth et al. (2016) found that soil-type-related yield variability can outweigh the simulated inter-annual variability in yields due to weather and can even determine if climate change impacts on crops are positive or negative. Further, the lack of field management data causes uncertainty in global crop modelling studies. Whilst some spatially explicit dataset on field management and land use exist, such as crop-specific fertiliser rates (Mueller et al., 2012), planting dates and growing seasons (Sacks et al., 2010), irrigation area, amount and timing (Siebert et al., 2015), and crop-specific irrigation shares (Portmann et al., 2010), other management aspects are typically assumed to be static in space and time (Mueller et al., 2017). In addition, globally gridded datasets on field management and land use are usually simplified. For example, farmers may chose different crop varieties or sowing dates, which are subject to a number of weather-induced conditions (e.g., soil wetness, soil temperature) and the timely availability of labour and machinery (Mueller et al., 2017).

Although adaptation strategies involving tillage and residues management, planting dates, irrigation, crop cultivars and fertiliser are considered in some crop model studies, studies often fail to represent the broad scope of adaptation strategies present in the real world and are often limited to practices that can be simulated with confidence (Challinor et al., 2017). Moreover, most global impact studies assume optimal agronomic management (Rosenzweig et al., 2013), which may only reflect the most intensive cultivation systems. On the contrary, low input systems, managed by smallholders, are usually not well represented as common farming techniques such as crop diversification and intercropping are often not considered (Claessens et al., 2012; Hertel and Lobell, 2014).

Drivers and constraints of field management are highly diverse and complex, which can be influenced by gender, access to capital, access to extension services, access to climate information and water, tenure security and farming experience (Gbetibouo et al., 2010; Bryan et al., 2009). Therefore, model assumptions about field management require detailed information on environmental and socio-economic circumstance at a study location, which are often not available. The complexity of farm management is an important source of uncertainty in large-scale and global studies, in which farm management and adaptation can only be simulated in a simplified way and cannot achieve the level of spatial detail necessary to identify the costs and benefits of adaptation measures (Patt et al., 2010). Moreover, crop model studies often do not consider that farmers react to changing environmental and socio-economic conditions by adapting field management (Below et al., 2012; Quinn et al., 2011). In addition, crop modelling studies usually fail to account for technological development, which may lead to systematic underestimation of future crop yields (Challinor et al., 2017; Lobell, 2014). The increase of yields in past decades is largely driven by technological development such as improved crop varieties and increased nutrient application, particularly in Asia; thus, studies on future climate impact should ideally take such developments into account (Ewert et al., 2005). To approximate future management, integrated assessment studies are necessary, in which biophysical models are linked to economic models to account for interactions between socio-economic and biophysical factors (Ewert et al., 2015).

To test the adaptive potential of different farming techniques against climate change impacts, field management scenarios building on agronomic measures applied today can be created. However, the effectiveness of climate change adaptation strategies are uncertain without considering soil quality and soil health factors, which can determine the adaptive potential of farming techniques against climate change impacts (Webb et al., 2017). Moreover, climate change impacts vary across degraded and non-degraded lands with different levels of nutrient availability, infiltration rates, and soil moisture retention (Herrick et al., 2013). Although the gap in the investigation of land degradation factors, such as changes in soil organic carbon, erosion, runoff, and soil humidity, and their interaction with yields has been raised partly two decades ago (Feddema and Freire, 2001), uncertainties due to the lack of the representation of land degradation in crop models are still mostly neglected in recent climate change impact assessments.

One notable exception is Balkovič et al. (2018), who used an EPIC-based GGCM to bracket the uncertainty of climate change impacts on major crops in Europe driven by varying model assumptions and parameters for simulating land degradation through nutrient depletion. They concluded that in parts of Eastern Europe where fertiliser use is comparatively low, soil degradation may negatively outweigh positive impacts of +2 °C warming for certain crops when not prevented by adaptation measures. Since fertilisation is often the most important factor controlling the vulnerability of yields to degrading soil nutrients, unclear future fertiliser use due to unknown economic and political constraints contributes strongly to the uncertainty of crop yield projections. As increasing fertiliser rates is often presented as an effective measure to reduce climate change impacts (Rosenzweig et al., 2014; Balkovič et al., 2014; Folberth et al., 2013), neglecting the impact of land degradation processes on soil fertility leads to uncertainty in climate change impact assessments. Next to fertiliser management, most farming techniques used to mitigate climate change impacts interact with soil process such as nutrient cycles and degradation processes. For example, Folberth et al. (2014) projected potential climate change impacts on maize yields in Africa under different intensification options involving crop rotation options to replenish soil nutrients, while recognizing the need to account for land degradation processes in their study. Although Folberth et al. (2014) simulated land degradation processes such as soil erosion, they were not able to assess the robustness of their model outputs.

3.7 Discussion

Among the different crop model types, process-based models provide the most possibilities to explore the links between climate change and crop production. Process-based crop models coupled with the outputs of climate models can simulate the daily interactions between the growth and development of crops and changing climate parameters to explore the impact of climate change on crop yields. In addition, process-based crop models can be used to explore the effectiveness of climate change adaptation strategies, involving the timing and amount of irrigation and fertilisation or planting dates, for maintaining crop yields. Complex process-based crop models also simulate carbon, nutrient and water dynamics in the plant-soil-system and thus are useful tools to assess the sustainability of crop production systems. The main disadvantages of process-based crop models are the substantial data requirement and the complicated parameterisation of the various crop development processes. However, these have been reduced recently due to increasing availability of global datasets on soil and field management and the growing efforts to improve the application of models through model intercomparison projects such as AgMIP.

The robustness and thoroughness of processes considered in crop production systems differs between models. Whilst numerous crop models exist, only a few models are commonly used in climate change adaptation or impact assessment studies. The most frequently used models to explore different links between climate change and crop production are EPIC, APSIM and DSSAT models (White et al., 2011). These models are also used in recent efforts to assess the impact of climate change on crops on a global scale (Mueller et al., 2017).

Climate change impact assessments based on GGCMs have provided insights on the effects of changes of the most important climate parameters on yield changes in different world regions. Crop models have been used most widely to study the geographic variations of long-term trends of major staple crops under different projected levels of warming. In addition, crop models have been used to assess crop yield changes due to increases in atmospheric CO_2, changes in precipitation, as well as extreme rainfall and heat events. However, simulating the impact of varying climate change parameters on crop yields includes many uncertainties driven by input data or model structures. Whilst some of these uncertainties are addressed frequently and quantified using uncertainty ranges, others are hardly addressed.

Often, uncertainty analysis is focused on the response of crops to climate parameters, whereas many soil processes affected by changes in climate and biomass are neglected. Interactions between soil and biomass in response to climate influence the availability of nutrients for crops and thus play a crucial role in projecting crop yields. Moreover, these interactions play an important role in the impact of field management on crop yields, which is often a major focus in climate change adaptation studies. Without accounting for relevant soil processes influencing nutrient availability for crops, studies on the potential of adaptation strategies to maintain or increase projected crop yields are highly uncertain. Therefore, the integration of processes influencing soil quality in crop modelling studies will be crucial for climate change adaptation studies to better assess the long-term sustainability of agriculture under different field management scenarios.

Moreover, accounting for the degradation of soil quality will support the identification of cropland prone to declining productivity, which is a major objective in climate change impact assessments. As declining yields are often the consequence of several processes, trying to understand how agricutlural systems are affected by several stressors simultaneously would be most realistic (Mittler, 2006). Further, interactions between climate change and land degradation may intensify negative impacts on agriculture (UNCCD, 2017). Whilst land degradation and climate change have been assessed extensively as separate phenomena, less is known about their interactions in different agroecological systems, and how land users must simultaneously adapt to their impacts (Reed and Stringer, 2016). Thus, climate change impact studies may underestimate a potential decline in crop yields if changes in soil quality in response to a changing climate are not considered. According to Webb et al. (2017), incorporating land degradation processes into systems analyses at all scales is needed to assess agroecosystem resilience, the agroecological and socioeconomic impacts of climate change, and scenarios by which agriculture may adapt to climate change.

Water erosion is among the land degradation processes most closely linked to climate change as it is directly linked to precipitation. Although water erosion has been addressed in some GGCM studies (Balkovič et al., 2018; Folberth et al., 2014), it is generally neglected in climate change impact assessment. Models used to simulate crops and water erosion are often similar in structure, and some models, such as EPIC, are frequently used for both crop and water erosion modelling. Due to the strong focus on soil processes in EPIC, it is one of the most suitable models among those often used in climate change impact assessments to simulate crop-water erosion interactions. Furthermore, EPIC has proven to be a reliable model that can be combined with a global data infrastructure to simulate changes in crop production on a global scale. Although these features of EPIC make it a suitable model for this study, there are many uncertainties and knowledge gaps in water erosion modelling that need to be addressed first (Chapter 2.3.4).

3.8 Conclusion

This literature review on crop modelling studies identified several knowledge gaps about the impact of climate change on crop yields. Among the many uncertainties, the lack of consideration of land degradation and its effects on the robustness of climate change impact and adaptation studies is rarely explored. This leads to important stress factors for crop yields being ignored. Moreover, the links between land degradation and climate change may significantly impact crop yields in the future, especially in the case of water erosion, which is closely linked to the climate system.

A major reason for this neglect is the difficulty of simulating land degradation processes such as water erosion and their impact on crops at large scale. As such, increasing the robustness of simulated crop-water erosion interactions to improve large-scale water erosion indicators, as discussed in Chapter 2, will also improve crop yield projections. By improving the representation of water erosion in GGCMs, the model results can be used to i) identify locations where crop productivity may decline due to the combined effects of water erosion and climate change, and ii) investigate the links between climate change and water erosion and their effects on crops. This analysis will be part of the third research objective of this thesis.

As many process-based crop models can simulate the daily interactions in the plant-soil system, including the dynamics of carbon, nutrients and water, they are useful tools for studying the effects of water erosion on crop yields. EPIC is a process-based crop model that has proven useful in both GGCM and water erosion studies. Thus, the GGCM EPIC-IIASA is suitable to fulfil the research objectives of this study.

Chapter 4

Overall methodology

4.1 Study framework

The framework in Figure 4.1 illustrates the modelling approach used to generate the results for this study, as well as the different steps to analyse the uncertainties, sensitivities and robustness of this approach. The input data are used to i) simulate daily maize and wheat growth and water erosion with EPIC and ii) analyse the sensitivity of the relevant model parameters to simulate global water erosion with all equations in EPIC. The output data is used to i) generate a baseline scenario for estimating global water erosion and maize and wheat yields and ii) address the uncertainty of simulated water erosion rates and impacts. The robustness of the model outputs is analysed using erosion values measured in the field and crop yields reported by FAOSTAT.

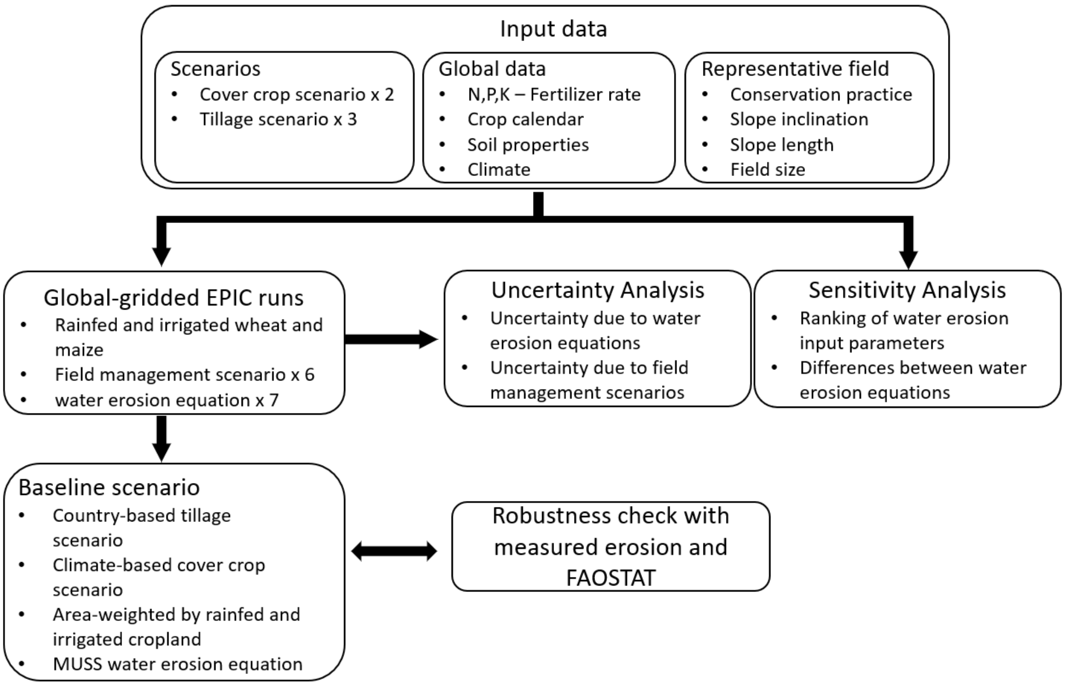

Figure 4.1: Scheme of the modelling framework for generating the model outputs and the different steps for analysing the uncertainties, sensitivities and robustness of the modelling approach

4.2 The EPIC crop model

This study uses the Environmental Policy Integrated Climate (EPIC), v. 0810 model. EPIC simulates the growth of a wide range of crops as a response to crop growing conditions (a combination of climate, soil and field management) and has a sophisticated representation of carbon, nutrient and water dynamics as well as a wide variety of possible field management options, including tillage operations and crop rotations (Izaurralde et al., 2006; Sharpley and Williams, 1990). EPIC operates with a daily time step and requires detailed input data on weather, topography, soil, crop, and crop management. Originally EPIC was named Erosion-Productivity Impact Calculator and was developed to determine the relationship between erosion and soil productivity. Due to its origin, EPIC has several options to simulate water erosion caused by precipitation, runoff and irrigation (Williams, 1990). Compared to other commonly used crop models in climate change impact assessments of the agricultural sector, EPIC has the most detailed representation of soil processes and the interactions between farming techniques and soil resources (Folberth et al., 2019). In addition to estimates on crop yields, EPIC generates outputs on nutrient consumption (N, P), components of water and soil organic carbon cycle, sediment loss, and loss of nutrients and soil organic carbon with sediments. EPIC is regularly used in both assessments of climate change impacts on global crop production and in assessments of farming techniques on water erosion rates.

4.2.1 Crop growth

The following routines are used in the EPIC model and are relevant for interpreting the results presented in this study. Their description is based on the original documentation of the EPIC model (Sharpley and Williams, 1990) and on the summary provided by Folberth et al. (2016, 2019).

In EPIC, phenological development of a crop is based on the heat unit (HU) approach. Daily HU are calculated as

$$HU_k = \frac{T_{max,k} + T_{min,k}}{2} - T_b \tag{4.1}$$

where HU_k are the accumulated HUs, maximum temperature and minimum temperature (°C) on day k, and T_b is the base temperature (°C) of a specific crop. The base temperature provides a crop-specific threshold under which no growth occurs. A crop reaches maturity when the sum of daily HU equals potential HUs (°C), which are based on long-term climate data and reported growing seasons provided by Sacks et al. (2010).

Daily potential biomass increase is estimated with the equation

$$\Delta B_p = 0.001 * BE * PAR \tag{4.2}$$

where ΔB_p (t ha^{-1}) is biomass gain, BE is a crop-specific coefficient for converting energy to biomass (kg MJ^{-1}) and PAR is intercepted photosynthetic active radiation based on leaf area index (LAI), solar radiation (MJ m^{-2}) and plant row width. The daily potential biomass is subsequently adjusted to daily actual biomass by accounting for the maximum stress factor out of nutrient and water deficiency, temperature and aeration stress (further details below). The LAI of wheat and maize is initially zero or close to zero, increases exponentially during early vegetative growth and decreases after reaching a maximum. LAI is calculated as a function of heat units, crop stress, and crop development stages.

Total biomass is split between above and below-ground biomass. The fraction of total biomass partitioned to the root system usually decreases from emergence to maturity, which is simulated as a linear reduction in EPIC. Rooting depth usually increases rapidly from the seeding depth to a crop-specific maximum, which is based on heat units, crop-specific parameters and the soil profile depth. At maturity, crop yield is calculated by multiplying total aboveground biomass with a water stress-adjusted harvest index (HI_a). HI_a is estimated from simulated potential HI (HI_{max}; depending on HU accumulation) and a defined minimum HI (HI_{min}) according to

$$HI_a = (HI_{max} - HI_{min}) * \frac{WUR}{WUR + exp(6.13 - 0.0883 * WUR)} + HI_{min} \tag{4.3}$$

where WUR is the water use ratio. WUR is estimated at harvest as

$$WUR = 100 * \frac{\sum_{i=1}^{K} U_i}{\sum_{i=1}^{K} E_{Pi}} \tag{4.4}$$

where U_i ($mm\ d^{-1}$) is the actual and E_{Pi} ($mm\ d^{-1}$) the potential plant water use rate for day i. K is the total number of days of the growing season.

4.2.2 Crop growth constraints

Potential crop growth and crop yields are constrained mainly by water, nutrients (N and P), temperature and aeration stress. The most severe stress factor on a given day limits biomass accumulation, root growth and yield by a fraction ranging from 0 to 1. The stress factors are calculated as follows.

Water stress is based on water deficit for the crop controlled by water supply and demand, which is consistent with the concept that drought stress limits biomass accumulation proportional to the transpiration reduction. It is calculated according to

$$WS_k = \frac{\sum\limits_{i=1}^{M} u_{l,k}}{E_{Pk}} \tag{4.5}$$

where WS_k is the amount of water stress on day k, l is a given soil layer, M is the total number of soil layers, $u_{l,k}$ is the plant available water in layer l on day k (mm), and E_{Pk} is the potential ET on day k (mm).

Temperature stress occurs if the air temperature is above the optimum temperature or below the base temperature of a specific crop according to

$$TS_k = sin\left(\frac{\pi}{2} * \frac{TG_k - T_b}{T_o - T_b}\right) \tag{4.6}$$

where TS_k is the plant temperature stress factor on day k, TG_k is the soil surface temperature (°C) on day k, T_b is the base temperature, and T_o is the optimal temperature for a specific crop.

The nutrient stresses, Nitrogen (N) and Phosphorus (P) stress, are based on the ratio of accumulated plant N and P to the optimal values. N and P stress vary nonlinearly from 1 at optimal or excess N and P supply to 0, when N or P is half the optimal level. As a first step in determining nutrient stress, a scaling factor is calculated.

$$SNS_k = 2 * \left(\frac{UN_k}{c_{NBk} * B_k}\right) \tag{4.7}$$

where SNS_k is the scaling factor for calculating N stress on day k, UN_k is the N uptake on day k (kg ha^{-1}), c_{NBk} is the optimum N concentration of the crop on day k (kg ha^{-1}) and B_k is the total plant biomass on day k (kg ha^{-1}). The scaling factor is used to calculate actual N stress (NS_k) using the equation

$$NS_k = \frac{SNS_k}{SNS_k + exp(3.39 - 10.93 * SNS_k)} \tag{4.8}$$

The same equations used for the N stress factor apply for the P stress factor.

Aeration stress occurs when soil water content approaches saturation. To estimate the degree of stress, the water content and pore volume of the top 1 m of soil is considered with the following equation

$$SAT_k = \frac{SW1_k}{PO1_k} - CAF \tag{4.9}$$

where SAT_k is the saturation factor at day k, $SW1_k$ is the water content of the top 1 m of soil (mm) at day k. $PO1_k$ is the porosity of the top 1 m of soil (mm) at day k and CAF is the critical aeration factor for a specific crop, which can vary between 0 and 1. If SAT_k>0, aeration stress (AS) is calculated as

$$AS_k = 1 - \frac{SAT_k}{SAT_k + exp(-1.291 - 56.1 * SAT_k)} \tag{4.10}$$

Crop growth can be additionally constrained through stresses affecting root development due to soil strength, aluminium toxicity and temperature stress.

Soil strength depends on bulk density and soil sand content according to

$$SS_{l,k} = 0.1 + \frac{0.9 * BD_{l,k}}{BD_{l,k} + exp(bt_1 + bt_2 * BD_{l,k})} \tag{4.11}$$

where $SS_{l,k}$ is the soil strength of layer l on day k, $BD_{l,k}$ is the bulk density (g cm^{-3}) of layer l on day k and bt_1 and bt_2 are coefficients based on the soils sand content.

Aluminium toxicity stress is estimated if the crop-specific aluminium tolerance is lower than the amount of dissolved aluminium controlled by the soils pH according to

$$ATS_k = \frac{100 - ALS_{l,k}}{100 - (10 + 20 * (ALT - 1))} \tag{4.12}$$

where ATS_k is aluminium toxicity stress on day k, ALT is a crop-specific aluminium tolerance index that can vary between 1 (=highly sensitive) and 5 (=very tolerant) and $ALS_{l,k}$ is the amount of dissolved aluminium in soil layer l on day k.

4.2.3 Soil

The soil organic matter (SOM) model in EPIC is based on the Century model (Izaurralde et al., 2006). SOM is split into different compartments, which differ in size, function and turnover rates: standing dead residue and roots, structural and metabolic litter, slow humus and passive humus and microbial biomass. The coupled organic C and N module in EPIC distributes organic C and N between the different soil organic matter compartments. The system interacts directly with soil moisture, temperature, erosion, tillage, soil density, soil texture, leaching, and translocation functions. Erosion, surface runoff, leaching and volatilization can lead to the loss of C, N and P from the system.

In EPIC, the main impact of water erosion on crops is driven by nutrient stress through the export of organic C, organic N and P from the topsoil layer through sediment runoff. The loss of all three nutrients with sediment runoff is estimated in relation to the eroded soil after a common approach used in SOM models (Polyakov and Lal, 2004; Sharpley and Williams, 1990).

$$M_{loss} = E * M_{soil} * ER \tag{4.13}$$

where M_{loss} is the runoff loss of either organic C, organic N or P (kg ha^{-1}); E is soil loss (Mg ha^{-1}); M_{soil} is the concentration of either organic C, organic N or P in the top soil layer (gt^{-1}); ER is the enrichment ratio, which is the concentration of either organic C, organic N or P in the sediment relative to the original soil (dimensionless). The enrichment ratio in sediment is logarithmically related to sediment loss.

4.2.4 Hydrology

Daily precipitation is split at the surface into runoff and infiltration. Daily runoff Q (mm) is estimated according to the USDA SCS curve number equation

$$Q = \frac{(R - 0.2s)^2}{R + 0.8s}; if R > 0.2s \tag{4.14}$$

where R is precipitation (mm) and s is the retention parameter (mm). If $R \leq 0.2s$, no runoff occurs. Parameter s depends on the curve number (CN) according to

$$s = 254 * \frac{100}{CN} - 1 \tag{4.15}$$

The CN reflects different types of soils, landuse and management, and are adjusted for slope, surface roughness, and soil humidity in the model. The curve number can be obtained by using the SCS hydrology handbook (USDA, 1972).

4.2.5 Water erosion

EPIC includes seven empirical equations to calculate water erosion (Wischmeier and Smith, 1978). The basic equation is:

$$E = P * K * LS * C * P \tag{4.16}$$

where E is soil erosion in Mg ha^{-1} (mass/area), R is the erosivity factor (erosivity unit/area), K is the soil erodibility factor in Mg MJ^{-1} (mass/erosivity unit), LS is the slope length and steepness factor (dimensionless), C is the soil cover and management factor (dimensionless) and P is the conservation practices factor (dimensionless).

The main difference between the water erosion equations available in EPIC is their energy components used to calculate the erosivity factor. The USLE, RUSLE and RUSLE2 equations use precipitation intensity as an erosive energy to calculate the detachment of soil particles. The MUSLE equation and its variations MUST and MUSS use runoff variables to simulate water erosion and sediment yield. The Onstad-Foster equation combines energy through rainfall and runoff (Table 4.1).

Table 4.1: Equations to calculate the erosivity factor in each water erosion equation available in EPIC.

Erosivity factor	**Equation**
$R = EI$	USLE, RUSLE, RUSLE2 (Renard et al., 1997; Wischmeier and Smith, 1978; USDA-ARC, 2013)
$R = 0.646 * EI + 0.45 * (Q * Q_p)^{0.33}$	Onstad-Foster (Onstad and Foster, 1975)
$R = 1.586 * (Q * Q_p)^{0.56} * WSA^{0.12}$	MUSLE (Williams, 1975)
$R = 2.5 * Q * q_p^{0.5}$	MUST (Williams, 1995)
$R = 0.79 * (Q * q_p)^{0.65} * WSA_{0.009}$	MUSS (Williams, 1995)

The erosion energy component is calculated as a function of either runoff volume Q (mm), peak runoff rate q_p (mm h^{-1}) and watershed area WSA (ha), or via the rainfall erosivity index EI (MJ ha^{-1}). The latter determines the detachment of soil particles through the energy of daily precipitation and a statistical estimate of the daily maximum intensity of precipitation falling within 30 minutes. RUSLE2 is the only equation calculating soil deposition. If the sediment load exceeds the transport capacity, determined by a function of flow rate and slope steepness, soil is deposited, which is calculated by a function of flow rate and particle size (USDA-ARC, 2013).

The soil cover and management factor is updated for every day where runoff occurs using a function of crop residues, biomass cover and surface roughness.

$$C = FRSD * FBIO * FRUF \tag{4.17}$$

where $FRSD$ is the crop residue factor, $FBIO$ is the growing biomass factor and $FRUF$ is the soil random roughness factor, which are calculated with the following equations (Wang et al., 2011; Williams et al., 2012):

$$FRSD = exp(-P23 * CVRS) \tag{4.18}$$

$$FBIO = 1 - \frac{STL}{(STL + exp(SCRP1(23) - SCRP2(23) * STL))} * exp(-P26 * CPHT) \tag{4.19}$$

$$FRUF = exp(-0.026 * (RR - 6.1)) \tag{4.20}$$

where $P23$ is an exponential coefficient ranging from 0.01-0.5, $CVRS$ is the amount of above ground crop residue (t ha^{-1}), STL is the amount of standing live biomass of the crop (t ha^{-1}), $SCRP1(23)$ and $SCRP2(23)$ are coefficients defining an S-shaped growth curve used to estimate the fraction of the ground covered by the plant as a function of the Leaf Area Index, $P26$ is an exponential coefficient ranging from 0.01-0.2, $CPHT$ is the crop height (m) and RR is the soil surface random roughness (mm).

Although the root system of plants is important for erosion through its regulation of soil infiltration and its stabilising effect on soil structure, it is not directly considered in the erosion calculation in EPIC. The root system is however included in the calculation of crop growth (Chapter 4.2.1) and soil organic matter (Chapter 4.2.3) that directly affect erosion.

The impact of soil erodibility on simulated water erosion is calculated for the top-soil layer at the start of each simulation year. The soil erodibility factor is calculated the same way for the USLE, Onstad-Foster, MUSLE, MUST and MUSS equation using a function of sand, silt, clay and organic carbon contents in the soil:

$$K = X1 * X2 * X3 * X4 \tag{4.21}$$

$$X1 = 0.2 + 0.3 * exp(-0.0256 * SAND * (1 - 0.01 * SILT)) \tag{4.22}$$

$$X2 = \left(\frac{SILT}{CLAY + SILT}\right)^{0.3} \tag{4.23}$$

$$X3 = \frac{1 - 0.25 * OC}{OC + exp(3.718 - 2.947 * OC)}, IF\ OC \leq 5 \tag{4.24}$$

$$X3 = 0.75, IF\ OC > 5 \tag{4.25}$$

$$X4 = \frac{1 - 0.7 * SN1}{SN1 + exp(-5.509 + 22.899 * SN1)} \tag{4.26}$$

$$SN1 = 1 - 0.01 * SAND \tag{4.27}$$

Where $SAND$, $SILT$, $CLAY$, and OC are the sand, silt, clay, and organic carbon contents of the soil (%). For the RUSLE and RUSLE2 method soil erodibility is calculated without the organic carbon contents of the soil using the following equation:

$$KR = 9.811 * \left(0.0034 + 0.0405 * exp\left(-0.5 * \left(\frac{Log10(DG) + 1.659)}{0.7101}\right)^2\right)\right) \tag{4.28}$$

$$DG = exp(SUM) \tag{4.29}$$

$$SUM = \frac{SAND * 0.0247 - SILT * 3.65 - CLAY * 6.908}{100} \tag{4.30}$$

The topographic factor is calculated the same way for the USLE, Onstad-Foster, MUSLE, MUST and MUSS equation using a function of slope length and slope steepness:

$$LS = \left(\frac{SLPL}{22.127}\right)^{XM} * (SLP * (65.41 * SLP + 4.56) + 0.065) \tag{4.31}$$

$$XM = 0.3 * \frac{SLP}{SLP + exp(-1.47 - 61.09 * SLP)} + 0.2 \tag{4.32}$$

Where $SLPL$ is the slope length (m), SLP is the land surface slope (m/m) and XM is an exponent dependent upon slope. The topographic factor for the RUSLE method is calculated using a function of slope length and slope steepness as well:

$$LSR = RSF * RLF \tag{4.33}$$

$$RSF = 10.8 * SLP + 0.03,\ IF\ SLPL > 4.57\ \&\ SLP < 0.09 \tag{4.34}$$

$$RSF = 16.8 * SLP - 0.5,\ IF\ SLPL > 4.57\ \&\ SLP > 0.09 \tag{4.35}$$

$$RSF = X1,\ IF\ SLPL < 4.57 \tag{4.36}$$

$$X1 = 3 * SLP^{0.8} + 0.56 \tag{4.37}$$

$$RLF = \frac{SLPL^{RXM}}{22.127} \tag{4.38}$$

$$RXM = \frac{B}{1+B} \tag{4.39}$$

$$B = \frac{SLP}{0.0894 * X1} \tag{4.40}$$

Where $SLPL$ is slope length (m) and SLP is land surface slope (m/m). The slope steepness factor RSF is adjusted for different slope steepness and slope length thresholds based on experimental data (Renard et al., 1997). The slope length factor RLF includes an exponent RXM, which is a function of the ratio B of rill erosion caused by flow and interill erosion caused by raindrop impact (USDA-ARC, 2013). B reflects how steepness affects rill erosion differently than it does interrill erosion. Rill erosion is assumed to vary linearly with steepness. The topographic factor for the RUSLE2 method is calculated the same way as for the RUSLE equation if the transport capacity determined by a function of flow rate and slope steepness exceeds sediment load. When sediment load exceeds transport capacity, RUSLE2 computes deposition. Interrill erosion is assumed to occur even when RUSLE2 computes deposition, which can be calculated without a distance term as detachment is solely caused by impacting raindrops (USDA-ARC, 2013). Therefore, the slope length factor is not considered in the RUSLE2 equation when deposition occurs.

The conservation practice factor is included in all equations as a static coefficient ranging between 0 and 1, where 0 represents conservation practices that prevent any erosion and 1 represents no conservation practices. Typical conservation practice factors can be derived from tables, which include values ranging from 0.01 to 0.35 for terracing strategies and from 0.25 to 0.9 for different contouring practices (Morgan, 2005; Wischmeier and Smith, 1978). Alternatively, values can be derived from local field studies and remote sensing (Karydas et al., 2009; Panagos et al., 2015), from equations using topographical data (Fu et al., 2005; Terranova et al., 2009), or from economic indicators (Scherer and Pfister, 2015).

4.3 EPIC-IIASA

GGCMs are integrated modelling frameworks for process-based crop modelling at large scale. Global datasets on static (topography, soil texture) and dynamic (climate, crop management, soil nutrient and water pools) factors are organised within geographical grids to provide inputs for process-based crop models to generate spatially-explicit estimates of crop yields over the globe. EPIC-IIASA is a GGCM based on EPIC, which has been used as a tool for climate change impact studies on food security and the agricultural sector (Mueller et al., 2017; Balkovič et al., 2018).

4.3.1 Global grids and input data

EPIC-IIASA requires global soil and topography data and daily weather data. The basic spatial resolution of the model is 5' x 5' at which soil and topographic data are provided. These are aggregated to homogenous units (based on the same topography and soil classes) and further intersected with a 30' x 30' climate grid, the resolution at which global gridded climate data are available. This results in a total of 131,326 grid cells with a spatial resolution ranging between 5' to 30' (about 9 km to 56 km near the equator) depending on landscape heterogeneity (Skalský et al., 2008). Weather parameters for the simulation period 1980 - 2010 are taken from historic bias-corrected daily weather data combining data from the Modern-Era Retrospective Analysis for Research and Applications (MERRA), station data, and remotely-sensed datasets, covering the years 1980 – 2010 (Ruane et al., 2015). Weather parameters for representative concentration pathways (RCP) are taken from the HadGEM2 RCP 2.6 and 8.5 datasets covering the years 2005 - 2099 (Hempel et al., 2013). These datasets represent two contrasting climate scenarios and are used to bracket varying projections of weather parameters. Soil information is taken from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012), and topography from USGS GTOPO30 (USGS, 1997). Each grid cell is represented by a single field characterized by the combination of topography and soil conditions prevailing in this landscape unit. Each representative field has a defined slope length (20 – 200 m) and field size (1 - 10 ha) based on a set of rules for different slope classes (Table 4.2). The slope of each representative field is determined by the slope class covering the largest area in each grid cell (Table 4.2). Slope classes are taken from a global terrain slope database (IIASA/FAO, 2012) and are based on a high-resolution 90 m SRTM digital elevation model (Figure A.1).

Table 4.2: Set of rules for field size and slope length estimation for each dominant slope class. The area/dominant slope class was assigned to each grid cell from a global slope and terrain dataset (IIASA/FAO, 2012) providing 3 arc-sec spatial resolution distributions of nine slope gradient classes: 0–0.5%, 0.5–2%, 2–5%, 5–8%, 8–16%, 16–30%, 30–45%, and $>$ 45% interpreted from SRTM elevation data (CGIAR-CSI, 2006). The mid-interval value of the dominant slope class was used as an input for each grid cell in EPIC-IIASA.

Dominant slope class	Lower value (%)	Upper value (%)	Mid value (%)	Slope length (m)	Field size (ha)
1	0	0.5	0.25	200	10
2	0.5	2	1.25	200	10
3	2	5	3.5	200	10
4	5	8	6.5	200	10
5	8	16	12	100	5
6	16	30	18	75	5
7	30	45	35.5	50	1
8	45	100	60	20	1

4.3.2 Climate change scenarios

The two contrasting RCPs used for the climate inputs for EPIC-IIASA represent different socio-economic and emission scenarios and were produced in collaboration between integrated assessment modelers, climate modelers, terrestrial ecosystem modelers and emission inventory experts (van Vuuren et al., 2011). The scenarios are created to improve the understanding of complex interactions of the climate system, ecosystems, and human activities and conditions to provide plausible descriptions of how each of these components might change in the future. However, the goal of scenarios is not to predict the future, but to better understand uncertainties to reach decisions that are robust under a wide range of possible futures. As such, these scenarios support the analysis of complex issues such as costs, benefits and risks of different policy choices and climate and socioeconomic futures (Moss et al., 2010). In total, a set of four pathways were produced that lead to radiative forcing levels of 8.5, 6, 4.5 and 2.6 W m^{-2}, by the end of the 21st century (Moss et al., 2010). The radiative forcing levels are used as inputs for climate models to project daily climate parameters covering the years 2005 - 2099. The RCPs selected for this study are based on climate data from the HadGEM2-ES model (Collins et al., 2008). The data are available via the CMIP5 website (https://pcmdi.llnl.gov/mips/cmip5/) and were further bias-corrected with respect to historical observations by Hempel et al. (2013) in line with the ISI-MIP project.

RCP 2.6 was developed by the IMAGE modelling team of the PBL Netherlands Environmental Assessment Agency to represent the scenarios that lead to very low greenhouse gas concentration levels (van Vuuren et al., 2011). The radiative forcing level in RCP 2.6 peaks at a value of around 3.1 W m^{-2} and a concentration of 490 ppm CO2- equiv. by mid-century, and returns to 2.6 W m^{-2} by the year 2100; thus, it is referred to as a "peak-and-decline" scenario. To reach such radiative forcing levels, greenhouse gas emissions (and indirectly emissions of air pollutants) are reduced substantially over time (van Vuuren et al., 2011).

RCP 8.5 was developed using the MESSAGE model and the IIASA Integrated Assessment Framework (Riahi et al., 2007). The radiative forcing level in the RCP 8.5 reaches more than 8.5 W m^{-2} and a concentration of more than 1370 ppm CO2-equiv. in 2100. It represents scenarios for increasing greenhouse gas emissions over time leading to the highest greenhouse gas concentration levels (van Vuuren et al., 2011).

4.3.3 Field management scenarios

Maize and wheat are chosen as two contrasting crop types for analysing water erosion in different cultivation systems. Maize is a row crop with relatively large areas of bare and unprotected soil between the crop rows. The plant density in wheat fields is much higher, which improves the protection of soils against water erosion. Growing seasons for maize and wheat in each grid cell are taken from Sacks et al. (2010), and spatially explicit nitrogen and phosphorus fertiliser application rates are taken from Mueller et al. (2012).

In the absence of spatial data for crop-specific water application rates at the global level, irrigated crops are provided with sufficient amounts of water to avoid water stress. Irrigation water is supplied to refill soil water content to its field capacity each time the plants are under stress, with an annual limit of 1000 mm per crop (Balkovič et al., 2018).

Field management techniques influencing soil properties and soil cover have a significant impact on the amount of water erosion. However, these methods vary greatly around the world and data on different field management techniques is sparse. Therefore, each crop is simulated for six field management scenarios (three tillage x two cover crop scenarios), each influencing soil properties, water erosion and plant growth differently. The tillage management scenarios represent conventional, reduced and no-tillage, which differ by the amount of cultivation operations, tillage depth, mixing efficiency of tillage and sowing mechanisations, surface roughness and the amount of plant residues left on the field after crop harvest. Further, runoff curve numbers are altered for each tillage scenario to account for different runoff intensities for the cover treatment classes presented in Table 4.3. Runoff curve numbers indicate the runoff potential of a hydrological soil group, land use and treatment class and allow to take the impact of different tillage practices on the hydrologic balance into account (Chung et al., 1999). The different tillage intensities account for the impact of gradually changing surface cover and roughness on water erosion rates. Each tillage scenario is simulated with and without green fallow (grass-type green fallow) cover in between growing seasons, leading to a total of six field management scenarios.

Table 4.3: Tillage management scenarios for maize and wheat cultivation.

	Conventional tillage	**Reduced tillage**	**No- tillage**
total cultivation operations	6-7	4-5	3
max. tillage depth	150 mm	150 mm	40-60 mm
mixing efficiency	99 %	75 %	2 %
max. surface roughness	30-50 mm	20 mm	10 mm
plant residues left	25 %	50 %	75 %
cover treatment class	straight	contoured	contoured & terraced

Irrigation and additional conservation practices in all field management scenarios are based on the underlying slope class of each grid cell. On slopes steeper than 5%, only rainfed agriculture is considered, as hilly cropland is irrigated predominantly on terraces that prevent water runoff.

P-factors are used to simulate additional, or more efficient conservation practices. These are static coefficients ranging between 0 and 1, where 0 represents conservation practices that prevent any erosion and 1 represents no conservation practices. Whilst conservation practices are introduced implicitly through various crop growth assumptions as presented in Table 4.3, additional erosion control measures are simulated on slopes $> 16\%$ assuming that conservation practices are most likely implemented on steep slopes. On slopes steeper than 16%, a P-factor of 0.5 is used, and on slopes steeper than 30%, a P-factor of 0.15 is used to simulate contouring and terracing based on the range of P-values presented in Morgan (2005).

To determine the impact of water erosion on maize and wheat yields, all field management scenarios are additionally simulated with no erosion (P=0). The comparison of crop yields simulated with a P-factor value of zero with crop yields simulated under higher P-factor values can be used to identify grid cells where crop yields are reduced by water erosion. The simulation outputs at those grid cells are used to quantify the reduction of maize and wheat production and the relative reduction of crop yields due to water erosion.

4.3.4 Baseline field management scenario

The six field management scenarios reflect a range of potential impacts occurring due to different farming techniques on water erosion rates and erosion–crop yield relationships. To account for geographic variations in field management while addressing each thesis objective, the model outputs are aggregated using a baseline scenario determined by climatic and country-specific indicators.

As the only global statistical data on the type of tillage systems are provided for the extent of Conservation Agriculture area at the national scale (FAO, 2016), only the lowest tillage intensity scenario is assigned to specific countries in the baseline scenario. Therefore, conventional and reduced tillage are simulated in each grid cell globally, whereas the additional no-tillage scenario is simulated only for countries in which at least 5% of cropland is cultivated under conservation agriculture according to AQUASTAT (2007–2014) (FAO, 2016).

The main Koeppen-Geiger regions (Peel et al., 2007) were used to avoid unsuitable cover crop options. The off-season green fallow cultivation is not simulated in dry regions due to high competition for water. In contrast, the off-season green fallow is always considered in tropical areas with high rainfall, where a year-round growing season is common. In temperate and snow regions, average simulation results from both cover crop scenarios are used (Figure 4.2).

The MUSS equation is chosen for the baseline scenario as it generates the lowest deviation between simulated and measured water erosion, which will be discussed in Chapter 5. Table 4.4 summarises the field management assumptions.

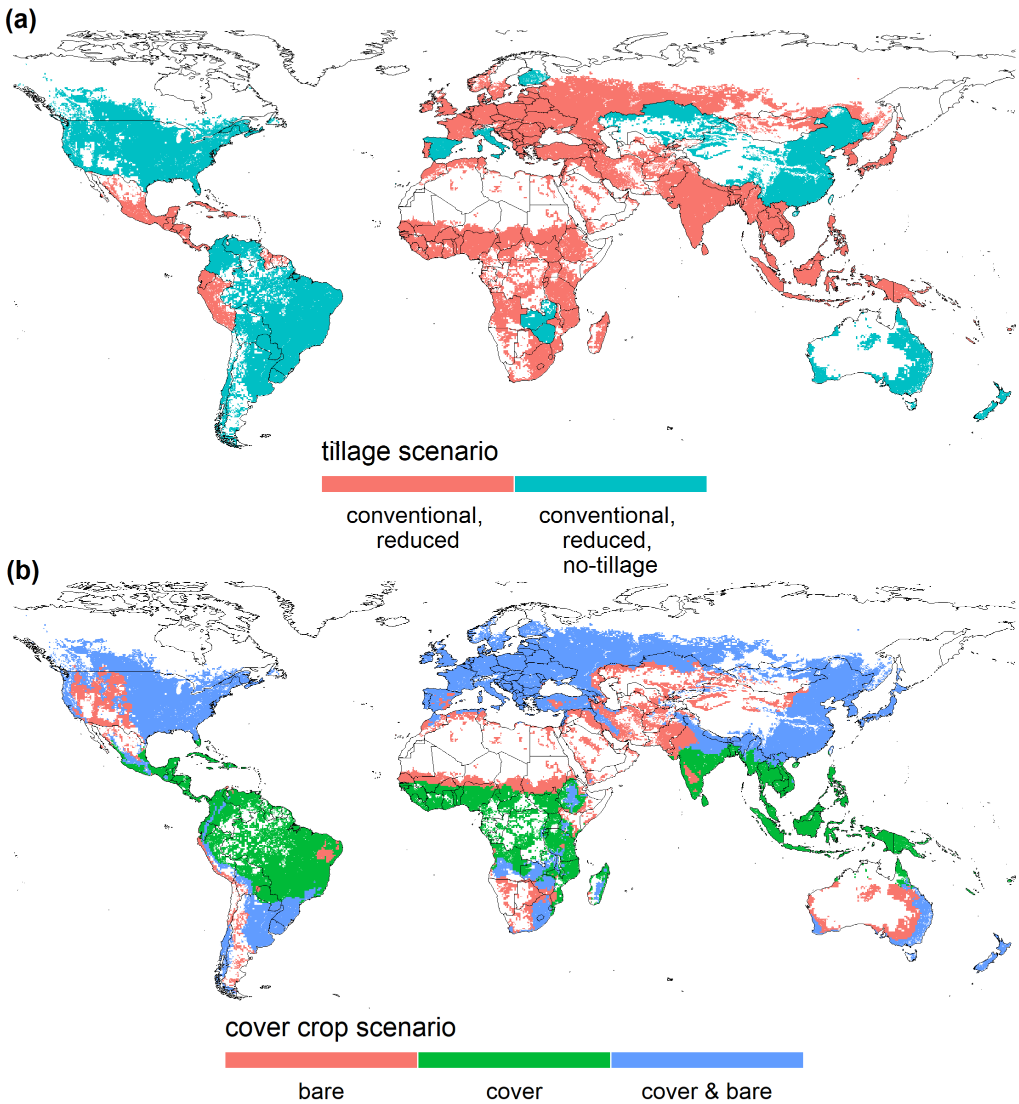

Figure 4.2: Distribution of selected (a) tillage and (b) cover crop scenarios determined by country-specific and environmental indicators used for compiling the baseline scenario. In each grid cell, crop yields are averaged over all selected field management scenarios.

