Modelling agricultural production under sustainable water management, climate change and agricultural adaptation

Bram Droppers

Propositions

1. Severe irrigation constraints are needed to achieve sustainable water management.
   (this thesis)
2. Worldwide agricultural assessments overestimate climate-change impacts.
   (this thesis)
3. Quantifying the ecological impact of human development is impossible.
4. Sustainable development is presently primarily a political challange, not an engineering one.
5. Scientific publishing is an ineffective method for communicating actionable information.
6. Interdisciplinary research is more affected by COVID than disciplinary research.

Propositions belonging to the thesis, entitled

Modelling agricultural production under sustainable water management, climate change and agricultural adaptation

Bram Droppers
Wageningen, 23 September 2022 (Date defence ceremony)

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Abstract

The world has entered a human-dominated epoch, often referred to as the Anthropocene, where human activities are shaping local environments as well as the earth system. As a result, these activities potentially adversely affect one another, and quantification of their interactions is needed to support integrated decision making. My thesis quantifies whether sufficient agricultural production can be achieved under sustainable water management and climate change. Agricultural production, water resources and their interactions are quantified using the robust process-based hydrology-crop model VIC-WOFOST, which is a dynamic coupling of the Variable Infiltration Capacity (VIC) hydrological model and the WOrld FOod STudies (WOFOST) crop model. Using VIC-WOFOST, I first quantify present-day worldwide water use and the impact of sustainable water management on worldwide agricultural production. My results show that present-day human water use severely exceeds sustainable water use, and irrigation should be constrained under sustainable water management. These irrigation constraints would result in substantial reductions in worldwide agricultural production, in particular for croplands in the Indus basin, which contains almost all of Pakistan's agriculture. For the Indus basin, I subsequently assess the impacts of climate-change mitigation and agricultural adaptation on agricultural production and water use. In these regions, temperature increases under climate change and associated crop-heat stress adversely affect agricultural production, even though climate-change and elevated atmospheric carbon dioxide concentrations benefit water use. However, if appropriate agricultural adaptation measures are taken, sufficient agricultural production can be achieved in Pakistan for all but the highest population growth scenario, even under sustainable water management and climate change. My thesis clearly indicate the strong interactions between agriculture, water and climate and the opportunities of adaptation. This information contributes to integrated policies and decision making for both sufficient agricultural production and sustainable water management in the epoch of the Anthropocene.

Contents

Chapter 1

Introduction

1.1 Integrated development in the Anthropocene

The world has entered a human-dominated epoch, often referred to as the Anthropocene [Crutzen, 2006; Lewis & Maslin, 2015]. In the Anthropocene, human activities are shaping the local environment as well as the earth system [Steffen et al., 2007, 2018; Waters et al., 2016]. Therefore, these activities can no longer occur in isolation, as they potentially adversely affect other activities and risk destabilizing crucial earth systems [Griggs et al., 2013; Steffen et al., 2015]. In face of this realization, the United Nations, in 2015, agreed on 17 Sustainable Development Goals (SDGs) [United Nations, 2015] to succeed the Millennium Development Goals that were adopted 15 years earlier [United Nations, 2000]. The SDGs aim to guide human development to achieve a better and more sustainable future through a greater focus on environmentally sustainable and integrated development than their predecessor [Sachs, 2012].

As a result from a greater focus on integrated development, the SDGs include a high number of interlinkages that can be trade-offs (i.e. developments towards one goal adversely affect developments towards another) or synergies (i.e. developments towards one goal benefits developments towards another) [Pradhan et al., 2017]. However, these linkages are not explicitly reflected in the SDGs and decision making towards different SDGs often still occurs in isolation [Le Blanc, 2015; Nilsson et al., 2016; Stafford-Smith et al., 2017]. To support integrated decision making towards joint SDG implementation, the interactions between different SDGs need to be quantified [Bazilian et al., 2011]. In particular, the interactions between developments to achieve sufficient agricultural production (as part of SDG2), sustainable water management (as part of SDG6) and reduced climate change impacts (as part of SDG13) need to be quantified as they are strongly interlinked [Hanjra & Qureshi, 2010].