Table 4.4: Summary of management assumptions and erosion equation selected for the baseline scenario.

Option	**Baseline**
Tillage	• Mix of conventional, reduced and no-tillage in regions where the national share of conservation agriculture is $>$ 5% according to the latest reported data in FAO AQUASTAT (2007-2014) (FAO, 2016): Argentina, Australia, Bolivia, Brazil, Canada, Chile, China, Colombia, Finland, Italy, Kazakhstan, New Zealand, Paraguay, Spain, USA, Uruguay, Venezuela, Zambia and Zimbabwe. • Mix of conventional and reduced tillage in the rest of the world.
Off-season cover	• Cultivation only with cover crops in tropics according to Koeppen-Geiger regions (Figure A.4) (Peel et al., 2007). • No cover crops in arid regions. • Mix of off-season cover with and without cover crops in temperate and snow zones.
Conservation Practice Factor (P)	• $P = 1$, $IF\ SLOPE < 16\%$ • $P = 0.5$, $IF\ SLOPE \geq 16\%$ & $SLOPE < 30\%$ • $P = 0.15$, $IF\ SLOPE \geq 30\%$
Crop	• Model outputs are generated for wheat and maize fields based on the global crop distribution by MIRCA2000 (Figure A.3) (Portmann et al., 2010).
Irrigation	• irrigation if $SLP \leq 5\%$. • Weighted average of irrigated and rainfed cropland based on Portmann et al. (2010).
Water erosion equation	• MUSS

4.4 Uncertainty analysis of model outputs

The large spatial resolution of GGCMs causes uncertainty from various input sources including climate, soil, field management, distribution of crop cultivars and cropland, irrigation area, growing seasons, as well as model structure and model parametrisation, most of which have been addressed by prior studies (Folberth et al., 2016, 2019; Mueller et al., 2017; Porwollik et al., 2017). Since not all uncertainties can be considered, the most important ones for the simulation of water erosion in EPIC are analysed. This includes the uncertainties due to different field management scenarios, different water erosion equations, and slope steepness data.

Field management practices have a major influence on the extent of water erosion. However, their application is not well known worldwide, which could lead to errors in the model results. Further, the different water erosion equations in EPIC differ in their parameters and sensitivities, which causes varying water erosion estimates. To account for both sources of uncertainty, uncertainty ranges are calculated globally in Chapter 5 based on the varying water erosion estimates with different water erosion equations and field management scenarios. In addition, uncertainty ranges are calculated globally for the estimated impacts of water erosion on crops in Chapter 6 based on different field management scenarios.

While the range of slopes and the fraction of cropland in each grid cell is known, it is not possible to determine how much land in each slope class is cultivated. Therefore, it is assumed that the cropland in each grid cell is on the slope class that is most common in the grid cell, as this represents the prevailing topographical conditions. This assumption is likely to introduce spatially-varying uncertainty as the fraction of each grid cell containing the dominant slope category varies from 20% to 100%, with an average share of 48%. The share of land covered by cropland in each grid cell also varies greatly, from 1% to 100%, with an average share of 14% (Figure A.5). Therefore, the extrapolation of the simulation outputs to the entire cultivated area in a grid cell can provide only a rough estimate. The implications of this assumption are explored in Chapter 5 and Chapter 6 by comparing the simulation results to a second set of simulation outputs based on an ideal cropland distribution scenario, in which the flattest terrain available rather than the most common slope in each grid cell is cultivated. This assumes that farmers would prefer to cultivate flatter land where possible.

The uncertainty from slope steepness data will be addressed in an example region, as this requires a large number of additional model runs for various combinations of slope assumptions and field management scenarios per grid cell. Italy is chosen as an example region, as it is susceptible to water erosion and includes large and heterogeneous maize and wheat cultivation areas on flat terrain in the north and mountainous regions in the south.

4.5 Sensitivity analysis of water erosion simulation

The most essential input parameters to the factors in the seven water erosion equations are identified with a sensitivity analysis in Chapter 5. The Sobol method (Sobol, 1990), a variance-based sensitivity analysis, is popular in environmental modelling (Nossent et al., 2011). With this method, it is possible to quantify the amount of variance that each parameter contributes to the total variance of the model output. These amounts are expressed as sensitivity indices, which rank the importance of each input parameter for simulated water erosion. In addition, the sensitivity indices can be used to determine the impact of parameter interactions on the model output.

The sensitivity analysis is run for 30 parameters directly connected to the water erosion equations in EPIC. In total, 126,976 random values are assigned to all input parameters along a pre-defined triangular distribution or a range of discrete values (Table A.1). Water erosion is simulated with EPIC using the seven available equations for each random input combination at 40 locations where wheat and maize are cultivated. To represent a heterogeneous distribution of global precipitation regimes, the natural break optimisation method is used to choose locations based on average annual precipitation amounts from 1980 to 2010 (Jenks, 1967). For each location and equation, the most sensitive parameters are ranked. To analyse the impact of precipitation regimes on the sensitivity of each parameter, Spearman coefficients (ρ) are used to determine if positive or negative relationships exist between each parameter's sensitivity and annual precipitation.

4.6 Evaluation of model outputs

4.6.1 Evaluation of simulated water erosion against field measurements

Simulated water erosion rates are compared with 606 soil erosion measurements on arable land from 36 countries representing plot and field scale in Chapter 5. Most of the selected erosion rates are based on the ^{137}Cs method. In addition, data from erosion plots and volumetric measurements of rills collected by Auerswald et al. (2009), Benaud et al. (2020) and García-Ruiz et al. (2015) are used. In total, 315 records are derived by the ^{137}Cs method, 188 records from runoff plots, and 103 records from volumetric measurements of rills. An overview of the field data is presented in Figure A.6 - A.9, and the full dataset is available in Carr et al. (2020).

The overwhelming effect of the experimental methodology on measured erosion rates (Chapter 2.3.5), the lack of sufficient metadata accompanying erosion measurements and the granular spatial resolution of the simulation setup hinders a direct comparison between simulated and observed water erosion rates. Instead aggregated simulated and observed erosion values are compared for different slope and precipitation classes to analyse the robustness of simulated water erosion rates under different environmental conditions. Therefore, only measurements with recorded slope steepness and annual precipitation are used. Where annual precipitation is not recorded, it is taken from the WorldClim2 dataset (Fick and Hijmans, 2017).

4.6.2 Evaluation of simulated crop yields against reported yields

Maize and wheat yields simulated under the baseline field management scenario are evaluated against FAOSTAT reported yields per country in Chapter 6. As simulated crop yields are calculated in t ha^{-1} dry matter in EPIC, they are converted to fresh matter assuming a net water content of 12% following

Wirsenius (2000), so that they can be compared with yields reported by FAOSTAT (FAO, 2020). In addition, calculated total crop production per country are compared against FAOSTAT statistics in Chapter 6. Simulated crop yields and total production per country are compared against FAOSTAT statistics for the years 1995–2005. The years are chosen based on the years of reported fertiliser application rates that are used to simulate maize and wheat yields. The agreement between simulated and reported data is determined by the coefficient of determination (R^2) and the relative error (%) between both datasets.

4.7 The computation process

The IIASA computer platform was used to run EPIC-IIASA to simulate water erosion and maize and wheat for each grid cell and for each combination of climate and field management scenarios. A total of 288 scenarios were created.

Model outputs were aggregated using the programming language R (Version 4.0.5) and RStudio (Version 1.4.1106). The aggregation method differs for the different results and is explained in the Methodology section of Chapters 5, 6, and 7.

Chapter 5

Uncertainties, sensitivities and robustness of simulated water erosion with EPIC-IIASA

5.1 Introduction

Water erosion models such as the USLE and the RUSLE have been widely used to estimate global water erosion (Borrelli et al., 2017; Doetterl et al., 2012; Van Oost et al., 2007). However, a comprehensive evaluation of erosion estimates is lacking in the previous studies. Because the USLE and its modifications were developed using field data from the Midwestern United States, their outputs should ideally be evaluated against soil erosion measurements from other agro-environmental zones when applied in those environments (Evans and Boardman, 2016b). However, the uneven distribution of field data around the world, the lack of long-term soil measurements in most global regions, and the great variability of the designs of erosion rate measurements hamper the evaluation of global soil loss estimates derived from models (Auerswald et al., 2004; Borrelli et al., 2017; García-Ruiz et al., 2015). In addition, model input data on topography, soil properties and land use are often aggregated over large areas and thus simulation results cannot be directly compared to single field measurements at specific locations. Thus, evaluating global erosion models is difficult on a global scale, but improvements are needed due to their widespread application (Chapter 2.3.1).

Beyond improving the robustness of global erosion models, there is a need to consider water erosion in GGCMs (Chapter 3.6). Throughout the past decade, GGCMs have become essential tools for climate change impact assessments, evaluations of agricultural externalities, and as input data providers for agro-economic models (Mueller et al., 2017). However, few assessments have considered land degradation processes and found their inclusion and understanding crucial for evaluating climate change mitigation and adaptation strategies (Balkovič et al., 2018; Chappell et al., 2016).

Moreover, crop models can be used to simulate water erosion in agricultural fields more realistically by considering the daily interactions between crops and water erosion. Most global soil removal estimates using water erosion models are based on static observation approaches or on very coarse timescales that do not fall below annual time steps (Borrelli et al., 2017). Therefore, seasonal patterns of soil cover and precipitation intensities are neglected even though they are crucial factors for water erosion. The state of soil and its cover is influenced by land management, such as the choice of crops, planting and harvest dates, tillage and plant residue management. Accordingly, neglecting the impact of seasonal changes in vegetation cover and field management practices constitutes large uncertainty in global water erosion estimates. Crop models usually simulate crop growth on a daily timescale, which allows attached water erosion models to account for daily changes in weather, soil properties and vegetation cover. However, uncertainty remains due to the increasing requirement of input data for daily simulations, which is especially challenging at a global scale (Chapter 2.3.4).

Given the difficulties of simulating water erosion on large scales, this chapter will focus on the uncertainties, sensitivities and robustness of simulated water erosion in EPIC-IIASA. First, the global water erosion estimates and their uncertainties due to different estimates under different field management scenarios and water erosion equations are presented. The sensitivities of the water erosion equations are then analysed to discuss the main causes of variability in the simulation results. Finally, the simulated erosion values will be compared with field data to investigate the robustness of the water erosion estimates in all global agro-environmental regions simulated with EPIC-IIASA.

5.2 Methodology

5.2.1 Summary of methodology

Water erosion in maize and wheat fields is simulated with seven different empirical erosion equations in EPIC under different field management scenarios. Global water erosion is estimated from the baseline field management scenario based on the environmental and country-specific assumptions and indicators presented in Chapter 4.3.4.

The uncertainties of the estimated water erosion rates due to the different field management scenarios are calculated for each grid using the range between the minimum and maximum water erosion rates simulated with all field management scenarios. Similarly, the range of uncertainty due to different water erosion equations per grid is calculated using the minimum and maximum water erosion rates simulated with all available equations.

The sensitivity of the model to all inputs used in the simulation of water erosion is calculated using the method presented in Chapter 4.5. Sensitivity indices are used to interpret the variability and uncertainties of the simulation results and to discuss the differences between the water erosion equations.

To evaluate the robustness of the simulated water erosion rates, they are compared to field measurements for different slope and precipitation classes (Chapter 4.6.1). Due to the non-normal distribution of the simulated and measured data, the median deviation (MD) is used as a measure to compare the agreement between aggregated simulated and measured water erosion values.

5.2.2 Aggregation of model outputs

Simulated water erosion rates are averaged over the historic simulation period (1982 - 2010). Subsequently, water erosion rates simulated for irrigated and rainfed maize and wheat fields are averaged per grid cell and weighted by the area of the respective crop and irrigation scenario (Equation 5.1). Finally, water erosion rates are presented as median values of all baseline field management scenarios per grid cell or of all grid cells per country, region or globally.

$$Ew_{cgm} = Eav(r)_{cgm} * Af(r)_{cg} + Eav(i)_{cgm} * Af(i)_{cg} \tag{5.1}$$

Ew_{cgm} is area-weighted mean water erosion (tha^{-1}) for crop c, grid cell g and management scenario m; Eav is yield averaged over the selected years simulated under rainfed (r) and irrigated (i) conditions; $Af(r)$ is the rainfed area fraction; and $Af(i)$ is the irrigated area fraction.

5.3 Results

Global median water erosion rates are 7 t ha^{-1} and 5 t ha^{-1} in maize and wheat fields, respectively. The total removal of soil in global maize and wheat fields is estimated to be 5.3 Gt yr^{-1} and 1.9 Gt yr^{-1}, respectively. The map in Figure 5.1 illustrates the global distribution of simulated water erosion rates. Highest water erosion is simulated in mountainous regions and regions with strong precipitation, especially in tropical climate zones. In Asia, those regions are widespread in the east, south-east and the Himalaya region. In Africa, similar areas with high water erosion values are spread around the continent and are most common at the west coast and in East Africa including broad areas in Guinea, Sierra Leone, Liberia, Ethiopia and Madagascar. In South America, highest water erosion is simulated in the south of Brazil and regions around the Andes mountain range and the Amazon river basin. The highest water erosion values on the American continent are simulated in tropical Central America and the Caribbean. In North America, highest water erosion occurs along the west coast and in the east. Water erosion in Europe is highest in Mediterranean areas and around the Alps.

Median annual water erosion values for the five largest maize and wheat producing countries demonstrate the strong impact of climate and topography on simulated water erosion. In Brazil, China and India, where a large proportion of cropland is in tropical areas, simulated water erosion is relatively high with annual median values of 10 t ha^{-1}, 6 t ha^{-1}, and 37 t ha^{-1}, respectively. In Russia and the United States annual median values are much lower with 1 t ha^{-1}, and 2 t ha^{-1}, respectively. Overall, Figure 5.1 illustrates the large variation in simulated water erosion between tropical climate regions and regions with a large proportion of flat and dry land.

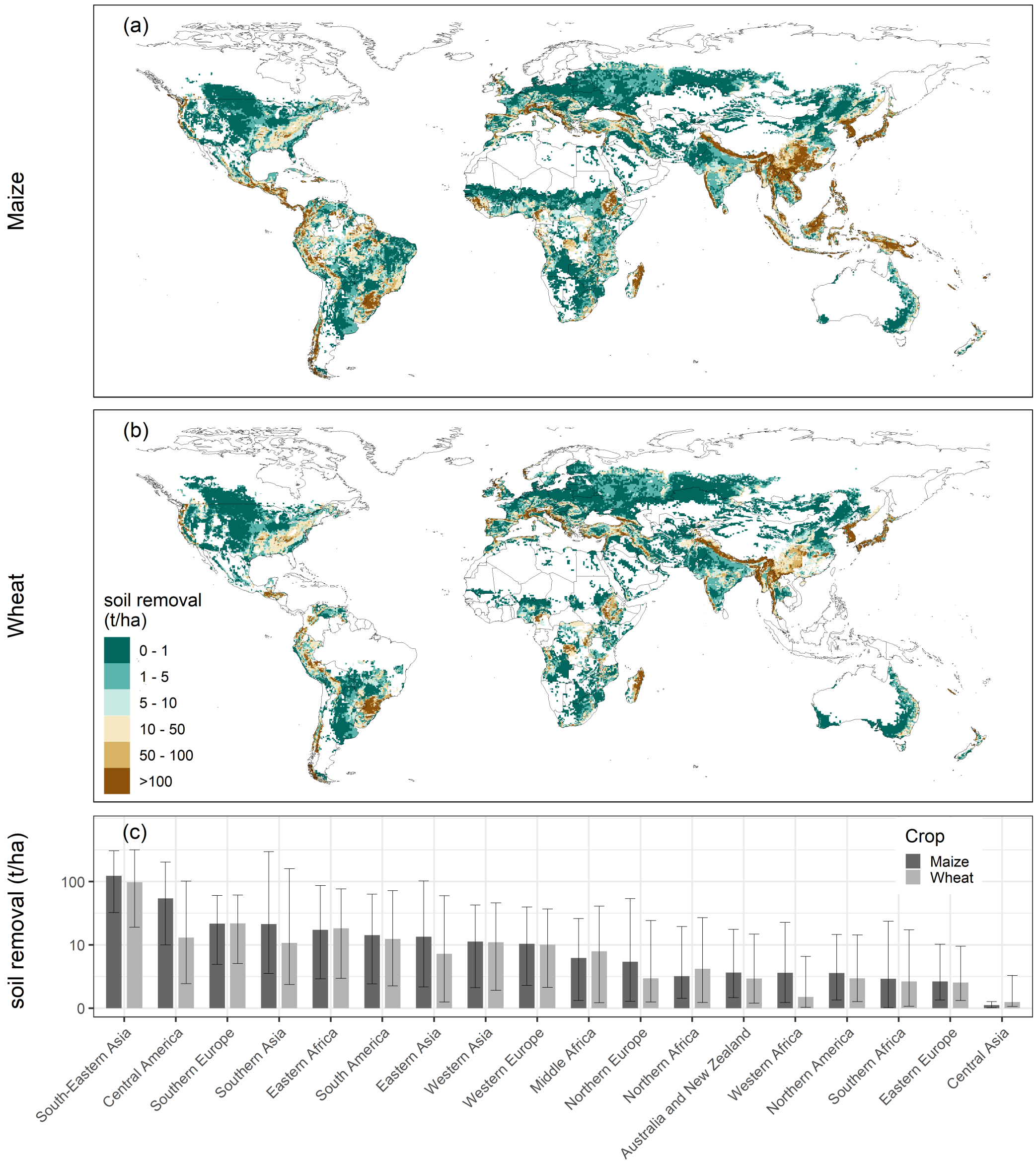

Figure 5.1: (a) Soil loss due to water erosion in maize and wheat fields simulated with the baseline scenario. (b) The bars in the bottom plot illustrate the median, 25^{th} and 75^{th} percentile of simulated soil loss for major world regions. The classification of world regions is illustrated in Figure B.1. Due to the large gap between aggregated values, all values in the bottom plot have been log-transformed to improve the visual presentation.

5.3.1 Sources of model uncertainty related to management assumptions and method selection

Uncertainty in simulation results due to management scenarios and choice of water erosion equations is highest in the regions most at risk of water erosion (Figure 5.2). The annual median uncertainty range at each grid cell due to management is 30 t ha^{-1}. For 97% of grid cells, the lowest erosion rates are simulated with management scenarios including no-tillage and cover crops. For 86% of grid cells, maximum erosion rates are simulated under conventional tillage without cover crops. The annual median uncertainty range at each grid cell due to the choice of erosion equation is 23 t ha^{-1}. In 74% of grid cells, the lowest erosion rates are simulated with the MUSS equation. The highest erosion values are simulated with the RUSLE equation (46%), followed by the USLE equation (25%).

In most locations, uncertainty due to field management exceeds the uncertainty caused by the choice of erosion equation. For 46% of grid cells, management scenarios cause the prevailing uncertainty, which is defined as the higher uncertainty range by at least 5 t ha^{-1}. The selected erosion equation causes higher uncertainty by at least 5 t ha^{-1} in 14% of grid cells. The map in Figure 5.3 illustrates the global distribution of prevailing uncertainty sources.

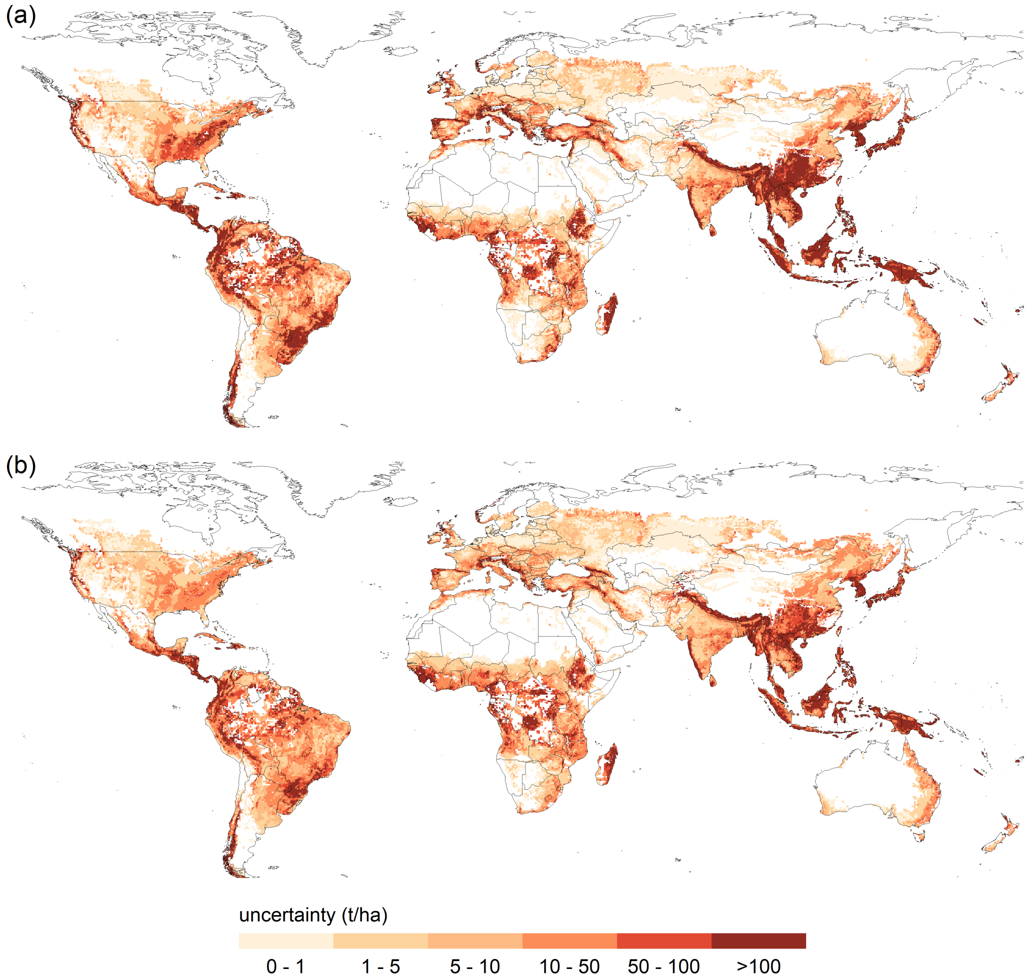

Figure 5.2: Water erosion uncertainty due to (a) field management assumptions and (b) water erosion equations.

5.3.2 Main drivers of the global erosion model

The sensitivity study is designed to explain the large variability of simulated water erosion rates in different regions and to discuss the main differences between water erosion equations. Water erosion is highly sensitive to slope steepness (SLP) for all equations. The first-order sensitivity index of the

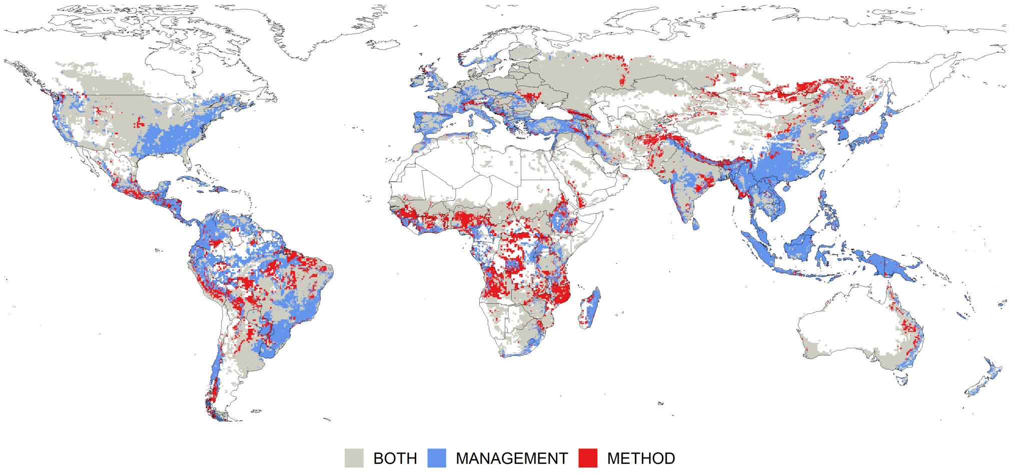

Figure 5.3: Prevailing uncertainty due to field management assumptions and water erosion equations, defined as the higher uncertainty range by at least 5 t ha^{-1}.

slope parameter indicates that 46–54% of the variance in the model output is attributable to the slope, without considering interactions between the input parameters (Table 5.1). Daily precipitation (PRCP) is the second most important parameter for calculating water erosion, with an individual contribution of around 9–20% to the variance of the output. The remaining parameters contribute together 4–13% to the output variance.

Table 5.1: First-order sensitivity indices (SI) ranking for the five most sensitive input parameters (PARM) for each water erosion equation including slope steepness (SLP), daily precipitation (PRCP), soil hydrologic group (HSG), land use number (LUN), soil silt content (SILT), soil sand content (SAND), curve number parameter (S301), maximum air temperature (TMX) and crop residues left after harvest (ORHI). The sensitivity indices of the remaining parameters are available in Carr et al. (2020).

	AOF		MUSL		MUSS		MUST		RUSLE2		RUSLE		USLE	
	PARM	SI	PARM	SI	PARM	SI	PARM	SI	PARM	SI	PARM	SI	PARM	SI
1	SLP	0.47	SLP	0.46	SLP	0.46	SLP	0.48	SLP	0.46	SLP	0.5	SLP	0.54
2	PRCP	0.13	PRCP	0.1	PRCP	0.12	PRCP	0.09	PRCP	0.16	PRCP	0.2	PRCP	0.18
3	HSG	0.03	HSG	0.04	HSG	0.05	HSG	0.04	HSG	0.02	SAND	0.05	SILT	0.02
4	SILT	0.02	LUN	0.02	LUN	0.02	LUN	0.02	SAND	0.01	TMX	0.01	TMX	0.01
5	LUN	0.01	SILT	0.02	S301	0.01	SILT	0.02	LUN	0.01	ORHI	0.01	ORHI	0
	sum	0.69	sum	0.68	sum	0.71	sum	0.68	sum	0.71	sum	0.78	sum	0.76

The first-order sensitivity indices do not include interactions between input parameters, which leads to the sum of all first-order sensitivity indices being lower than 1. The total-order sensitivity indices sum all first-order effects and interactions between parameters, which leads to overlaps in case of interactions and a sum greater than 1. The differences between the first-order and the total-order indices can be used as a measure to determine the impact of the interactions between a specific parameter with other parameters. The total-order sensitivity indices show that slope steepness, including interactions to other parameters, contributes 63–75% of the output variance from which 18–21% are due to interactive effects with other parameters (Table 5.2). The total-order sensitivity indices from precipitation range from 21–36%, from which 10–18% is due to interactions with other parameters.

Table 5.2: Total-order sensitivity indices (SI) ranking for the five most sensitive input parameters (PARM) for each water erosion equation including slope steepness (SLP), daily precipitation (PRCP), soil hydrologic group (HSG), land use number (LUN), soil silt content (SILT), soil sand content (SAND), maximum air temperature (TMX) and crop residues left after harvest (ORHI). The sensitivity indices of the remaining parameters are available in Carr et al. (2020).

	AOF		MUSL		MUSS		MUST		RUSLE2		RUSLE		USLE	
	PARM	SI	PARM	SI	PARM	SI	PARM	SI	PARM	SI	PARM	SI	PARM	SI
1	SLP	0.68	SLP	0.68	SLP	0.63	SLP	0.68	SLP	0.66	SLP	0.69	SLP	0.75
2	PRCP	0.28	PRCP	0.23	PRCP	0.22	PRCP	0.21	PRCP	0.32	PRCP	0.36	PRCP	0.36
3	HSG	0.09	HSG	0.12	HSG	0.13	HSG	0.12	HSG	0.08	SAND	0.12	SILT	0.05
4	SILT	0.07	LUN	0.07	LUN	0.07	LUN	0.07	LUN	0.05	TMX	0.02	TMX	0.02
5	LUN	0.05	SILT	0.07	SILT	0.05	SILT	0.07	SAND	0.04	ORHI	0.01	SAND	0.01
	sum	1.29	sum	1.3	sum	1.25	sum	1.27	sum	1.34	sum	1.27	sum	1.27

The high sensitivity to slope and precipitation is similar for all equations, but the importance of the other parameters varies between equations. Equations estimating erosion energy by surface runoff and the RUSLE2 equation are very sensitive to the hydrological soil group (HSG), which determines the soils infiltration ability. This parameter is used in the calculation of the curve number, which defines the partition of precipitation into runoff and infiltration. Also, the land use number (LUN), which is ranked among the most sensitive input parameters, is used for the calculation of the curve number. The most sensitive parameters of the USLE and RUSLE equation, following slope inclination and daily precipitation, are soil texture classes (SAND and SILT) followed by daily temperature changes (TMX). Crop residues (ORHI) are relatively important for all equations but especially important for equations based on rainfall-energy. Other parameters relevant for field management, such as surface roughness and mixing efficiency of the topsoil, have little influence on water erosion.

The sensitivity of slope steepness has a strong positive correlation with the amount of annual precipitation at each location (ρ = 0.69, p<0.01). The increase in the sensitivity of slope steepness with increasing annual precipitation is demonstrated in Figure 5.4, which illustrates substantially lower sensitivity indices at dry locations compared to wet locations. In contrast, the sensitivity indices of daily precipitation are negatively correlated to annual precipitation with moderate strength (ρ = 0.45, p<0.05). Depending on the equation, strong positive or negative correlations between SIs and annual precipitation also exist for other parameters such as slope length, soil texture, soil organic carbon, channel length, channel slope and watershed area.

5.3.3 Evaluation of simulation results against field data

The most recent estimated global water erosion rates on cropland of 11 - 13 t ha^{-1} derived from a comparable method (Borrelli et al., 2017; Doetterl et al., 2012; Van Oost et al., 2007) lie above the simulated median water erosion rates of 7 t ha^{-1} and 5 t ha^{-1} for maize and wheat fields, respectively. Similarly, the global water erosion estimates in maize and wheat fields are lower than the median value of 9 t ha^{-1} from 606 water erosion measurements from cropland around the world.

To evaluate the agreement between simulated and observed data, median values between simulated and measured erosion rates are compared while grouped by precipitation and slope classes, which are

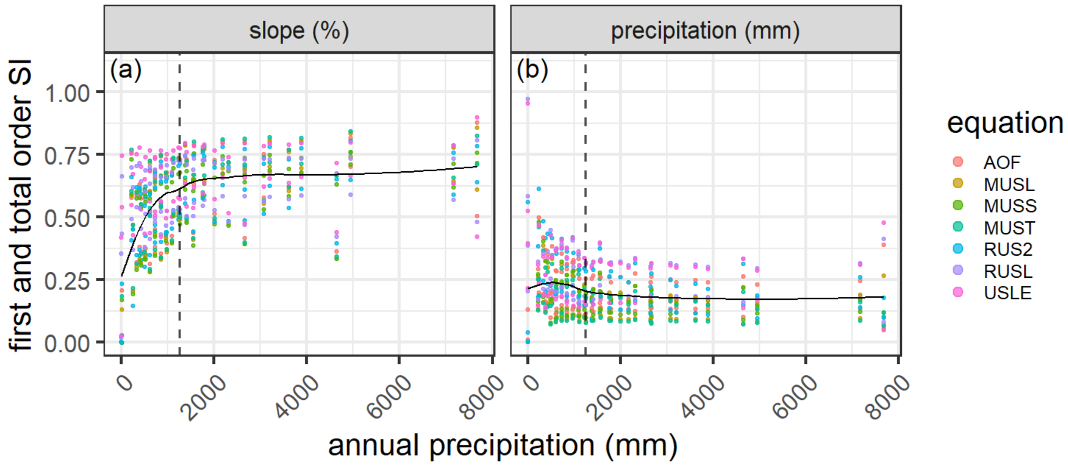

Figure 5.4: First-order and total-order Sensitivity indices for (a) slope steepness (%) and (b) precipitation (mm). The dashed vertical line illustrates median annual precipitation at all tested locations (1248 mm).

defined along the whole range of recorded slope inclinations and annual precipitation amounts of the field data (Figure 5.5a). Although slope and precipitation classes from the field are spread unevenly, they cover most climatic and topographic characteristics relevant to global agriculture. The comparison illustrates that the deviation between simulated data and field data is highest for locations with steep slopes and high annual precipitation. Where slopes are steeper than 8% and annual precipitation is higher than 1000 mm, the median of simulated water erosion exceeds the median of measured water erosion in most cases by at least 50 t ha^{-1}. With decreasing slope steepness and annual precipitation, the median deviation between simulated and measured data is decreasing. Where both slope steepness is below 8% and annual precipitation is below 1000 mm, the median deviation is lower than 5 t ha^{-1} in most cases. A comparison of measured and simulated water erosion using other equations with the baseline scenario can be found in Figure B.2.

The boxplots in Figure 5.5b illustrate the range of water erosion values measured in the field and simulated with the baseline scenario. The high deviation between observed and simulated values for grouped locations with slopes steeper than 8% and annual precipitation higher than 1000 mm can also be observed between the range of simulated and measured water erosion values. Outside locations combining steep slopes and strong precipitation, median deviation between simulated and measured data is lower than the variability within the field data. The range of values at locations with lower precipitation and slope steepness demonstrates that simulated values are mostly below measured values in those environments.

The uncertainty in the choice of management scenarios and water erosion equations included in the baseline scenario leads to an uncertainty of the deviation between simulated and measured erosion values. This uncertainty is demonstrated in Figure 5.5b by additional three bars illustrating the range of simulated medians due to contrasting tillage management scenarios, cover crop scenarios and different water erosion equations. At locations with low to moderate slope steepness and annual precipitation, the measured water erosion values agree best with the simulation values generated under scenarios implying larger water erosion, such as high intensity tillage and low soil cover. On the other hand, at locations with steep slopes and intensive precipitation, the measured values are closer to the simulated values under scenarios with less intensive tillage and more soil cover. In addition, the varying sensitivities of each water erosion equation lead to a different magnitude of water erosion values in different environments. On low to moderate slopes, water erosion simulated with the MUSS equation is lowest, whereas RUSLE generates the highest values. On steep slopes, the RUSLE equation generates the lowest water erosion values, which agree best with the measured values. The options to increase and decrease simulated water erosion with different field management scenarios and water erosion equations creates both uncertainty in the model results, but also the possibility to closely match field data.

At locations combining steep slopes and intense precipitation, most management scenarios and equations generate water erosion values that are higher than the measured values. However, those environmental conditions cover only a small share of global cropland. Cultivation areas with slopes steeper than 8% and annual precipitation higher than 1000 mm represent only 7% of global maize and wheat cropland in the grid cells. The map in Figure 5.6 illustrates that the highest concentration of these areas is in East and Southeast Asia, followed by Central and South America, and sub-Saharan Africa.

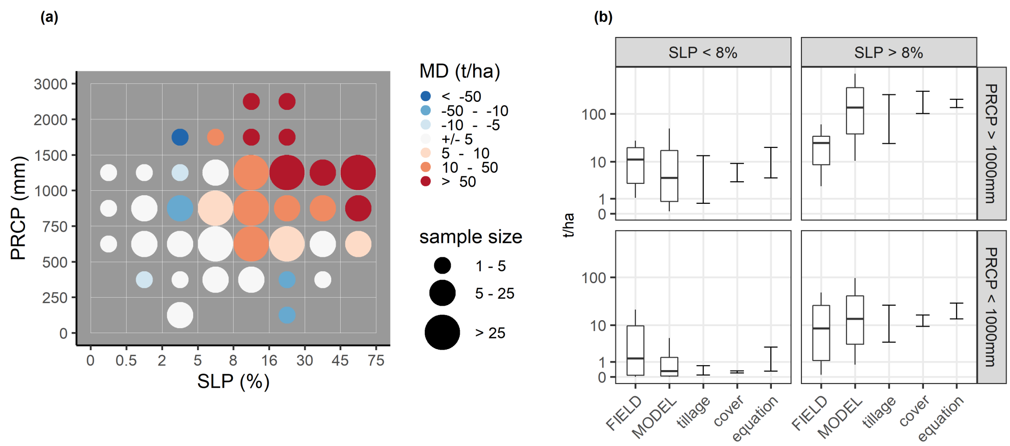

Figure 5.5: Comparison of simulated erosion with measured erosion for different slope and precipitation classes. a) Median deviation (MD) in t ha^{-1} between simulated erosion using the baseline scenario and measured erosion. Simulated and measured data is grouped into precipitation classes and slope classes used for the simulation setup. b) Distributions of measured erosion rates, erosion rates simulated with the baseline scenario and uncertainty ranges for management assumptions and erosion equations. The boxplots are defined by the median, the 25th percentile and the 75th percentile of simulated and measured erosion rates. Whiskers illustrate the 10th and 90th percentiles. The three bars next to the boxplots illustrate minimum and maximum median erosion rates calculated with all tillage and cover crop scenarios and with all water erosion equations. The values have been log-transformed for better visualisation.

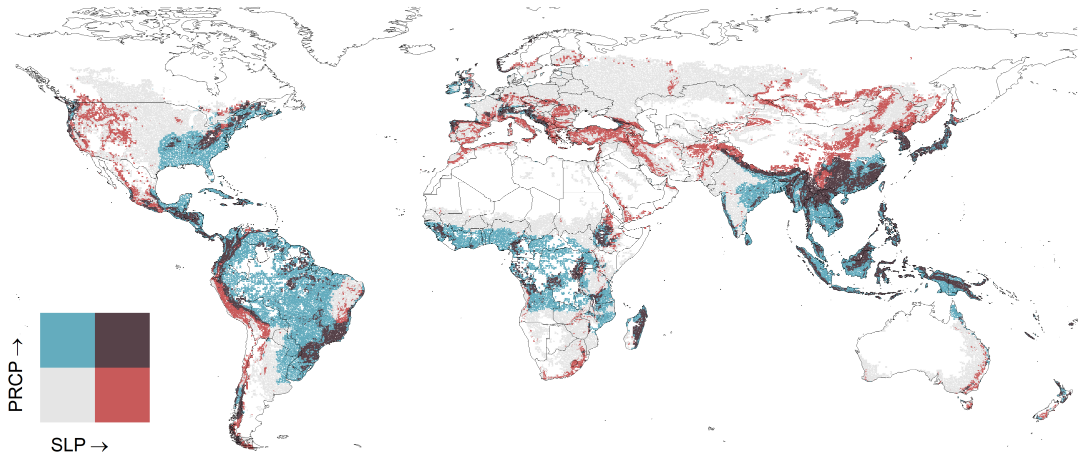

Figure 5.6: Distribution of low to high slope steepness (SLP) and annual precipitation (PRCP) in maize and wheat fields. Dark areas illustrate grids where slopes are steeper than 8% and annual precipitation is above 1000 mm. Correspondingly, blue, red, and grey pixels are below one or both thresholds.

5.4 Discussion

5.4.1 Varying robustness of simulated water erosion in different global regions

Global water erosion estimates generated with EPIC-IIASA and the baseline scenario overlap with observed water erosion values under most of the climatic and topographic environments where maize and wheat are grown. However, global maize and wheat land include locations where environmental characteristics differ significantly from the Midwestern United States, where the data was collected to develop the water erosion equations embedded in EPIC. The USLE model and its modification were developed with data for slopes of up to 20%, which makes model application for steeper slopes uncertain (McCool et al., 1989; Meyer, 1984). Furthermore, the relations between kinetic energy and rainfall energy in the American Great Plains differ from other regions in the world (Roose, 1996). Similarly, the runoff curve number method, which is the key methodology for the calculation of surface runoff, is based on an empirical analysis in watersheds located in the United States and might be less reliable in different regions of the world (Rallison, 1980). Due to the high sensitivity of slope steepness and daily precipitation for the calculation of water erosion, the reliability of the tested equations decreases in regions where typical slope and precipitation patterns differ from the Midwestern USA. Although some studies have successfully used USLE and its modification under a different environmental context (e.g., Alewell et al., 2019; Almas and Jamal, 2009; Fischer et al., 2018; Sadeghi and Mizuyama, 2007), many studies have concluded that the accuracy of these models may be reduced outside the environments they were created without calibration and model adaptation (Cohen et al., 2005; Labrière et al., 2015).

The skewed distribution of simulated water erosion values influenced by extreme soil loss rates in few fields highly sensitive to water erosion results in a large difference between the global median value of 6 t ha^{-1} a^{-1} and the global average value of 19 t ha^{-1} a^{-1} (Figure B.3). Due to the strong influence of outliers on average values, median values better represent global values and the differences in regional water erosion rates in wheat and maize fields. The high sensitivity of the simulation results to slope inclinations and precipitation suggests that a significant share of the estimated soil removal of 7.2 Gt a^{-1} originates from small wheat and maize cultivation areas on steep slopes with strong annual precipitation.

5.4.2 Sources of uncertainties in global water erosion estimates

Uncertain land use in mountainous regions

Changing climatic conditions with increasing elevation and the variable soils in mountainous regions can favour crop cultivation in higher elevations over lower elevations (Romeo et al., 2015). However, upland farming without soil conservation measures can lead to exhaustive soil erosion and can become a critical problem for agriculture (Montgomery, 2007). Large areas of land have been abandoned due to high erosion rates as soils were no longer able to support crops (Figure 5.7) (Romeo et al., 2015). As mountain agriculture is determined by various environmental and socio-economic factors, the cultivation of steep slopes can be very variable between regions. Regional erosion assessments in mountainous cropland suggested that areas with extreme water erosion rates are mainly limited to marginal steep land cultivated by smallholders (Haile and Fetene, 2012; Long et al., 2006a; Nyssen et al., 2019). In some mountainous regions, efforts to remove marginal farmlands from agricultural production, and programs to improve land management on steep slopes have reduced high water erosion rates (Deng et al., 2012; Nyssen et al., 2015). On the contrary, recent pressure through increasing population and crop production demands has resulted in re-cultivation of hillslopes and a reduction of fallow periods, which limits the recovery of eroded soil (Turkelboom et al., 2008; Valentin et al., 2008).

To analyse the sustainability of simulated maize and wheat cultivation systems that are exposed to high erosion rates, the simulated annual eroded soil depth is compared with a global dataset on modelled sediment deposition thickness (Pelletier et al., 2016) in Figure 5.8. The comparison shows that at 4% of grid cells permanent maize and wheat cultivation would not be sustainable as the entire soil profile would be eroded at the end of the simulation period. Most of the unsustainable agriculture is simulated on steep slopes. Although conservation techniques and cover crops are considered in the field management scenarios, the highly complex cultivation methods, including intercropping and fallow periods, common on hills that are normally farmed by smallholders, could not be modelled (Turkelboom et al., 2008). Moreover, the modelling approach assumes that the slope class representing the largest area in each grid cell most likely represents the largest share of arable land. This builds on the idea that a spatially extensive and diverse landscape can be represented by a single "representative field" characterised by the prevailing topography and soil conditions found in the landscape. On hilly terrain this setup simulates maize and wheat cultivation on steep slopes and thus mainly represents unsustainable agriculture. Although unsustainable maize and wheat cultivation can be observed in several mountain regions, cropland is very heterogeneously distributed in mountains and thus erosion rates from one representative field are highly uncertain.