1.1.1 Sufficient agricultural production

Food demands for a growing and developing population are ever-increasing and agricultural production should increase to meet these demands. The latest projections of the United Nations show that worldwide population likely continues to grow and reach almost 11 billion people by the end of the current century [United Nations, 2019]. In addition to the growing number of people to feed, socioeconomic growth additionally contribute to a greater food demand per capita, including a greater share of animal products [Godfray et al., 2018; Tilman & Clark, 2014]. Therefore, worldwide food demands are increasing more rapidly than due to population growth alone. Meeting these demands requires substantial increases in agricultural production, with up to double the 2005 production in 2050 [Tilman et al., 2011]. In particular, production needs to increase as dietary shifts towards a greater intake of animal products requires additional feed production [Keyzer et al., 2005].

However, increasing agricultural production is not straightforward. To meet worldwide food demands, agriculture initially mostly expanded and now covers almost 40% of the ice-free land area [Ellis et al., 2010]. Although this expansion raised worldwide agricultural production, the conversion of natural biomes to managed croplands has had adverse environmental consequences [Foley et al., 2005]. Land-use change results in widespread biodiversity loss through habitat fragmentation and ecosystem degradation [Laurance et al., 2014; Sala et al., 2000]. In addition, forest conversion to croplands substantially contributes to carbon emissions. As forest are cut down, their carbon stocks are released, whereas the croplands that replace these forests provide minimal to no carbon storage [Houghton et al., 2012].

To minimize these environmental impacts, agricultural expansion should be minimized. Therefore, agricultural intensification, which aims to increase productivity on current croplands, has recently received attention [Godfray et al., 2010]. Already in the 1960s, during the so-called 'green revolution', widespread adoption of high-yielding cultivars, increased fertilizer use and mechanization led to major production increases under minimal cropland expansion [Evenson & Gollin, 2003]. Morover, the green revolution saw major irrigation expansion, tripling irrigated croplands between 1950 and 2000 [Siebert et al., 2015]. Today, major agricultural production increases are still possible by closing yield gaps through improving water and nutrient management [Mueller et al., 2012; Pingali, 2012; van Ittersum et al., 2013].

However, although agricultural intensification avoids the need for expansion, it should be implemented with care. Due to a lack of sustainable policies and improved resource use efficiency, intensification often goes hand-in-hand with too much fertilizer application, pesticide over-use and, of particular interest to my thesis, excessive water use [Foley et al., 2011; Geiger et al., 2010; Matson et al., 1997; Springmann et al., 2018; Tilman et al., 2002].

1.1.2 Sustainable water management

Agriculture is by far the biggest water user worldwide, accounting for more than two-thirds of water withdrawals for irrigation [Huang et al., 2018]. The remaining one-third is used for a range of domestic (e.g. drinking water and sanitation) and industrial (e.g. manufacturing and thermoelectric energy generation) purposes. Although water use for these remaining purposes is relatively minor, they are highly locally relevant. Water demands are mostly met by naturally renewable water resources, such as river streamflow or groundwater recharge. Although worldwide water demands are small compared to worldwide renewable water availability, they are often highly concentrated in time and space [Oki & Kanae, 2006; Postel et al., 1996]. Therefore, water demands often exceed renewable water availability, resulting in a 'water-gap'.

To meet this gap, water is often withdrawn from non-renewable groundwater storage (i.e. in excess of groundwater recharge) [Siebert et al., 2010], resulting in rapid groundwater storage depletion around the world [Gleeson et al., 2012; Rodell et al., 2018, 2009]. Groundwater depletion can be problematic as groundwater is an strategically important water resource that acts as a water buffer for human use and maintains river streamflow in times of drought [Alley et al., 2002; Famiglietti et al., 2011]. Excessive groundwater withdrawals thus presents a major threat to regional and global water security [Aeschbach-Hertig & Gleeson, 2012; Famiglietti, 2014]. In addition, groundwater depletion and associated groundwater table declines necessitate ever-greater costs and energy to pump the groundwater to the surface, thereby limiting the economic feasibility of agriculture that depends on these groundwater resources [Jasechko & Perrone, 2021; Konikow & Kendy, 2005].

Beside their impact on non-renewable groundwater storage, human water use also threatens the integrity of freshwater ecosystems. These ecosystems require sufficient freshwater flows that follow the natural flow regime to maintain their the habitats and biodiversity [Poff et al., 1997; Poff & Zimmerman, 2010; Richter et al., 2003], so-called 'environmental flows' [Arthington et al., 2018; Pastor et al., 2014]. In turn these ecosystems provide valuable ecosystems services, such as the fish availability and water cleaning [Dudgeon et al., 2006]. However, human water withdrawals in combination with reservoir construction reduce and disrupt river streamflow, thereby threatening the river and wetland ecosystem functioning [de Graaf et al., 2019; Grill et al., 2019; Vörösmarty et al., 2010]. As a result, these ecosystems are already experiencing biodiversity declines far greater than most other terrestrial ecosystems [Pimm et al., 2014; Strayer & Dudgeon, 2010].

Worldwide water demand and competition likely continues to increase during this century [Alcamo et al., 2007; Flörke et al., 2018; Flörke et al., 2013; Strzepek & Boehlert, 2010]. However, as large-scale relocation of water (e.g. inter-basin water transfers and reservoir operation) is mostly controversial [Grill et al., 2019; Shumilova et al., 2018], optimizing renewable water availability in time and space remains difficult. Therefore, managing the gap between water demand and availability is key for sustainable development.

1.1.3 Reduced climate change impacts

In addition, developments to achieve sufficient agricultural production and sustainable water management are strongly affected by climate change [Misra, 2014]. Climate change affects water availability and agricultural productivity through changes in the water cycle and cropland suitability respectively.

In general, the water cycle will accelerate (intensify) under climate change, with increased annual precipitation and evaporation [Huntington, 2006]. However, these increases are unequally distributed in time and space. Precipitation likely reduces in many regions, whereas the frequency and magnitude of precipitation extremes (e.g. droughts and floods) increases [Dore, 2005; Pfahl et al., 2017; Trenberth, 2011]. Besides affecting water availability [Oki & Kanae, 2006; Taylor et al., 2013], these precipitation changes also affect cropland suitability for rainfed agriculture [Lobell et al., 2008]. At the same time, cropland suitability will shift due to temperature increases. Crops currently cultivated in warm regions will shift to regions with similar temperatures in the future [Pugh et al., 2016; Sloat et al., 2020]. Although such shifts are beneficial for agriculture in northern regions, they are likely adverse for agriculture in tropical and subtropical regions where temperatures likely exceed suitable temperatures for crop cultivation [Zhao et al., 2017].

Besides these potentially adverse climate-change impacts on water availability and agricultural productivity, climate change also benefits agriculture through elevated atmospheric carbon dioxide concentrations ([CO_2]) [Ainsworth & Long, 2005; Toreti et al., 2020]. Maximum carbon assimilation rates of crops increase under elevated [CO_2] (especially for annual C3 crops), thus increasing maximum agricultural productivity in the absence of other limiting factors [Kimball, 2016]. Moreover, elevated [CO_2] also decreases plant stomatal resistance and transpiration, thereby leading to a higher crop water use efficiency and reduced impact of water limitations on crop growth [Ainsworth & Rogers, 2007].

Although these individual climate-change impacts are well studied, their interactions are understood less as they are complex and distributed in time and space. Nevertheless, agricultural and water developments will have to account for and adapt to climate change, and its uncertainties, to avoid ineffective or even adverse development decisions [Hallegatte, 2009; Milly et al., 2008].