The uncertainty in cropland distribution could partly be reduced by developing a higher resolution global gridded data infrastructure, which is currently not available for EPIC-IIASA. However, due to

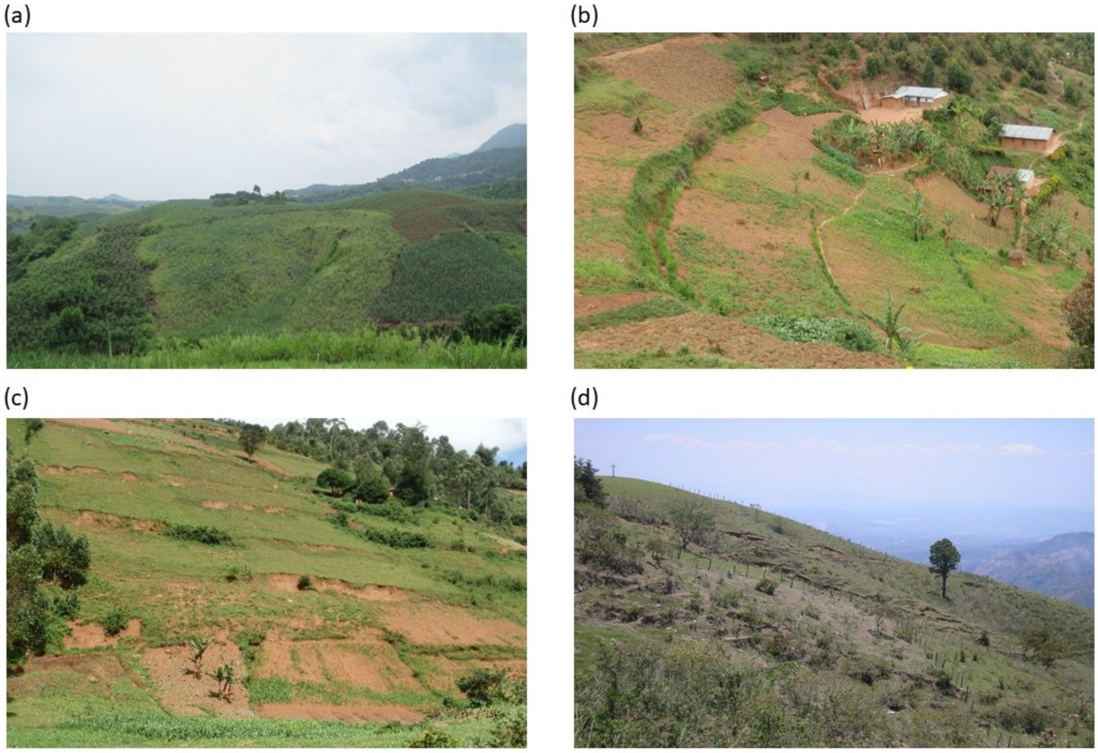

Figure 5.7: (a) Sugar cane cultivation on steep slopes in southern China (Nanning, Guangxi Zhuang Autonomous Region). The steepest slopes are already abandoned and reforested by eucalyptus trees. (b) Maize cultivation on strongly eroded slopes (30%–60%) in south-west Uganda (Kigwa, Kabale District). (c) Abandoned fields and maize cultivation on a steep slope (30%–60%) in south-west Uganda (Kigwa, Kabale District). (d) Degraded and abandoned maize fields on steep slopes (20%–60%) in northern El Salvador (San Ignacio, Chalatenango Department) (Carr et al., 2020).

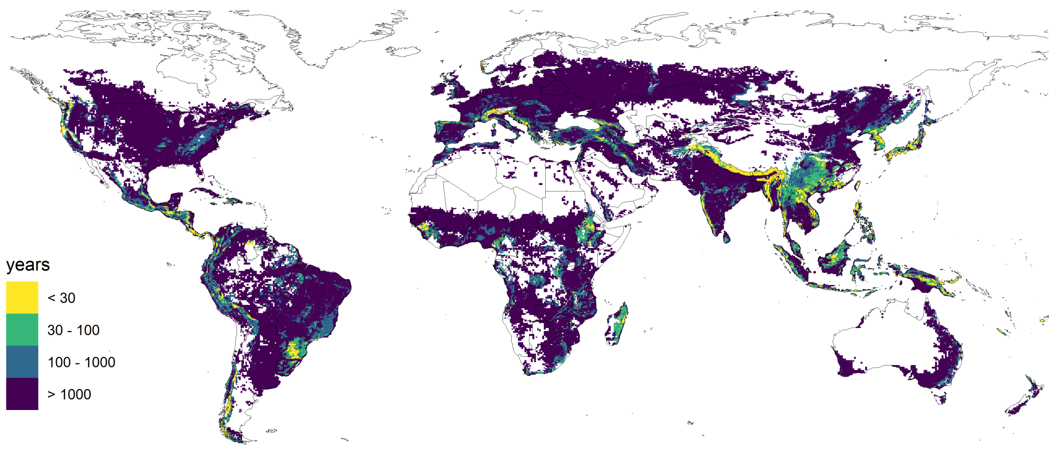

Figure 5.8: Simulated years left until the whole soil profile is eroded under permanent maize and wheat cultivation. Calculated as a ratio of the sedimentary deposit thickness (m) (Pelletier et al., 2016) and the eroded soil depth per year (water erosion (t ha^{-1} a^{-1}) x bulk density (g m^{-3})).

the large uncertainty in global land cover maps (Fritz et al., 2015; Lesiv et al., 2019), an explicit spatial link between cropland distribution and the corresponding slope category cannot be established without on-site observations. The effect of this uncertainty on erosion estimates is analysed for Italy, where large maize and wheat growing areas are spread across both flat terrain in the north and mountainous areas in the south. In an ideal scenario where cropland is limited to flattest land available per grid cell, median simulated water erosion in Italy would be reduced to tolerable levels below 1 t ha^{-1}. However, in a scenario, where the most common slopes per grid cell are cultivated, median simulated water erosion increases to 14 t ha^{-1} due to high water erosion simulated in Italy's mountainous regions (Figure B.4). This suggests a high uncertainty in global water erosion estimates due to uncertain spatial links between maize and wheat cultivation areas and different slope categories.

Uncertain field management

Simulated water erosion values are highly variable depending on the field management scenario. Simulating cover crop and no-tillage worldwide results in the lowest global soil removal of 2 Gt a^{-1} with median water erosion rates of 1 t ha^{-1} a^{-1} and simulating no cover crops and conventional tillage worldwide results in the highest global soil removal of 13 Gt a^{-1} with median water erosion rates of 17 t ha^{-1} a^{-1}. These variations cause further uncertainties in the simulation results.

Indeed, a proper reconstruction of a business-as-usual field management is important to further narrow down the uncertainty in global crop modelling (Folberth et al., 2019). In this study, the predominant field management was assigned based on a series of environmental and country-specific indicators, similar to Porwollik et al. (2019). For example, conservation agriculture was only considered in countries where this management strategy is likely according to AQUASTAT (FAO, 2016). In addition, by assuming cover crops between the wheat and maize seasons, more complex cultivation systems were simulated in the tropics, in which long and year-round vegetation periods and frequent multi- cropping practices hardly leave the soil uncovered. Bare fallow land was therefore not simulated in the tropics, as high water erosion values would have been falsely simulated at locations where heavy precipitation fell on bare ground. In addition, conservation practices such as contouring and terracing are crucial to reduce the simulation of high water erosion values on steep slopes. These practices were simulated for specific slope classes under the assumption that farmers around the world uniformly use conservation practices when cultivating on steep slopes. The most relevant parameters used for tillage scenarios are related to crop residues left in the field. In addition, equations directly connected to surface runoff are strongly influenced by the land use number used to determine the impact of cover type and treatment on soil permeability. While both crop residues and green fallow decrease water erosion significantly, especially in the tropics, their use varies widely between regions and even farms, based on a complex web of factors such as institutional factors, farm sizes, risk attitudes, interest rates, access to markets, farming systems, resource endowments, and farm management skills (Pannell et al., 2014). Also, soil conservation measures such as terraces or contour farming significantly influence water erosion but are very heterogeneously used between regions, farming systems and farmers. The baseline scenario is a very crude representation of the complex patterns of field management around the world, but attempts to depict these highly influential practices with the limited data available.

Variable estimates from different water erosion equations

The water erosion equation chosen for the baseline scenario generates the lowest global soil removal estimate. Different water erosion equations embedded in EPIC estimate a higher global soil removal of up to 11 Gt a^{-1} as well as higher median water erosion rates up to 19 t ha^{-1} a^{-1}. The MUSS water erosion equation chosen for the baseline scenario generates water erosion rates closest to the field data. The focus of equations on either rainfall energy or runoff energy is relevant for the different simulation results under specific environmental conditions. Equations based on rainfall-energy such as RUSLE and USLE simulate higher water erosion values than the other equations at most locations. However, on steep slopes they generate the lowest water erosion values as runoff becomes a greater source of energy than rain with increasing slope steepness (Roose, 1996). Also, the varying sensitivities of other parameters to the equations such as soil properties and management parameters lead to a varying agreement between simulated data and field data depending on the equation selection. Detailed field data would facilitate the choice of an appropriate equation to simulate water erosion worldwide or for a specific region.

5.4.3 The difficulty of evaluating large-scale erosion estimates with field data

The selection of field data for evaluating simulated water erosion was limited by the low availability of suitable water erosion observations covering the entire globe. The lack of reliable data on water erosion rates is a severe obstacle for understanding erosion, developing and validating models and implementing soil conservation (Boardman, 2006; Nearing et al., 2000; Poesen et al., 2003; Trimble and Crosson, 2000). The main reasons for the low availability of suitable data to evaluate simulated water erosion rates are twofold: i) erosion monitoring is expensive, time consuming and labour demanding; and, ii) primary data and metadata of measurement sites accompanying final results are often not available and many older measurements are poorly accessible as they are not available online (Benaud et al., 2020).

A variety of factors influencing water erosion such as climate, field topography, soil properties and field management need to be considered when modelling water erosion but are often not reported in available field measurements (García-Ruiz et al., 2015). This hampers a direct comparison between simulated and observed water erosion values. The varying match between measured and simulated water erosion on the basis of different tillage and cover crop scenarios was demonstrated in this chapter. Metadata on field management often only provides the crop cultivated and therefore the conditions under which erosion was measured in the field are not known sufficiently to evaluate erosion values simulated under different field management scenarios. Similarly, information on field topography and soil properties is often not provided with recorded field measurements and thus their use is limited in an evaluation of water erosion estimates simulated in different global environments. Moreover, most data are concentrated in the United States, West Europe and the West Mediterranean (García-Ruiz et al., 2015). In summary, there is a lack of field data representing all needed regions, situations and scenarios (Alewell et al., 2019).

The appropriate selection of field data to evaluate model outputs needs to be considered as well. At different spatial scales different erosion processes are dominant and consequently different erosion measurement methods are suitable (Boix-Fayos et al., 2006; Stroosnijder, 2005). Most authors use very heterogeneous data sets to evaluate their models, involving data generated by different methods at variable time and spatial scales and variable quality. For example, Doetterl et al. (2012) used plot data, suspended sediments from rivers, and data from RUSLE modelling. Borrelli et al. (2017) used soil erosion rates (measurement methods are not specified), remote sensing, vegetation index (NDVI) and results of RUSLE modelling. In his review on erosion rates under different land use, Montgomery (2007) used field data derived from erosion plots, field-scale measurements, catchment-scale measurements using hydrological methods, ^{137}Cs-method, soil profile truncation and elevated cemetery plots.

While all erosion measurement methods can be criticised, only data obtained through field measurements from runoff plots, using the ^{137}Cs-method, and volumetric surveys were used in this study, as these methods are best suited on the plot, slope and field scales. Geodetic methods such as erosion pins and laser scanner are also used at plot to field scales, but their accuracy is much lower than the accuracy of plot measurements and ^{137}Cs-method. Furthermore, erosion pins are mainly suitable for areas with extreme erosion rates (Hsieh et al., 2009; Hudson, 1993), and laser scanners have difficulties to recognize vegetation (Hsieh et al., 2009). Other commonly used methods such as hydrological methods (measurements of discharge and suspended sediment load) and bathymetric methods are more suitable for larger scales and involve a significant portion of channel erosion, which is not related with agricultural land (García-Ruiz et al., 2015). Plot experiments using rainfall simulators have also been neglected as they are usually performed on small plots with artificially generated rainfalls, which mostly have very low energies and therefore generate low erosion rates (Boix-Fayos et al., 2006; García-Ruiz et al., 2015).

The ^{137}Cs method was criticised by Parsons and Foster (2011), who questioned assumptions about the ^{137}Cs behaviour in the environment (variability of the ^{137}Cs input by wet fallout, its microspatial variability at reference sites, its possible mobility in certain soils, the ^{137}Cs uptake by plants and other aspects of ^{137}Cs behaviour in soil). To confront the criticism against the ^{137}Cs method, Mabit et al. (2013) discussed all objections raised by Parsons and Foster (2011) and confirmed its accuracy by listing several studies, in which ^{137}Cs based erosion rates are compared with erosion rates derived from direct measurements. The ^{137}Cs method is based on a set of presumptions which should be met to produce useful results and thus careful interpretation of the obtained results is needed (Fulajtar et al., 2017; Mabit et al., 2014a; Zapata, 2002).

Similarly, erosion rates obtained by volumetric measurements require careful interpretation as they are exposed to various potential sources of errors and do not account for interill erosion. Although the latter can be neglected under certain circumstances, studies from Europe and semiarid areas of the USA have reported that interill erosion contributed significantly to the amount of soil eroded in fields (Boardman and Evans, 2020; Parsons, 2019). Further, measuring the lengths and cross-sections of rills during field surveys or on terrestrial and aerial photos can be very subjective (Panagos et al., 2016). Different approaches used to detect and measure rills in fields can cause variability in calculated erosion volumes up to a factor of two (Boardman and Evans, 2020; Casali et al., 2006; Watson and Evans, 1991). In order to obtain soil erosion rates in weight units, soil volumes need to be converted using the soil bulk density, which is often based on estimates (Evans and Brazier, 2005).

The shortcomings of erosion plot measurements were discussed by several authors (Auerswald et al., 2009; Brazier, 2004; Evans, 2002; Loughran et al., 1988). Erosion plots have various sizes and shapes (few meters to few hundreds of meters) and various approaches of sediment recording are used (total collection, multislot divisors, tipping buckets, Coshocton wheels), which all involve significant uncertainties. Although some long-term plot experiments exist, many plot measurements fail to cover the whole year erosion cycle (Auerswald et al., 2009). Often, they have to be removed during land management operations such as seeding, ploughing, or they are too expensive and labour demanding.

Despite all the shortcomings of available soil erosion data, most data provide valuable information (Benaud et al., 2020). The evaluation against field measurements in this study provided a first indication of the robustness of results under specific topographic and climatic conditions. In most environments relevant for maize and wheat cultivation the deviation between simulated and measured water erosion values is lower than the variability within the field data. The mentioned uncertainties cannot be narrowed down further on the basis of the reported data. Although the metadata accompanying the field measurements includes information on slope steepness and annual precipitation (or geographic coordinates allowing for overlay with climatic data), information on soil types or texture classes, crop type and tillage system implemented over time are provided only for few points. Also, the various methods used to measure erosion rates, their complex implementation and the bias of field studies towards locations sensitive to erosion lead to an uncertain representation of large-scale erosion rates based on field measurements. To facilitate in-depth evaluation of erosion models across different scales, it is crucial to provide detailed information on site characteristics and to harmonise approaches to measure erosion in the field. Moreover, the accessibility of field data should be improved as raw data is often not published or needs to be collected from numerous publications, grey literature and conference proceedings to obtain the large amount of data necessary for regional or global erosion studies. Recent efforts to compile erosion measurements and metadata from existing studies on a single platform (Benaud et al., 2020) will likely increase the availability of field data, which will greatly benefit future modelling studies and understanding of soil erosion at all levels.

5.5 Conclusion

The simulation of water erosion with GGCMs is largely influenced by the resolution of global datasets providing topographic, soil, climate, land use and field management data, which is currently not available at the field scale. Yet, considering water erosion in global crop yield projections can provide useful outputs to inform assessments of the potential impacts of erosion on global food production and to identify soil erosion hotspots on cropland for management and policy interventions. To improve the quality of the estimates and to further develop these models, it is crucial to identify, communicate and address the existing uncertainties. Increasing the resolution of global soil, topographic and precipitation data is central for improving global water erosion estimates. In addition, the model results provide an insight into the importance of considering field management. The numerous options to simulate the cultivation of fields result in a large range of possible water erosion values, which can only partly be narrowed down at a global scale. Further improvement of global water erosion estimates requires detailed and harmonised field measurements across all environmental conditions to validate and calibrate simulation outputs. On the basis of existing field data, it was possible to identify specific environments for which the modelled erosion rates show poor robustness. These are mainly found in the tropics and mountainous regions due to the high sensitivity of simulated water erosion to slope steepness and precipitation strength, and the complexity of mountain agriculture. However, these areas represent only a small fraction of global cropland for maize and wheat. The overlap of simulated and measured water erosion values in most environments used to produce maize and wheat underlines the robustness of EPIC-IIASA to simulate the differences in water erosion rates of major global crop production regions.

Chapter 6

The impact of water erosion on global maize and wheat yields

6.1 Introduction

The negative effects of land degradation on social and economic wellbeing has been widely recognised. Yet its present and future impacts are not adequately quantified globally in physical and economic terms to inform major environmental and agricultural policies (Montanarella, 2007; Nkonya et al., 2011).

Soil loss due to water erosion has been estimated at many sites worldwide and modelled globally (Borrelli et al., 2017; Doetterl et al., 2012; García-Ruiz et al., 2015; Montgomery, 2007). However, from a food security standpoint, it is more relevant to quantify the impact of water erosion on crop productivity. There are substantial variations in the estimates of productivity losses from the few studies in the literature (Bakker et al., 2004, 2007; Den Biggelaar et al., 2004a; van den Born et al., 2000; De la Rosa et al., 2000; Lal, 1995; Larney et al., 2009; Oyedele and Aina, 1998). This variability is not surprising as erosion-productivity relationships are difficult to generalise due to the location-specific nature of soil erosion determined by soil properties, climate and management (Den Biggelaar et al., 2004a). Moreover, the choice of method to measure water erosion impacts on crops is one of the most important factors explaining variations between studies (Bakker et al., 2004). Hence, different methodological approaches in field studies can mask the impact of regional differences on water erosion impacts on crops.

Previous global erosion impact assessments (Pimentel et al., 1995; Sartori et al., 2019) relied on simple linear assumptions about the impact of water erosion on crop yields, and neglected differences between crops and regional characteristics (Chapter 2.4). Crop models can facilitate the extrapolation of experimental and small-scale data across a range of environments and management strategies (Nelson et al., 1996). Moreover, models are essential to determine long-term effects of degradation processes, which are challenging to observe in short-term field experiments (Enters, 1998). However, due to the lack of evaluated global water erosion estimates, GGCM studies have so far neglected soil erosion and its impact on crop yields and production (Chapter 3.6).

After confirming in Chapter 5 that EPIC-IIASA can represent the differences in water erosion rates between major global cropping regions, the simulated water erosion rates are used to quantify their impact on global maize and wheat yields and production. In addition, regions where crops are most exposed to the risks of water erosion are identified based on the environmental conditions and the use of fertilisers. Finally, the uncertainties of the simulated water erosion impacts on crops are addressed.

6.2 Methodology

6.2.1 Summary of methodology

To simulate the impact of water erosion on maize and wheat yields, the same modelling approach as in the previous chapter is used. As such, the model outputs are based on the baseline field management scenario presented in Chapter 4.3.4. The range between minimum and maximum water erosion impacts on crops simulated with all field management scenarios is used to bracket the field management uncertainties for each grid cell and country.

6.2.2 Aggregation of model outputs

Water erosion impact

Water erosion impacts on maize and wheat yields are calculated for the end of the simulation period for the years 2001–2010. Crop yields generated with all field management scenarios selected under the baseline scenario assumptions are averaged over the respective years and weighted by the irrigated and rainfed cultivation area (Portmann et al., 2010) of the respective crop per grid cell (Equation 6.1). The difference between average maize and wheat yields, simulated with and without the impact of water erosion, are used to filter grid cells where water erosion reduces crop yields (i.e. the area where crop yields are vulnerable to water erosion). Subsequently, the relative reduction of maize and wheat yield due to water erosion is calculated on grid cell level (Equation 6.2).

$$Yw_{cpg} = Yav(r)_{cpg} * Af(r)_{cg} + Yav(i)_{cpg} * Af(i)_{cg} \tag{6.1}$$

$$dYrel_{cg} = \frac{Yw(e0)_{cg} - Yw(e1)_{cg}}{Yw(e0)_{cg}}; ifYw(e0)_{cg} > Yw(e1)_{cg} \tag{6.2}$$

Yw_{cpg} is area-weighted mean crop fresh matter yield (tha^{-1}) for crop c, P-factor value p and grid cell g; Yav is yield averaged across the tillage and cover crop scenarios selected in each grid following the baseline scenario assumptions and for the selected decade simulated under rainfed (r) and irrigated (i) conditions; $Af(r)$ is the rainfed area fraction; and $Af(i)$ is the irrigated area fraction. $dYrel$ is the relative loss of the yield of crop c, at grid cell g; Yw is weighted average yield simulated with a P-factor value of 0 ($e0$) and a P-factor value greater than 0 ($e1$).

To calculate the loss of crop production in each country, first, the absolute reduction of crop yields is estimated as the difference in the mean yield for the selected decade simulated without and with water erosion ($e0$ and $e1$, respectively) (Equation 6.3). Subsequently, this yield reduction is multiplied by the total area of rainfed and irrigated cropland of each grid cell in the country (Equation 6.4).

$$dYabs_{cwg} = Yav(e0)_{cwg} - Yav(e1)_{cwg}; if Yw(e0)_{cpg} > Yw(e1)_{cpg} \tag{6.3}$$

$$dP_{lc} = \sum_{g=1}^{n} dYabs(i)_{cg} * A(i)_{cg} + dYabs(r)_{cg} * A(r)_{cg} \tag{6.4}$$

$dYabs_{cwg}$ is the absolute yield loss for crop c, irrigation scenario w and grid cell g; Yav is yield averaged across the tillage and cover crop scenarios selected in each grid cell following the baseline scenario assumptions and for the selected decades with P=0 ($e0$) and P>0 ($e1$); dP_{lc} is the loss of production (in tonnes) of crop c in country l; n is the number of grid cells in country l; $dYabs(i)$ is the absolute decline in irrigated yields and $dYabs(r)$ is the absolute decline in rainfed yields; $A(r)$ is the rainfed area (in *ha*); and $A(i)$ is the irrigated area (in *ha*).

The national market prices of crops taken from the FAOSTAT producer price (average 2013–2018, or the last five annual records available) is used to calculate the economic maize and wheat production losses (in USD) due to water erosion per country and globally (FAO, 2020). Two-tailed T-tests are used to filter countries with significant differences between average yields simulated with and without water erosion.

Evaluation of simulated crop yields

Simulated maize and wheat yields, which are calculated in t ha^{-1} dry matter in EPIC, are converted to fresh matter assuming a net water content of 12% following Wirsenius (2000), so that they can be compared with yields reported by FAOSTAT (FAO, 2020). Fresh matter crop yields are aggregated for each country using the same approach as for grid cell-level aggregation in Equation 6.1. Irrigated and rainfed crop yields (generated with all P-factor values, tillage and cover crop scenarios selected for the baseline scenario and the years 2001 and 2010) are averaged for each country and weighted by the cultivated area of the respective irrigated or rainfed crop per country (Portmann et al., 2010) (Equation 6.5). In addition, average maize and wheat yields per grid cell are used to summarise the total maize and wheat production for each country (Equation 6.6).

$$Yw_{cl} = Yav(r)_{cl} * Af(r)_{cl} + Yav(i)_{cl} * Af(i)_{cl} \tag{6.5}$$

$$Pcl = \sum_{g=1}^{n} Yav(r)_{cg} * A(r)_{cg} + Yav(i)_{cg} * A(i)_{cg} \tag{6.6}$$

Yw_{cl} is weighted yield for crop c in country l; Yav is yield averaged for the years 2001–2010, with all P-factor values and all tillage and cover crop scenarios selected under the baseline scenario assumptions simulated under rainfed (r) and irrigated (i) conditions; $Af(r)$ is the rainfed area fraction and $Af(i)$ is the irrigated area fraction; P_{cl} is the total production (in tonnes) of crop c in country l; g is any grid cell in country l; n is the number of grid cells in country l; $A(r)$ is the rainfed area and $A(i)$ is the irrigated area in hectares.

6.3 Results

6.3.1 The impact of water erosion on global maize and wheat yields

In the last decade of the 30-year simulation period, the average annual maize and wheat yields are reduced due to water erosion at 58% and 62% of grids cells, respectively, by a global median of 3% for each crop. The affected grid cells represent 51% and 46% of global maize and wheat cultivation areas, respectively. Median annual soil loss at grid cells where crop yields are reduced is 11 t ha^{-1} and 6 t ha^{-1} on maize and wheat fields, respectively. The simulated relative reduction of average annual maize and wheat yields per grid cell at the end of the simulation period is illustrated in Figure 6.1. Most grid cells where high yield reduction is simulated represent fields with low fertiliser input on steep slopes exposed to intensive precipitation.

The distribution of annual average crop yield losses for the 40 most vulnerable maize- and wheat-producing countries is plotted in Figure 6.2. Countries in which the median annual reduction of maize yields due to water erosion is higher than 5% by the end of the simulation period are most abundant in sub-Saharan Africa and across Asia. There are similarly high median maize yield losses for countries in Central America and the Caribbean, but only Chile and Uruguay are badly affected in South America, and only Albania, Croatia and Greece in Europe. Median wheat yield losses per country are generally lower than for maize. Countries with median wheat losses higher than 5% are mostly in Asia and Europe. In Africa, annual median wheat yield losses higher than 5% are simulated in Ethiopia, Uganda and Tanzania, and in South America in Uruguay, Bolivia and Chile. These crop yield losses are modelled using the prevailing environment and management conditions in each country. Actual crop yield losses could only be determined based on an explicit spatial link between the extent of crop cultivation areas and areas vulnerable to water erosion, which would only be possible with on-site observations.

The distribution of the magnitude of crop yield losses and the share of grid cells affected by water erosion needs to be considered to assess each countries vulnerability to water erosion. In some large countries, the majority of cropland is exposed to low water erosion despite extensive vulnerable areas within the country. For example, large areas in the United States, Brazil, India and China are affected by water erosion. However, as these areas are only a small part of the entire cropland area, overall median crop losses are low. On the other hand, in some countries a small number of grid cells with high water erosion cause high median crop productivity losses. Afghanistan, Pakistan and Iran are ranked among the most vulnerable countries even though fewer than half of the grid cells are affected by water erosion under all scenarios.

In several countries, field management scenarios have a significant impact on the area affected by water erosion and on the magnitude of crop yield losses, as demonstrated by the uncertainty ranges in

Figure 6.2. In most countries, the median maize and wheat yield losses are lowest with no tillage and cover crops and highest with conventional or reduced tillage and bare soil fallow. On a global scale, annual maize and wheat yield losses simulated under all field management scenarios range from 2–5% and 3–4%, respectively.

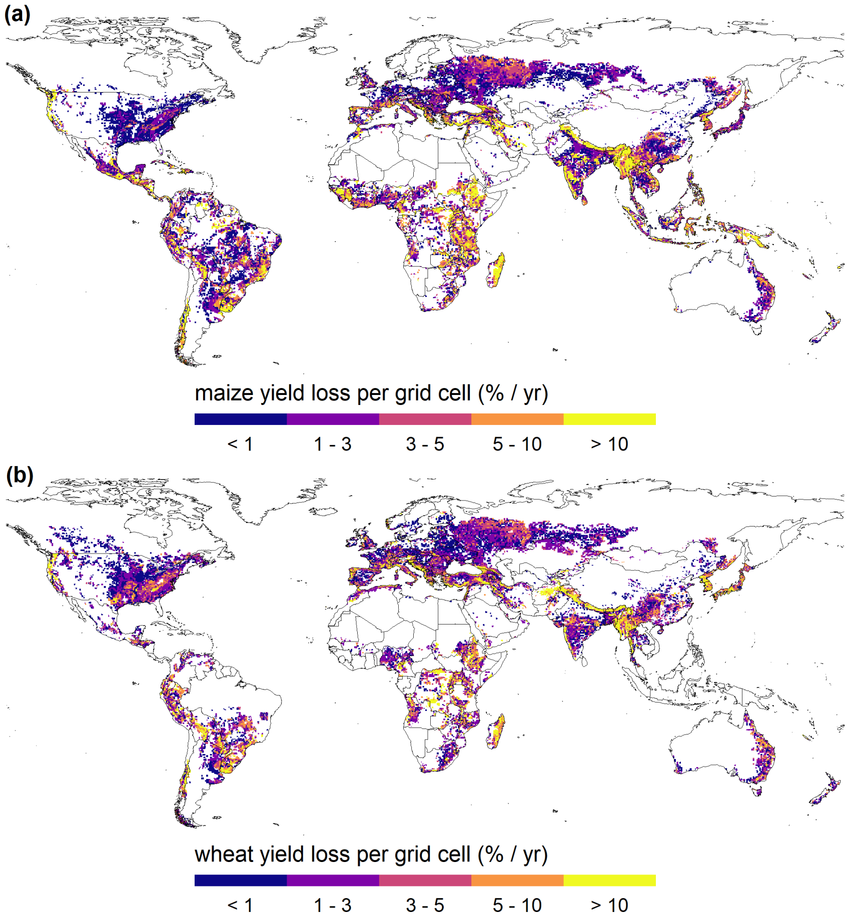

Figure 6.1: Maize (a) and wheat (b) yield loss due to water erosion (% yr^{-1}) simulated with the baseline scenario and averaged for the years 2001 – 2010. Each grid cell is represented by one representative field capturing the most common site characteristics. Cropland areas are not considered in grid cell size.

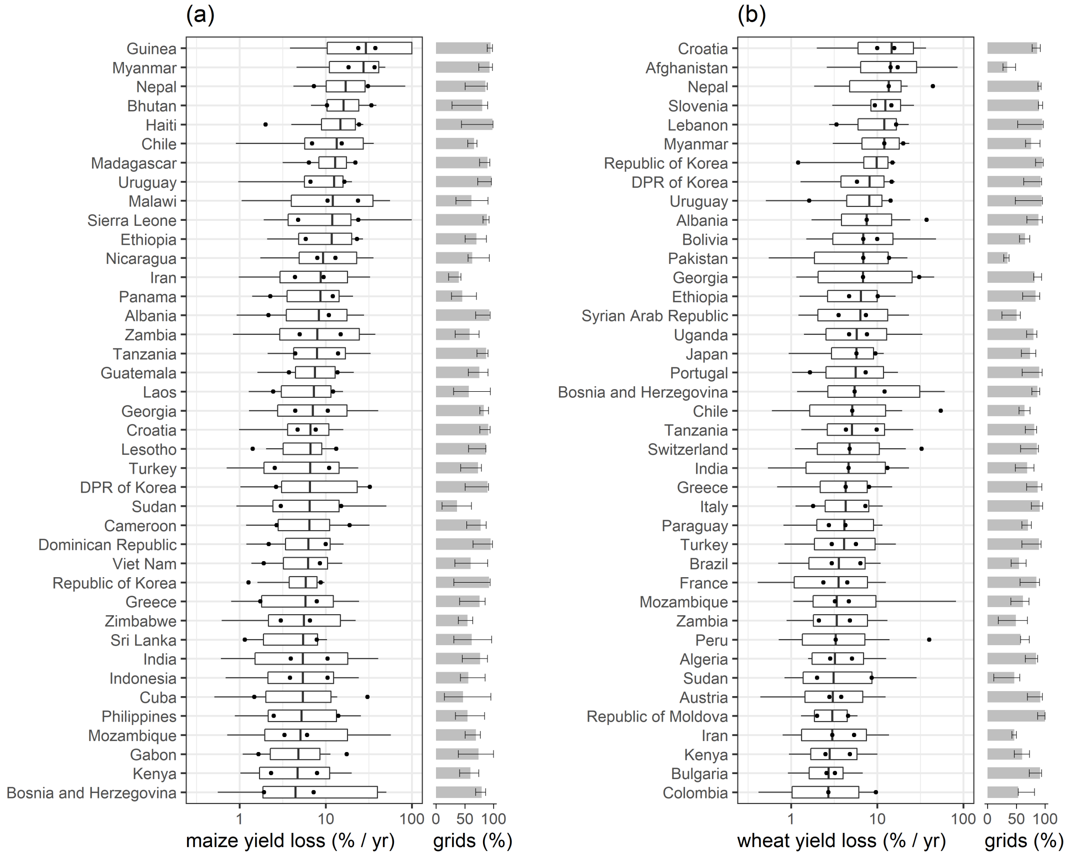

Figure 6.2: Maize (a) and wheat (b) yield losses due to water erosion (% yr-1) for the 40 most vulnerable countries estimated with the baseline scenario. Countries contributing less than 0.01% to global maize and wheat production are excluded. The countries are ranked by median crop yield losses. Boxes include values from the 25^{th} to the 7^{5th} percentiles and whiskers bracket values between the 10^{th} and the 90^{th} percentiles. The points illustrate minimum and maximum median crop yield losses generated from all field management scenarios. Medians and percentiles are converted to logarithmic scale. Grey barplots on the right illustrate the share of grid cells affected by water erosion impacts in each country, and errorbars indicate the variability of affected grid cells due to all management scenarios. The distributions of all relevant maize and wheat producing countries are provided in Figure C.2 and Figure C.3.

6.3.2 Fertiliser use and environmental drivers affect the impacts of water erosion

The simulated impact of water erosion on crop yields is strongly influenced by fertiliser input and environmental drivers in each country such as slope inclination and precipitation amount. Figure 6.3a shows that median maize and wheat yield losses per country tend to be higher in countries with higher levels of water erosion. Losses are relatively lower in countries with high rates of fertiliser application, which replace nutrients lost through soil runoff (Figure C.4). Global median rates of organic nitrogen runoff from maize and wheat fields are 7 kg ha^{-1} yr^{-1} and 5 kg ha^{-1} yr^{-1}, and the global median rates of soil organic carbon runoff from maize and wheat fields are 107 kg ha^{-1} yr^{-1} and 72 kg ha^{-1} yr^{-1} during the whole simulation period (global maps of nitrogen and carbon runoff are provided in the supplementary information in Figures C.5 and Figure C.6).

Slope steepness and precipitation strength are the most important environmental drivers influencing the impact of water erosion on crop yields. Figure 6.3b and 6.3c show how yield losses increase as a function of slope classes and rainfall erosivity classes. The distribution of maize and wheat cropland in the grid cells per slope and rainfall erosivity classes is illustrated by the grey bars in the same plots. Around 73% of maize and wheat cropland is on slopes whose steepness does not exceed 5%. On those slopes, median global maize and wheat yield losses range from 0% to 1%. On steeper slopes, median yield losses range from 3% to 9%. Similarly, 69% of maize and wheat land is exposed to rainfall erosivity below 3000 MJ mm ha^{-1} h^{-1} yr^{-1}, which is the average rainfall erosivity on global cropland. For those areas, median crop yield losses range from 1% to 2%. Median crop yield losses on fields exposed to higher rainfall erosivity range from 2% to 4%.

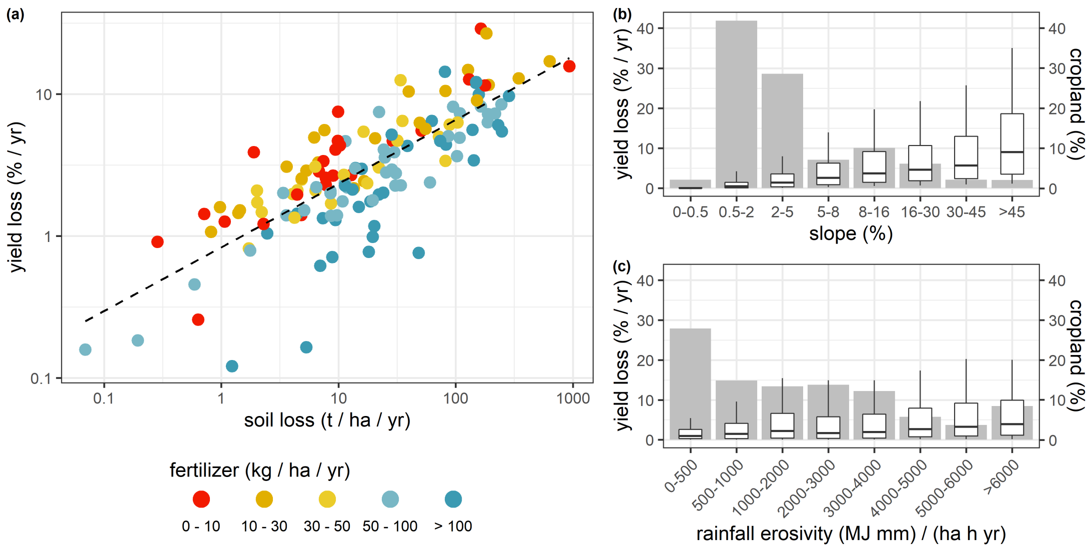

Figure 6.3: (a) Modelled median maize and wheat yield loss plotted against median soil loss through water erosion for each country. The linear relationship between national soil loss and crop yield loss is illustrated by the dashed regression line. Colours indicate the rate of fertiliser application per country. (b,c) Maize and wheat yield losses, respectively, per grid cells classified by slope steepness and rainfall erosivity. Grey bars illustrate the share of cropland in grid cells summarised for the different slope and rainfall erosivity classes.

The highest yield losses tend to occur in regions with low fertiliser input and high rates of water erosion. Figure 6.4 identifies agricultural regions susceptible to water erosion as indicated by overlapping areas of slope steepness (IIASA/FAO, 2012) and rainfall erosivity (Panagos et al., 2017), and shows the average fertiliser application rates for maize- and wheat-producing countries (Mueller et al., 2012). Dark areas highlight most vulnerable locations characterised by high abundance of steep slopes in regions of high rainfall erosivity. These are most common in South, East and Southeast Asia, sub-Saharan Africa, and Latin America. The cultivation on steep slopes is a common factor of vulnerability outside the tropics as well, but rainfall erosivity decreases there, reducing the energy of rainfall to erode soil. fertiliser application per country varies significantly. In most African countries and in several countries in Asia and Latin America, the fertiliser use is substantially lower than in the rest of the world.

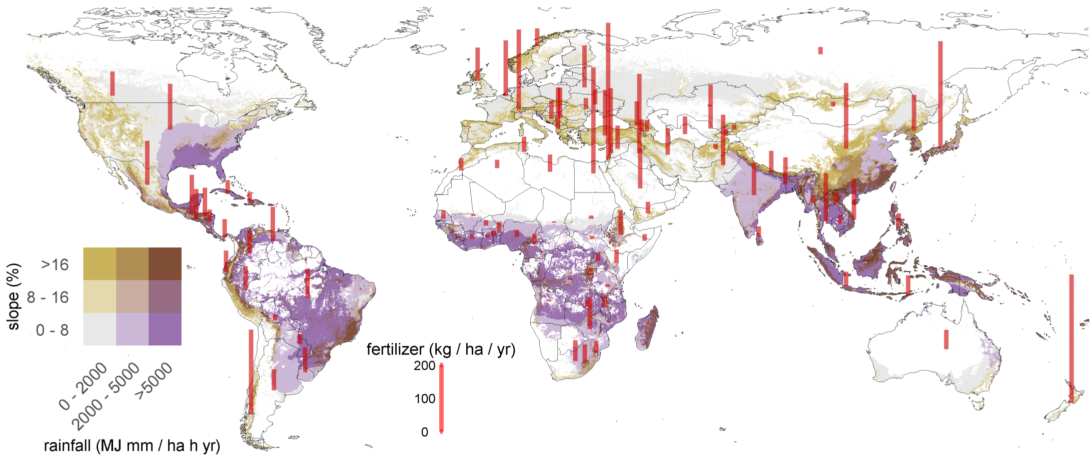

Figure 6.4: water erosion vulnerability on global cropland indicated through the most important environmental drivers, rainfall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}) and slope steepness (%), and the average sum of Nitrogen, Phosphorous and Potassium fertiliser application rates (kg ha^{-1}) per country represented by the red bars. To improve the overview of the map, fertiliser application from countries contributing less than 0.1% to global maize and wheat production have been excluded, and fertiliser application from all relevant EU27 countries has been averaged.

6.3.3 The impact of water erosion on total maize and wheat production

The total annual production losses per country are based on the average absolute yield losses of maize and wheat, which were extrapolated over the entire irrigated and rainfed cultivation area of each crop in a grid cell (Figure 6.5). Water erosion reduces the global production of maize and wheat by 9 million tonnes and 6 million tonnes annually. This accounts for less than 1% of the global average maize and wheat production of 1,091 million tonnes and 739 million tonnes, respectively, from 2013–2018 reported by FAOSTAT (FAO, 2020). Market values of the national maize and wheat production losses, derived by multiplying production losses with the average market prices (USD t^{-1}) in each country, add up to an annual global loss of approximately USD 2bn in maize production, and USD 1.3bn in wheat production. Highest production losses in absolute terms are in countries with the largest maize and wheat cultivation areas rather than in the most vulnerable countries. Tables 6.1 and 6.2 list the 20 countries with the highest annual reduction in maize and wheat production due to water erosion. These countries account for 84% and 77% of the global maize and wheat production.

The largest maize production declines are estimated for the most important producers such as Mexico, Brazil, United States, India, China and Indonesia. Nevertheless, losses in the United States and China are only 0.2% of their national production, but reach 5% of Mexico's production. Few countries with the highest absolute losses have low shares of global production (e.g. Guatemala; Nicaragua; Nepal; Myanmar).

Similarly, the modelled loss of wheat production due to water erosion in absolute terms is highest for India and China as they produce nearly a third of global wheat, but is less than 1% of their total production. High production losses in absolute terms for small producers are rarer than for maize. Countries with lowest production losses in absolute terms are most abundant in Africa, Southeast Asia and Latin America.

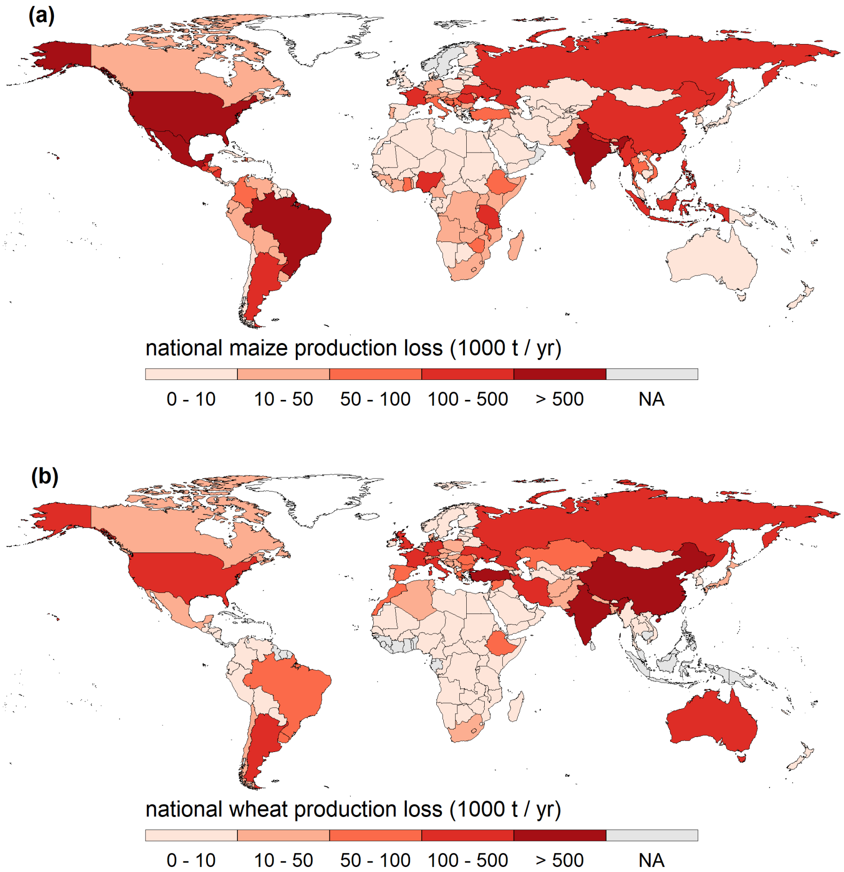

Figure 6.5: The impact of water erosion on national maize (a) and wheat (b) production based on the sum of estimated production losses in all grid cells in each country. NA marks countries without maize or wheat production area. Estimates of production losses in each grid cell assume uniform site characteristics for the entire cropland in each grid cell.

country	prod. (million t)	prod. loss (million t)	prod. loss (%)	prod. loss (million $)
Mexico	25.6	1.3	5.0	264.8
Brazil	81.6	0.8	1.0	157.7
USA	376.7	0.7	0.2	104.9
India	25.6	0.6	2.5	92.0
China	246.7	0.5	0.2	199.8
Indonesia	23.3	0.5	2.1	151.8
Philippines	7.6	0.4	5.2	111.3
Nepal	2.2	0.3	12.5	74.2
Guatemala	1.9	0.2	12.8	37.2
Russia	12.7	0.2	1.5	24.6
Argentina	38.6	0.2	0.5	31.1
Tanzania	6.0	0.2	2.7	29.8
Nigeria	10.2	0.1	1.3	41.2
Myanmar	1.8	0.1	6.5	27.1
Nicaragua	0.4	0.1	27.8	31.9
Romania	12.7	0.1	0.9	20.6
Ukraine	28.6	0.1	0.4	14.8
France	14.4	0.1	0.7	17.9
Ethiopia	7.5	0.1	1.3	20.8
Viet Nam	5.2	0.1	1.7	26.4
World	1091.1	8.9	0.8	1960.7

Table 6.1: National maize production (FAO, 2020) and absolute and relative maize production losses for the countries with the highest absolute losses.

country	prod. (million t)	prod. loss (million t)	prod. loss (%)	prod. loss (million $)
India	94.4	0.7	0.7	137.4
China	130.0	0.6	0.5	213.7
Turkey	21.0	0.5	2.5	139.4
USA	55.1	0.5	0.8	89.4
Russia	67.5	0.4	0.6	60.2
France	37.4	0.3	0.8	56.9
Argentina	13.2	0.2	1.8	56.5
Iran	12.4	0.2	1.6	77.4
United Kingdom	14.6	0.1	1.0	30.1
Italy	7.3	0.1	1.9	32.5
Germany	24.8	0.1	0.5	22.9
Ukraine	25.0	0.1	0.5	17.7
Australia	24.5	0.1	0.4	22.0
Kazakhstan	14.1	0.1	0.6	11.3
Spain	6.9	0.1	1.2	17.9
Syria	2.0	0.1	3.6	9.7
Morocco	6.2	0.1	1.1	19.4
Romania	8.6	0.1	0.8	11.9
Greece	1.5	0.1	4.4	15.8
Ethiopia	4.4	0.1	1.4	23.4
World	739.5	5.6	0.8	1292.5

Table 6.2: National wheat production (FAO, 2020) and absolute and relative wheat production losses for the countries with the highest absolute losses.