1.2 Quantifying trade-offs and synergies

As seen above, agriculture, water and climate change are strongly interconnected. To support integrated decision making thus requires quantification of their trade-offs and synergies. Therefore, my thesis aims to:

Quantify whether sufficient agricultural production can be achieved under sustainable water management and climate change

As agriculture, water and climate change are highly biophysically interlinked, quantification is often performed by process-based models. Process-based models represent and simulate a multitude of interconnected processes that together characterize a delimited biophysical system (e.g. the terrestrial water system by process-based hydrological models) [Clark et al., 2017]. Although empirical and statistical models are highly suited to accurately quantify historical dependencies between agriculture, water and climate (e.g. Lobell & Asseng [2017]; Ray et al. [2019]; Rosa et al. [2018]), they are limited by the context in which the dependencies were quantified [Roberts et al., 2017]. Process-based models allow for a better understanding of processes that make up these dependencies and, if properly set-up, can extrapolate these processes, or at least their trends, to other (management and climatic) conditions.

Over the past decades a multitude of process-based hydrological (e.g. Hanasaki et al. [2018]; Müller Schmied et al. [2021]; Sutanudjaja et al. [2018]) and crop (e.g. Izaurralde et al. [2006]; Jones et al. [2003]) models have been developed to assess climate-change impacts. However, results between hydrological and crop model studies remains largely unconnected. Most hydrological studies solely estimate changes in water resources, ignoring the impacts of these changes on agriculture, while agricultural studies often assume unlimited water availability for irrigated crops. The few models that account for both agriculture and water resources often poorly represent agricultural management. For example, one of the most notable models, LPJmL [Bondeau et al., 2007], represents sub-optimal crop productivity under a simulated water regime with calibrated scaling parameters instead of agricultural management practices [Fader et al., 2010]. Although these models are able to quantify the interaction between agriculture and water, they are less suited to quantify non-water related agricultural adaptation options, such as increased fertilizer application. Therefore, during my thesis I developed and used the VIC-WOFOST hydrology-crop model.

1.2.1 The VIC-WOFOST model

VIC-WOFOST is a combination of the Variable Infiltration Capacity (VIC) hydrological model [Hamman et al., 2018; Liang et al., 1994] and the WOrld FOod STudies (WOFOST)

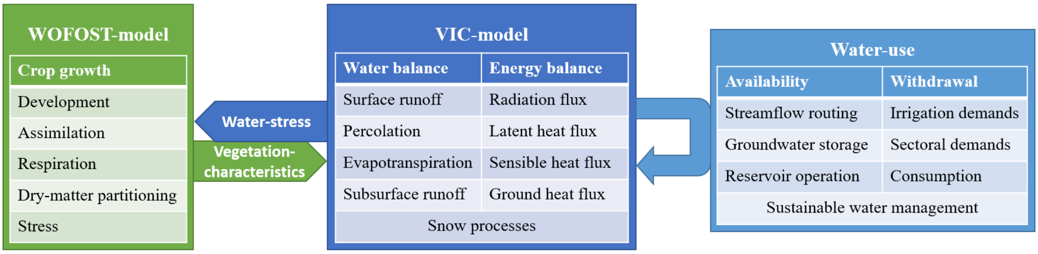

Figure 1.1: Conceptualization of the VIC-WOFOST model implementation. The VIC hydrological simulates the water and energy balance for various land-cover tiles and the WOFOST crop model simulates crop growth for agricultural land-cover tiles. Water use is based on the simulated water availability and withdrawal.

crop model [de Wit et al., 2019, 2020] (Figure 1.1). The VIC model started out as a Land Surface Model (LSM) [Liang et al., 1994], which estimates water and energy fluxes at the earth surface to be combined with a climate model. However, VIC quickly developed into a stand-alone hydrological model [Nijssen et al., 1997] with a strong and detailed representation of both the water and energy balance. In my thesis VIC is extended with modules that integrate river streamflow routing, reservoir operation and human water withdrawal and consumption. The WOFOST model was originally developed to monitor and predict potential productivity based on weather forecasts [van Diepen et al., 1989]. Over time WOFOST also included impacts of agricultural management on water and nutrient limited productivity [Shibu et al., 2010; Supit et al., 1994].

In VIC-WOFOST I dynamically coupled these models. VIC handles the estimation of water availability and simulates the water and energy balance for each land-cover tile separately, whereas WOFOST handles the estimation of agricultural productivity and simulates crop growth for agricultural land-cover tiles. Water stress, estimated by VIC, will affect crop growth as simulated by WOFOST, while vegetation characteristics, estimated by WOFOST, will affect the hydrological simulations of VIC. Additionally, I implemented the effects of $[CO_2]$ on plant transpiration [Ainsworth & Rogers, 2007; Li et al., 2019] and calibrated the effects of $[CO_2]$ on crop maximum productivity following several Free Air Carbon dioxide Enrichment (FACE) experiments [Bloom et al., 2014; Hasegawa et al., 2017; Kimball et al., 2017; Yang et al., 2006]. By combining these two models, VIC-WOFOST has a strong basis for simulating the interactions between agriculture and water under climate change and adaptation.

1.3 Research approach

To accomplish the main research objective of my thesis, **quantify whether sufficient agricultural production can be achieved under sustainable water management and climate change**, I follow four steps that are each accompanied by their own research question (RQ) (Figure 1.2):

RQ1. To what extent does present-day human water use exceed sustainable water use?

RQ2. What is the impact of sustainable water management on agricultural production?

RQ3. What is the impact of climate change on agricultural production and water use?

RQ4. To what extent can agricultural adaptation enable agricultural production increases?

In the first step, present-day human water demands are compared with water availability under sustainable water management. Water availability under sustainable water management entails renewable water resources, as estimated by VIC, minus environmental flow requirements, which were determined as a fraction of the historical natural streamflow. Present-day human water demands were estimated for agricultural, domestic, industrial and livestock purposes. These demands were integrated in the VIC model with and dynamically (i.e. in space and time) compared to water availability to indicate to what extent sustainable water use is exceeded.

In the second step, agricultural irrigation withdrawals are constrained to the extent that human water withdrawals no longer exceed water availability under sustainable water management. These constrains therefore increase crop water stress and limit agricultural productivity in regions where sustainable water use is exceeded. Productivity is estimated for wheat, rice, maize and soybean, as they are major contributors to worldwide food production. Productivity decreases were estimated using the VIC-WOFOST coupling. VIC estimates water availability under sustainable water management and WOFOST estimates crop growth under the given irrigation regime, thereby indicating the impact of sustainable water management on agricultural production.

In the third step, the climate-change impacts on water resources and crop growth were included. In VIC-WOFOST, climate-change impacts on water resources were estimated by VIC, whereas impacts on crop growth were estimated by WOFOST. Impacts were estimated by forcing VIC-WOFOST with future climates following several climate-change mitigation scenarios up to the end of this century (i.e. 2100). By combining these impacts in VIC-WOFOST, the impact of climate change on agricultural production and water use was estimated.

In the fourth and last step, several agricultural adaptation options are explored: management adaptation options that increase agricultural production, through (1)

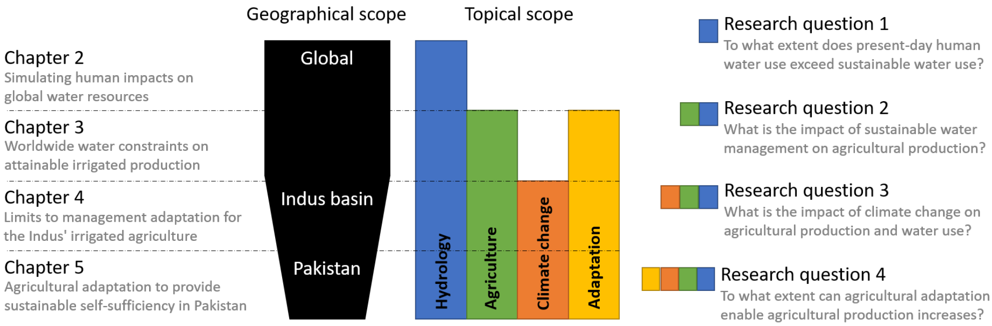

Figure 1.2: Thesis chapter outline including the geographical and topical scope. The geographic scope (black bar) narrows throughout the thesis, with assessments from the whole world to Pakistan. The topical scope (colored bars) expands through the thesis, starting with present-day hydrological assessments and ending with future irrigated agricultural adaptation assessments. The topics are related to the research questions as shown by the colored boxes.