6.3.4 The relevance of slope and field management assumptions

The impact of the assumption that the most common slope represents the whole grid cell is examined for Italy in Figure 6.6. The plots compare the distribution of modelled maize and wheat yield losses due to water erosion for cases in which all cropland is either on the most common slope class or on the flattest terrain in each grid cell. Median annual maize and wheat yield losses for the flattest terrain assumption are 0.2% and 1.2%, respectively, leading to annual maize and wheat production losses of 0.01 million tonnes and 0.04 million tonnes, respectively. For the most common slope scenario, median annual maize and wheat yield losses are 2.1% and 4.1%, with substantially higher annual maize and wheat production losses of 0.05 million tonnes and 0.1 million tonnes, respectively.

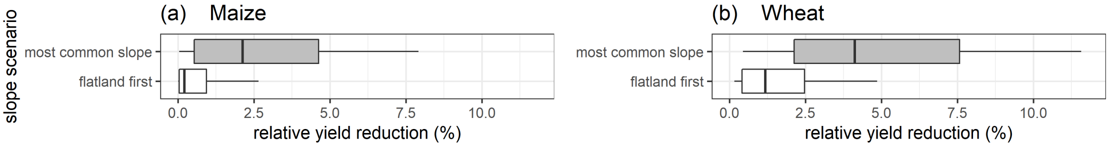

Figure 6.6: Range of simulated maize and wheat yield losses (% yr^{-1}) in Italy simulated with different cropland distribution scenarios for maize (a) and wheat (b). Boxes illustrate medians and 25^{th} and 75^{th} percentiles, whiskers illustrate values between the 10^{th} and the 90^{th} percentiles. Grey bars mark the baseline scenario used for the main results of this study.

The uncertainty due to lacking field management information varies around the globe and is most pronounced in erosion-sensitive areas, where soil conservation techniques can reduce extreme water erosion rates considerably. In those areas, contrasting field management scenarios generate a large range of values with varying degrees of water erosion impacts on crop yields (Figure 6.7). This large uncertainty range is reduced in the baseline scenario by identifying and removing field management practices that are unlikely to be used in specific regions. However, due to the multitude of field management practices around the world, this uncertainty can only be limited in part.

6.3.5 Evaluation of simulated crop yields

To evaluate simulated wheat and maize yields (Figure C.1), national yields reported by FAOSTAT are compared to national averages of the simulation outputs (Figure 6.8). National maize yields are evaluated for the most important maize producers, which account for 99.9% of global maize production. Due to the low agreement between simulated and reported national average maize yields for countries contributing only a small share to the global production, the smallest maize producing countries have been excluded to facilitate the evaluation in respect to the global focus of this study. The evaluation of the simulation of global wheat production is conducted with all countries as small wheat producing countries do not significantly influence the evaluation results.

With an R^2 of 0.58 simulated national maize yields are significantly related to reported values. The regression intercept of 1.71 and slope of 0.49 indicates overestimated maize yields at low yield levels and underestimated yields at higher yield levels. Simulated wheat correlates stronger to observed values than simulated maize yields. The comparison of simulated and observed national wheat yields results in

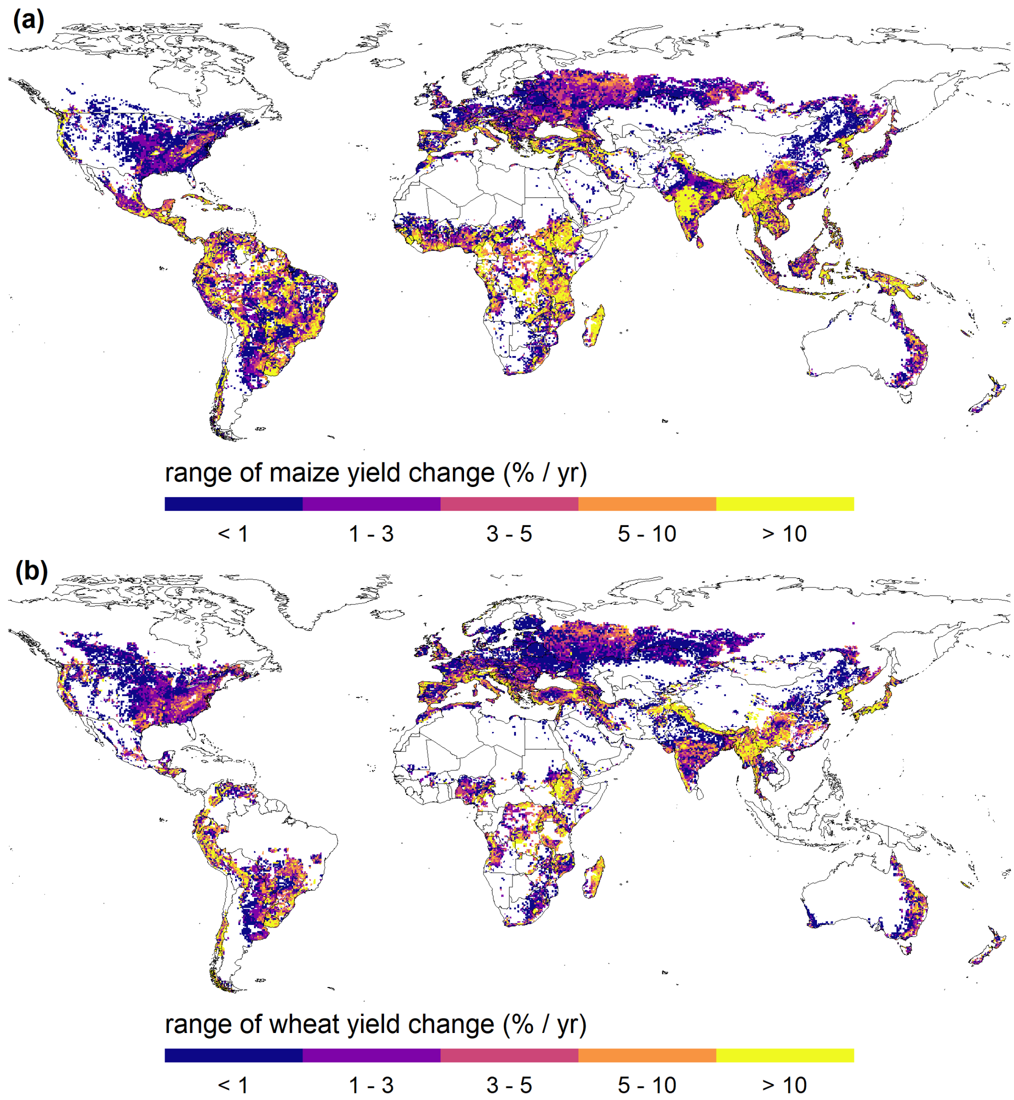

Figure 6.7: Uncertainty range of the impact of water erosion on maize (a) and wheat (b) yields due to contrasting management scenarios.

an R^2 of 0.65. The regression intercept of 0.45 and slope of 0.76 indicates overestimated wheat yields at low yield levels and underestimated yields at higher yield levels, as observed for maize yields but by a smaller magnitude. National production estimates for both maize and wheat are sufficiently simulated for most countries with R^2 values of 0.85 and 0.95, respectively.

Relative errors between simulated and reported national average maize and wheat yields and production are presented in Figure 6.9. Relative errors between $\pm$ 30% are defined as acceptable and errors above a threshold of $\pm$ 50% as high. The majority of average simulated maize yields of the 20 most important maize producing countries lay within an error range of $\pm$30%. High producing countries with a larger error include Argentina, Ethiopia, Hungary, Mexico and the Philippines. The latter two exceed the $\pm$ 50% threshold. The highest occurrence of countries with high errors exceeding $\pm$ 50% is in Africa, followed by Central and South American countries, which is caused mostly due to an overestimation of simulated maize yields. In the majority of countries in North America and Europe, simulated maize

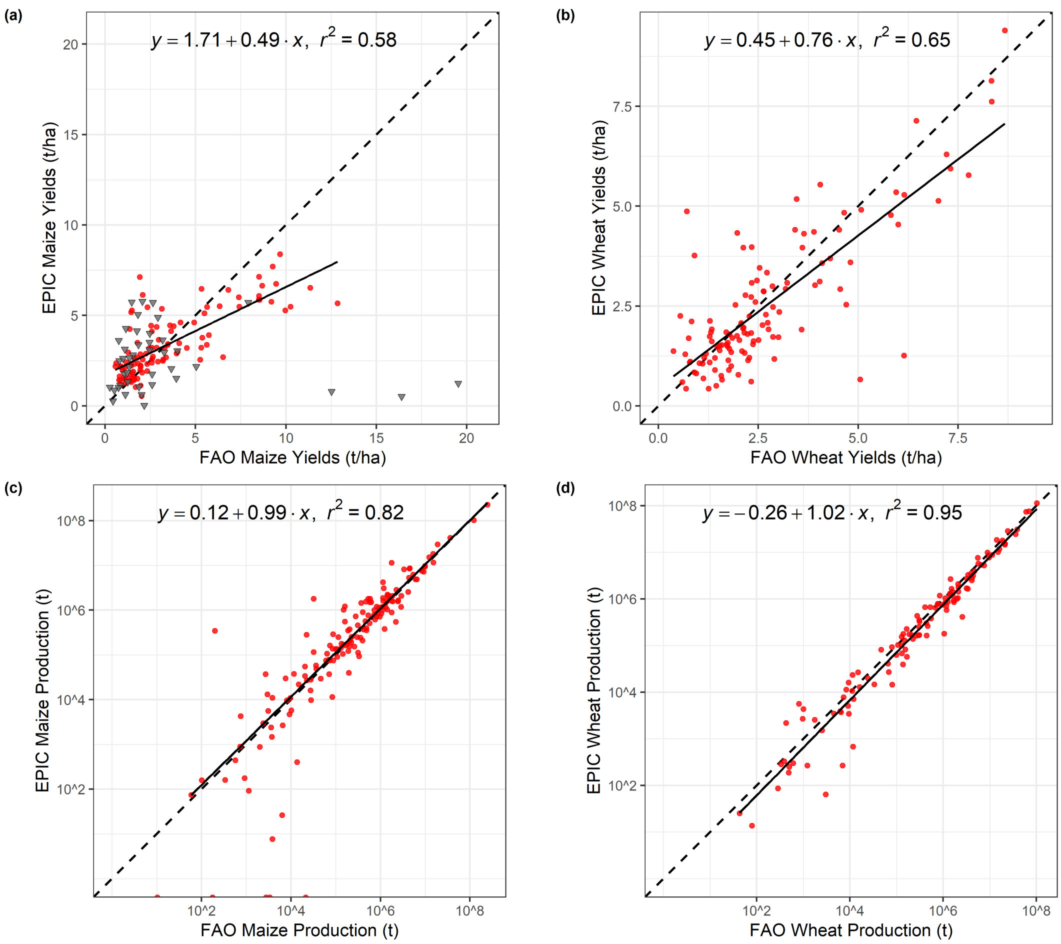

Figure 6.8: Comparison of average national maize (a) and wheat (b) yields simulated with EPIC and reported by the FAO. Comparison of national maize (c) and wheat (d) production simulated with EPIC and reported by the FAO (FAO, 2020).

yields are below reported yields.

For the majority of the 20 most important wheat producing countries average simulated wheat yields have an error within the magnitude of ± 30%. Exceptions are average wheat yields in Argentina and Spain, which have a relative error of 32% and 36%. Generally, most countries have a relative error below the ± 50% threshold on all continents. The highest proportion of countries with simulated wheat yields above the ± 50% threshold is in Africa, mostly due to lower simulated values than reported values.

Relative errors between estimated national maize production and reported production for most of the top-20 maize producers lay within the ± 30% margin defined as the acceptable error range. Relative errors for the major producers Ethiopia, Mexico, Russia, Philippines and Ukraine are high, exceeding the ± 50% threshold. Countries with high relative errors are most abundant in Africa on a continental level and on a regional level in Western Asia followed by Central America. The majority of relative errors in Africa, America and Europe is positive, whereas in Asia the majority of countries has a negative relative error.

Relative errors of national wheat production estimates are lower than for national maize production estimates. Relative errors for most of the top-20 wheat producing countries lay within the acceptable ±

30% margin. Argentina, France, Italy, Spain and United Kingdom have a slightly larger relative error, without exceeding the ± 50% threshold. Countries exceeding the ±50% threshold are most abundant in Asia and Africa, mostly due to underestimations. Generally, wheat production on all continents is underestimated rather than overestimated.

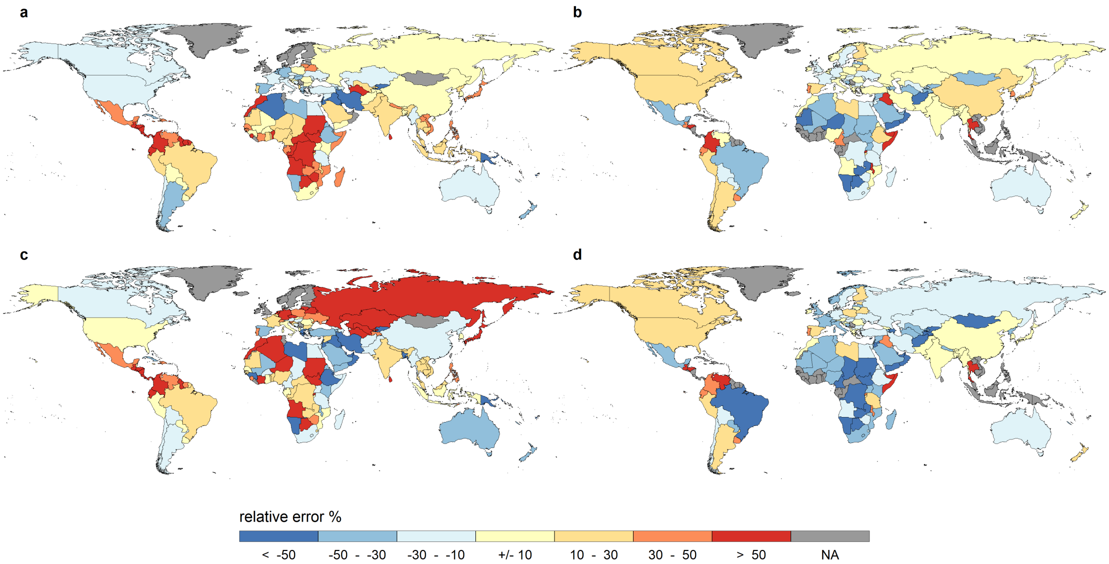

Figure 6.9: relative difference between national maize (a) and wheat (b) yields simulated with EPIC and reported by the FAO. Relative difference between national maize (c) and wheat (d) production simulated with EPIC and reported by the FAO (FAO, 2020).

6.4 Discussion

6.4.1 Erosion-induced crop yield losses and fertiliser requirements for compensation

Previous studies suggest that soil loss rates up to 11 t ha^{-1} are tolerable to maintain crop productivity for soils in the United States (Schertz and Nearing, 2006) and in Europe (Panagos et al., 2018) based on the assumption that fertiliser will compensate for nutrient runoff. On fields with higher water erosion rates, Panagos et al. (2018) assumed that crop productivity would reduce by 8%, based on a review of relevant studies on erosion-crop productivity relationships. Similarly, the estimates of this study suggest a median global reduction of maize and wheat yields of 6% for grid cells with water erosion of at least 11 t ha^{-1}. In fields with water erosion below 11 t ha^{-1} a considerably lower median crop yield reduction of 1% is simulated. However, large variations in fertiliser input between countries affect the impact of water erosion on crop yields. If fertiliser were not sufficiently supplied to compensate for nutrient losses in certain countries, their crop yield losses would likely be higher than in countries with both higher water erosion and fertiliser application rates (Balkovič et al., 2018). Although synthetic fertilisers can quickly compensate for nutrient loss, the recovery of lost organic matter and the consequent damage to soil structure can take decades (Poulton et al., 2018). Therefore, acceptable soil loss rates should not consider only the extent to which fertiliser application can replenish soil fertility. An assessment should also consider soil formation rates and off-site concerns such as the proximity to sensitive areas (Montgomery, 2007; Schertz and Nearing, 2006).

The additional fertiliser costs to compensate for water erosion can be higher than the loss of income due to production losses (Graves et al., 2015). Global median nitrogen runoff of 7 kg ha^{-1} yr^{-1} in maize fields and 5 kg ha^{-1} yr^{-1} in wheat fields, which are estimated in this study, would cost USD 1.7 ha^{-1} yr^{-1} and USD 1.2 ha^{-1} yr^{-1} [1]. The global annual nitrogen fertiliser replacement costs for maize and wheat fields would be USD 642m and USD 255m, respectively. Although this is lower than the estimated annual maize and wheat production losses (USD 2.0bn and USD 1.3bn), replacement costs for lost nutrients would be considerably higher if phosphorus and potassium runoff would be considered. In addition, carbon runoff of median 107 kg ha^{-1} yr^{-1} and 72 kg ha^{-1} yr^{-1} in maize and wheat fields might add additional costs through nutrient replacement efforts such as manure application. On a global scale, the relative fertiliser replacement costs might be too low to incentivise farmers to introduce soil conservation measures, but they can be considerably higher for vulnerable areas (Hein, 2007).

For a comprehensive assessment of water erosion impacts, off-site impacts on surrounding environments such as the pollution of surface water and emission of greenhouse gases also need to be considered (Chappell et al., 2016; Tilman et al., 2001). Several studies estimate higher costs of off-site impacts due to erosion than on-site costs through production losses and fertiliser replacement (Görlach et al., 2004; Graves et al., 2015). In addition, sediment redistribution is not considered in this study as global assessments are currently based on simple water erosion models (Chapter 2.3.4). Topsoil accumulation in deposition areas may improve nutrient availability and soil properties and could offset the negative effects on crops in eroded areas (Bakker et al., 2007; Duan et al., 2016).

Due to high fertiliser use in major maize and wheat production areas, which are mostly located on flat terrain and in regions with lower rainfall erosivity than the global average, water erosion has had a low impact on annual global production losses in absolute terms. Vulnerable regions with potentially high crop yield losses are mostly outside major production regions and therefore they hardly affect changes in global maize and wheat production. Den Biggelaar et al. (2004a) also estimated a low impact of water erosion on a global scale, and concluded that the small losses would likely be masked over the short term by market fluctuations, weather, and other environmental perturbations. Furthermore, market mechanisms such as trade flows can considerably reduce production losses. Sartori et al. (2019) used a global market simulation model that accounted for market impacts of soil erosion, which reduced direct production losses by three times. Nevertheless, as erosion impacts are cumulative, they may cause more serious losses if erosion continues unabated over a long period of time (Den Biggelaar et al., 2004a), and could ultimately lead to total topsoil loss and the land being abandoned. Moreover, water erosion could be self-reinforcing, by decreasing the protective cover through reduced crop cover and residues on the soil surface (Ponzi, 1993).

[1] based on global urea price for the period 2015–2019 taken from World Bank (2020a).

Slope inclination and precipitation intensity are the dominant environmental characteristics affecting water erosion (Chapter 5.3.2). Soil types are generally relevant in GGCM crop yield simulations (Folberth et al., 2016) and for erosion-productivity relationships (den Biggelaar et al., 2001; Lal, 1995), but on a global scale their impact on water erosion is small compared to slope steepness and precipitation. This means water erosion impacts are highest in hilly areas, in the tropics and in other regions with heavy precipitation. In countries with diverse environmental conditions, the variation in water erosion impacts is usually wide ranging and therefore a comparison of the extent of cropland vulnerable to water erosion should be further analysed on a sub-national scale.

6.4.2 Potential impacts of water erosion on livelihoods

High production losses from water erosion on a national or regional scale can severely impact livelihoods of farmers (Wynants et al., 2019). The agricultural sector of both sub-Saharan Africa and South Asia contributes roughly 16% to their GDP, compared to a worldwide share of approximately 4% (World Bank, 2020b). Moreover, food security is a pressing issue in those regions (von Grebmer et al., 2012). Whilst in some of these regions water erosion was recently reduced through programs improving land management (Nyssen et al., 2015), increasing crop demand through population growth and market effects led to re-cultivation of tropical steep slopes (Turkelboom et al., 2008) or soils prone to degradation (Wildemeersch et al., 2015). Pressures are likely to increase through climate change impacts on agriculture, which are projected to decrease agricultural productivity highest in low latitudes (Iizumi et al., 2017; Rosenzweig et al., 2014), which will likely enhance food security issues (Knox et al., 2012; Wheeler and Von Braun, 2013). The impact of climate change on water erosion impacts is still unclear but projected increases in rainfall intensity (Olsson et al., 2019; Wang et al., 2014) and diminishing vegetation cover through increasing temperature (Zhao et al., 2017) may accelerate water erosion and its impacts on crop yields (Li and Fang, 2016). The simulation results presented here show that several countries in regions that are most affected by food security problems today and that are likely to be under high pressure in the future from population growth and climate change are most affected by high relative production losses due to water erosion.

6.4.3 Uncertainties in water erosion estimates

Uncertain slopes of modelled fields

Slope data is the most critical parameter for estimating water erosion. However, due to the uncertainty of the global land use datasets (Fritz et al., 2015; Lesiv et al., 2019), no explicit spatial links between maize and wheat growing areas and slopes can be established without on-site observations. Instead, the slope that covers the largest area in a grid cell is used to capture the slope that is most likely covered by most of the cropland. This approach represents the prevailing topographic differences of global crop production regions but cannot capture the heterogeneity of fields in certain areas. In an ideal situation where all cultivated areas are concentrated on the flattest terrain available, simulated water erosion impacts on crop yields are reduced substantially. However, the distribution of cropland is based on more factors than the topography of land, such as the suitability of soil, climate and socio- economic circumstances or limitations such as land tenure and competing land use (Hazell and Wood, 2008; Nyssen et al., 2019).

Uncertainties in field management

Field management can vary substantially between regions, farming systems and farmers, and is based on a complex web of factors (Pannell et al., 2014). While the management scenarios bracket the range of field management intensities and soil surface coverage, the baseline scenario narrows down prevailing field management by selecting or excluding scenarios based on environmental- and country-specific indicators. Apart from similar approaches (Porwollik et al., 2019), no detailed representation of the diversity in global field management currently exists. Moreover, the field management scenarios are constant for every season and do not account for the farmer's actions to mitigate soil erosion, which might significantly reduce water erosion impacts (Tiffen et al., 1994).

However, one advantage of simulating constant field management is that the effects of water erosion on soil resources can be recorded over the long term, which otherwise might have been masked by technological advances such as higher yielding crop varieties, herbicides, insecticides, new planting technologies, and increased fertiliser input to compensate for sediment runoff (Littleboy et al., 1996). Moreover, the potential differences in water erosion impacts with different intensities of field management can be addressed, as the model outputs reflect the ability of cover crops, crop residues and low tillage intensity to decrease water erosion rates and to maintain and replenish soil nutrients. Although this reduces crop yield losses due to water erosion, it does not necessarily translate into higher crop yields due to other growth constraints being influenced by the choice of farming techniques. Since field management practices greatly influence crop yields in general, and water erosion in particular, improving their representation and understanding the decision processes of farmers responding to changing physical conditions in their fields would help to improve our understanding of water erosion impacts on crop yields.

6.4.4 Uncertainties in crop yield estimates

The agreement between simulated and reported yields can be negatively influenced by the lack of representation in field management, fertiliser input, irrigation strategies, crop cultivars, and factors influencing crops, such as windstorms, pests, diseases, weeds or freezing of seeds in winter (Balkovič et al., 2013). Typically, GGCMs underestimate yields in high-yielding countries and overestimate yields in low-yielding countries (Balkovič et al., 2014; Mueller et al., 2017). This is also indicated by Figure 6.8.

Non-weather-related events, which are not simulated, can be especially important in low-input regions where unsuitable management or pest outbreaks, may contribute substantially to yield variability (Mueller et al., 2017). In addition, the automatic application of irrigation to effectively minimise daily water stress, may lead to an overestimation of irrigation efficiency in less intensively managed fields. Other reasons can be that crop technologies are overestimated in low-yielding countries, whereas in highly developed countries, they may be underestimated (Balkovič et al., 2013).

Another important consideration for the robustness of crop yield estimates is that the choice of model used to simulate crops affects the results due to differences in model sensitivities. As a result, the simulated impact of soil, weather and management parameters on crop yields varies depending on the model. For example, variations in crop yields in response to temperature rise could be attributed in large part to differences in the simulation of this relationship between models (Asseng et al., 2013). A further discussion of uncertainties in crop models simulating the effects of climate parameters on crops can be found in Chapter 7.4.6.

Compared to other commonly used GGCMs, EPIC-IIASA repeatedly performs well. In Mueller et al. (2017) the performance of EPIC-IIASA for simulating maize and wheat was compared against 13 different GGCMs. EPIC-IIASA showed relatively high correlation coefficients with national reported maize and wheat yields compared to the other GGCMs. Similarly, in Yin and Leng (2021) the correlation of reported and simulated national maize yields using EPIC-IIASA was among the highest of the eight analysed GGCMs. Folberth et al. (2019) compared the agreement between simulated and reported maize yields among five different EPIC-based GGCMs. EPIC-IIASA agreed best with national reported yields among the five tested EPIC-based GGCMs. The robustness of yield estimates in the EPIC-based GGCMs was highly sensitive to simulated crop management, soil parameters and soil process reparametrisation, including hydrology and nutrient turnover. The necessary improvements in model mechanisms, parametrisation and agricultural data for model input and model evaluation to reduce errors have been addressed in detail in numerous studies (e.g., Folberth et al., 2019; Mueller et al., 2017).

6.5 Conclusion

In this chapter, EPIC-IIASA was used to analyse the vulnerability of maize and wheat producing regions to water erosion. Locations that are highly vulnerable to water erosion are concentrated in regions combining hilly terrain, strong precipitation and low fertiliser inputs. But water erosion has only a small impact on global maize and wheat production, because the major maize and wheat production areas are on relatively flat terrain and nutrient losses through water erosion are offset by high fertiliser applications. However, this compensation of soil loss with fertilisers to maintain crop yields hides the negative impacts of water erosion on soil resources and surrounding environments.

The simulation results provide the first globally-consistent and transparent analysis of the effects of water erosion on maize and wheat production. The most crucial data requirements to improve the robustness of simulated water erosion impacts on global crops include well-defined field data covering all global regions to evaluate water erosion estimates, higher-resolution global land use datasets and detailed information on field management patterns (Chapter 5.4). A better understanding of the soil protection and erosion control measures that are used in the cultivation of slopes in each region would make it possible to improve the representation of regions at risk. As these datasets are currently not available in higher detail at the global scale, further research on water erosion impacts could focus on the most vulnerable regions by analysing land use patterns and all environmental circumstances on-site at a finer resolution. The high vulnerability to water erosion in sub-Saharan Africa, and parts of South Asia and Latin America, where future changes in population growth and climate could amplify land degradation processes, should be priorities for further research.

Chapter 7

The combined effects of climate change and water erosion on global maize and wheat yields

7.1 Introduction

Climate change impacts on agriculture include irregular rainfall and prolonged droughts, which are among the biggest threats for farmers. It has been suggested that interactions between climate change and land degradation are likely to exacerbate the negative impact on agriculture (Olsson et al., 2019). Although climate change and land degradation are interacting processes, which may affect farmers simultaneously, they have been studied separately in the past (Webb et al., 2017). As these interactions are highly complex, the impact of climate change on soil functions is seen as the largest source of uncertainty in any projections of the trends in key ecosystem services provided by the soil (Montanarella et al., 2016).

Water erosion is influenced directly through changing precipitation amount and intensity and indirectly through the impact of precipitation, temperature and atmospheric CO_2 on vegetation. In addition, interactions between the climate system, soil hydrology and microbial activity, as well as land use changes due to climate change may influence future water erosion rates (Nearing et al., 2004). Thus, the impact of climate change on water erosion is very diverse and can be both positive and negative. Due to the complex interactions between water erosion and climate change, future changes in water erosion rates are unclear. In a comprehensive review of studies on the effects of climate change on water erosion by Li and Fang (2016), the authors concluded that in most studies, future water erosion rates are increasing due to climate change. However, due to different geographic locations, climate scenarios, precipitation patterns, topographic conditions, and land management scenarios the result of prior studies on climate change impacts on water erosion are highly variable (Chapter 2.5). One study concluded that water erosion can be expected to increase where precipitation increases are significant, but if precipitation decreases, water erosion may both increase or decrease depending on the complex interactions between plant biomass, runoff, and erosion (Pruski and Nearing, 2002a). Many studies concluded that field management practices and planting dates are decisive in climate change impacts on water erosion and may sometimes affect changes in water erosion more than changes in precipitation (O'Neal et al., 2005; Pruski and Nearing, 2002a; Routschek et al., 2014). Positive climate change impacts on vegetation cover through warmer temperatures and CO_2 fertilisation may even mitigate impacts of increased precipitation on water runoff (Nunes et al., 2013).

The complex interactions between climate change and water erosion and the high variability of study results lead to difficulties extrapolating study results to larger scales. As most studies are focused on the United States, Europe and China (Li and Fang, 2016), direct insights on climate change impacts on water erosion do not exist in many world regions. Only three studies were found that include estimates of the impact of climate change on global soil erosion (Ito, 2007; Yang et al., 2003; Borrelli et al., 2020). These studies focused on estimating future changes in water erosion rates based on current land use and climate change. Ito (2007) included estimates of changing water erosion impacts on the soil carbon cycle. However, these studies do not consider interactions between water erosion and crops. As previous field scale studies have shown, the interactions between soil and biomass are critical to the effects of changing climate on water erosion.

Field scale studies on climate change impacts on water erosion have often used process-based crop models such as EPIC (Chapter 2.5). EPIC is also a commonly used model for global climate change impact assessments based on GGCMs (Chapter 3.5). Climate change impact assessments based on GGCMs are among the most important studies that provide information on the varying resilience of agriculture to climate change around the world. Although the models used to conduct these studies simulate interactions between soil resources and crop yields, soil degradation processes are not considered as they are not included in most models or have been neglected due to their complexity and lack of evaluation (Chapter 2.3.4).

In this chapter, model outputs from EPIC-IIASA generated under different climate change scenarios are used to link the analysis of climate change and water erosion impacts on maize and wheat. The modelling approach is similar to that in Chapter 5 and Chapter 6, except that different climate data are used. The model outputs are first used to identify hotspots where maize and wheat production is vulnerable to climate change and water erosion due to environmental conditions and geographical differences in fertiliser use and irrigated cropland. Subsequently, the model outputs are used to show the interactions between crops and water erosion in response to climate change and to discuss in which regions water erosion may increase in the future. The final results chapter provides estimates of global maize and wheat production losses due to water erosion under different climate change scenarios, which are compared to changes in maize and wheat production due to climate change.

7.2 Methodology

7.2.1 Summary of methodology

The daily growth of maize and wheat is simulated for the years 2005-2099 with and without considering water erosion under the two contrasting Representative Concentration Pathways RCP 2.6 and RCP 8.5, as well as different field management scenarios. Water erosion impacts are calculated using the baseline field management scenario presented in Chapter 4.3.4. The impact of climate change on crops is calculated without considering water erosion and with a static soil profile, which reinitialises all soil properties except plant-available nutrients and water at the beginning of each year. This disables the impact of soil degradation processes on crop yields to focus on the impact of changing climate parameters on crop yields. To further increase the focus on the impact of climate parameters on crops, only the field management scenario simulating conventional tillage without cover crops is considered to minimise the impact of different farming techniques on crop yield changes.

7.2.2 Aggregation of model outputs

Water erosion impact

Water erosion impacts on maize and wheat yields are calculated using the model outputs for the years 2050-2059 to estimate medium-term erosion impacts and for the years 2090-2099 to estimate long-term erosion impacts. The aggregation of the respective model outputs to estimate water erosion impacts on crops for grid cells, countries and regions follows the same approach as in Chapter 6.2.2.

Climate change impact

Crop yield changes due to climate change are calculated as the relative difference of average crop yields between the years 1980 - 2010 simulated with the AGMERRA climate data and the years 2050-2059 and 2090-2099 simulated under the RCP 2.6 and the RCP 8.5 scenario (Equation 7.2). Relative crop yield changes for each decade are based on average crop yields weighted by the irrigated and rainfed cultivation area (Portmann et al., 2010) of the respective crop per grid cell (Equation 7.1).

$$Yw_{cgd} = Yav(r)_{cg} * Af(r)_{cg} + Yav(i)_{cg} * Af(i)_{cg} \tag{7.1}$$

$$dYrel_{cgd} = \frac{Yw_{cgd} - Yw(d0)_{cg}}{Yw(d0)_{cg}} * 100 \tag{7.2}$$

Yw_{cgd} is area-weighted mean crop yield (tha^{-1}) for crop c, grid cell g and decade d; Yav is yield averaged for the selected decade simulated under rainfed (r) and irrigated (i) conditions; $Af(r)$ is the rainfed area fraction; and $Af(i)$ is the irrigated area fraction; $dYrel_{cgd}$ is the relative change in area-weighted mean yields of crop c and grid cell g between the decade d and area-weighted mean crop yields of the years 1980 - 2010 ($d0$).

National crop production losses and gains due to climate change are calculated by first calculating the difference in crop yields between the selected decades and the years 1980 - 2010 (Equation 7.3), and subsequently multiplying the difference with the rainfed and irrigated area per crop of each grid cell and summarising all positive and negative values of all grid cells per country (Equation 7.4).

$$dYabs_{cwgd} = Yav_{cwgd} - Yav(d0)_{cwg} \tag{7.3}$$

$$dP_{lcd} = \sum_{g=1}^{n} dYabs(r)_{cgd} * A(r)_{cg} + dYabs(i)_{cgd} * A(i)_{cg} \tag{7.4}$$

$dYabs_{cwgd}$ is the absolute yield change for crop c, irrigation scenario w and grid cell g and decade d; Yav is yield averaged across the selected decade d or the years 1980 - 2010 ($d0$); dP_{lcd} is the change of production (in tonnes) of crop c in country l and decade d; n is the number of grid cells in country l; $dYabs(r)$ is the absolute change in rainfed yields and $dYabs(i)$ is the absolute change in irrigated yields; $A(r)$ is the rainfed area (in *ha*); and $A(i)$ is the irrigated area (in *ha*).

7.3 Results

7.3.1 Regions and countries vulnerable to both climate change and water erosion

The impacts of water erosion on maize and wheat yields are shown in Figure 7.1 and Figure 7.2 as medium-term (2050s) and long-term (2090s) relative declines in crop yields due to water erosion under the RCP 2.6 and RCP 8.5 scenario, respectively. In addition, regions with negative and positive climate change impacts on maize and wheat are coloured in the maps. The plots next to the maps illustrate the median changes in crop yields due to climate change per latitude.

A region's vulnerability to climate change and water erosion is strongly determined by geographic differences in environmental characteristics. While topography, precipitation amount and intensity largely determine the extent of water erosion in a region, the effects of climate change are strongly dependent on latitude. At low latitudes, defined here as latitudes between $\pm$ 30 degrees, negative climate change impacts dominate for both maize and wheat in both RCP scenarios and both observed time periods. At mid- to high-latitudes, the distribution between positive and negative climate change impacts is more variable and depends strongly on the crops and the rate of climate change.

Under the RCP 8.5 scenario, maize yields decline at most latitudes. The decline is most severe at low latitudes and worsens over the long term. Under the RCP 2.6 scenario, climate change impacts on maize are less severe and can be both positive and negative at mid- to high-latitudes, but are mostly negative at lower latitudes. Wheat yields in temperate latitudes in both hemispheres are largely positively affected by climate change under both RCP scenarios. The negative impacts of climate change on wheat yields are most severe and widespread at low latitudes, especially in the long term under the RCP 8.5 scenario.

The global patterns of water erosion impacts on maize and wheat yields are similar under both RCP scenarios and largely follow the patterns described in Chapter 6. The strongest impacts of water erosion on maize and wheat are observed in hilly terrain and in regions with heavy precipitation, most commonly in tropical climates. While the regions most vulnerable to water erosion remain the same over time for both RCP scenarios, the magnitude of water erosion impacts increases globally over time under both RCP scenarios.

To illustrate the differences among global regions in their vulnerability to climate change and water erosion, the medium- and long-term relative changes in maize and wheat yields due to climate change and water erosion per region are summarised in Figure 7.3 and Figure 7.4. Trends in yield changes due to climate change and water erosion, as well as areas affected by water erosion over the entire simulation period, are shown in Figures D.3,D.4,D.5.

The regions with the greatest impact of water erosion on affected maize fields at the end of the simulation period include Western, Southern and Southeast Asia (16%, 14%, 10% decline in median maize yields simulated with both RCP scenarios, respectively), Eastern Africa (14%) and Southern Europe (11%) (Figure 7.3). Unlike water erosion impacts, climate change impacts on maize vary greatly among RCP scenarios. In all regions, the most negative climate change impacts on maize are projected for the 2090s under the RCP 8.5 scenario. The most affected regions are Western Africa (61% decline in median maize yields compared to 1980-2010), Western Europe (44%), Southeast Asia (41%), Eastern Europe (39%) and Central Asia (38%). The positive effects of climate change on maize at the end of the simulation period are greatest in the RCP 2.6 scenario. The most positively affected regions are Southern Africa (14%), Western Asia (3%), Australia and New Zealand (3%), Eastern Asia (3%), and Central Asia (2%). In some regions, the positive effects of climate change on maize are greatest in the medium term and decrease in the long term (Northern Europe, Northern Africa, Australia and New Zealand), while in other regions the positive effects increase over time (Southern Africa, Western Asia, Eastern Asia).

The decline in wheat yields due to climate change in the most affected regions is greatest at the end of the simulation period and under the RCP 8.5 scenario. Wheat yields are projected to decline the most in Western Africa (59%), Southeast Asia (58%), Central America (53%), Southern Asia (31%) and Eastern Africa (27%) (Figure 7.4). The largest positive impacts of climate change on wheat are also simulated at the end of the simulation and under the RCP 8.5 scenario. The regions with the highest increase in wheat yields by the 2090s include Western and Central Asia (20% and 17%, respectively), Northern America (13%), Northern Europe (13%), and Eastern Asia (10%). Similar to maize, positive climate change impacts on wheat are least likely in sub-Saharan Africa, South and Southeast Asia, and Central America. Similarly, the largest yield losses in wheat fields due to water erosion are projected for the same regions as for maize, but to a slightly lesser extent: Western, Southern and Southeast Asia (9%,7%,14%, respectively), Eastern Africa (8%) and Southern Europe (10%). Water erosion impacts on maize and wheat and cropland affected by erosion are greatly influenced by the management scenarios (Figure D.6, D.7).

To narrow down where crop yields are affected by both water erosion and adverse climate change impacts, Figure 7.5 shows aggregated medium- and long-term relative crop yield changes at the country

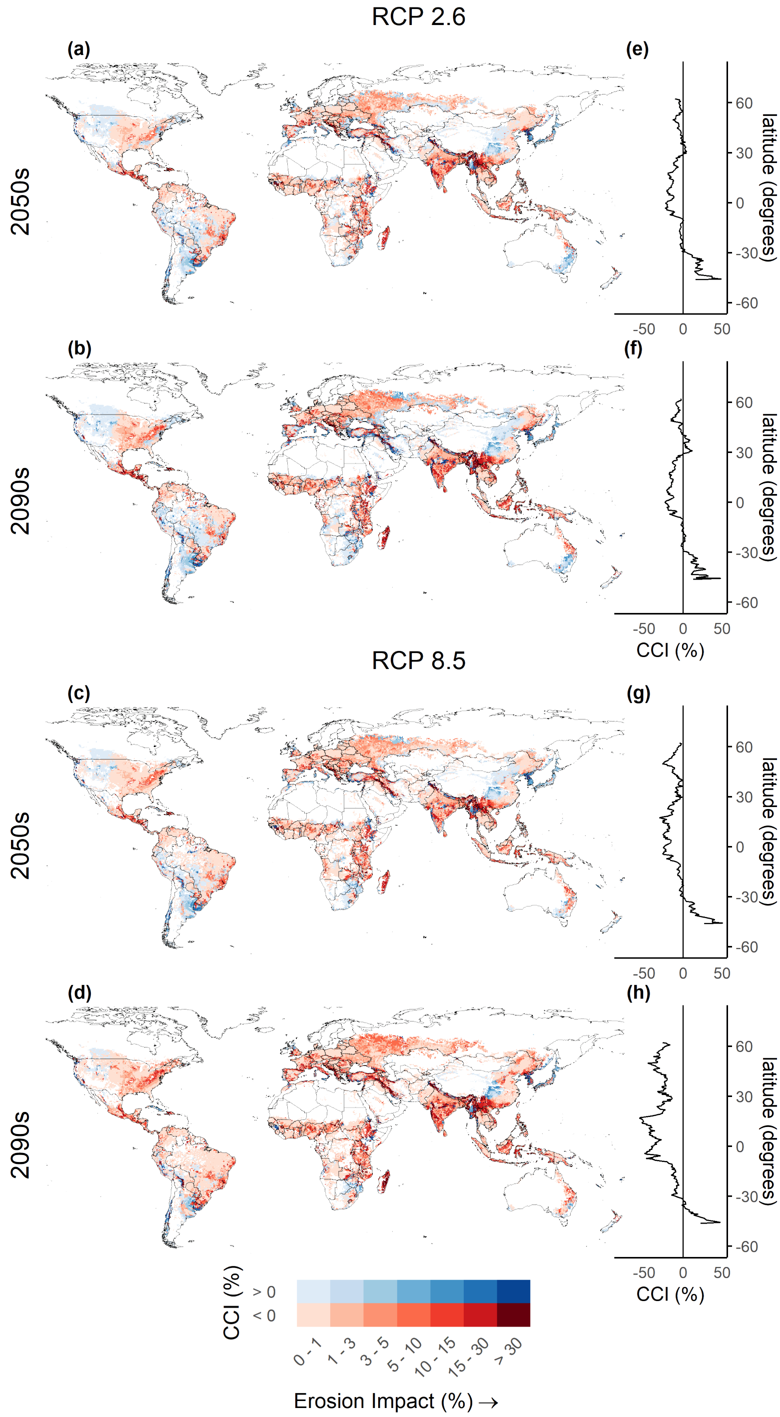

Figure 7.1: Relative reduction of maize yields due to water erosion per grid cell in the medium-term (2050-2059) and the long-term (2090-2099) simulated with the RCP 2.6 (a-b) and the RCP 8.5 scenario (c-d). Blue and red grid cells indicate positive and negative climate change impacts (CCI) on maize yields. The plots on the right to each map indicate median maize yield changes per latitude due to climate change (e-h). Climate change impacts are calculated by comparing mean maize yields from 2050-2059 and 2090-2099 simulated with the RCP scenarios to mean maize yields from 1980-2010 simulated with the AGMERRA dataset.

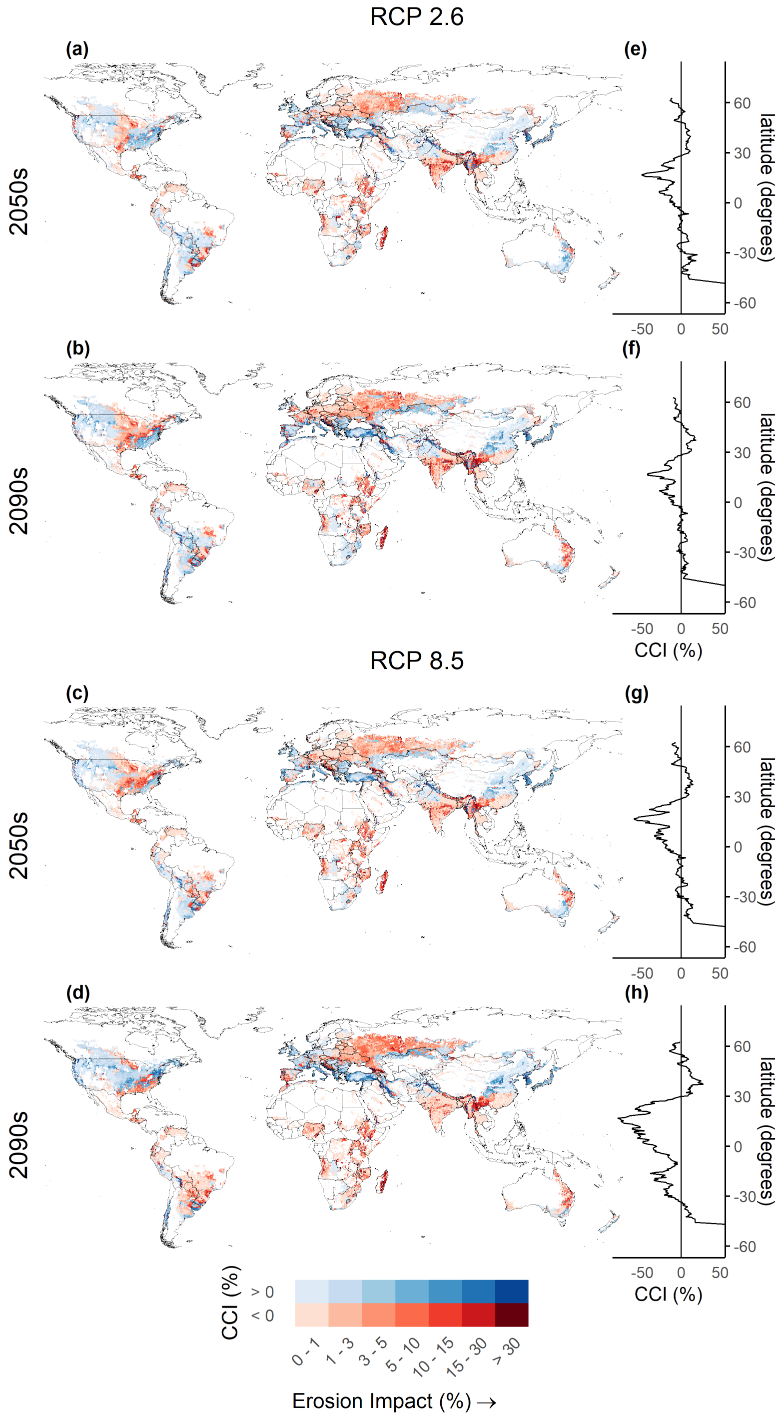

Figure 7.2: Relative reduction of wheat yields due to water erosion per grid cell in the medium-term (2050-2059) and the long-term (2090-2099) simulated with the RCP 2.6 (a-b) and the RCP 8.5 scenario (c-d). Blue and red grid cells indicate positive and negative climate change impacts (CCI) on wheat yields. The plots on the right to each map indicate median wheat yield changes per latitude due to climate change (e-h). Climate change impacts are calculated by comparing mean wheat yields from 2050-2059 and 2090-2099 simulated with the RCP scenarios to mean wheat yields from 1980-2010 simulated with the AGMERRA dataset.

level.

In most countries, median maize yield losses in areas affected by water erosion are higher than the negative medium- and long-term impacts of climate change under the RCP 2.6 scenario. Under the RCP 8.5 scenario, the negative impacts of climate change on maize increase substantially and thus outweigh the impacts of water erosion in the long term in most countries. The countries most affected by both the negative impacts of climate change and water erosion are mostly located in Southern Europe, sub-Saharan Africa, Central and South America and South and Southeast Asia.

In several countries where water erosion impacts on wheat yields are most severe, climate change impacts are positive in the RCP 2.6 scenario. Under the RCP 8.5 scenario, both the positive and negative impacts of climate change on median wheat yields increase in most countries. Countries with greatest negative impacts of climate change include several countries from Central and South America, South and Southeast Asia and sub-Saharan Africa that are vulnerable to water erosion. Wheat yields in several countries with high water erosion risk areas are positively affected by climate change, especially in Northern America, Europe, and Eastern Asia.

7.3.2 Interactions between crops and water erosion in response to climate change

The impacts of climate change on water erosion and crop yields are shown in Figure 7.6, which plots relative changes in water erosion rates and crop yields against relative changes in precipitation and absolute temperature changes. The values shown in Figure 7.6 reflect the relationship between long-term changes in climate parameters based on the two RCP scenarios and changes in crop yields and water erosion in the low and mid to high latitudes. In wheat fields, latitude has a notable effect on the relationships between changing climate parameters, crop yields, and water erosion, while for maize fields these relationships vary less between latitudes.

At all latitudes, water erosion in maize fields mostly increases with increasing precipitation, while a strong decline in precipitation results in less water erosion. When precipitation decreases only slightly, water erosion mostly increases. Decreasing precipitation is causing maize yields to decline at all latitudes. An increase in precipitation reduces maize yields in low latitudes, while maize yields in mid- to high-latitudes change little. Small temperature increases up to 2 °C hardly affect maize yields, whereas greater warming reduces maize yields at all latitudes. Water erosion mostly increases with rising temperatures at all latitudes. Despite minor differences at low levels of warming, the relationships between temperature, maize yields, and water erosion are similar at all latitudes.

Water erosion in wheat fields increases with increasing precipitation and decreases at all latitudes when precipitation decreases by more than 30%. In most cases, a smaller decrease in precipitation increases water erosion at low latitudes. Wheat yields at low latitudes decrease considerably with both increasing and decreasing precipitation, while wheat yields at higher latitudes increase with increasing precipitation. The effects of temperature on wheat also vary greatly depending on latitude. While mid- and high-latitude wheat yields increase with increasing temperature, they decrease significantly at low latitudes. Water erosion in wheat fields increases significantly with increasing temperature at low lati-

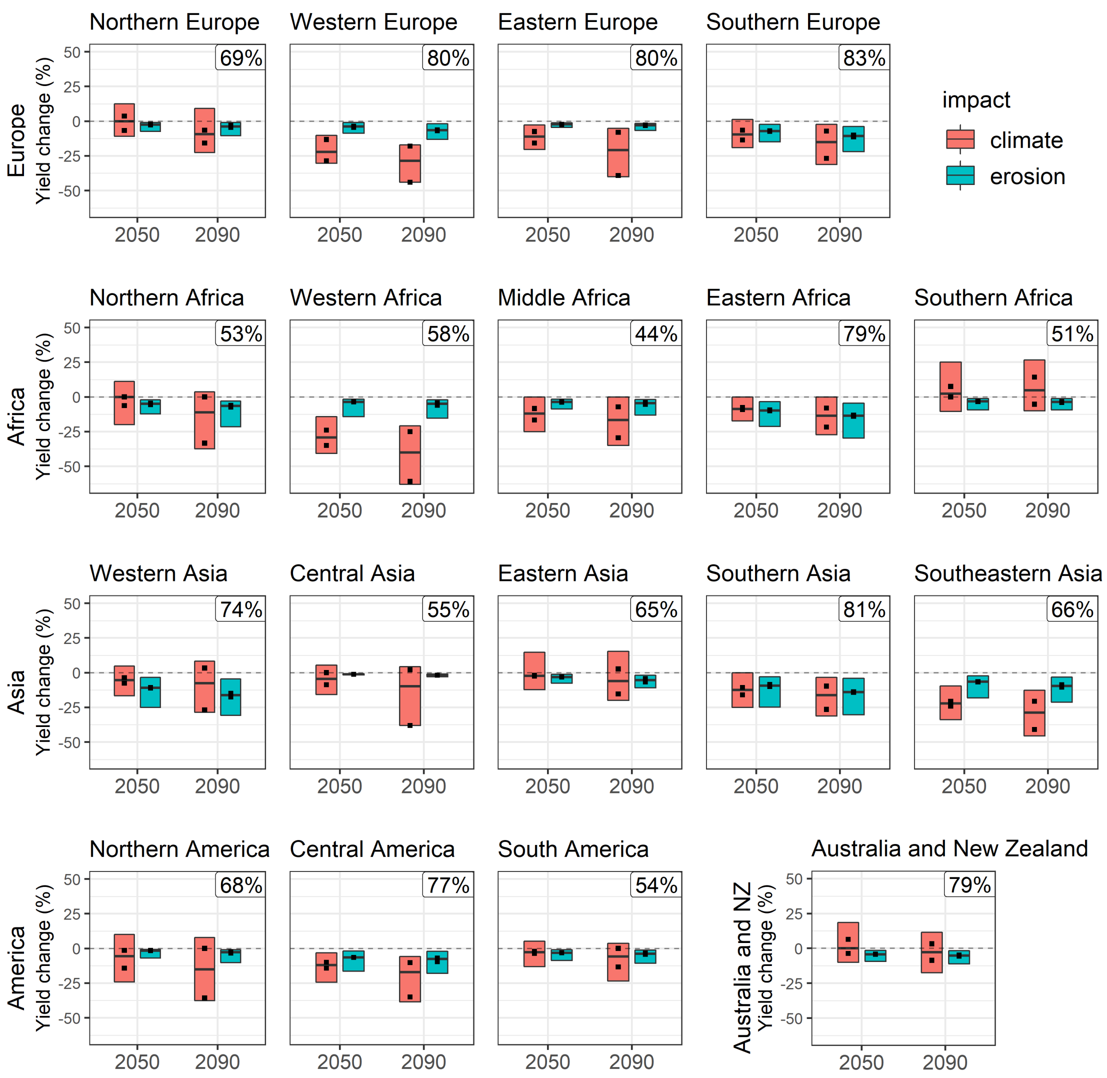

Figure 7.3: Relative medium and long-term changes in maize yields due to climate change and water erosion in major world regions. Boxes illustrate median changes and the range of values between the 25^{th} and 75^{th} percentile. Yield changes are averaged over the RCP 2.6 scenario and the RCP 8.5 scenario. Black squares indicate the variability of the median changes between both RCP scenarios. Values on the top right in each plot indicate the share of grid cells per region, where water erosion reduces crop yields.

tudes, while changes in water erosion are smaller at mid- and high-latitudes and vary between positive and negative changes.

The above relationships illustrate that an increase in precipitation is the most obvious impact of climate change on water erosion (Figure D.9, D.10). The effects of increasing precipitation on water erosion vary by crop, field management, RCPs and latitude (Figure 7.7). Water erosion increases most with increasing precipitation at low latitudes in both RCP scenarios. The most significant difference is simulated for wheat fields under the RCP 8.5 scenario, where water erosion increases by median 3.5% per 1% increase in precipitation at mid to high latitudes and by median 11.4% per 1% increase in precipitation at low latitudes. In most cases, water erosion increases more under the RCP 8.5 scenario than under the RCP 2.6 scenario. Only in wheat fields located in mid to high latitudes, median increase in

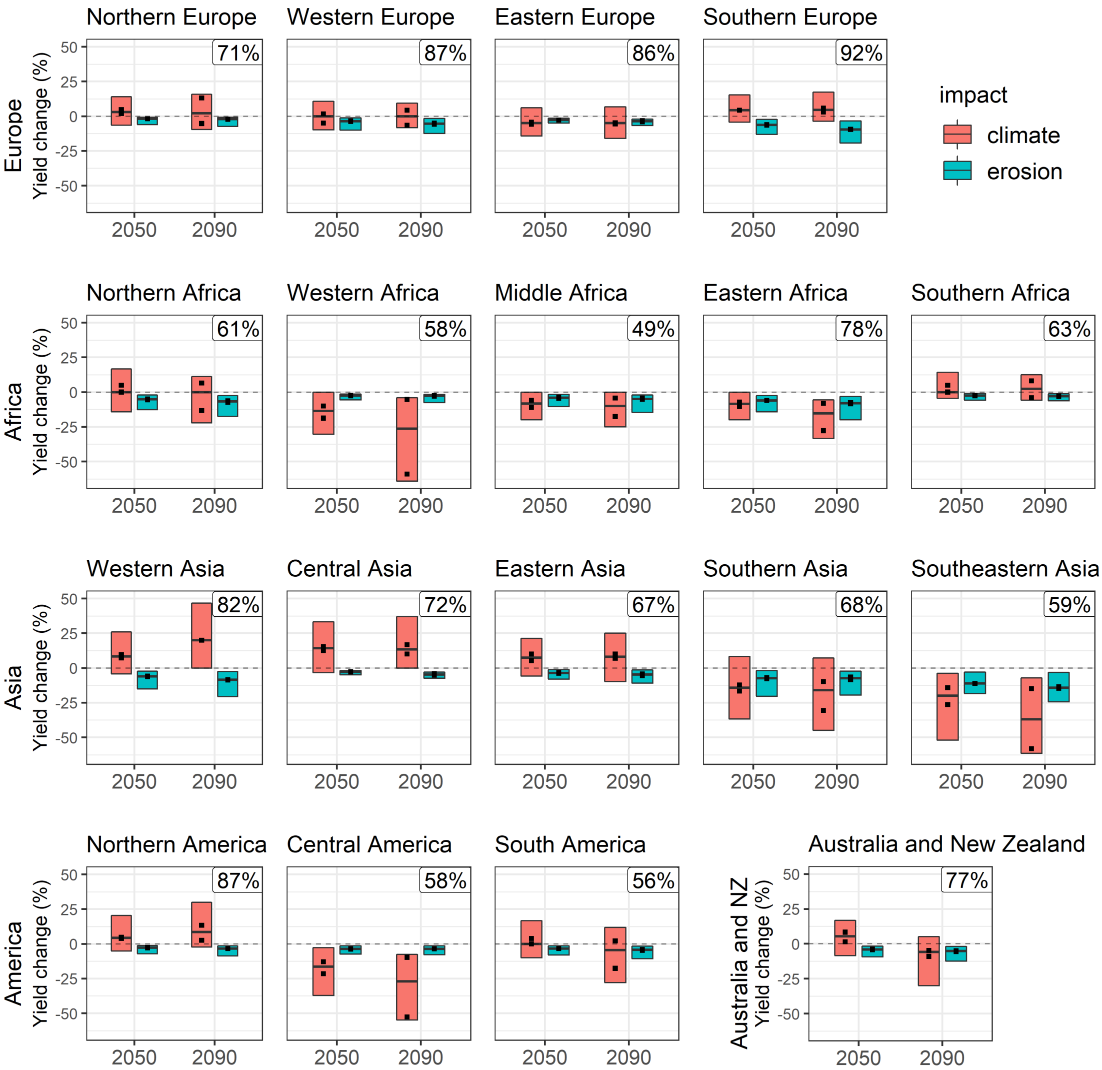

Figure 7.4: Relative medium and long-term changes in wheat yields due to climate change and water erosion in major world regions. Boxes illustrate median changes and the range of values between the 25^{th} and 75^{th} percentile. Yield changes are averaged over the RCP 2.6 scenario and the RCP 8.5 scenario. Black squares indicate the variability of the median changes between both RCP scenarios. Values on the top right in each plot indicate the share of grid cells per region, where water erosion reduces crop yields.

water erosion is slightly lower under the RCP 8.5 scenario than under the RCP 2.6 scenario. The impact of field management scenarios on precipitation-erosion relationships is indicated by the variability of median values in Figure 7.7. In most cases, the range between median changes in water erosion simulated under different field management scenarios is larger than the range between median changes in water erosion due to different RCP scenarios and latitudes.

7.3.3 Global production changes due to climate change and water erosion

At the global level, annual production losses of maize and wheat due to climate change are strongly influenced by the RCP scenario and time scale (Figure 7.8). Average annual production losses for maize due to climate change in the 2090s compared to 1980-2010 are 120 and 290 million tonnes for RCP

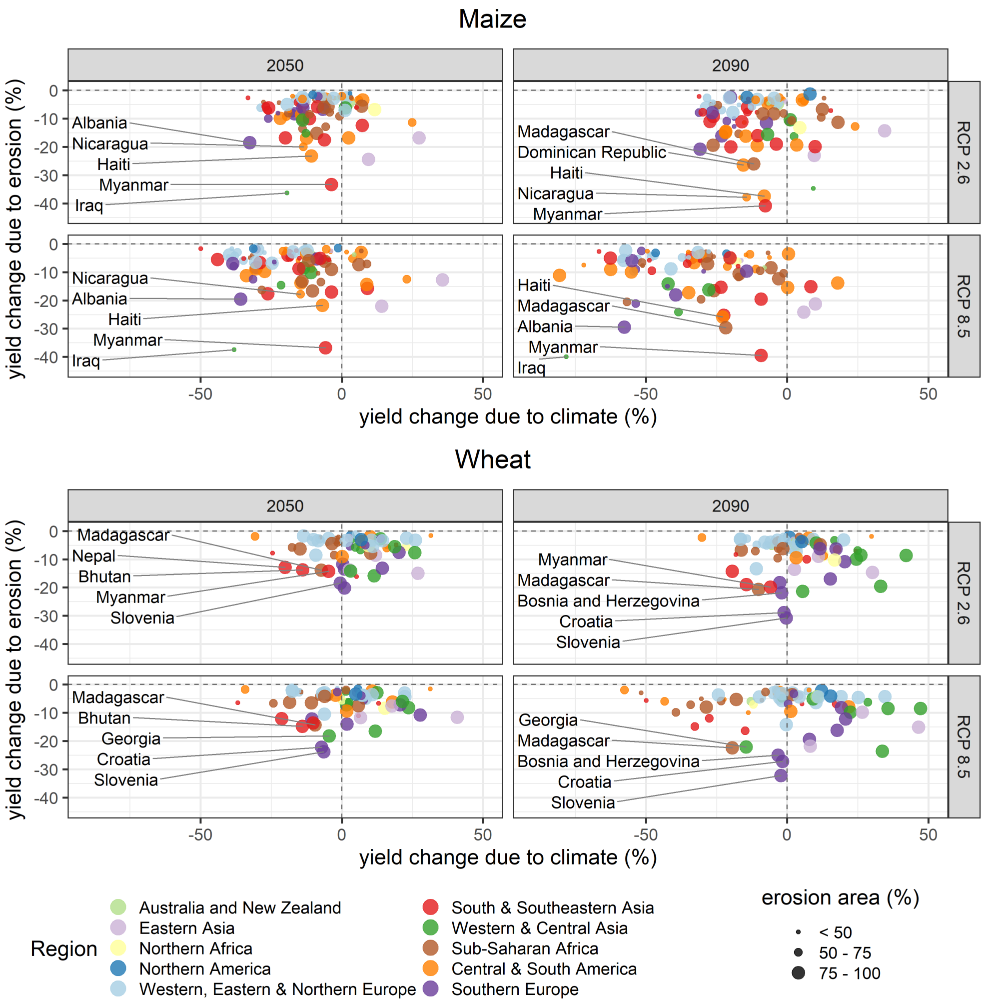

Figure 7.5: Relative medium and long-term changes in median maize and wheat yields due to climate change and water erosion per country and RCP. Country names mark top five countries per panel with highest erosion impact and negative climate change impacts. The size of the dots shows the relative extent of the national cropland affected by water erosion. Smallest maize and wheat producers have been excluded (<0.001% share of global production).

2.6 and RCP 8.5, respectively, while production gains are 20 and 7 million tonnes, respectively. Wheat production losses due to climate change in the 2090s are 40 to 80 million tonnes for RCP 2.6 and RCP 8.5, respectively, while production gains are 80 to 100 million tonnes for each. Changes in global maize and wheat production are mainly driven by the main growing regions in Europe, Asia and North America (Figure D.11).

Compared to the climate change impacts on maize and wheat production between contrasting RCP scenarios, the variations in production losses due to water erosion are small. Average annual production losses for maize due to water erosion in the 2090s are 14 and 11 million tonnes for RCP 2.6 and RCP 8.5, respectively, and production losses for wheat reach 13 million tonnes for both RCPs. Relative to the global production of maize and wheat reported by FAOSTAT (2013-2018) of 1091 million tonnes and 739 million tonnes, respectively, the production losses of maize and wheat due to water erosion are 1% and 2%, respectively. While production losses are similar across the different RCP scenarios, production

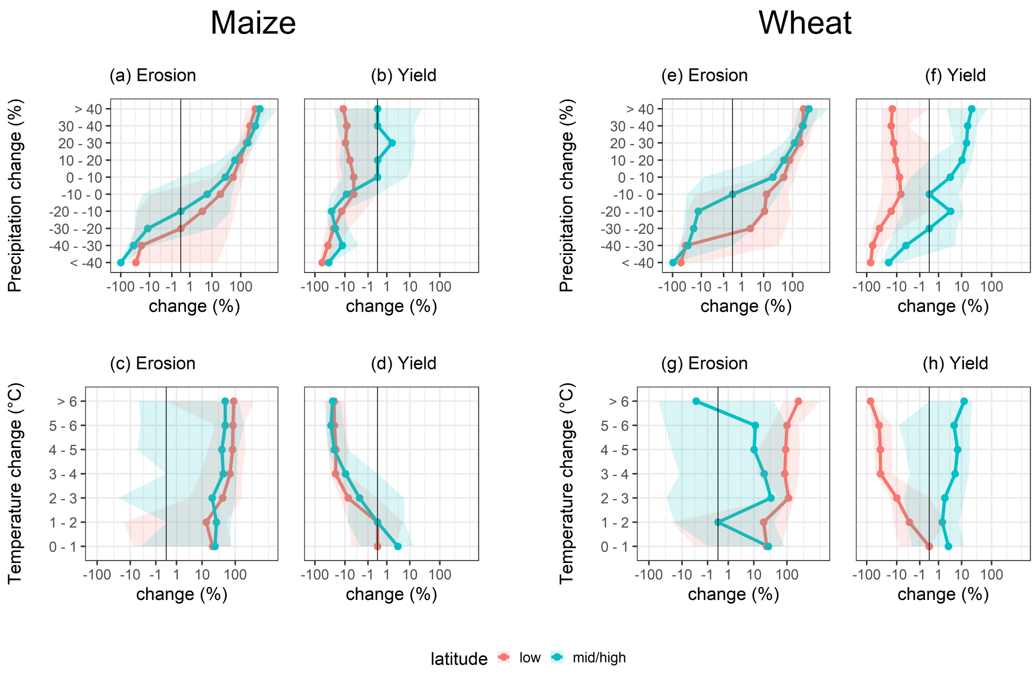

Figure 7.6: Relative change in water erosion and crop yields in maize fields (a-d) and wheat fields (e-h) due to changing precipitation and increasing temperature for the years 2090-2099 compared to the years 2010-2019 and aggregated for both RCP scenarios. Changes in water erosion and crop yields are log-transformed. Changes in precipitation are relative, while changes in temperature are absolute. Dots illustrate median changes and shadows illustrate the range of values between the 25^{th} and 75^{th} percentile. Blue represents values from mid to high latitudes, red represents values from low latitudes.

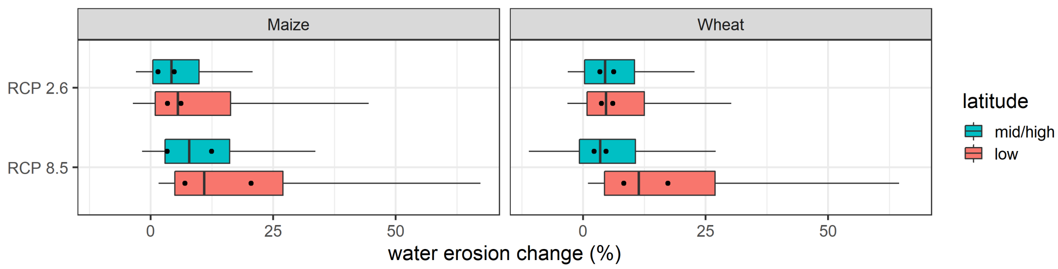

Figure 7.7: Increase in water erosion (%) per 1% increase in precipitation for contrasting crops, RCPs and latitudes for the years 2090-2099 compared to the years 2010-2019. Boxes illustrate medians, 25^{th} and 75^{th} percentiles. Whiskers mark 10^{th} and 90^{th} percentiles. Points illustrate the variance of the medians due to different field management scenarios.

losses vary significantly between different field management scenarios (Figure D.12).

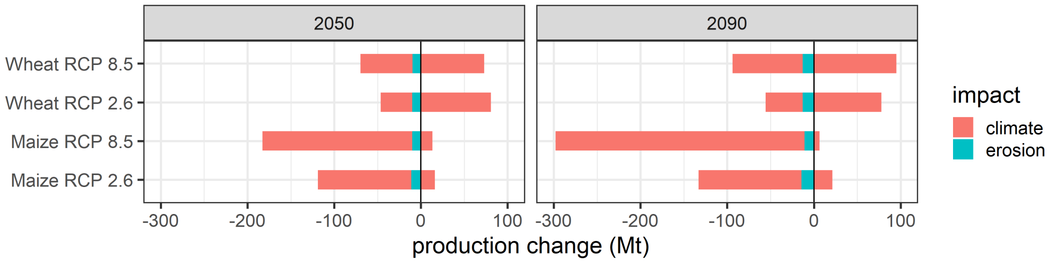

Figure 7.8: Changes in global annual average maize and wheat production due to climate change and water erosion in the 2050s and the 2090s for RCP 2.6 and RCP 8.5.

7.4 Discussion

The simultaneous effects of climate change and water erosion on maize and wheat yields vary widely across regions. The factors influencing these differences are diverse and complex, and require detailed discussion, which will form the first part of this discussion chapter. Potential regional changes in future water erosion due to climate change are then discussed based on the simulated interactions between climate parameters, crops, and water erosion. Because the impacts of water erosion and climate change on crops are strongly influenced by land use and field management, their role in mitigating the negative impacts is discussed subsequently. The final part of the discussion revolves around model uncertainties in simulating changes in future crop growth and water erosion.

7.4.1 Factors driving regional differences in climate change and water erosion impacts

The model outputs suggest that maize and wheat production in sub-Saharan Africa, South and South-eastern Asia, Central and South America include most regions with highest water erosion impacts and is overwhelmingly negatively affected by climate change. Although maize and wheat production in other regions may be also heavily affected by climate change and water erosion, wide areas where both crops are severely affected by both impacts are less common. Hotspots where crop production is susceptible to both climate change and water erosion impacts are determined by many factors such as regional characteristics of climate and topography, as well as farmer's management of crops, soil, fertiliser and irrigation.

Environmental factors

The environmental factors that most significantly influence the simulated differences of water erosion impacts in global regions are slope steepness and precipitation. Therefore, hilly agricultural land exposed to strong precipitation is most vulnerable to water erosion (in accordance with the results of Chapter 5 and Chapter 6). The impact of other environmental factors on water erosion, most specifically soil types and soil texture, are not further discussed as the strong sensitivity of slope and precipitation in the water erosion model used for this study strongly determine regional differences at this scale of analysis

(Chapter 5.3.2). In addition, global soil datasets are highly uncertain (Folberth et al., 2016).

The energy of precipitation to initiate water erosion can be expressed by the rainfall erosivity factor, which is strongest in tropical regions (Panagos et al., 2017). In the same climate regions, maize and wheat are most negatively affected by climate change. Generally, the regional differences in climate change impacts are strongly influenced by changing climatic conditions along latitudes. The model outputs of this study confirm previous studies, which suggested that negative climate change impacts on maize and wheat increase from high to low latitudes (Rosenzweig et al., 2014; Iizumi et al., 2018; Zhao et al., 2017; Mora et al., 2015).

The spatial differences in climate change impacts can vary significantly between crops. Each crop has a defined temperature range within which growth occurs and an optimum temperature at which plant growth progresses fastest (Hatfield et al., 2011). Therefore, warming can both increase and decrease crop yields by shifting temperature inside or outside the optimum temperature range for the respective crop. Maize has an optimum temperature range of 18 - 30 °C, which varies depending on the maize cultivar and differs for individual crop growth stages (Ramirez-Cabral et al., 2017; Sánchez et al., 2014). The optimum temperature of wheat is more narrow and is generally considered to be between the range 17 – 23 °C over the course of an entire growing season (Porter and Megan, 1999). The hill-shaped yield-temperature function determines that decreases in yields due to increasing temperatures are larger the warmer a country is (Lobell and Burke, 2008). In this study, the long-term impacts of increasing temperatures are most severe for wheat yields at low latitudes, suggesting that warming increases the mean temperatures above the optimum for wheat. Thus, wheat in warm regions is highly susceptible to warming. For maize, the contrast in the reduction of crop yields with increasing temperatures between higher and lower latitudes is visible for small levels of warming, whereas under higher levels of warming, maize yields are reduced widely in all latitudes.

Next to changes in mean temperature, crop yield changes due to climate change are also determined by extremes of temperature and precipitation at key stages of crop development (Slingo et al., 2005). Tolerance to temperature stress and water stress during different crop cycle periods can be very variable between crops and cultivars and thus the effects of changing weather extremes on crops are highly complex. For example, strong precipitation events have been observed to reduce crop yields due to flooding (Rosenzweig et al., 2002). In addition, anomalously low precipitation often reduces crop yields due to stress effects from droughts, especially during critical crop development stages (Grassini et al., 2009; Krishna Kumar et al., 2004; Sivakumar et al., 2005; Verdin et al., 2005). The model results show that wheat at low latitudes is more susceptible to decreasing precipitation than at higher latitudes. An increased susceptibility of crops to reduced rainfall may be caused by increased evapotranspiration through warming, which can increase drought stress (Carter et al., 2016). Generally, precipitation changes are an important driver of interannual yield variability, but are less relevant for long-term crop productivity trends (Lobell and Burke, 2008; Lobell et al., 2011).

Management factors

Next to environmental conditions, differences in fertilisation and irrigation management determine global differences of both water erosion and climate change impacts significantly. Mueller et al. (2012) estimated that 60 - 80 % of global yield variability for most major crops are related to climate, fertiliser and irrigation. Irrigation and fertiliser use varies extensively around the globe. High fertiliser application rates are concentrated in high-income and some rapidly developing countries (Mueller et al., 2012) (Figure A.2). Irrigation is heavily concentrated in South, West and East Asia, as well as parts of the United States, where water availability is an important limitation for crop growth (Mueller et al., 2012; Portmann et al., 2010) (Figure A.3). However, in many developing regions where crops are limited by water availability, irrigation is lacking, which increases the vulnerability of crops to weather variability (Rosegrant et al., 2009; Van Ittersum et al., 2013). Sub-Saharan Africa is often named as a large region where crops suffer nutrient and water deficiencies leading to currently low levels of agricultural productivity (GYGA, 2015; Sánchez, 2010; Cassman and Grassini, 2013; Folberth et al., 2013). In addition, outside of the major maize and wheat growing areas, there are large yield gaps due to lack of irrigation and fertilisation, indicating potential to improve agricultural resilience in many regions vulnerable to climate change and water erosion (Licker et al., 2010; Mueller et al., 2012; Jägermeyr et al., 2016).

In summary, geographic differences in environmental characteristics and field management practices result in varying crop vulnerability to climate change and water erosion around the world. The climatic conditions at low latitudes combine high levels of rainfall erosivity and high susceptibility of maize and wheat to rising temperatures, two important factors for the adverse effects of climate change and high rates of water erosion. In addition, low application of fertilisers and lack of irrigation infrastructure reduce the resilience of crop production systems to both soil degradation and climate change in several developing regions. On the contrary, the largest maize and wheat producing regions in Europe, Asia and North America are predominantly on flat terrain with high fertiliser inputs and often have an abundant irrigation infrastructure. Hence, resilience to the effects of climate change and water erosion is higher in these regions.

7.4.2 The effects of precipitation and temperature changes on water erosion

An increase in water erosion with increasing precipitation is the most consistent relationship between changing climate parameters and water erosion in all regions and for both crops. However, the rate of increase in water erosion varies widely between regions, RCP scenarios, field management and crops. Similarly, the impact of changing precipitation amounts on simulated water erosion varies widely in previous studies, which are based on different land use and climate change assumptions (Chapter 2.5).

According to the model results, the effects of increasing precipitation on water erosion in maize and wheat fields is strongest under the RCP 8.5 scenario at low latitudes. In addition, water erosion increases sharply in regions where rising temperatures reduce crop yields. At locations where warming does not reduce crop yields, water erosion does not change significantly. This suggests that the adverse effects of climate change on crops, and thus on the protective vegetation layer against rainfall and runoff energy, largely contribute to the spatially varying effects of precipitation changes on water erosion. Decreasing plant cover due to lack of precipitation could also explain the positive correlation between water erosion and slightly decreasing precipitation at several sites.

As such, the model outputs demonstrate the decisive role of land use in the relationships between climate change and water erosion. The different relationships between warming and water erosion in high-latitude maize and wheat fields indicate that the effects of climate change on water erosion can be mitigated by growing crops that are not negatively affected by warming. In addition, the large variability in the effects of increasing precipitation on water erosion between different field management scenarios suggests that the relationship between precipitation and erosion may be predominantly influenced by field management rather than the magnitude of climate change. This is in line with previous suggestions that changes in water erosion are primarily due to field management rather than climate change (Olsson et al., 2019).

Nevertheless, the model outputs from this study demonstrate that changes in precipitation contribute substantially to changes in water erosion. For example, increasing precipitation largely increases water erosion in wheat fields despite positive climate change impacts on wheat in mid and high latitudes. Despite some clear relationships between climate change and water erosion, there is large complexity in the impacts of climate change on water erosion as some of the interactions between climate, crops and water erosion are difficult to disentangle. For example, the relationship between decreasing precipitation amounts and water erosion is very variable as it controls both crop cover and rainfall runoff and can be both positive and negative. Also, the reasons for the increasing water erosion impacts on crops over time are difficult to identify. This can be caused by impacts of climate change on water erosion rates, but also by effects of water erosion on vegetation cover and soil stability, which amplify further water erosion.

7.4.3 Where is water erosion increasing due to climate change?

Spatial uncertainty in precipitation projections makes it difficult to identify regions where water erosion could increase

The model outputs of this study suggest that water erosion rates increase strongest in Eastern, Southern, and Southeast Asia throughout the simulation period (Figure D.8). The changes in water erosion are most directly driven by changes in precipitation, but these are difficult to project (Giorgi and Lionello, 2008).

It is well known that atmospheric moisture increases with warming. However, agreement about the spatial patterns of precipitation changes among different models is low. The largest regions where most models agree on an increase in precipitation at the end of the 21st century are in the highest latitudes including vast areas in Canada, Northern Europe, and Northern and Central Asia (Trenberth, 2011; Fischer et al., 2014; Pendergrass et al., 2017). In addition, several models predict an increase in precipitation in large areas of Eastern, Southern, and Southeast Asia, Eastern Africa and parts of South America, with moderate agreement between models in these regions. In other regions model agreement is low or models agree on a reduction of precipitation. The changes in water erosion in regions that are becoming drier are difficult to determine, as the model results of this Chapter show.

The agreement in projected increases in heavy precipitation is significantly higher among models and affects the majority of agricultural regions on all continents (Fischer et al., 2014). Pendergrass (2018) finds that extreme precipitation events are expected to increase faster than moderate precipitation events with increasing atmospheric moistening. Several studies already observed the intensification of precipitation with warming (Guerreiro et al., 2018; Blenkinsop et al., 2018; Liu et al., 2009; Bezak et al., 2020). Some observations even demonstrated that precipitation intensity can increase at locations where precipitation amounts decrease (Trenberth, 2011). Based on numerous studies on the relationships between climate change and precipitation, the IPCC concluded that heavy precipitation events have increased in frequency, and/or amount since 1950 (likely) and that further changes in this direction are likely to very likely during the 21st century (Stocker et al., 2013).

However, uncertainty about the spatial patterns of projected extreme precipitation changes remains. Tabari et al. (2019) showed that the uncertainty of modelled extreme precipitation changes due to variability between models is highest in tropical regions where rainstorms cannot be adequately represented by coarse-scale climate models, and where observation networks are sparse on which climate models can be tuned and improved.

Previous studies on spatial changes in erosion due to precipitation changes used an ensemble of climate models to capture this uncertainty (Panagos et al., 2022; Borrelli et al., 2020). For example, using 19 GCMs and three RCPs, Panagos et al. (2022) showed changes in rainfall erosivity by 2050 and 2070 that increased in most parts of the global land surface and were greatest in arid and cold zones. Rainfall erosivity generally increased with the RCP scenario. Whilst there was a strong agreement on the future directional trend of rainfall erosivity among the ensemble, the authors concluded that predicting changes in magnitude are uncertain, especially in low latitudes where the variability between models are very high.

Negative effects of warming on crops can help identify regions where water erosion could increase due to climate change

In addition to the direct impact of precipitation on water erosion, the indirect effects of increasing average temperatures on water erosion due to the decreasing crop cover are important for the localisation of hotspots of future changes in water erosion. The model outputs of this study demonstrate that in regions with severe negative climate change impacts on crop yields, water erosion will likely increase. Consequently, water erosion impacts are more likely to increase at low latitudes where important staple crops are more negatively affected by climate change. Combined with the expected increase in extreme rainfall in many tropical regions, this will particularly exacerbate erosion.

While the model results from this study can be used to explore key mechanisms that may lead to changes in future water erosion in different global regions, it is difficult to predict actual changes due to the uncertainties in climate change projections. In addition, other links between climate change and water erosion that were not considered in the analysis of model results must also be taken into account.

For example, another important impact of climate change on water erosion are temperature impacts on soil moisture through evapotranspiration, which influences the partitioning of water into surface and subsurface runoff (Li and Fang, 2016; Nearing et al., 2004). However, soil moisture changes depend on both temperature and precipitation; thus, they can be very variable around the globe and difficult to project (Trenberth, 2011). Next to the uncertainties in climate change projections, future land use is highly uncertain. Future water erosion rates will be strongly influenced through shifts in crop cultivation areas (Zabel et al., 2014) or changes in field management, which may be influenced by strategies for adapting to climate change (Borrelli et al., 2020).

7.4.4 Field management and land use planning will largely influence the future impact of water erosion

The model results show that climate change impacts on maize and wheat yields are strongly affected by RCPs, whereas water erosion impacts are most affected by field management. Due to the static field management scenarios and the uncertainties in the cropland distribution within the spatial unit studied, the modelling approach neglects many opportunities for farmers to reduce water erosion impacts. Nevertheless, the contrasting field management scenarios show that high production losses due to water erosion can be substantially reduced with farming techniques, which reduce the erosivity of precipitation and surface runoff. However, such strategies can limit the overall production volume as there may be a yield 'penalty' from employing Conservation Agriculture practices in the short-term (Giller et al., 2009). The trade-offs between farming techniques, crops and soil in response to climate change are highly complex; thus, the effectiveness of field management strategies to maintain or increase productivity should be analysed in areas susceptible to water erosion based on detailed data on environmental conditions and land use on-site.

Key to directly address water erosion will be to monitor cropland expansion. Increasing crop demand has already led to cultivation of tropical steeplands (Turkelboom et al., 2008) or soils prone to degradation (Wildemeersch et al., 2015). In many regions of Africa, Asia and Latin America, which are predicted to be most vulnerable to both climate change and water erosion, population growth and a high dependence on agriculture may lead to unpredictable impacts of cropland expansion on soil erosion. Due to the uncertainties in the spatial distribution of cropland in each grid cell in the modelling approach of this study, the model outputs reflect potential production losses that occur if the susceptibility of land to water erosion is not considered in the choice of cropland. Given the uncertainties in the distribution of current and future cropland and its significance on the resilience of agriculture to water erosion, further research and monitoring programs in the most affected regions are necessary.

7.4.5 Measures to reduce the adverse effects of water erosion and climate change can be combined

Since land degradation affects the resilience of agricultural systems to climate change, adaptation planning must consider the risks associated with ongoing land degradation to increase the effectiveness of climate change adaptation strategies (Reed and Stringer, 2016). To some extent, anti-erosion measures are integrated indirectly in climate change adaptation strategies, which maintain or increase crop cover. The most effective measures to reduce climate change impacts in food insecure regions are likely to arise from new crop varieties and new technology such as improved irrigation infrastructure (Lobell et al., 2008). Other adaptations strategies are shifting planting dates, modifying crop rotation and the up-take of pre-existing crop varieties (Knox et al., 2012), and are already in use to cope with variable weather conditions and shifting climate (Osbahr et al., 2010). Moreover, certain climate change adaptation strategies focus on the protection of soil moisture and soil fertility through increasing amounts of organic matter in the field, artificial and natural fertiliser application and lowering soil disturbance; thus, they include similar measures necessary to reduce water erosion impacts (Giller et al., 2015).

Whilst the flexibility of 'Climate-Smart Agriculture' as an option for addressing both land degradation and climate change has been recognised, the focus on land degradation needs to be increased in adaptation planning (Webb et al., 2017). A reduction in soil health may limit the adaptive capacity of farmers by increasing their socio-economic vulnerability and in addition, influences the exposure and sensitivity of crops to climate change (Webb et al., 2017; Laban et al., 2018). Despite uncertain climate change impacts, previous authors are confident that negative climate change impacts will be severe for low resilient agricultural systems in parts of Africa, Asia and South and Central America (Müller et al., 2011; Knox et al., 2012; Lobell et al., 2008).

7.4.6 Uncertainties related to crop yield projections and climate change impacts on crops and water erosion

The most important model uncertainties for estimating global water erosion impacts include the previously discussed uncertain resolution of the model input data (Chapter 6.4.3), global patterns of field management (Chapter 6.4.3), and the varying performance of the water erosion model in different global regions (Chapter 5.4). The simulation of crop yield projections in this chapter adds further uncertainty to the model outputs.

Future changes in field management and technologies have not been considered but will significantly influence the resilience of future maize and wheat production to climate change. For example, negative climate change impacts from warming such as droughts can be reduced through the adaptation of farming techniques, planting dates or the use of newly developed maize and wheat cultivars (Carr et al., 2022). Moreover, expansion of irrigation infrastructure or changes in water availability may alter climate change impacts (Balkovič et al., 2014). In addition, this study did not consider shifts in future crop production areas due to geographically changing climatic suitability for maize and wheat (Wu et al., 2007). Obviously, these changes will have a significant impact on future maize and wheat yields and production but are highly uncertain.

Additional important uncertainties include the robustness of RCPs and the simulated impact of climate parameters on crops, as well as water erosion. As these uncertainties directly affect the model outputs of this study they are discussed in more detail in the following.

Uncertain climate change scenarios

The RCPs chosen for this study represent two contrasting scenarios of possible future trajectories of the climate systems and climate change impacts on agriculture. Thus, they capture a wide spectrum of climate change impact possibilities, which are difficult to narrow down as they depend on future policy and socio-economic changes.

Under the RCP 2.6 scenario, global warming could be limited to < 2 °C above pre-industrial levels, which is defined as the long-term temperature target by most countries in the Paris Agreement (Schleussner et al., 2016). However, the likelihood that the intended national contributions are sufficient to meet the goals of the Paris Agreement is uncertain (Rogelj et al., 2016; Clark et al., 2020). Gasser et al. (2015) concluded that negative emissions (through capturing human-produced CO_2, direct removal of carbon dioxide from the atmosphere, or engineered enhancement of natural carbon sinks) are physically needed to keep global warming below 2 °C even in the case of very high conventional mitigation rates (e.g. through lower fossil fuel consumption and less CO_2 production).

RCP 8.5, which would increase global mean temperatures to approx. 5 °C above preindustrial levels, is seen as increasingly unlikely. Although the RCP 8.5 is often referred to as the business-as-usual scenario, it's assumptions about a fossil-fuel intensive future without considering any climate mitigation policies are contrary to recent climate policy efforts of most countries (Peters and Hausfather, 2020). Nevertheless, due to unpredictable political circumstances or the uncertainty of climate tipping points and rapidly increasing greenhouse gas levels through feedback loops (e.g. due to thawing Arctic permafrost), this is still a valuable worst-case scenario to consider (Tollefson, 2020; Lenton et al., 2019).

Uncertain simulation of climate change impacts on crops

Next to the uncertain trajectories of future greenhouse gas emissions, uncertainties in simulated climate change impacts on crops also arise from the model structures. Although crop models are usually reliable in simulating measured maize and wheat yields under a range of environments, the robustness of simulated crop response to climate change is often criticised. The simulated relationships between crops and changes in atmospheric CO_2, temperature and precipitation are critical in climate change impact studies. However, differences in model structure and parametrisation can lead to large differences in the simulated crop response to changing climate parameters.