improved nutrient management and (2) cropland expansion, and climate-change adaptation options that avoid negative climate-change impacts, through (3) growing season adjustments and (4) crop substitution with maize. The opportunities and limitations of these adaptation options to increase agricultural production are estimated by VIC-WOFOST. These agricultural production increases are subsequently compared to food requirements under several population growth scenarios, thereby indicating to what extent they are sufficient.

1.3.1 Outline

Following this introduction chapter, Chapter 2 to 5 deal with the various aspects of my research questions (Figure 1.2). Chapter 2, titled *"Simulating human impacts on global water resources using VIC-5"*, describes the impact present-day human water withdrawals on worldwide water resources and subsequently quantifies to what extent these withdrawals exceed renewable water availability and reduce water flows below their environmental requirements (RQ1). Chapter 3, titled *"Worldwide water constraints on attainable irrigated production for major crops"*, describes the impacts of sustainable water management, and its irrigation constraints, on worldwide agricultural production, while also exploring the potential benefits of improved nutrient management (RQ2 and RQ4). Chapter 4, titled *"Limits to management adaptation for the Indus' irrigated agriculture"*, describes the impacts of climate change on water availability and agricultural productivity in the Indus basin throughout this century, while also exploring

Figure 1.3: Location of the Indus basin on the map of southern Asia. The Indus basin is indicated by the white outline. The basin is mostly located in Pakistan and lays between Afghanistan in the west, India in the east and China in the north. [The Third Pole, 2022]

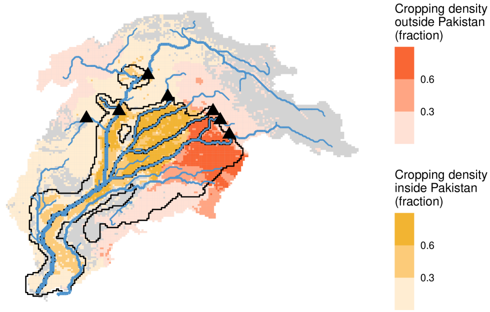

Figure 1.4: Indus basin agriculture including major reservoirs and irrigation scheme extent. Cropping density (i.e. harvest area as a fraction of the grid cell) is separated for (yellow) inside of Pakistan and (red) outside of Pakistan. Major reservoirs are shown as black triangles and the extent of the Indus basin irrigation scheme is outlined in black.

the potential benefits of improved nutrient management (RQ3 and RQ4). Chapter 5, titled *"Agricultural adaptation to provide sustainable self-sufficiency in Pakistan"*, describes the opportunities and limitation of climate-change and management adaptation to maintain cereal self-sufficiency in Pakistan throughout this century (RQ4). Lastly, Chapter 6 syntheses the main findings with regards to my research objectives and discusses their broader implications.

Note that throughout my thesis the geographic scope narrows (Figure 1.2). The first two chapters are answered for the whole world, while the last two chapters focus on the Indus basin and the country of Pakistan (Figure 1.3 and 1.4). This decrease in geographic focus was driven by the aim to provide more robust and locally relevant results. The Indus basin is heavily supported by unsustainable water use and is potentially highly affected by climate change [Archer et al., 2010]. In addition, Pakistan's rapidly growing population, currently exceeding 220 million people, is heavily dependent on irrigated agriculture for their food security [Ahmad & Farooq, 2010]. Therefore, this region's food security is highly threatened and vulnerable and could benefit from exporing the opportunities and limitations of adaptation.