Prior studies observed an increasing variability between models with increasing temperatures due to the difficulty of simulating high-temperature stress impacts on crops (Asseng et al., 2013; Mearns et al., 1999). Stress for crops due to high temperatures is initiated by enhanced phenology and the consequent reduction in time for light interception and photosynthesis, which can result in lower crop yields. This process involves complex interaction between leaf area expansion and biomass growth with other processes of the model, which are simulated differently between models (Asseng et al., 2013). In addition, prior studies concluded that the sharp decline of crop yields exposed to extreme temperatures (>30 °C) observed in field experiments is not reflected in crop models (Rötter et al., 2011). Thus, the impact of spatial and temporal changes in temperature extremes due to climate change on crops may not be captured adequately in the model results.

Although precipitation changes are difficult to project and significantly affect simulated crop yields, changes in precipitation have been reported to cause less uncertainty in climate change impact studies than changes in temperature, as the understanding of crop responses to changing precipitation is more robust than knowledge about crop responses to temperature (Lobell and Burke, 2008). Nevertheless, as rainfall is important for annual variability of crop yields, the large disagreement of global climate models on projected precipitation changes plays a crucial part in the uncertainty of climate change impacts. Obviously, robust estimates of water erosion impacts on crops under a changing climate requires improvements in the quality of precipitation projections.

The representation of the impact of increasing atmospheric CO_2 on crops is another major source of uncertainty. Negative climate change impacts may be offset to some extent by increased CO_2 levels, especially for C3 crops, although the magnitude of these effects are uncertain and the subject of much debate (Lobell and Field, 2007). In general, there are many uncertainties in our knowledge of the impact of atmospheric composition on crops (Slingo et al., 2005). In addition, changes in other key climatic parameters, including solar radiation, wind speed, and relative humidity, are difficult to project.

Uncertain simulation of climate change impacts on water erosion

As crop cover influences water erosion indirectly, the above discussed uncertainties of the impact of climate parameters on crops result in uncertainties in the impact of climate change on water erosion.

In addition, uncertainty in precipitation projections, their coarse resolution, and the robustness of the MUSS equation determines the uncertainty of simulated climate change impacts on water erosion directly. As described in Chapter 5 simulated water erosion tends to exceed water erosion measured in field experiments in environments with heavy and abundant precipitation. Thus, the decreasing robustness of simulated water erosion with increasing precipitation may lead to an overestimation of the increase in water erosion where an increase in precipitation amount and intensity due to climate change is projected.

Moreover, the coarse resolution of global climate models hampers the simulation of climate change impacts on erosion. As climate parameters are provided on a daily timescale, important variables to estimate erosion events such as 30-min rainfall intensity are not provided in climate models. Therefore, statistical relationships are used between monthly and annual precipitation and rainfall erosivity to explore erosion changes with climate models (Nearing et al., 2004). As single extreme rainfall events can be responsible for great soil loss, the lack of sub-daily resolution is an important uncertainty in studies analysing climate change impacts on water erosion (Li and Fang, 2016).

Assessing the uncertainties of simulated climate change impacts using model ensembles

To cover the range of model-derived uncertainties in climate change impact studies, the results of model ensembles can be useful. Model ensembles include a range of models that differ in their robustness in representing different variables and/or regions. The range of results from ensembles can be used to assess the certainty of the results by identifying consensus between models or large disagreements. While there are no global ensemble studies that have considered the links between crops and erosion in response to climate change, there are studies that used ensembles of crop or climate models to individually project changes in crop yields or water erosion (Borrelli et al., 2020; Jägermeyr et al., 2021; Panagos et al., 2022). These studies thus provide important insights into the robustness of projected spatially explicit changes in crop yields or erosion.

Studies based on model ensembles have shown that the projection of erosion changes is highly uncertain, as erosion changes strongly depend on precipitation changes (Chapter 5.3.2), which are projected very differently between individual climate models. The limitations of projecting erosion changes due to a low agreement in precipitation changes between models have been discussed in Chapter 7.4.3. The latest study on future changes in erosion driven by rainfall concluded that predicting the magnitude of changes in rainfall erosivity is uncertain, especially at low latitudes where inter-model variability is very high (Panagos et al., 2022).

The projected temperature changes agree better between climate models, as do the simulated impacts of temperature changes on crops. For example, models agree that the negative effects of climate change on maize and wheat yields are greater at low latitudes than at higher latitudes (Jägermeyr et al., 2021). This trend is also in agreement with the crop yield projections presented in this chapter. Building on this commonly found relationship, the results showed how future erosion changes can be attributed to the varying effects of temperature changes on plants at different latitudes.

Despite the difficulties in projecting future erosion changes, exploring the differences of climate-plant-soil relationships between global regions can provide insight into how vulnerable different regions are to increasing erosion. However, the existing model uncertainties make it difficult to project spatially explicit erosion changes due to climate change. In future studies, a combination of multiple climate models and crop models that take into account crop-erosion linkages can help identify erosion-prone regions where the ensemble finds both declining yields and increasing rainfall.

7.5 Conclusion

In this chapter, water erosion impacts on global maize and wheat yields were explored in the context of climate change. The results give insight into the complex links between climate change and water erosion and highlight regions where maize and wheat production is most vulnerable to both water erosion and climate change impacts. The simulation results show that maize and wheat production at low latitudes is most negatively affected by climate change and includes the majority of the areas most vulnerable to water erosion under both analysed climate change scenarios. Moreover, water erosion in maize and wheat fields is likely to increase due to diminishing vegetation cover at low latitudes, where substantial negative impacts of climate change on crops are expected.

The model outputs reflect the influence of geographic variations of environmental characteristics and field management on climate change and water erosion impacts. Low-latitude regions combine high precipitation erosivity and high temperatures; thus, they are most susceptible to both water erosion and climate change impacts on maize and wheat. In addition, the different impacts of climate change and water erosion across regions are determined by the varying levels of fertiliser application and irrigation. Thus, the simulation results illustrate the contrast between the effects of climate change and water erosion on crops between highly developed agricultural regions and regions with abundant smallholders with typically low volumes and efficiency of inputs. The main determinants of adverse effects from climate change and water erosion are found in sub-Saharan Africa, South and Southeast Asia, and Central and South America.

Whilst the relationships between climate change and water erosion are highly complex, there is a clear positive relationship between increasing precipitation and water erosion. The magnitude of increasing water erosion rates with increasing precipitation significantly depends on crops, warming levels and field management. The simulation results demonstrate that the impact of increasing precipitation on water erosion will be stronger with higher levels of climate change. Negative impacts of warming on crop yields play an important role in increasing water erosion rates with climate change. Thus, climate resilience of crops will be critical to the impact of climate change on water erosion on cropland. Moreover, the model outputs illustrate that field management can reduce water erosion impacts on crop production more than different levels of climate change.

Although identifying future hotspots of water erosion changes is difficult due to the uncertainty in precipitation projections and future land use, the model results show that climate change impacts on crops can indicate where crop production is likely to become more vulnerable to water erosion. In addition, the model results demonstrates the value of field management in controlling future impacts of water erosion. The adaptation to both climate change and water erosion is likely to become increasingly important in the most vulnerable regions.

Chapter 8

Overall summary and future research needs

8.1 Summary of insights

Water erosion poses a serious threat to soil resources as it removes topsoil, affecting soil fertility and other soil properties important for plant growth. Therefore, water erosion is an important process to consider when assessing the productivity and environmental impact of crop production. In addition, climate change influences water erosion through the various links between water erosion, vegetation and the climate system.

To understand the state of agriculture today and in the future, it is important to explore how water erosion affects crop yields and how climate change might influence this. To analyse this on policy-relevant scales, large-scale or global assessments are necessary. Models can account for the effects of geographical variations in land use and environmental characteristics on water erosion using a consistent methodology over large scales.

However, large-scale and global agricultural modelling studies need to be improved in terms of robustness and representation of plant-soil interactions. Water erosion is an often neglected process in agricultural assessments. Therefore, there is no consistent information on the impact of water erosion on agricultural productivity on a large and global scale. In addition, the links between water erosion, vegetation and the climate system in global agricultural assessments need to be explored in more detail to provide a more complete picture of the impacts of climate change on agriculture.

This study addressed the need for large-scale indicators on water erosion rates and impacts using the GGCM EPIC-IIASA. The robustness of the model with respect to simulated water erosion in different global regions was evaluated using field data. Subsequently, EPIC-IIASA was used to estimate the impact of water erosion on global maize and wheat yields. The combined impact of climate change and water erosion on maize and wheat yields, and the potential impact of climate change on water erosion, were also assessed. This section summarises the findings of the thesis.

8.1.1 Simulation and evaluation of water erosion with EPIC-IIASA

EPIC-IIASA was used to develop a modelling approach to estimate long-term average water erosion rates in global maize and wheat fields under different field management scenario (Chapter 5). Simulated water erosion rates differed greatly between temperate climate regions where crops are grown in lowlands and tropical regions with abundant hilly farmland. Water erosion rates in maize fields were higher than in wheat fields. In addition, model results showed that water erosion rates decrease with decreasing tillage intensity and increasing crop residue cover in many regions of the world.

The robustness of the simulated water erosion rates was confirmed for the major maize and wheat growing regions by using water erosion measurements from field studies as a comparison. In regions with steep slopes and heavy precipitation, simulated water erosion rates exceeded field values, reducing confidence in model results at these locations. However, these sites accounted for only 7% of the world's maize and wheat land.

One of the most important challenge to the evaluation of water erosion was the limited amount of suitable field data in different regions. In addition, field data were highly variable, as assessing water erosion based on field experiments can be difficult and subject to many uncertainties (Chapter 2.3.5).

To better interpret the robustness of simulated water erosion estimates, an analysis of the sensitivity and uncertainty of water erosion estimates was conducted in Chapter 5. The sensitivity analysis highlighted the high sensitivity of the model to precipitation and slope steepness. The uncertainty analysis showed a wide range of water erosion estimates with different water erosion equations and field management scenarios in regions vulnerable to water erosion. Improving the limited information on global field management and the spatial resolution of topography and land use data would improve the robustness of water erosion estimates.

The insights on the varying robustness and uncertainty of simulated water erosion estimates in Chapter 5 are useful to interpret the robustness and uncertainty of the results in Chapter 6 and Chapter 7.

8.1.2 The impact of water erosion on global maize and wheat yields

The modelling approach evaluated in Chapter 5 was used in Chapter 6 to explore the impact of water erosion on maize and wheat yields and production. In addition, the model results were used to identify the fields most at risk of water erosion based on the amount of rainfall, the slope of the fields and the use of fertilisers.

Model results showed that water erosion will reduce maize and wheat yields on about half of the world's cropland by an estimated 3% per year if farmers do not adapt to changing environmental conditions. The areas at risk are located on steep slopes exposed to heavy precipitation and where little fertiliser is available. Fields with these characteristics are found primarily in parts of sub-Saharan Africa, South Asia, and Latin America. Because the main areas of maize and wheat cultivation are in flat terrain outside the tropical heavy rainfall areas and are managed with large amounts of inputs such as fertilisers, they are less affected by water erosion. The model results showed that annual production losses of maize and wheat due to water erosion are less than 1% of global production volume. In addition, the calculated replacement cost of nitrogen fertiliser to offset nutrient runoff was low compared to crop production value. However, the analysis of water erosion impacts did not include the cost of replacing other plant nutrients (phosphorus, potassium, carbon), and external costs such as pollution from sediment runoff.

8.1.3 The impact of climate change and water erosion on maize and wheat yields

Chapter 7 extends the analysis of water erosion impacts on maize and wheat yields by using the modelling approach evaluated in Chapter 5 under two contrasting climate change scenarios. In addition to analysing regional differences in water erosion impacts as in Chapter 6, regional differences were also analysed for climate change impacts on maize and wheat yields.

The model results showed that low-latitude maize and wheat production are most affected by water erosion and climate change simultaneously. Climatic conditions at low latitudes include heavy precipitation, resulting in increased water erosion, and higher temperatures, which exacerbate the negative effects of warming on many crops. In addition, global differences in water erosion and climate change impacts are due to differences in agricultural intensity and associated differences in the quantity and efficiency of inputs such as fertilisers and irrigation. Regions most negatively affected by both climate change and water erosion are most abundant in sub-Saharan Africa, South and Southeast Asia, and Central and South America.

The model results were further analysed to explore the links between climate change and water erosion. There was a clear positive relationship between increasing precipitation and water erosion. The impact of increasing precipitation on water erosion was stronger with higher levels of climate change. The erosion-precipitation relationship was strongly affected by field management. In addition, the model results showed that water erosion likely increases where climate change reduces crop yields.

However, identifying regions where water erosion will change in the future has been difficult. This is primarily because changes in precipitation are most important, but these projections are highly uncertain. Nevertheless, the likelihood of a decline in vegetation cover due to climate change may indicate where water erosion could increase. Since the greatest negative impacts of climate change on crops worldwide are in low latitudes, these regions are also most at risk from increased water erosion due to decreasing vegetation cover.

Finally, the model results showed the strong influence of field management on the effects of climate change on water erosion. This indicates a huge potential for mitigating the negative effects of climate change on water erosion and thus crop yields.

8.2 Summary of research contributions

The results of this thesis contribute to a better understanding of regional differences in water erosion on global croplands and the effects of water erosion and climate change on global cereal production; thus, providing new insights into the impact of environmental changes on long-term agronomic trends. Specifically, this thesis addresses i) the need for improved large-scale indicators of water erosion rates and water erosion impacts on crops to inform major environmental and agricultural policies (Alewell et al., 2019; Montanarella, 2007; Nkonya et al., 2011), and ii) the neglect of land degradation processes in climate change impact assessments using GGCMs (Balkovič et al., 2018; Webb et al., 2017).

8.2.1 The first evaluation of global water erosion estimates from a GGCM

Proper model calibration is needed to match experimental data obtained from the field, foremost for a complex process such as soil loss due to water erosion (Favis-Mortlock, 1998). However, the evaluation of global water erosion estimates was lacking in previous global studies.

Whilst previous global erosion estimates lack evaluation, previous global crop yield estimates were evaluated against regional yield statistics to represent the crop yield patterns across regions and countries (Mueller et al., 2017). Following the same paradigm, this study evaluated the robustness of a GGCM to represent regional differences and spatial patterns in water erosion estimates based on the most important determinants for water erosion. Although the field data used in this study is insufficient to calibrate EPIC-IIASA to simulate actual erosion events observed in the field, it provides an initial indication of the robustness of estimated water erosion rates under certain topographical and climatic conditions.

As such, the evaluation against field data confirmed that EPIC-IIASA can be used to analyse global differences in water erosion rates and impacts between the most important crop production regions. Therefore, the results of Chapter 5 confirm the usefulness of EPIC-IIASA to address the previously neglected impact of water erosion in large-scale crop modelling studies and the previously neglected interactions between crops and water erosion in large-scale water erosion modelling studies.

8.2.2 New large-scale water erosion indicators

Large-scale indicators are necessary to address water erosion in policy programs (Alewell et al., 2019). To create the needed indicators simple models are required due to the limited availability of global input and experimental data. Therefore, most authors have recently opted for USLE-based models to estimate water erosion rates at large scales (Chapter 2.3.1). Since these models generally use static inputs, biomass-soil interactions in response to weather and field management have been neglected.

Unlike previous studies, the large-scale water erosion estimates in this study are based on USLE-type models combined with the process-based crop model EPIC. The more complex modelling approach allowed to simulate the effects of field management strategies on water erosion. As such, modelled global water erosion rates account for the first time for surface cover of individual crops, timing of planting and harvest, irrigation, fertilisation, cover crops, intercropping, tillage, and residue management.

The model results thus provide new insights into the variability of water erosion rates based on these management factors at large spatial scales and improve the availability of large-scale indicators for important environmental and agricultural policies.

8.2.3 New evidence on regional differences in the impact of water erosion in agriculture

Large-scale water erosion studies have focused primarily on the extent of erosion rather than the impact on crops. As a result, the large-scale impacts of water erosion have not been adequately quantified in physical and economic terms. In addition, the limited number of large-scale studies on the effects of water erosion on crops relied on field experiments based on different methodologies leading to different estimates, and they do not cover all agricultural areas worldwide (Chapter 2.4). Previous approaches are less suitable to extrapolate erosion-productivity relationships beyond field scale to compare regional differences and to derive robust conclusions on water erosion impacts on different crops on large and global scales.

The results in Chapter 6 provide the first globally consistent estimates of water erosion impacts on crops using state-of-the-art datasets on climate, soil, topography and management practices. These results provide the most accurate global assessment of the links between water erosion and crop productivity that is currently feasible, given data availability.

The globally consistent modelling method made it possible to illustrate the sharp contrast between the low on-site costs of erosion in the most productive agricultural regions and the significant impact of water erosion on crop yields in regions with heavy rainfall, hilly croplands, and low fertiliser use. By identifying agricultural regions most vulnerable to water erosion, the model results can highlight hotspots where anti-erosion measures are most needed to sustain crop productivity in the long-term.

In addition, the model results allow to question the globally uniform assumption by previous authors that annual water erosion rates up to 11 tha^{-1} are sustainable for crop production (Sartori et al., 2019; Pravalie et al., 2021). Whilst these rates may be sustainable to maintain agricultural productivity in high-input systems, the results in Chapter 6 demonstrates that lower water erosion rates can have a significant impact on crops in regions where low fertiliser use is a common limiting factor for crop yields.

Overall, the globally consistent modeling approach developed in this study provides a platform for assessing water erosion problems in multiple ways to identify risks and hotspots and support policy actions. For example, shifts in future risks and hotspots can be assessed by integrating models on land use change (e.g. new crops) and climate change. The latter has been explored in Chapter 7. In addition, the field management scenarios used for generating all model outputs demonstrate the decisive impact of farming techniques and soil conservation measures on water erosion rates and water erosion impacts on crop yields. Previous studies point out that there may be a yield penalty from employing soil conservation practices in the short-term and a yield gain in the long run (Giller et al., 2009). The model approach developed here can be used to create large-scale indicators on the trade-offs between lower water erosion rates due to soil conservation strategies and absolute crop yields to inform policies. In addition, the model outputs estimate the amount of organic nitrogen and carbon in sediment runoff that can potentially enter surrounding environments. These estimates can be used to assess off-site costs for different field management scenarios. Previous studies suggested that off-site impacts are the main concern of erosion in the highest developed agricultural regions and thus they are targeted by many policy programs (Graves et al., 2015; Montanarella et al., 2016).

8.2.4 Improvements in crop yield projections by considering water erosion

Future changes in crop yields are discussed mainly as a result of climate change, while many important processes that contribute to ongoing soil degradation are neglected (Chapter 3.6). This can lead to inconsistencies in the validity of model results in a world with different management intensities, as the influence of weather variability on yield variability decreases with decreasing inputs to farming systems, while other factors such as soil quality become more important (Ray et al., 2015). Because water erosion is one of the most common soil degradation process affecting crop yields (Chapter 2.2) and is closely related to climate (Chapter 2.5), it should be especially considered in crop yield projections.

Model results in Chapter 7 showed that water erosion affects projected crop yields at vulnerable sites characterised primarily by heavy rainfall, steep slopes, and low fertiliser use. Without accounting for water erosion, crop yield projections at these sites ignored an important factor that strongly influences crop productivity, which can lead to overestimation of future crop yields. In addition, model results showed that the susceptibility of sites to water erosion may change in the future due to the effects of climate change on vegetation cover and precipitation patterns. By considering water erosion and its link to climate change, large regions in the lower latitudes have been identified as being at risk of crop yield losses due to the simultaneous effects of soil erosion and climate change.

Moreover, consideration of water erosion provides greater insight into the effects of different field management scenarios on crop yields, which is often the subject of climate change impact studies (Chapter 3.5). The analysis of model results has shown that water erosion affects the links between field management and crops in several ways. These include the impact of water erosion on fertiliser and nutrient runoff, which affects climate change adaptation strategies that aim to increase fertiliser use (Rosenzweig et al., 2014; Balkovič et al., 2014) or adopt cropping practices that replenish soil nutrients (Folberth et al., 2014). In addition, changes in soil quality due to water erosion affect crop sensitivity to climate change (Laban et al., 2018; Herrick et al., 2013).

By including water erosion in the projection of global maize and wheat yields, the model results have taken into account another important factor for future changes in crop yields in many regions, in addition to climate change. This contributes to a more complete picture of the stressors affecting future cereal production trends. In addition, this improve the usefulness of climate change adaptation studies by accounting for an important process within the interactions between field management and crops.

8.2.5 New insights into the potential impacts of climate change on global water erosion

The effects of climate change on water erosion are the result of complex interactions of many factors including soil, topography, agricultural practices, biomass, and climate. As these factors vary widely around the world, the effects of climate change on water erosion can vary widely across regions. Because previous studies of the effects of climate change on water erosion focused on individual fields in various regions, they reached very different conclusions (Chapter 2.5). Due to the different modelling approaches used in previous studies, their results cannot be used to compare the effects of climate change on water erosion between regions.

The analysis of model results in Chapter 7 showed the interactions in different global regions based on the impact of varying precipitation changes and vegetation cover changes. While uncertainties in precipitation projections render them unsuitable for examining regional differences, the higher confidence in regional differences in future vegetation cover changes could provide insight into potential global differences in climate change impacts on water erosion.

The globally consistent modelling approach developed in this thesis enabled to analyse the interactions between crops and water erosion in response to climate change for the first time at the global scale. As such, the results of Chapter 7 contribute to a more comprehensive understanding of the potential impact of climate change on water erosion in different global regions.

8.2.6 New data on global water erosion rates and impacts on crops

Finally, this study provides novel data including global water erosion estimates for different farming techniques and crops, and estimates of water erosion impacts on global maize and wheat yields under historic climate and two contrasting climate change scenarios. All estimates are available on grid, national, regional and global scale.

8.3 Research needs

8.3.1 Most important needs to improve large-scale water erosion estimates

To improve the evaluation of simulated water erosion rates, the amount of appropriate field data needs to be increased to represent a wider range of global environments and crop management practices. A major challenge in this study was the collection of useful field data, which is often only published in aggregated values and needed to be collected from numerous publications, grey literature and conference proceedings. Moreover, field data is often not freely available (Benaud et al., 2020).

In addition, more data on field management would improve global water erosion estimates. Whilst information on rainfed and irrigated cropland, crop calendars and crop-specific fertiliser applications rates are based on spatially explicit datasets, the geographic variations in tillage intensity and soil conservation measures are based on rough assumptions in this study. Although they provide insights on the impact of changing surface cover and roughness on water erosion rates, they hardly capture the actual regional differences in farming techniques.

Also, a higher spatial resolution is needed for land use data to better approximate actual water erosion rates and impacts on crops. Improvements in spatial data informing about the distribution of cropland in mountainous regions is particularly important. Previous field studies identified highest water erosion rates on marginal cropland and on steep slopes, which also have been targeted by policy measures to reduce erosion (Long et al., 2006b; Deng et al., 2012). However, the evaluation against field data shows that water erosion on fields with steep slopes and strong precipitation is overestimated. The low confidence in simulated water erosion rates in mountainous regions is partly the result of the heterogeneity of upland farming and fields and the missing data on field management, anti-erosion measures and the low spatial resolution on cropland distribution and topography datasets. In addition, previous studies suggested that model improvements are needed to improve erosion estimates for locations with steep slopes and strong precipitation (Naipal et al., 2018; Labrière et al., 2015).

Due to the current uncertainties, global studies cannot replace field-scale assessments based on precise information on management practices and site characteristics. Due to higher spatial detail, field-scale assessments can be based on more complex water erosion models, which may include special elements such as channels and ponds to identify potential sources and sinks of sediments and associated nutrients within a field (Jetten et al., 2003). By including depositional areas within the spatial unit studied, positive effects of topsoil accumulation on crop productivity can be considered (Bakker et al., 2007). In addition, studies based on data with a higher temporal resolution can consider the impact of individual rainfall events on sediment runoff instead of focusing on average erosion rates as is common in global studies. In other words, smaller-scale studies can more precisely inform about actual water erosion impacts on a field to support effective anti-erosion measures on-site.

However, studies on erosion-productivity relationships cannot normally be scaled-up as the robustness of locally observed relationships need to be re-evaluated for different environmental and socioeconomic conditions in each location. Given the current lack of consistent field studies representing all global environments, a bottom-up approach to deliver large-scale indicators on erosion rates and impacts to inform agricultural and environmental policy programs is not currently feasible (Alewell et al., 2019).

Future global studies on water erosion impacts may benefit from current efforts to compile spatial data on representative management practices such as tillage systems (Porwollik et al., 2019), and remote sensing products for spatial attribution of field management practices (Hively et al., 2018; Zheng et al., 2014). In addition, the increasing availability of high-resolution data through improvements in remote sensing techniques will benefit future global water erosion assessments (Buchhorn et al., 2020). Moreover, recent efforts to collate erosion measurements and metadata from existing studies in a single platform may improve the global coverage of appropriate field data in the future (Benaud et al., 2020). In addition to the need for more spatial data on representative management practices and higher-resolution datasets on land use patterns and topography, a more consistent approach to field-based data collection to evaluate model outputs would enable such studies to be used in future large-scale water erosion assessments.

8.3.2 Scenarios on future land use and field management changes are needed to estimate future water erosion rates

The main uncertainties in simulating the effects of climate change on water erosion were discussed in Chapter 7. Among them, uncertainties in precipitation projections and simulated changes in crop cover due to climate change must be considered to improve estimates of future changes in water erosion rates and their regional variations.

However, numerous studies concluded that future water erosion rates may be primarily influenced by land use change instead of climate change (Li and Fang, 2016). This poses a major challenge for improving research on future water erosion rates because land use changes are determined not only by climate, but also by many other factors such as population growth, socioeconomic changes, and policies. These factors are often difficult to project and can affect land use in ways that both increase and decrease water erosion.

For example, projected population growth and the associated increase in food demand in many developing countries may exacerbate water erosion on cropland as agriculture expands and intensifies. On the other hand, some projections of future agricultural intensification suggest that the impact of water erosion on crops may be reduced in the future as fertiliser consumption and fertiliser-use efficiency are projected to rise (FAO, 2006). Whilst this could lead to increased off-site impacts of water erosion, the impact of water erosion on crops may be less relevant. Moreover, high rates of urbanisation and rural-urban migration are predicted in many developing countries, which could reduce degradation stemming from the cultivation of marginal lands and slopes (FAO, 2006). Examples in Europe from the 1950s onwards and in China more recently showed that urbanisation in conjunction with agricultural policy programs led to the abandonment of steep slopes and marginal land, which reverted to forest and caused a reduction in water erosion (Deng et al., 2012; García-Ruiz, 2010; Renwick et al., 2013; Tasser et al., 2007). However, this development may not occur everywhere. In Indonesia, where the rate of population growth is high, population drift to cities has not significantly reduced the density of rural settlement (FAO, 2006). Evidence from Southeast Asia show that increasing pressure on food production recently led to the expansion of cropland to steep slopes (Turkelboom et al., 2008; Valentin et al., 2008).

In addition, it is important to consider future changes in field management to project changes in water erosion. For example, the cultivation of crops that are more resilient to climate change may increase in certain areas in the future, reducing the indirect negative effects of climate change on water erosion. Millet is less susceptible to warming than maize and wheat and thus may be more common in arid regions in the future (Liu et al., 2008). Moreover, current efforts to shift to more sustainable land management may decrease future water erosion. Several policies encouraging sustainable management practices that reduce soil erosion, promote vegetation growth, enhance soil organic carbon and halt land degradation are already in place on all continents (excluding Antarctica) (Smith et al., 2016). The *World Overview of Conservation Approaches and Technologies* (WOCAT) provides an overview of sustainable measures and has been recently endorsed by the UN (Liniger et al., 2019). In addition, the UN promotes halting of land degradation and land restoration through several initiatives such as their SDGs (Keesstra et al., 2018).

In summary, to improve projections of water erosion changes, various field management and land use scenarios must be considered in addition to climate change scenarios. Future research on modelling water erosion changes can use existing global land suitability change maps to estimate land use changes due to climate change (Zabel et al., 2014). Land use change scenarios based on other factors such as population growth, policies and socio-economic changes are likely to be made easier on a smaller scale because of their complexity. Scenarios about future changes in field management may also be easier to create on a smaller scale. In exploring future scenarios for field management, it is possible to draw on existing guidelines that have been endorsed by the UN and are likely to be used more frequently in the future.

8.3.3 The effects of other land degradation processes must be considered

Next to erosion, specific threats to soil function are compaction, acidification, contamination, sealing, salinisation, waterlogging, nutrient imbalance (i.e., both nutrient deficiency and nutrient excess), and losses of soil organic carbon and of biodiversity (Montanarella et al., 2016). Similar to water erosion, the impact of other land degradation process may be low on a global scale but can be high in specific areas (Pravalie et al., 2021). Due to uneven distribution of dominant land degradation processes globally, it is important that future research addresses the impact of all land degradation processes on crops to better assess long-term agronomic trends in different global regions.

Land degradation processes other than water erosion may become more important in certain regions. For example, agricultural intensification is projected to lead to an expansion in irrigated land in developing countries, which likely does not increase water erosion as irrigated land is generally on flat or terraced land. However, other land degradation processes such as salinisation may increase as a consequent, especially on arid land (Norse et al., 2001). In addition, climate change may increase the severity of other land degradation processes through changes in soil organic matter and soil water balances due to warming and droughts (Olsson et al., 2019).

Several authors state that more policies are required to fully consider the risks associated with ongoing land degradation, or opportunities arising from restoration of degraded land (Webb et al., 2017; Pravalie et al., 2021). Soil degradation does not occur because of any lack of knowledge on how to protect soils, but a lack in policy governance (Alewell et al., 2019; Montanarella et al., 2016; Panagos et al., 2016). Additional data on global patterns of land degradation and its impacts on agriculture and the environment will help identify the most vulnerable regions. By identifying the regions most vulnerable to land degradation worldwide, as has been done with water erosion in this thesis, more knowledge of land degradation hotspots can be created to know where control measures are most urgent.

8.4 Final conclusion

Knowledge on future pathways of crop production and their environmental impacts is important to predict potential threats to human well-being and the sustainability of environmental resources. However, many relationships between biomass, soil and climate in agricultural systems are still not understood. By developing a modelling approach to explore global water erosion patterns and impacts on maize and wheat yields in response to historic climate and climate change scenarios, this thesis contributes to an improved understanding of the links between crop production and environmental change and their role in long-term agronomic trends. This thesis improves global water erosion assessments by analysing both water erosion patterns and water erosion impacts. In addition, this thesis contributes to the further development of global crop yield projections by addressing the need to integrate land degradation processes such as water erosion into large-scale and global impact assessments on climate change in the agricultural sector. As such, this research improves large-scale indicators to inform environmental and agricultural policy programs on land degradation and agricultural productivity.

EPIC-IIASA was previously considered to be a reliable tool for depicting the different productivities between global agricultural regions. This study shows it can also adequately estimate global water erosion patterns for specific crops and interactions between soil erosion and productivity. Although improvements are needed to increase the robustness of estimated water erosion rates in areas most sensitive to water erosion, the model results can illustrate potential impacts of erosion on global crop production and identify soil erosion hotspots on global cropland.

The new assessment of water erosion impacts on global maize and wheat yields illustrates the strong contrast of water erosion impacts between different global regions, which is caused by different environmental conditions and agricultural management. Maize and wheat cultivation areas most vulnerable to water erosion are concentrated in Latin America, sub-Saharan Africa and South and Southeast Asia. In addition, regions in low latitudes where maize and wheat is grown, are most likely to suffer from increased water erosion impacts in the future due to the negative impacts of climate change on both crops. The combined effects of water erosion and climate change require farmers to mitigate both stressors, as land degradation caused by water erosion can reduce the resilience of agricultural systems to climate change and, conversely, climate change can increase water erosion and thus land degradation. In contrast to potentially significant global changes in crop production induced by climate change, the severe impacts of water erosion on maize and wheat yields are likely to be concentrated in specific regions. Despite considerable uncertainties, the projections indicated that the impact of water erosion on maize and wheat production will remain small on a global scale, since the cultivation areas most affected by water erosion are currently outside the large maize and wheat production regions. The main difficulties in predicting the effects of water erosion are the uncertainty in projected changes in precipitation and future land use changes.

Simulated water erosion rates and impacts are strongly driven by land use and field management assumptions, which can only partly be narrowed down at a global scale. To improve the robustness of future global studies on water erosion patterns and impacts, more spatial data on representative management practices and higher-resolution datasets on land use patterns and topography are needed. In addition, a well-defined field-based data collection to evaluate model outputs will be critical to improve future large-scale assessments of water erosion.

This study demonstrated that an integrated biophysical modelling framework - considering plant growth, soil processes and input requirements - can provide a link between land degradation and global agricultural assessments. The modelling approach developed in this study thus provides a platform for expanding research on the impacts of soil degradation and climate change on global crop production.

Whilst maize and wheat are the most important staple crops affected by water erosion, focusing on just two crops is not sufficient to explore the threats of environmental change to future crop production. Thus, future research should focus on analysing the susceptibility and resilience of more crops to environmental change according to the impact assessment developed in this thesis. In addition, the modelling framework of this study can be used to incorporate additional climate change scenarios to capture the full spectrum of potential climate impacts on future crop yields and associated changes in water erosion. As global crop yield projections should ideally take into account all stress factors that affect crop yields, future research should also consider other land degradation processes. This study has shown that large-scale land degradation assessments can capture the regionally varying impacts on crop yields and identify priority areas for supportive management and policy interventions.

Appendix A

Chapter 4 - Methodology

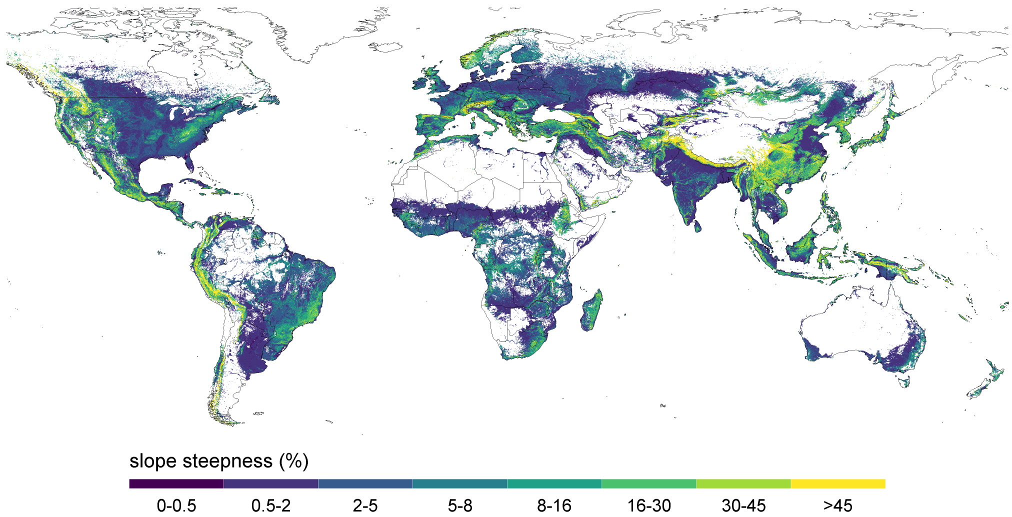

Figure A.1: Global dataset of slope classes (%) that are used to derive the slope steepness per grid cell (IIASA/FAO, 2012).

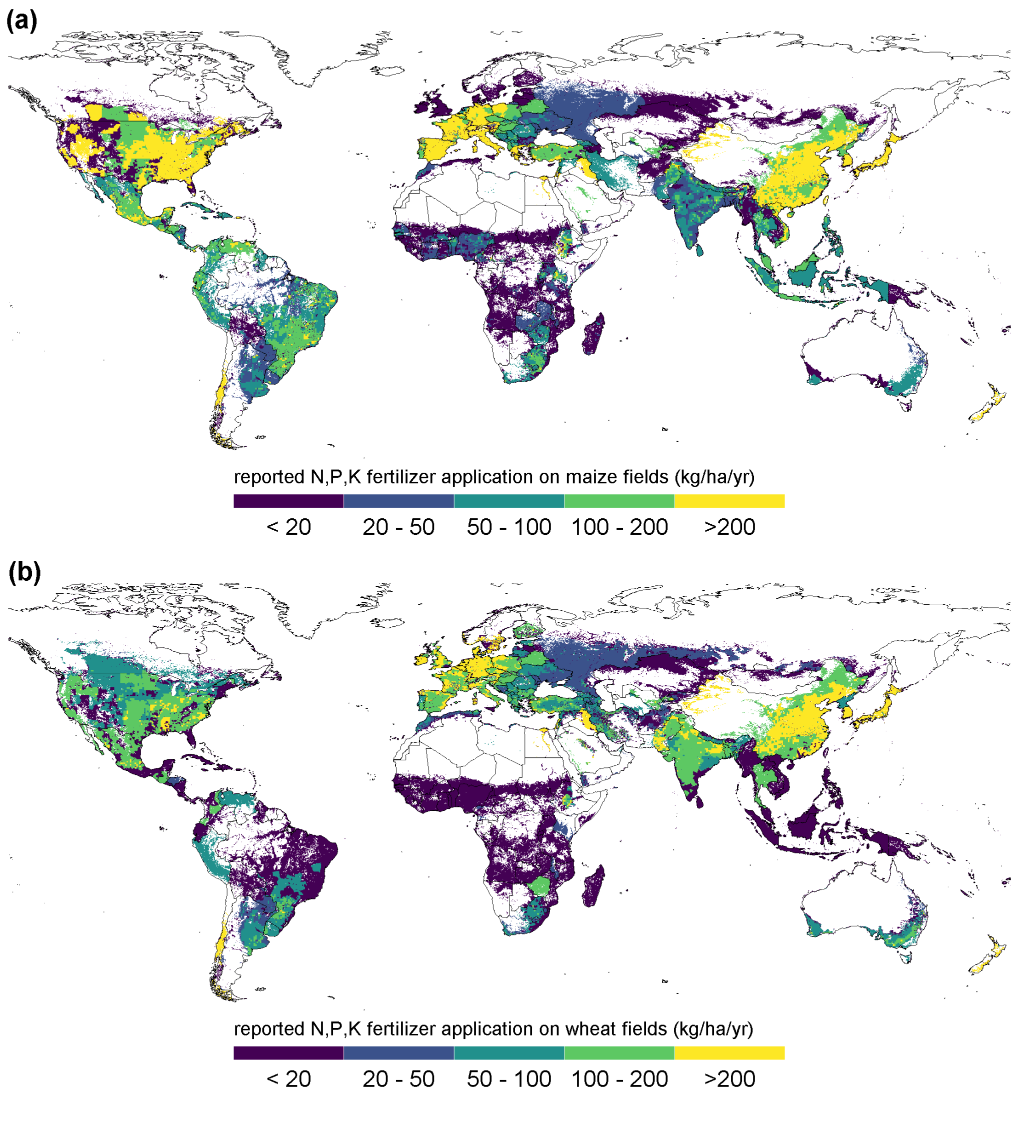

Figure A.2: Nitrogen (N), Phosphorus (P) and Potassium (K) application rates (kg ha^{-1} yr^{-1}) for maize (a) and wheat (b) on global cropland (Mueller et al., 2012).

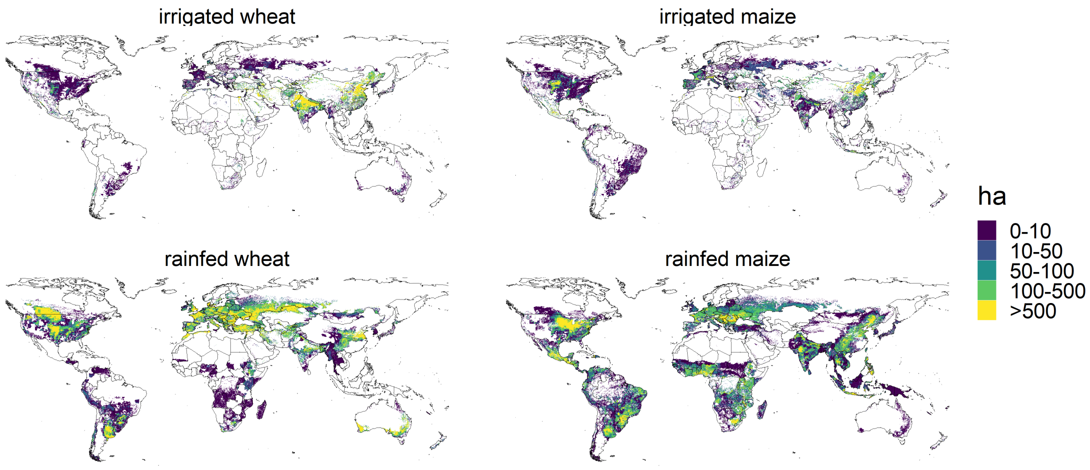

Figure A.3: Grid cells with irrigated and rainfed wheat and maize cultivation around the year 2000 (Portmann et al., 2010).

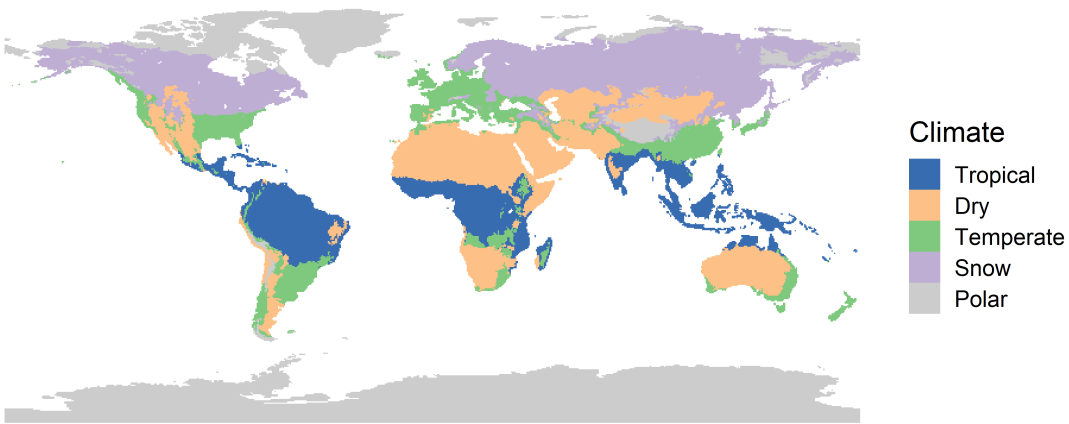

Figure A.4: Main climate zones based on the updated Koeppen-Geiger climate classification (Peel et al., 2007)

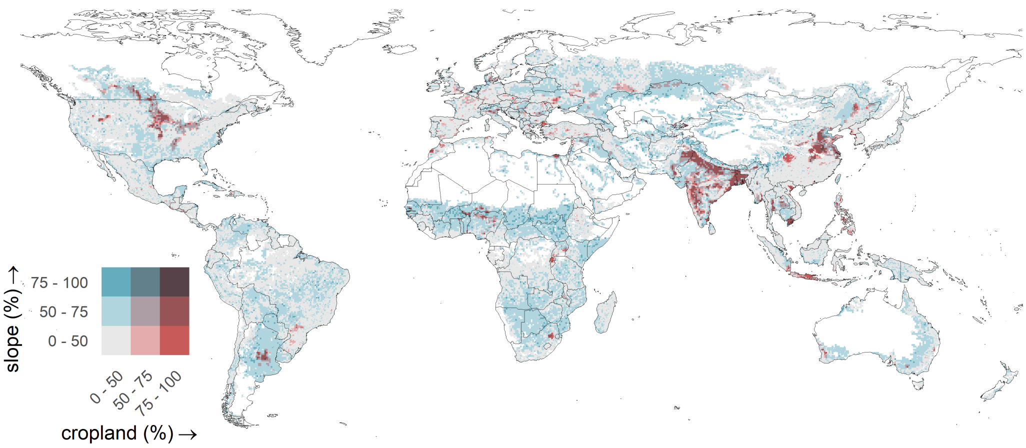

Figure A.5: Relative area covered by the dominant slope and cropland per grid cell.

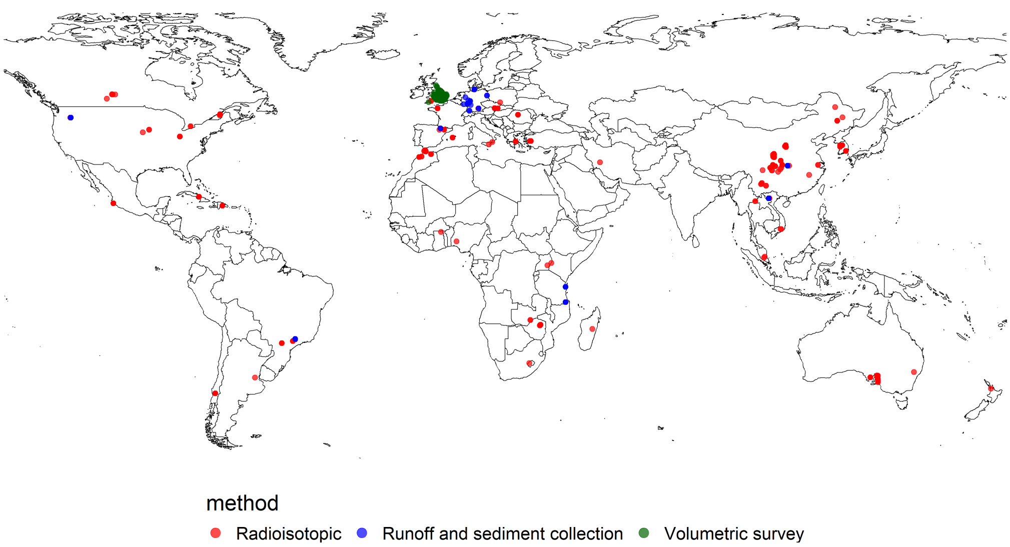

Figure A.6: Locations of water erosion field data from cropland where coordinates were recorded (n=554).

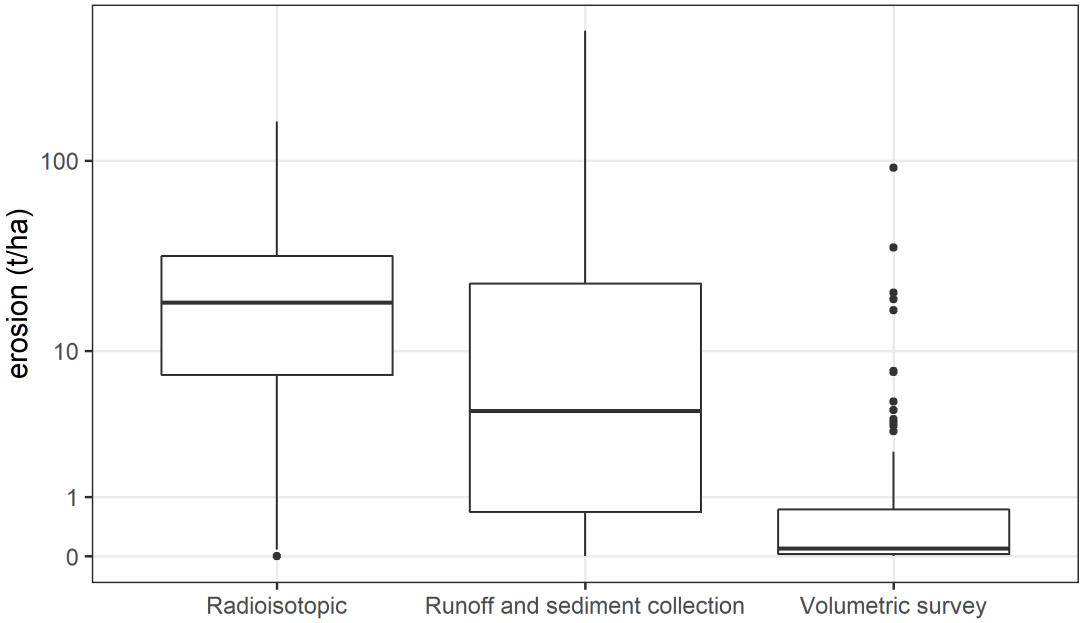

Figure A.7: Distribution of erosion values (t ha^{-1}) measured in agricultural fields using ^{137}CS method (n = 315, Mean = 24 t ha^{-1}; Median = 18 t ha^{-1}), runoff and sediment collection (n = 188, Mean = 21 t ha^{-1}; Median = 4 t ha^{-1}) and volumetric surveys (n = 103, Mean = 2 t ha^{-1}; Median = 0.1 t ha^{-1}).

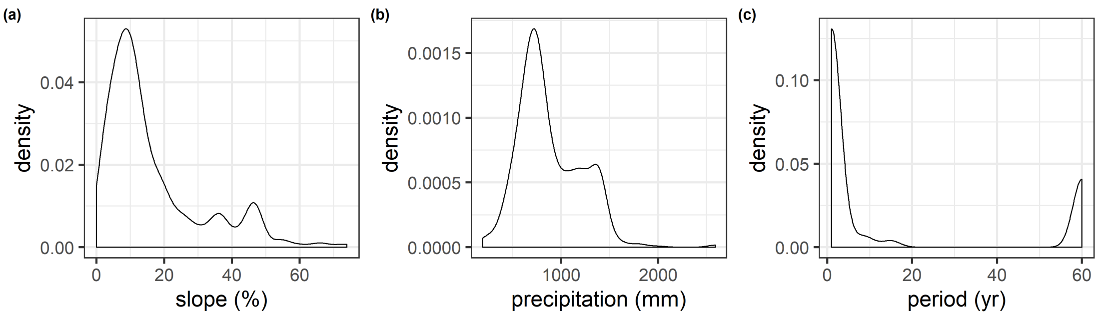

Figure A.8: (a) Distribution of slope steepness (%) for measured erosion values (n = 606; Mean = 16%; Median = 11%). (b) Distribution of annual precipitation (mm) for measured erosion values (n = 606; Mean = 879 mm; Median = 774 mm). (c) Distribution of recorded measurement periods for soil loss experiments excluding radioisotopic methods (n = 95; Mean = 15 a; Median = 1 a).

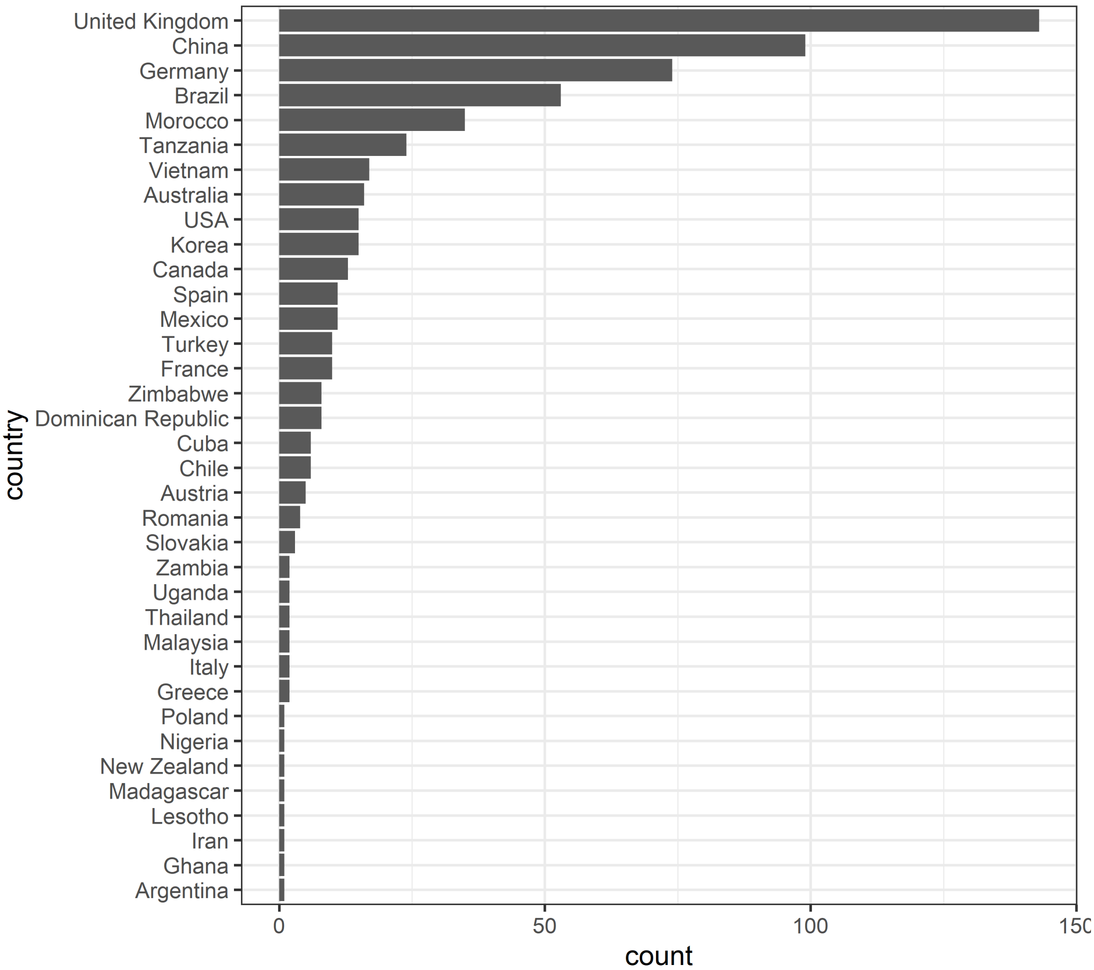

Figure A.9: Number of measured water erosion records (n=606) per country (n=36).

Table A.1: Input parameters directly connected to the water erosion equations in EPIC. Range of discrete values or values used to define the triangular distribution to generate random values for each parameter for the sensitivity analysis.

EPIC Parameter	Description	Distribution	Range
CHL	Channel length	Triangular	0.2; 0.8; 1.3
CHN	Manning N channel	Triangular	0.02; 0.1; 0.3
CHS	Channel slope	Triangular	0; 0.05; 0.3
EMX	Mixing efficiency	Triangular	0.2; 0.5; 0.8
HSG	Soil hydrologic group	Discrete	1; 2; 3; 4
LUN	Land use number	Discrete	1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13
OC	Organic carbon concentration	Triangular	0.001; 0.02; 0.1
OPV5	Plant population at planting	Triangular	50; 150; 200
ORHI	Crop residues left after harvest	Discrete	0; 0.25; 0.5; 0.75; 1
P23	Coefficient in RUSLE C factor equation	Triangular	0.3; 0.5; 1.5
P26	Coefficient in RUSLE C factor equation	Triangular	0.01; 0.05; 0.2
P42	Curve number (CN) coefficient	Triangular	0.5; 1; 1.5
P65	CN coefficient	Triangular	0.05; 0.25; 0.5
P73	CN coefficient	Triangular	1;1.5;2
P75	CN coefficient	Triangular	0; 0.05; 0.3
PRCP	Daily rainfall	Triangular	0.5; 1; 1.5
RIN	Ridge interval	Discrete	0.2; 0.4; 0.6; 0.8
ROK	Coarse fragment content	Triangular	0; 0.05; 0.5
RR	Random surface roughness	Triangular	10; 20; 50
S18	Soil temperature effect	Triangular	0.97; 1; 1.02
S23	Fraction plant ground cover	Triangular	0.5; 1; 1.5
S301	CN2 as % of the volume between FC and WP	Triangular	10; 20; 70
S302	CN3 as % of the volume between saturation and FC	Triangular	10; 20; 70
SAND	Sand content	Triangular	0.1; 0.5; 0.8
SILT	Silt content	Triangular	0.1; 0.3; 0.8
SLP	Slope steepness	Triangular	0; 0.05; 0.3
SLPL	Slope length	Triangular	100; 120; 200
SN	Surface N channel	Triangular	0.02; 0.1; 0.3
TMX	Air temperature max	Triangular	-4; 0; 4
WSX	Watershed area	Triangular	10; 50; 200

Appendix B

Chapter 5 - Uncertainties, sensitivities and robustness of simulated water erosion with EPIC-IIASA

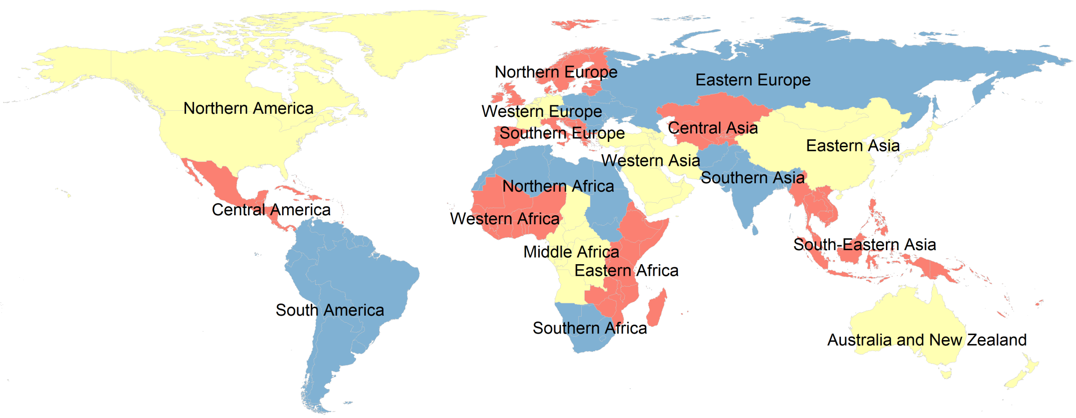

Figure B.1: World regions classified according to the United Nations geo-schema (UN, 1999) with minor modifications: Melanesia has been added to Southeast Asia and the Caribbean has been added to Central America.

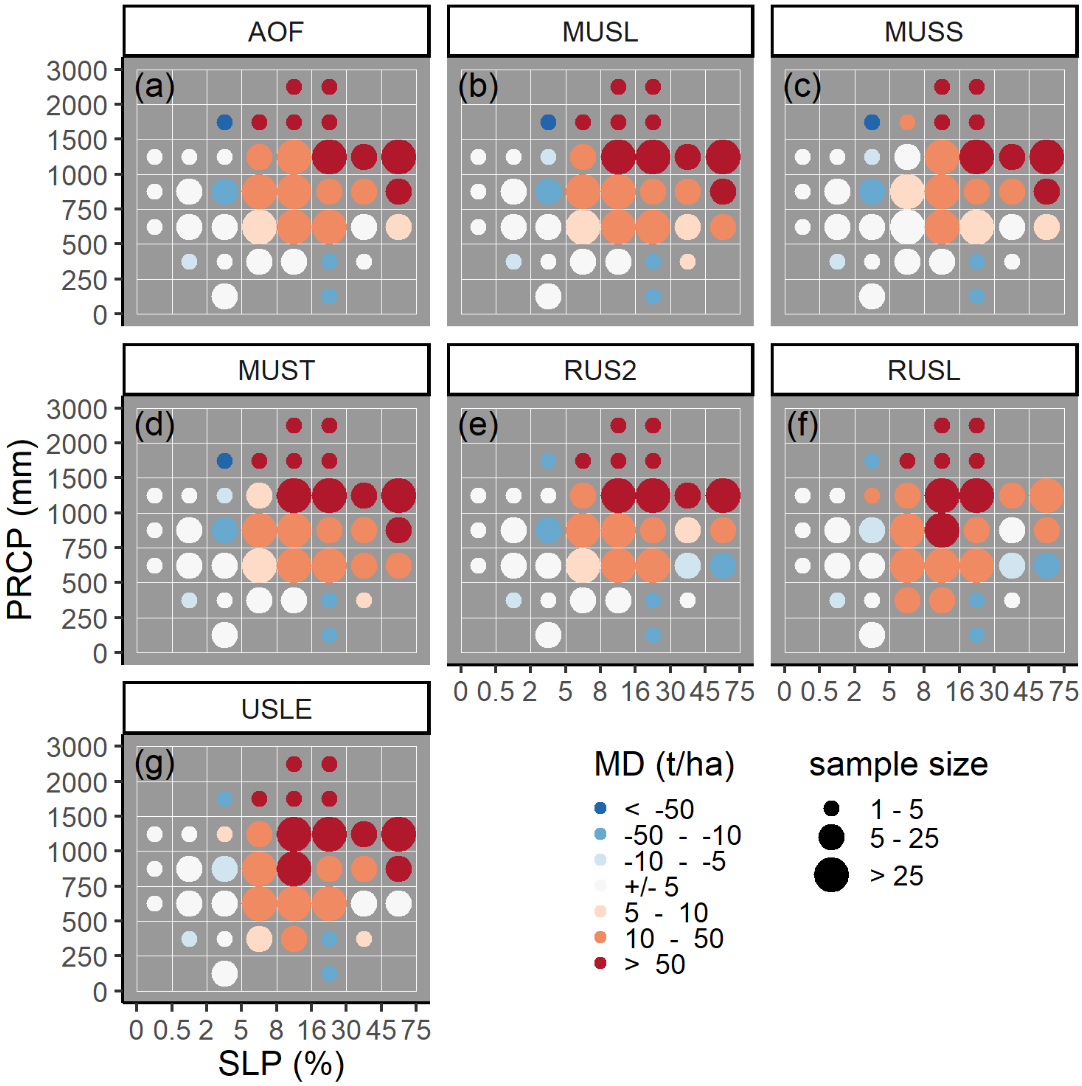

Figure B.2: Median deviation (MD) in t ha^{-1} between measured and simulated water erosion using the baseline scenario with different water erosion equations. Measured and simulated medians were calculated for different slope and precipitation classes.

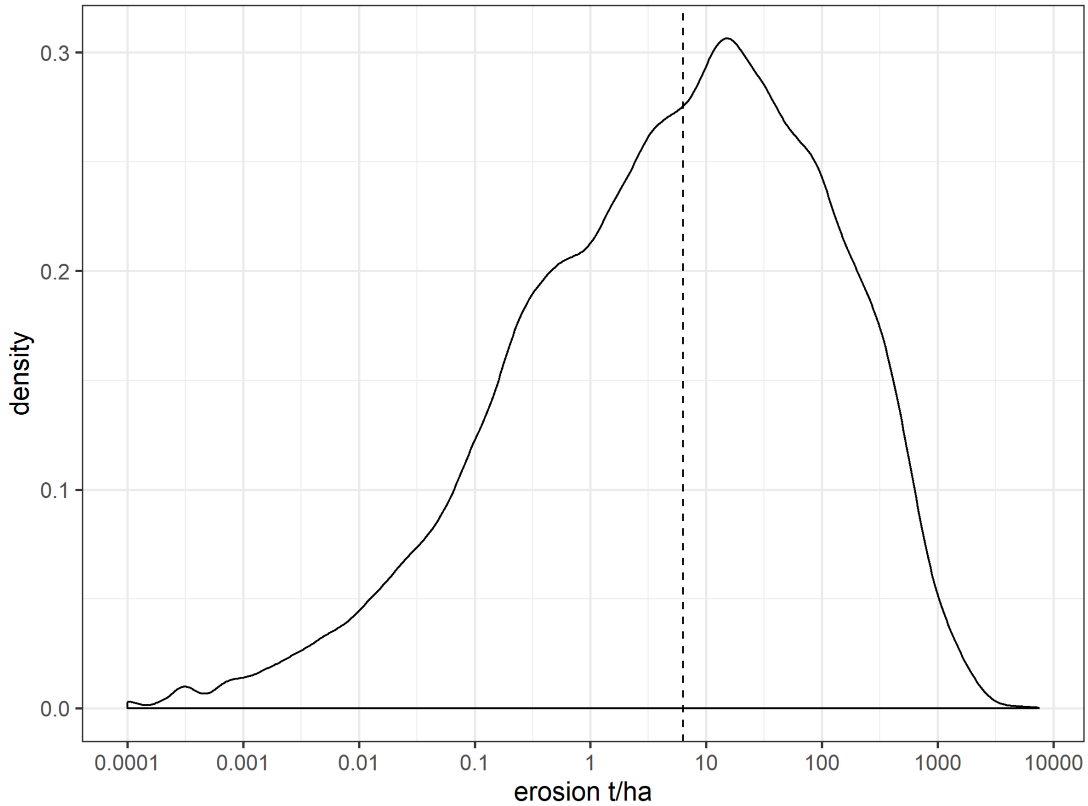

Figure B.3: Distribution of average water erosion values from 1980 – 2010 simulated with the baseline scenario and weighted for each grid cell. The dashed vertical line illustrates the median of the distribution, which represents global median water erosion of 6 t ha^{-1} a^{-1}. Average water erosion at each grid and the global average water erosion of 19 t ha^{-1} a^{-1} has been calculated as a weighted average based on the distribution of irrigated and rainfed maize and wheat acreage (Portmann et al., 2010).

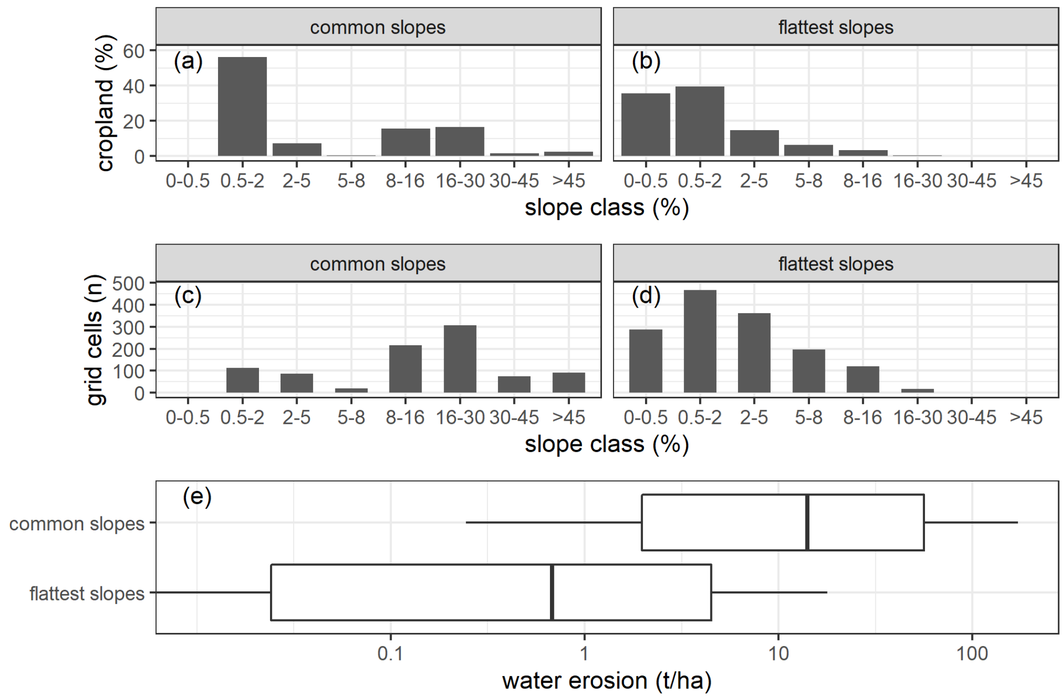

Figure B.4: Comparison of slope inputs and simulated water erosion outputs between the cropland distribution scenario using the most common slopes and the cropland distribution scenario using the flattest terrain available in Italy. (a, b) distribution of the cropland share (Portmann et al., 2010) per slope class. (c, d) distribution of grid cells per slope class. (e) Simulated water erosion for Italy using both cropland distribution scenarios. Midlines visualise median values, boxes include values from the 25th to the 75th percentiles and whiskers bracket values between the 10th and the 90th percentiles.

Appendix C

Chapter 6 - The impact of water erosion on global maize and wheat yields

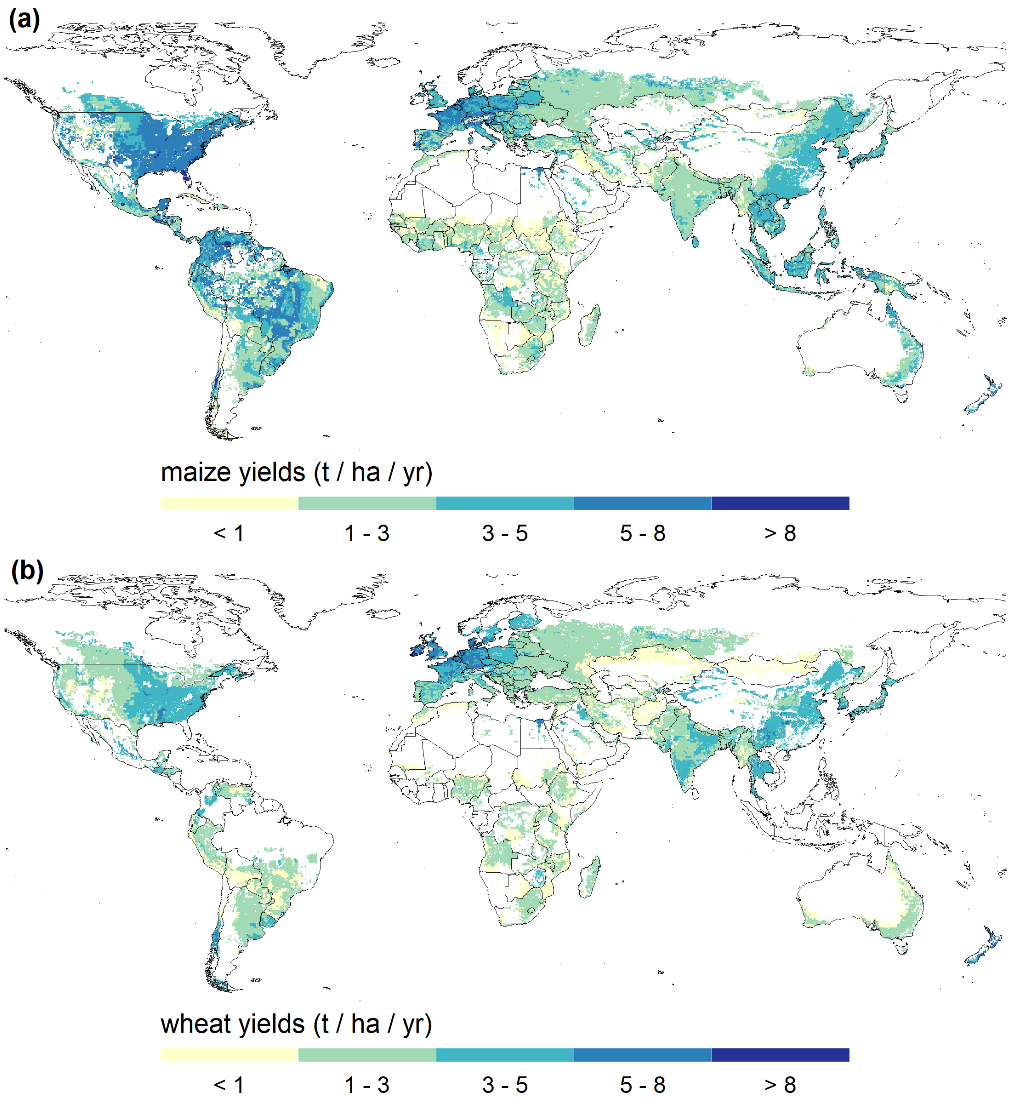

Figure C.1: Maize (a) and wheat (b) yields (t ha^{-1} yr^{-1}) for each grid cell simulated with the baseline scenario with and without the impact of water erosion, averaged for the years 2001-2010 and weighted for irrigated and rainfed areas.

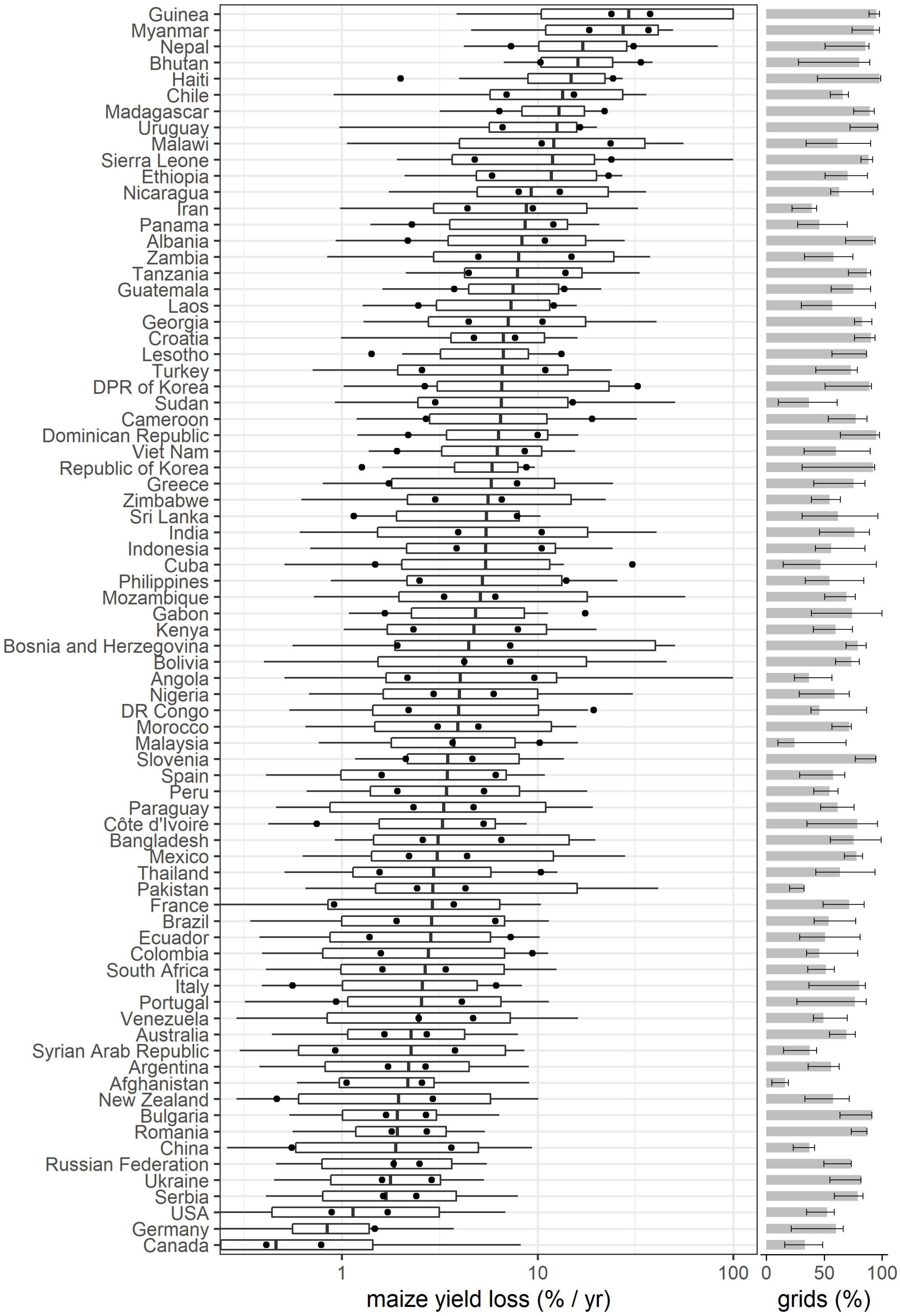

Figure C.2: Maize yield losses due to water erosion (% yr^{-1}) for all countries with significant crop yield losses due to water erosion. Countries contributing less than 0.01% to global maize production are excluded. The countries are ranked by median crop yield losses. Boxes include values from the 25^{th} to the 75^{th} percentiles and whiskers bracket values between the 10^{th} and the 90^{th} percentiles. The points illustrate minimum and maximum median crop yield losses generated from all field management scenarios. All values are converted to logarithmic scale. Countries without significant differences between average yields simulated with and without water erosion are excluded (T-Test, p>0.05). Grey barplots illustrate the share of grid cells affected by erosion impacts in each country, and errorbars indicate the variability of affected grid cells due to all management scenarios.

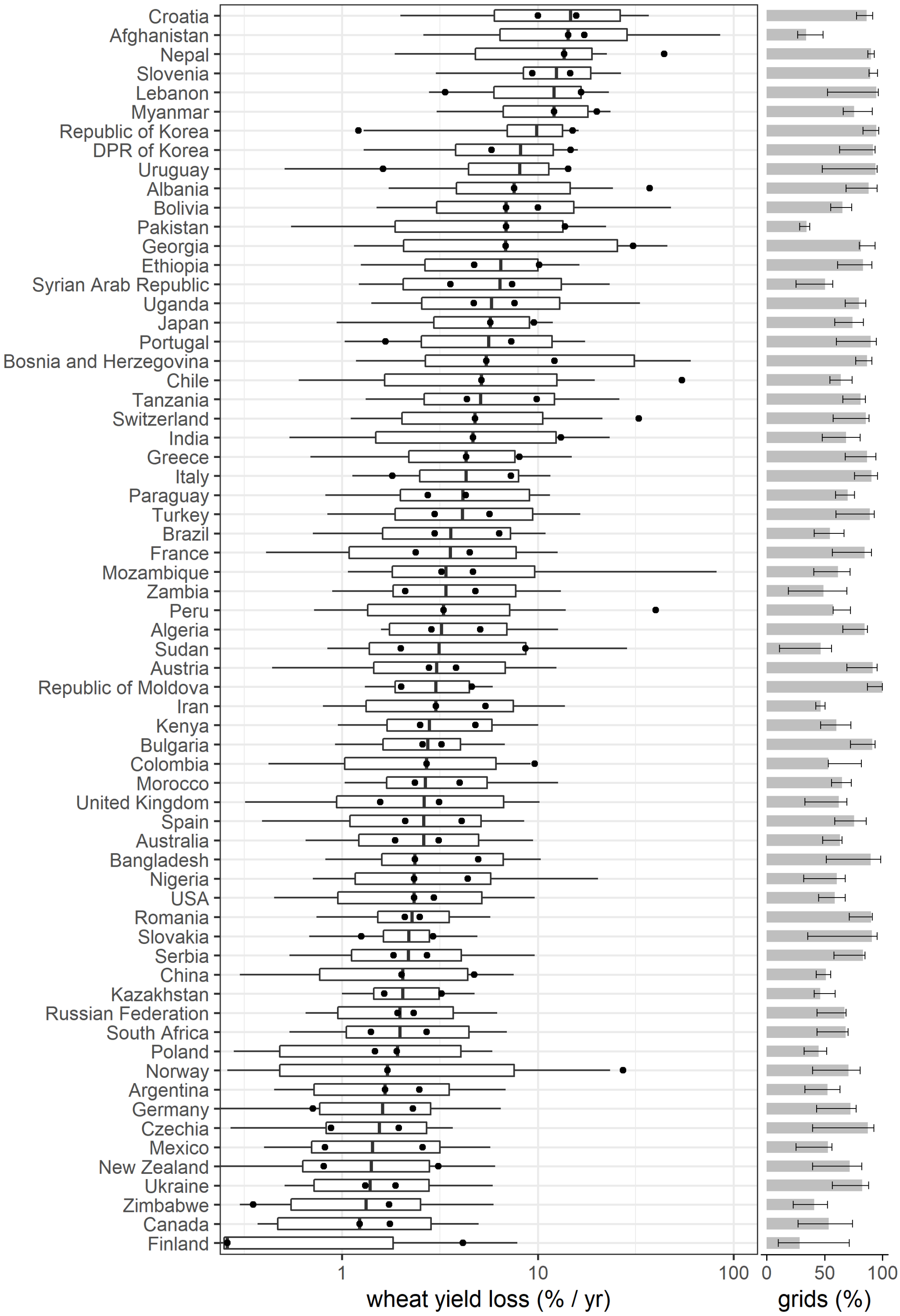

Figure C.3: Wheat yield losses due to water erosion (% yr^{-1}) for all countries with significant crop yield losses due to water erosion. Countries contributing less than 0.01% to global maize production are excluded. The countries are ranked by median crop yield losses. Boxes include values from the 25^{th} to the 75^{th} percentiles and whiskers bracket values between the 10^{th} and the 90^{th} percentiles. The points illustrate minimum and maximum median crop yield losses generated from all field management scenarios. All values are converted to logarithmic scale. Countries without significant differences between average yields simulated with and without water erosion are excluded (T-Test, p>0.05). Grey barplots illustrate the share of grid cells affected by erosion impacts in each country, and errorbars indicate the variability of affected grid cells due to all management scenarios.

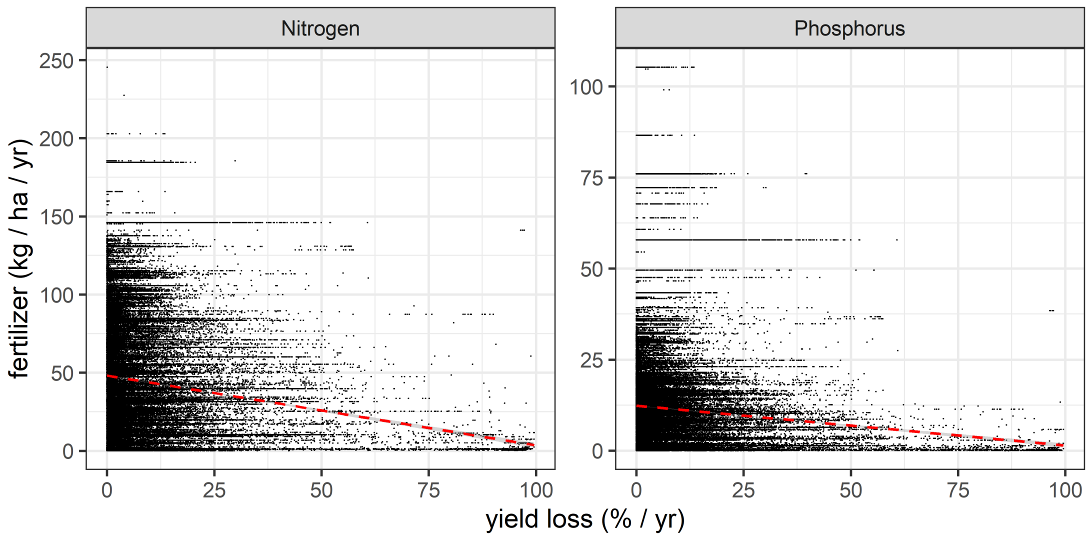

Figure C.4: Yield loss due to water erosion plotted against Nitrogen and Phosphorus fertiliser use per grid cell. The fertiliser application rates are taken from (Mueller et al., 2012), which have been used to prepare the model inputs. The linear relationship between crop yield loss and fertiliser application rates is illustrated by the dashed regression line.

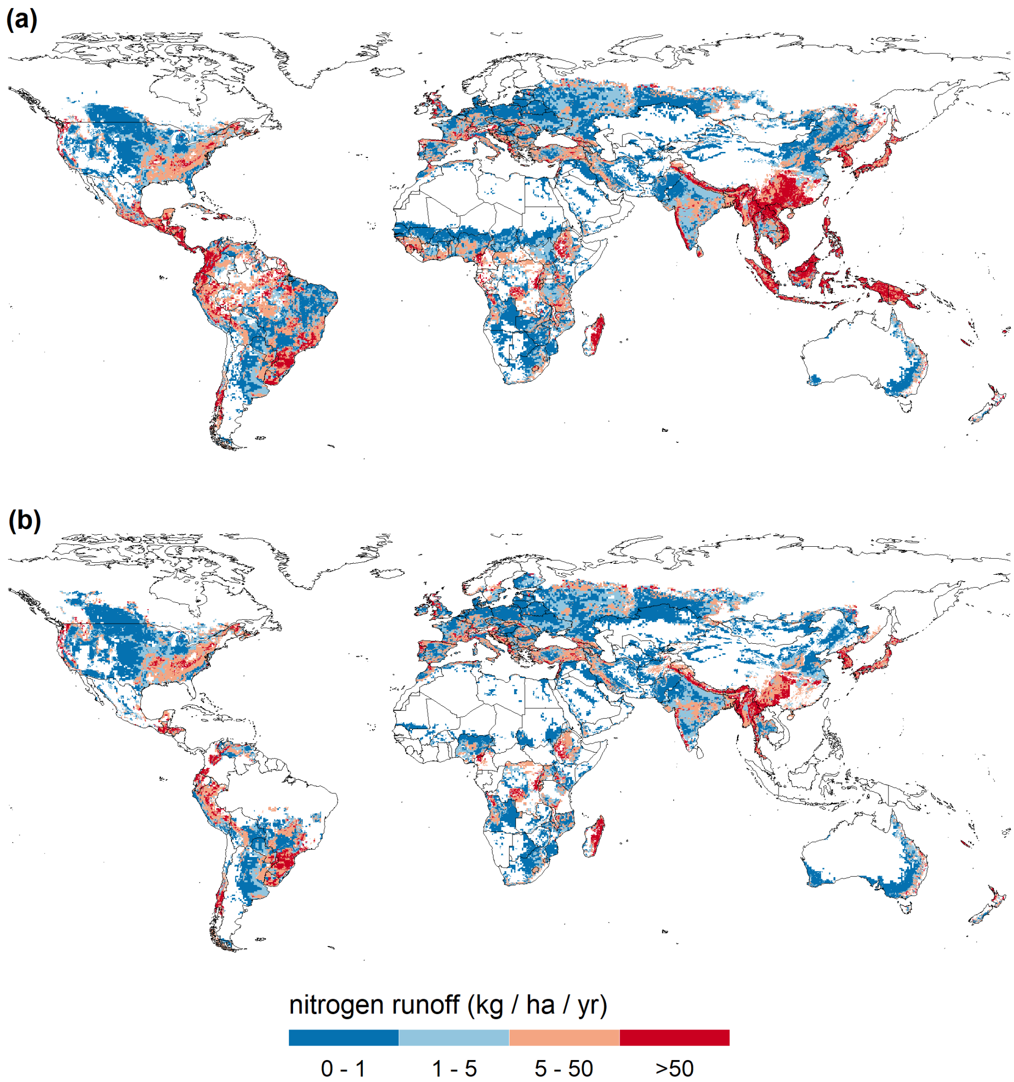

Figure C.5: Soil organic nitrogen loss with sediment runoff from the topsoil layer (kg ha^{-1} yr^{-1}) simulated for each grid cell in maize fields (a) and wheat fields (b) averaged for management scenarios and the simulation period 1980-2010 and weighted for irrigated and rainfed areas.

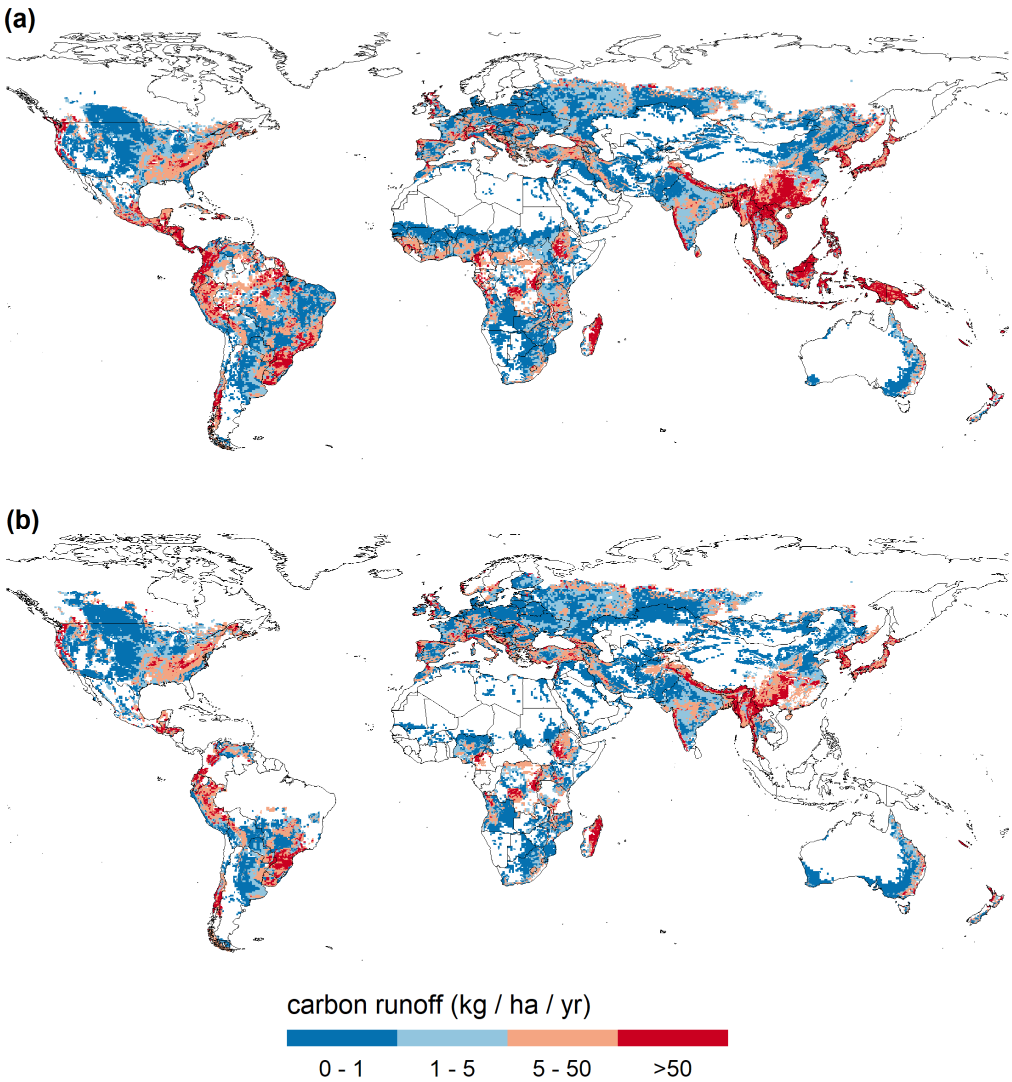

Figure C.6: Soil organic carbon loss with sediment runoff from the topsoil layer (kg ha^{-1} yr^{-1}) simulated for each grid cell in maize fields (a) and wheat fields (b) averaged for management scenarios and the simulation period 1980-2010 and weighted for irrigated and rainfed areas.