Chapter 2

Simulating human impacts on global water resources using VIC-5

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Abstract

Questions related to historical and future water resources and scarcity have been addressed by several macroscale hydrological models. One of these models is the Variable Infiltration Capacity (VIC) model. However, further model developments were needed to holistically assess anthropogenic impacts on global water resources using VIC. Our study developed VIC-WUR, which extends the VIC model using (1) integrated routing, (2) surface and groundwater use for various sectors (irrigation, domestic, industrial, energy and livestock), (3) environmental flow requirements for both surface and groundwater systems and (4) dam operation. Global gridded datasets on sectoral demands were developed separately and used as an input for the VIC-WUR model. Simulated national water withdrawals were in line with reported Food and Agriculture Organization (FAO) national annual withdrawals (adjusted $R^2 > 0.8$), both per sector and per source. However, trends in time for domestic and industrial water withdrawal were mixed compared with previous studies. Gravity Recovery and Climate Experiment (GRACE) monthly terrestrial water storage anomalies were well represented (global mean root-mean-squared error, RMSE, values of 1.9 mm and 3.5 mm for annual and interannual anomalies respectively), whereas groundwater depletion trends were overestimated. The implemented anthropogenic impact modules increased simulated streamflow performance for 370 of the 462 anthropogenically impacted Global Runoff Data Centre (GRDC) monitoring stations, mostly due to the effects of reservoir operation. An assessment of environmental flow requirements indicates that global water withdrawals have to be severely limited (by 39%) to protect aquatic ecosystems, especially with respect to groundwater withdrawals. VIC-WUR has potential for studying the impacts of climate change and anthropogenic developments on current and future water resources and sector-specific water scarcity. The additions presented here make the VIC model more suited for fully integrated worldwide water resource assessments.

2.1 Introduction

Questions related to historical and future water resources and scarcity have been addressed by several macroscale hydrological models over the last few decades [Alcamo et al., 1997; Best et al., 2011; Bondeau et al., 2007; Hagemann & Gates, 2001; Hanasaki et al., 2008b; Krinner et al., 2005; Liang et al., 1994; Takata et al., 2003; van Beek & Bierkens, 2009]. Early efforts focused on the simulation of natural water resources and the impacts of land cover and climate change on water availability [Nijssen et al., 2001a,c; Oki et al., 1995]. Recently, a larger focus has been on incorporating anthropogenic impacts, such as water withdrawals and dam operations, into water resource assessments [Alcamo et al., 2003; Biemans et al., 2011; Haddeland et al., 2006b; Hanasaki et al., 2018; Wada et al., 2011b].

Global water withdrawals have increased 8-fold over the last century and are projected to increase further [Shiklomanov, 2000; Wada et al., 2011a]. Although water withdrawals are only a small fraction of the total global runoff [Oki & Kanae, 2006], water scarcity can be severe due to the variability of water in both time and space [Postel et al., 1996]. Severe water scarcity is already experienced by two-thirds of the global population for at least part of the year [Mekonnen & Hoekstra, 2016]. To stabilize water availability for different sectors (e.g. irrigation, hydropower and domestic uses) dams and reservoirs, which are able to strongly affect global river streamflow, have been built [Grill et al., 2019; Nilsson et al., 2005]. In addition, groundwater resources are being extensively exploited to meet increasing water demands [Famiglietti, 2014; Rodell et al., 2009].

One of the widely used marcoscale hydrological models is the Variable Infiltration Capacity (VIC) model. This model was originally developed as a land surface model [Liang et al., 1994], but it has mostly been used as a stand-alone hydrological model [Abdulla et al., 1996; Nijssen et al., 1997] using an offline routing module [Lohmann et al., 1996, 1998a,b]. Where land-surface models focus on the vertical exchange of water and energy between the land surface and the atmosphere, hydrological models focus on the lateral movement and availability of water. By combining these two approaches, VIC simulations are strongly process based; this provides a good basis for climate-impact modeling.