Appendix D

Chapter 7 - The combined effects of climate change and water erosion on global maize and wheat yields

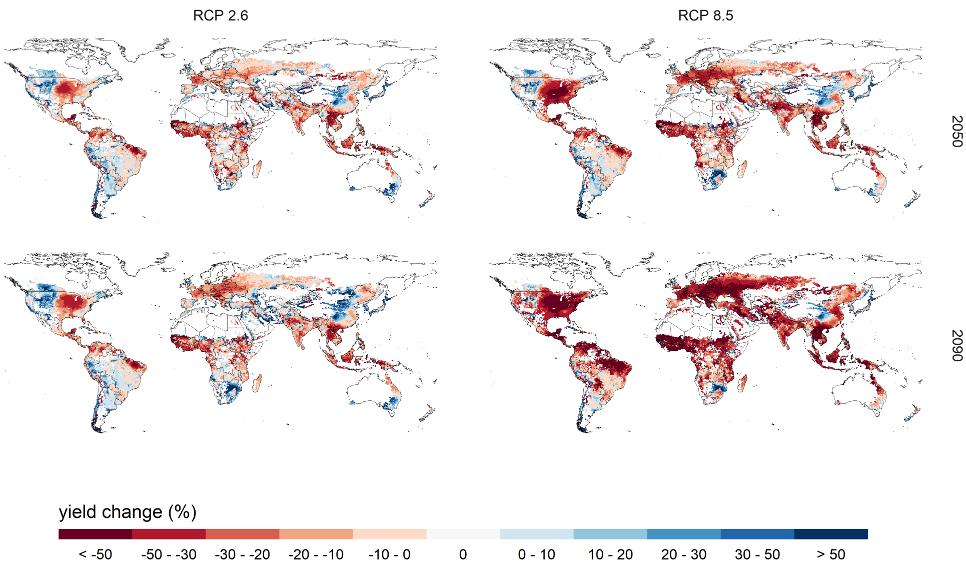

Figure D.1: Relative changes in mean maize yields for the years 2050-2059 and 2090-2099 simulated with RCP 2.6 and RCP 8.5 compared to mean maize yields of the years 1980-2010 simulated with the AGMERRA climate data.

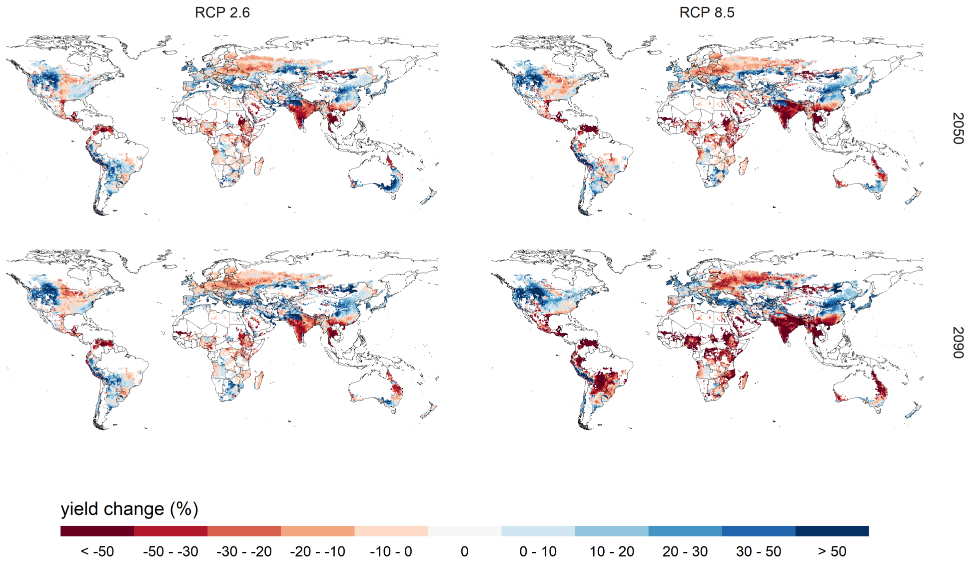

Figure D.2: Relative changes in mean wheat yields for the years 2050-2059 and 2090-2099 simulated with RCP 2.6 and RCP 8.5 compared to mean wheat yields of the years 1980-2010 simulated with the AGMERRA climate data.

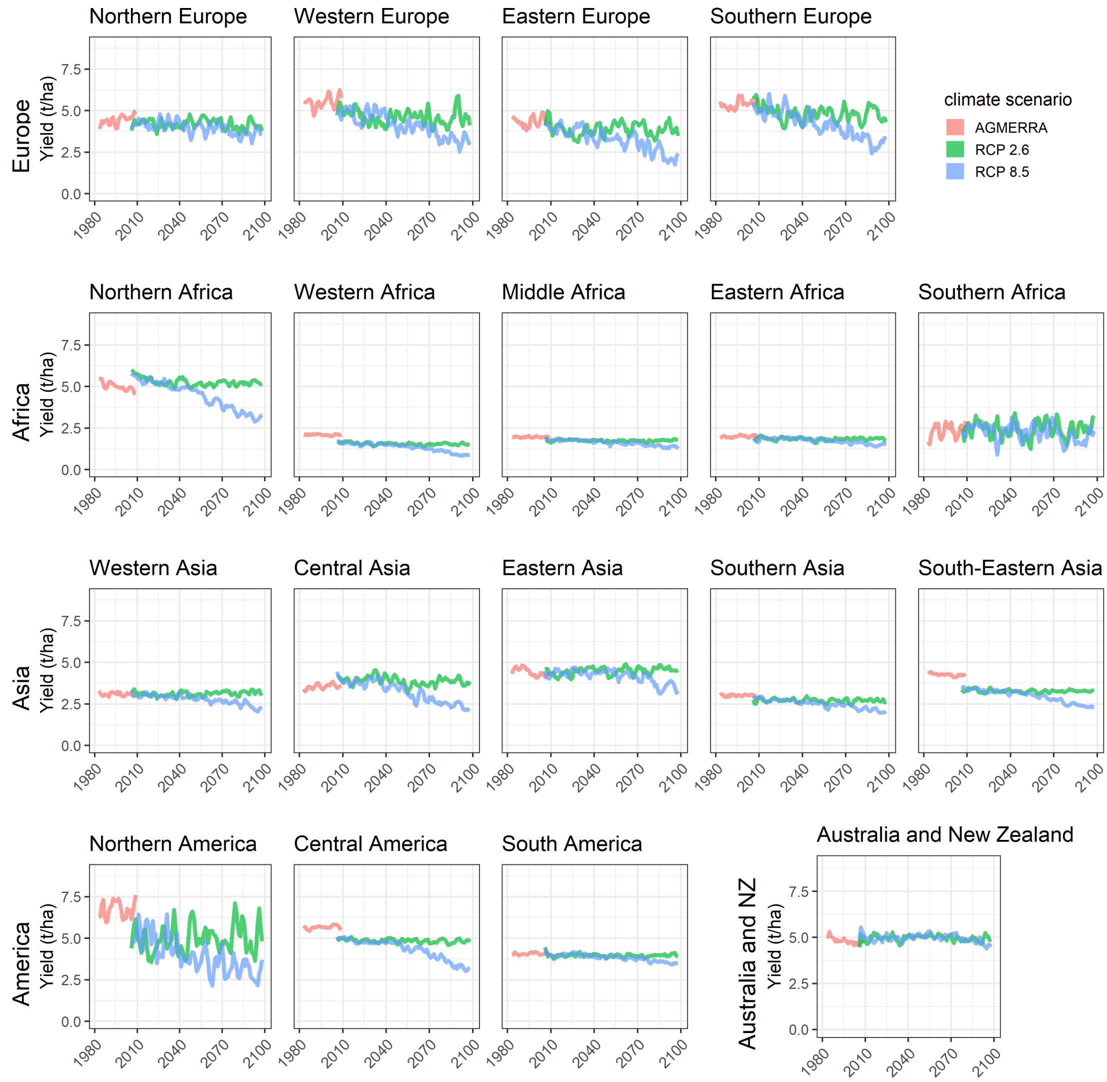

Figure D.3: Regional trends in maize yields 1980 - 2099 expressed as the three-year rolling mean based on annual average maize yields simulated with the AGMERRA climate data (1980-2010) and the RCP 2.6 and RCP 8.5 (2005-2099). Annual average maize yields are weighted with the rainfed and irrigated area of the respective region.

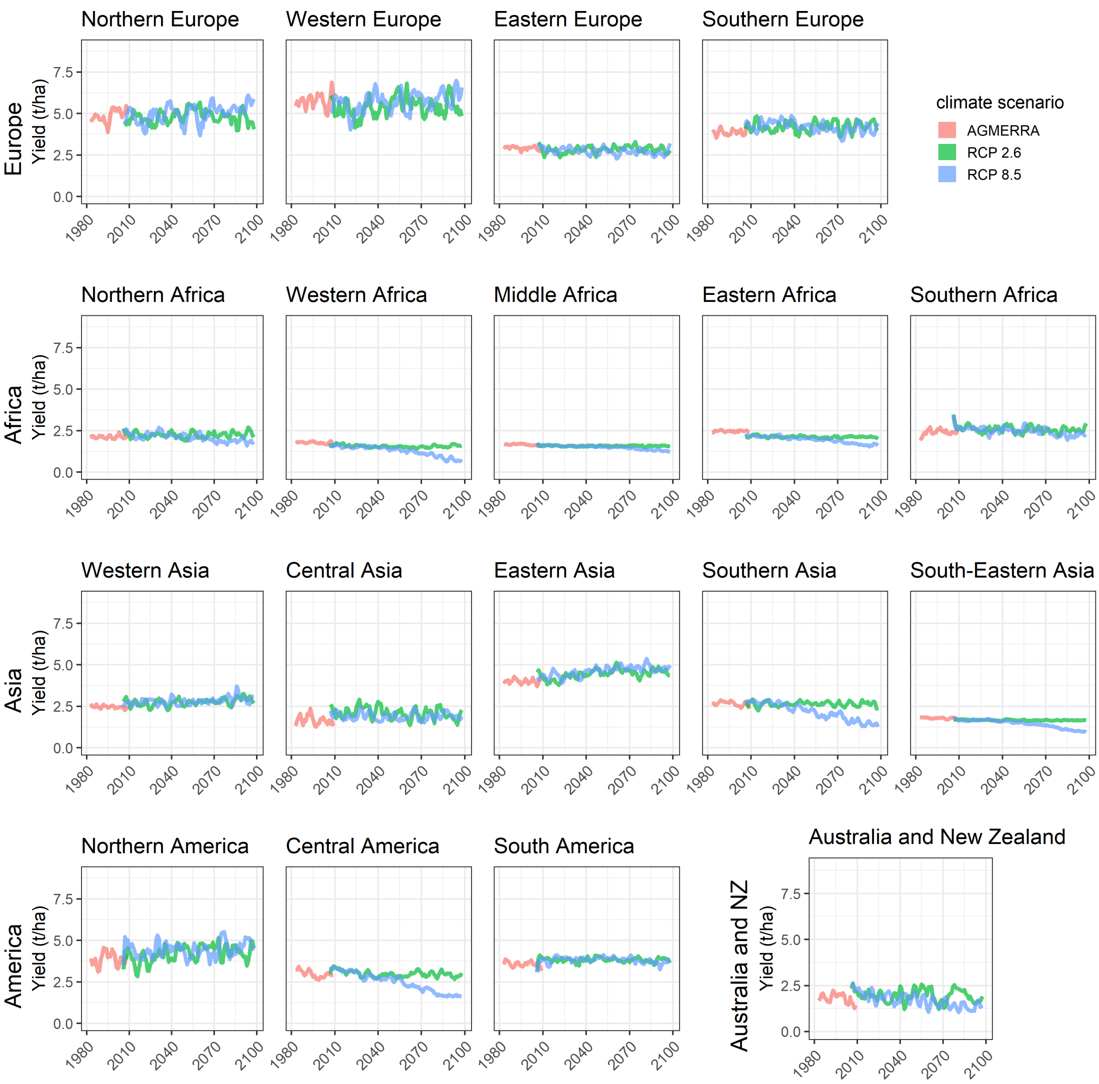

Figure D.4: Regional trends in wheat yields 1980 - 2099 expressed as the three-year rolling mean based on annual average maize yields simulated with the AGMERRA climate data (1980-2010) and the RCP 2.6 and RCP 8.5 (2005-2099). Annual average wheat yields are weighted with the rainfed and irrigated area of the respective region.

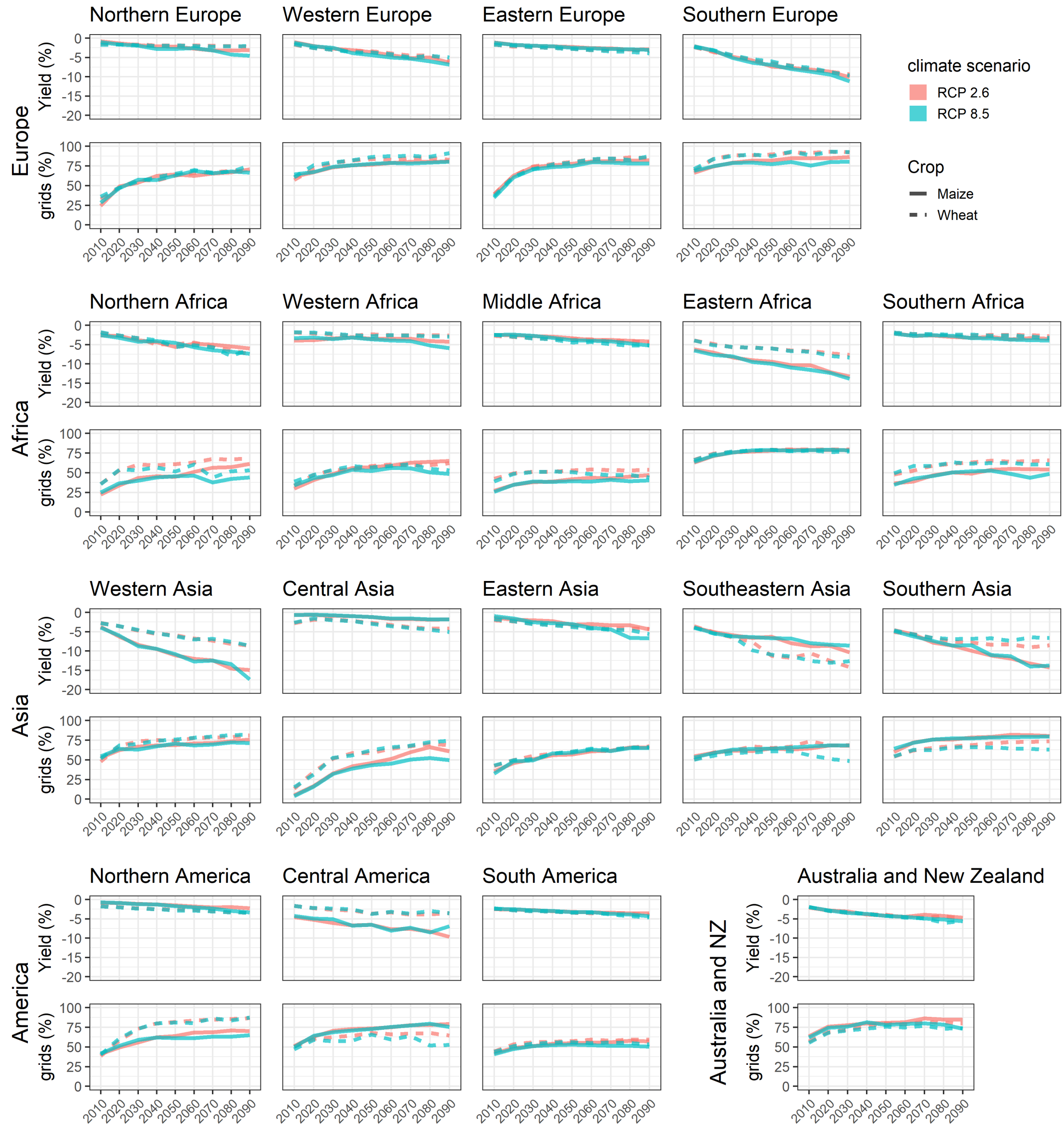

Figure D.5: Regional trends in the relative decrease in maize and wheat yields due to water erosion, as well as share of grid cells where water erosion reduces crop yields for 2010-2099 simulated with RCP 2.6 and RCP 8.5.

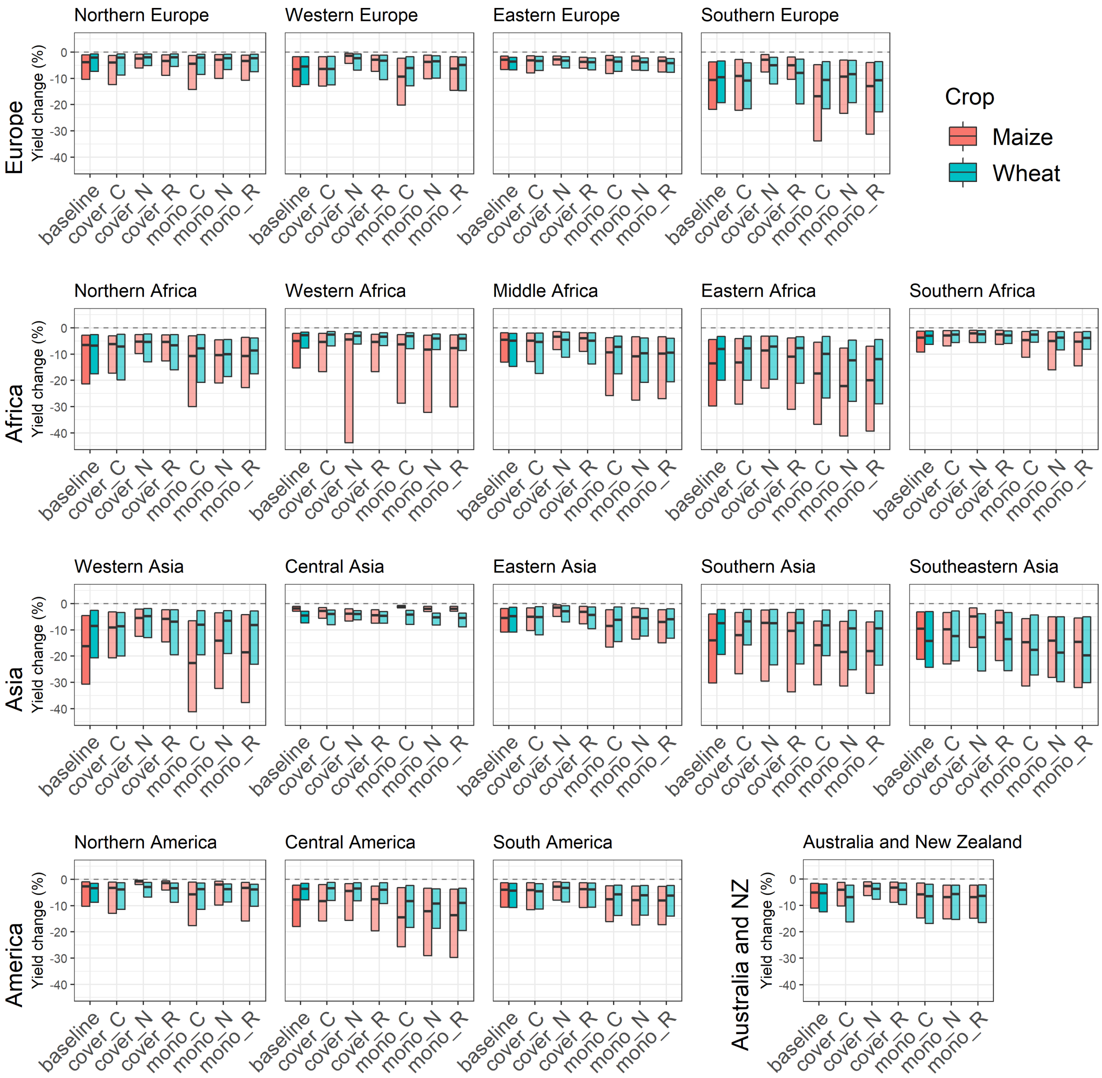

Figure D.6: Maize and wheat yield reduction due to water erosion for 2090-2099 simulated with different field management scenarios per world region. The boxes represent median values and 25th and 75th percentiles. Each box per region represents a different field management scenario, including the baseline scenario and all combinations with the cover crop (cover, mono) and the tillage management scenarios (conventional (C), reduced (R), no-tillage (N)).

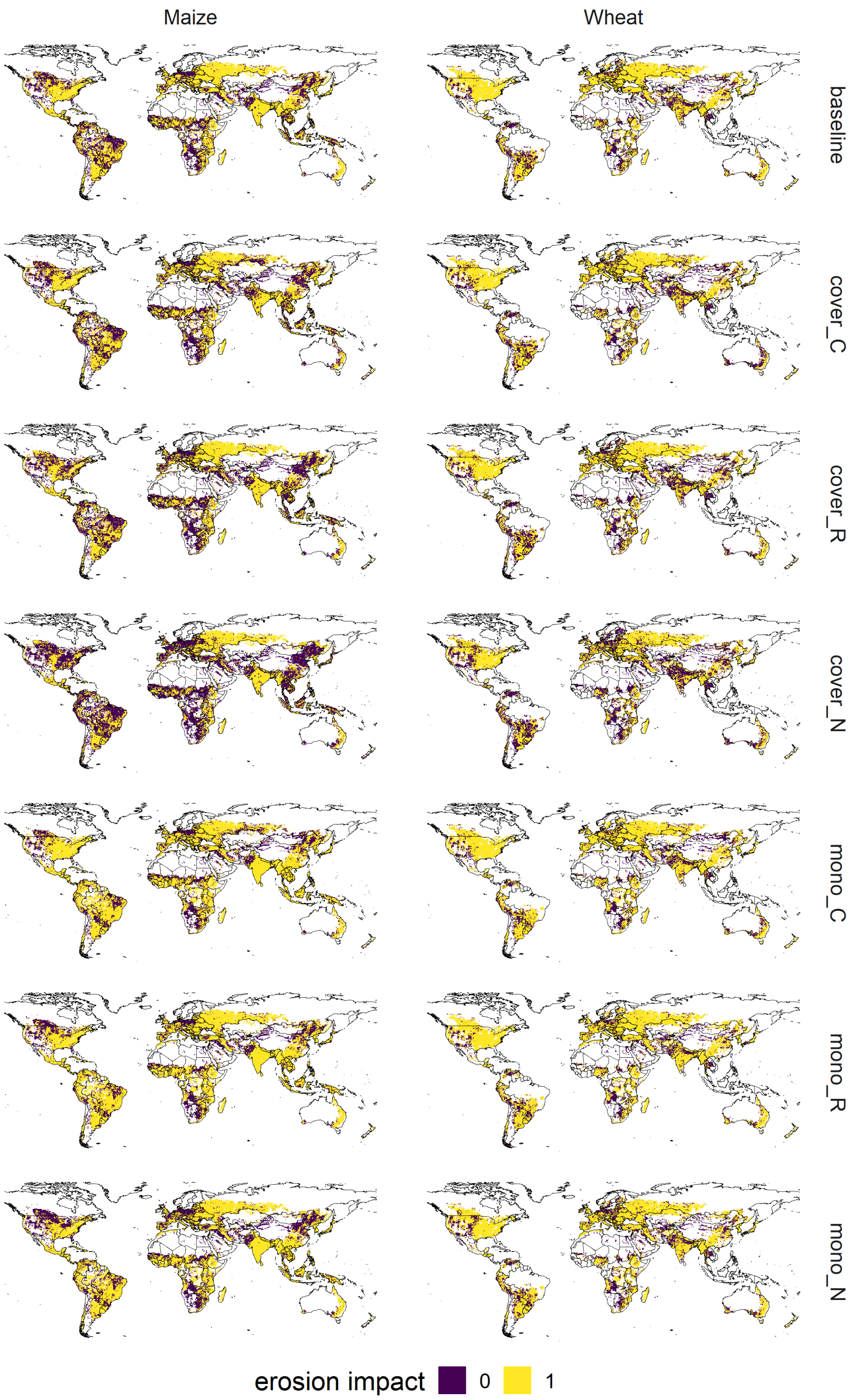

Figure D.7: Grid cells where maize and wheat yields are reduced due to water erosion per field management scenario for the years 2090-2099. The field management scenarios include the baseline scenario and all combinations with the cover crop (cover, mono) and the tillage management scenarios (conventional (C), reduced (R), no-tillage (N)).

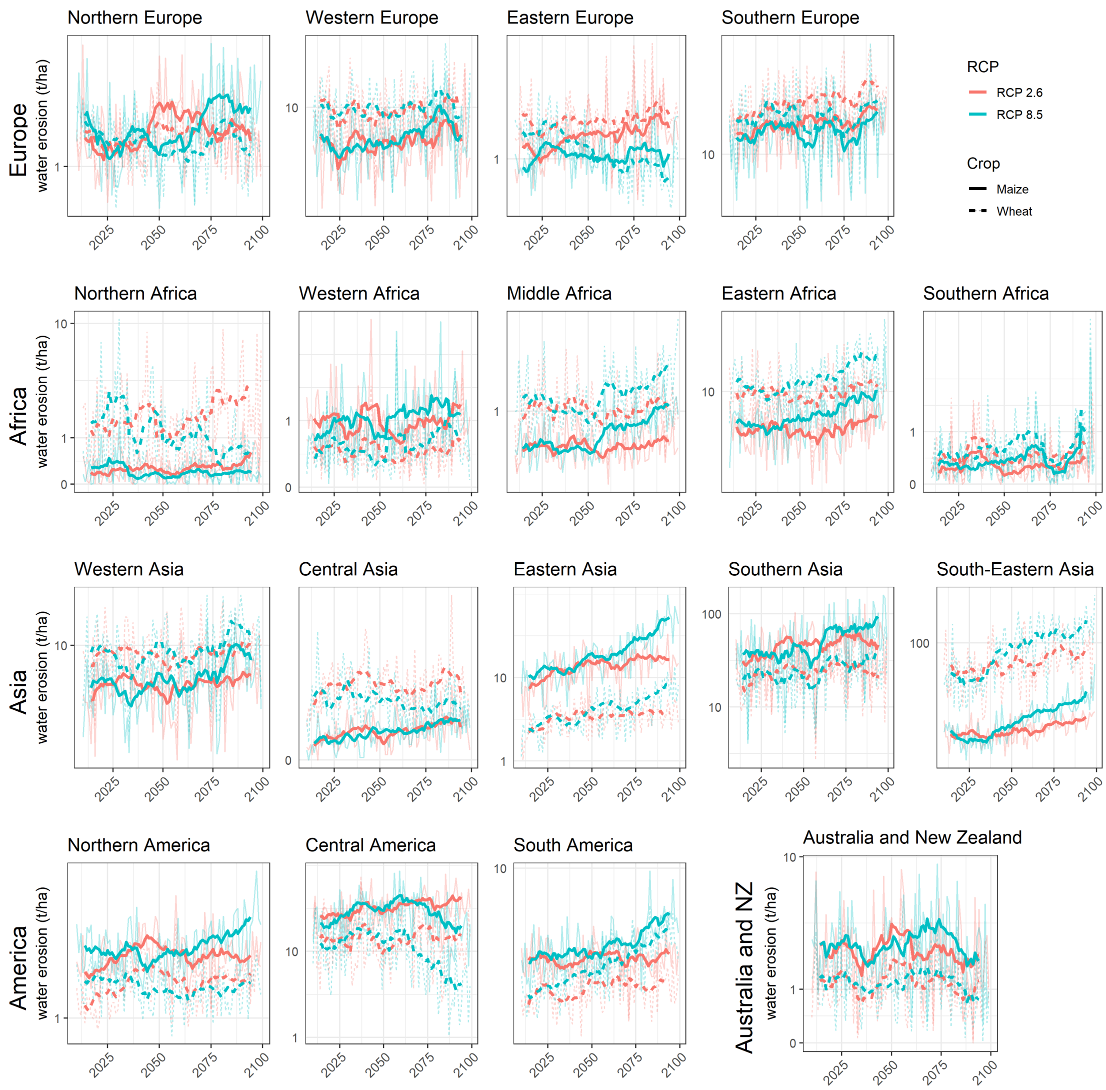

Figure D.8: Regional trends in water erosion rates in maize and wheat fields between 2010-2099 simulated with the RCP 2.6 and RCP 8.5. Thick lines represent ten-year rolling means. Thin lines represent annual average. All values are log-transformed.

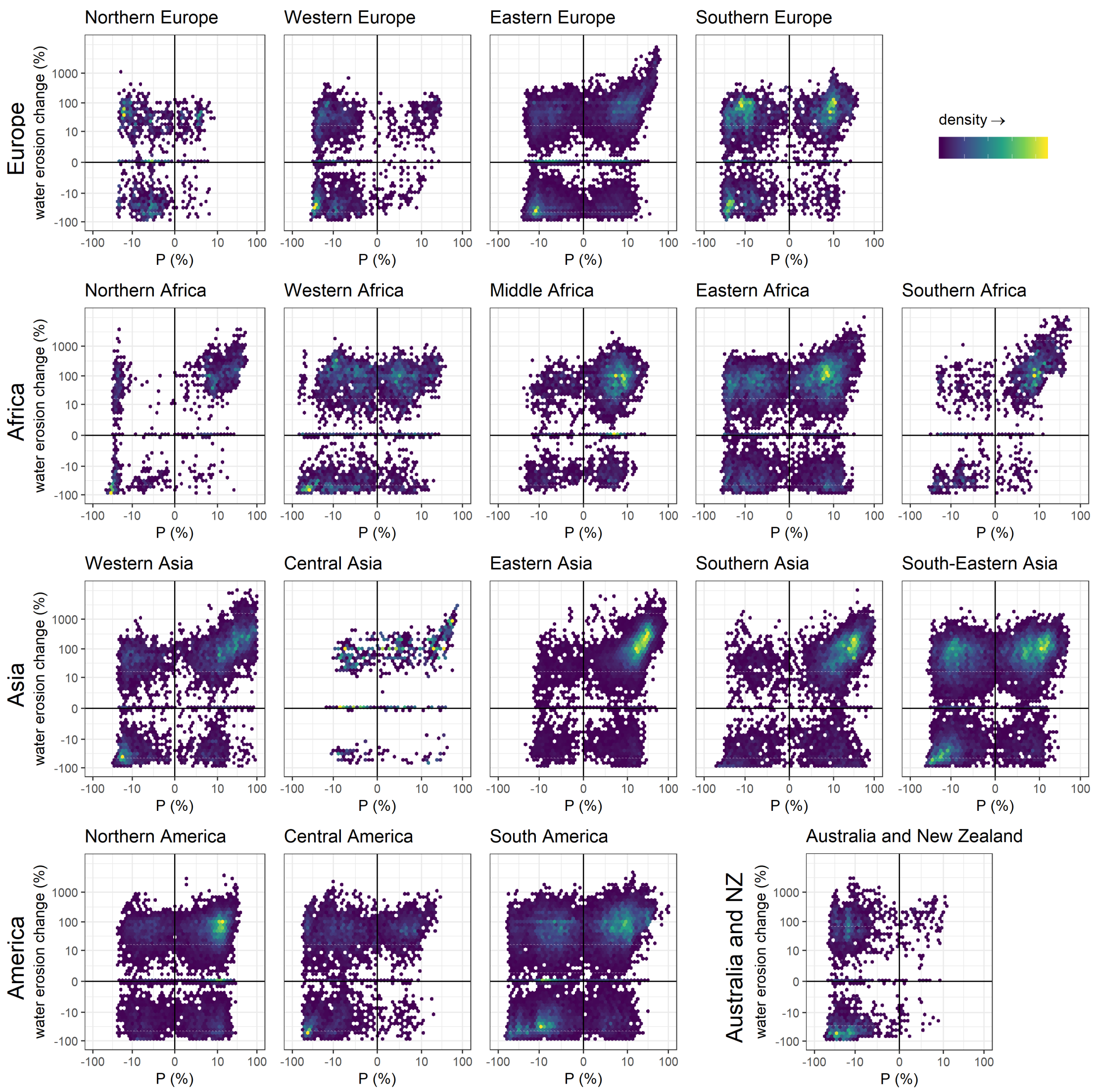

Figure D.9: Regional changes in average precipitation (%) plotted against regional changes in average water erosion (%) between the decade 2010-2019 and the decade 2090-2099 in maize fields. Both datasets are log-transformed.

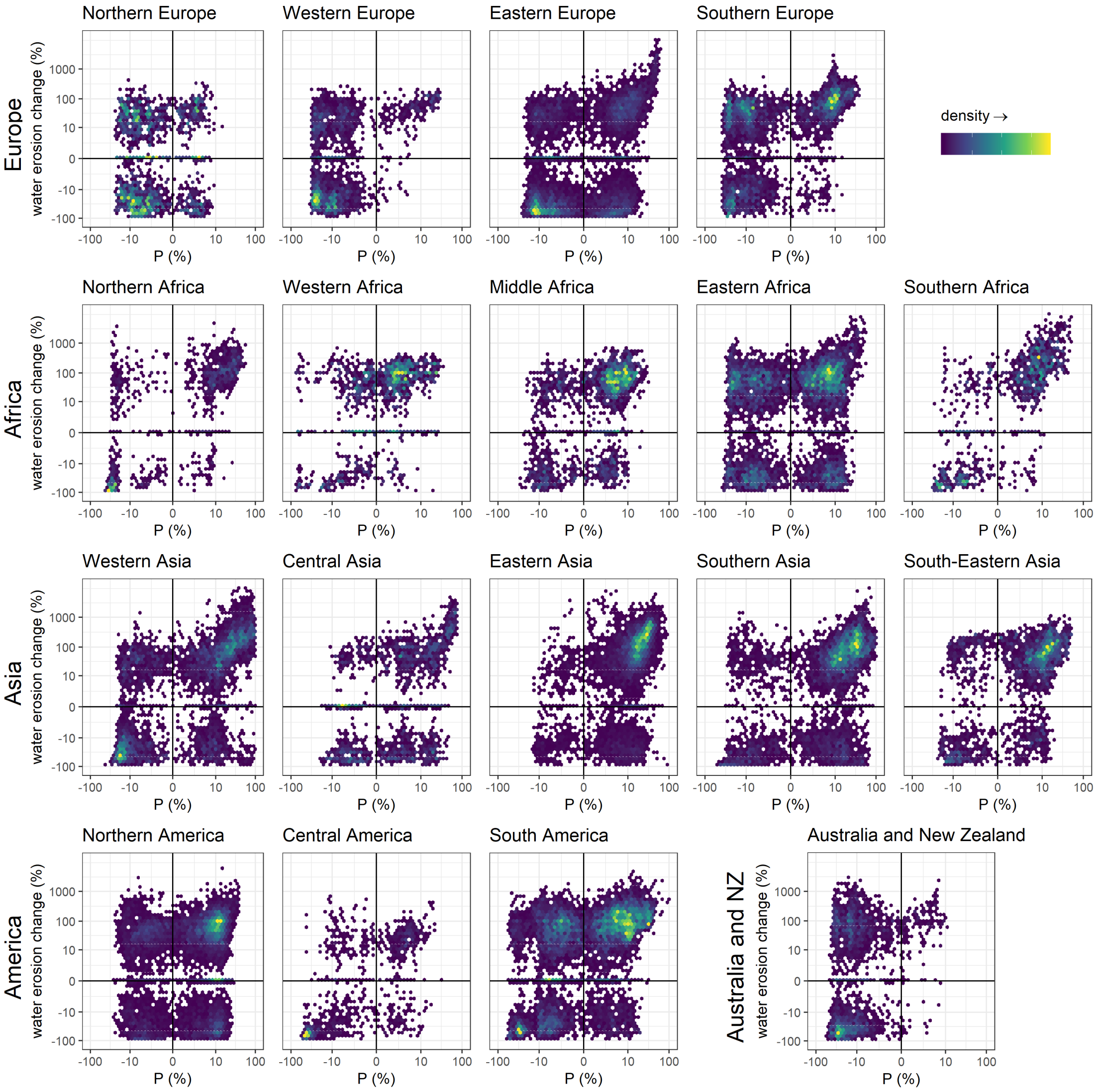

Figure D.10: Regional changes in average precipitation (%) plotted against regional changes in average water erosion (%) between the decade 2010-2019 and the decade 2090-2099 in wheat fields. Both datasets are log-transformed.

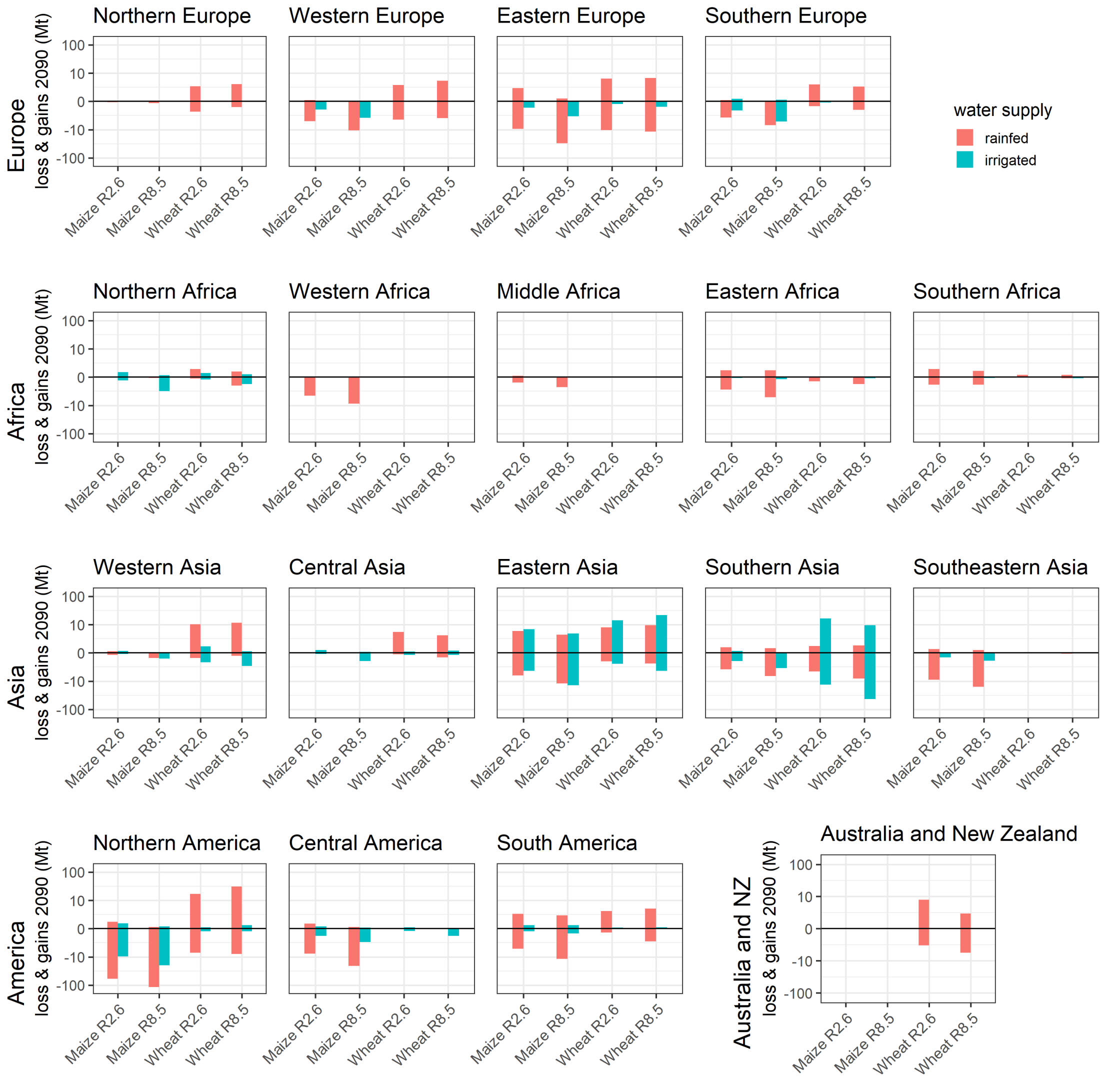

Figure D.11: Regional gains and losses in annual average maize and wheat production (million tonnes) simulated with the RCP 2.6 and RCP 8.5 scenario for the decade 2090-2099 compared to average production for the years 1980-2010 simulated with the AGMERRA climate data. Values are log-transformed.

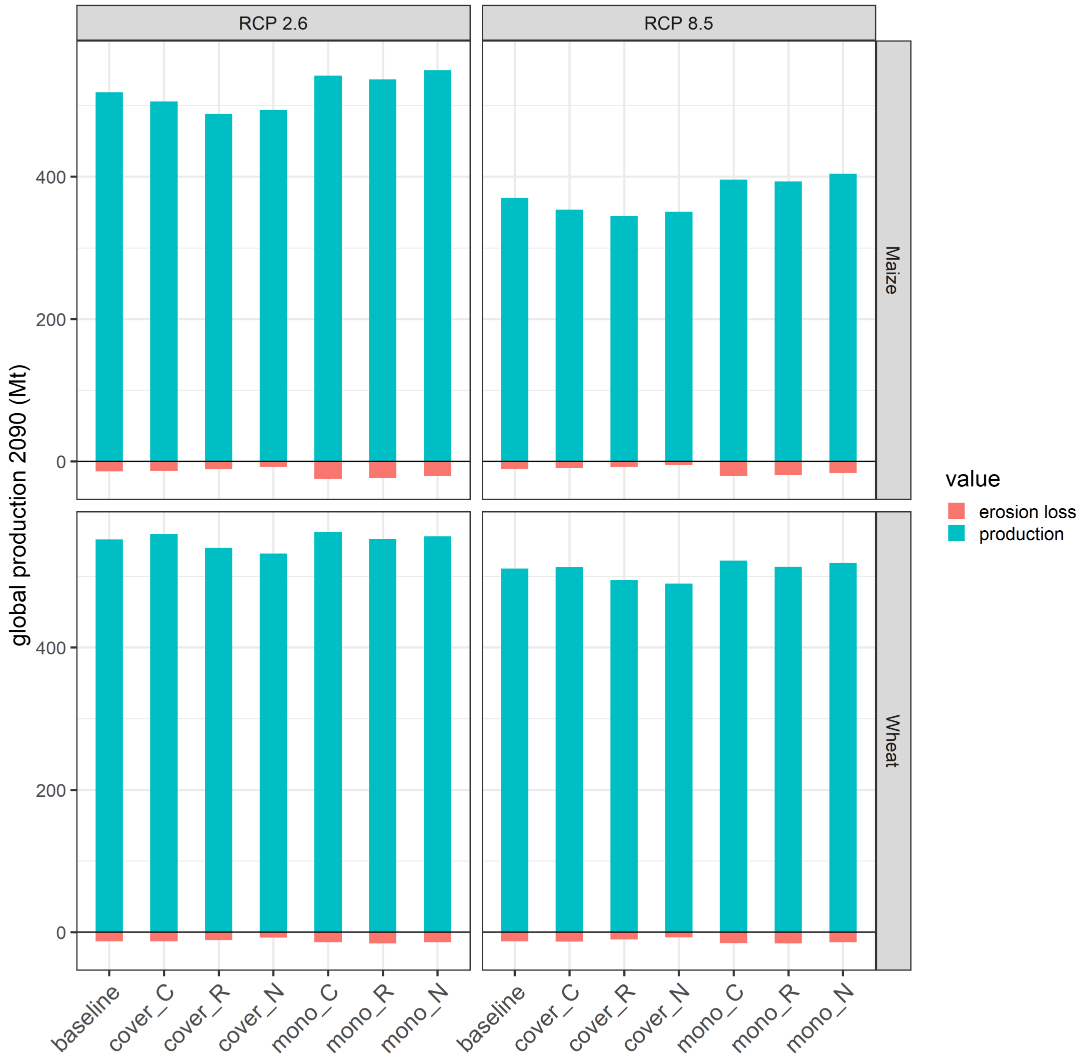

Figure D.12: Global maize and wheat production (million tonnes) and production losses (million tonnes) due to water erosion per field management scenario simulated with the RCP 2.6 and RCP 8.5 scenario, calculated for the decade 2090-2099. The field management scenarios include the baseline scenario and all combinations with the cover crop (cover, mono) and the tillage management scenarios (conventional (C), reduced (R), no-tillage (N)).

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