VIC has been used extensively in studies such as coupled regional climate model simulations [Hamman et al., 2016; Zhu et al., 2009], combined river streamflow and water temperature simulations [van Vliet et al., 2016], hydrological sensitivity to climate change research [Chegwidden et al., 2019; Hamlet & Lettenmaier, 1999; Nijssen et al., 2001c], global streamflow simulations [Nijssen et al., 2001a], sensitivity in flow regulation and redistribution research [Voisin et al., 2018; Zhou et al., 2018] and real-time drought forecasting [Mo, 2008; Wood & Lettenmaier, 2006]. Several studies have also used VIC to simulate the anthropogenic impacts of irrigation and dam operation on water resources [Haddeland et al., 2006a,b; Zhou et al., 2016a,b] based on the model set-up of Haddeland et al. [2006b]. However, further developments were needed to holistically assess anthropogenic impacts on global water resources using this model [Döll et al., 2016; Nazemi & Wheater, 2015a,b; Pokhrel et al., 2016].

Firstly, the original VIC model did not include groundwater withdrawals or water withdrawals from domestic, manufacturing and energy (thermoelectric) sources. Although these sectors use less water than irrigation [Grobicki et al., 2005; Hejazi et al., 2014; Shiklomanov, 2000] they are important actors locally [Gleick et al., 2013], especially for the water-food-energy nexus [Bazilian et al., 2011]. Sufficient water supply and availability are essential for meeting a range of local and global sustainable development goals related to water, food, energy and ecosystems [Bijl et al., 2018]. Secondly, environmental flow requirements (EFRs) have often been neglected [Pastor et al., 2014], even though they are "necessary to sustain aquatic ecosystems which, in turn, support human cultures, economies, sustainable livelihoods and well-being" [Arthington et al., 2018]. Anthropogenic alterations already strongly affect freshwater ecosystems [Carpenter et al., 2011], with more than a quarter of all global rivers experiencing very high biodiversity threats [Vörösmarty et al., 2010]. By neglecting EFRs, the sustainable water availability for anthropogenic uses is overestimated [Gerten et al., 2013]. Lastly, while the model set-up of Haddeland et al. [2006b] already included important anthropogenic impact modules (i.e. irrigation and dam operation), these were not fully integrated. Therefore, multiple successive model runs were required (see Section 2.2.1) which was computationally expensive - especially for global water resources assessments.

Recently version 5 of the VIC model (VIC-5) was released [Hamman et al., 2018], which focused on improving the VIC model infrastructure. These improvements provide the opportunity to fully integrate anthropogenic impacts into the VIC model framework while also reducing computation times. Here the newly developed VIC-WUR model is presented (named after the development team at Wageningen University and Research). The VIC-WUR model extends the existing VIC-5 model using several modules that simulate the anthropogenic impacts on water resources. These modules will implement previous major works on anthropogenic impact modelling and will also integrate environmental flow requirements into VIC-5. The modules include the following: (1) integrated routing, (2) surface and groundwater use for various sectors (irrigation, domestic, industrial, energy and livestock), (3) environmental flow requirements for both surface and groundwater systems and (4) dam operation.

The next section first describes the original VIC-5 hydrological model (Section 2.2.1), which calculates natural water resource availability. Subsequently the integration of the anthropogenic impact modules, which modify the water resource availability, is described (Section 2.2.2). Global anthropogenic water uses for each sector are also estimated (Section 2.3). To assess the capability of the newly developed modules, the VIC-WUR results were compared with Food and Agriculture Organization (FAO) national water withdrawals by sector and by source [Food and Agricultural Organization, 2020]; with Huang et al. [2018], Steinfeld et al. [2006] and Shiklomanov [2000] data on water withdrawals by sector; with Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage anomalies [National Aeronautics and Space Administration, 2017]; with Global Runoff Data Centre (GRDC) streamflow time series [Bundesanstalt für Gewässerkunde, 2020]; and with Yassin et al. [2019] and Hanasaki et al. [2006] data on reservoir operation (Section 2.4.2 to 2.4.5). VIC-WUR simulation results are also compared with various other state-of-the-art global hydrological models. Lastly, the impacts of adhering to surface and groundwater environmental flow requirements on water availability are assessed (Section 2.4.6). This assessment is included to indicate the effects of the newly integrated surface and groundwater environmental flow requirements on worldwide water availability.

2.2 Model development

2.2.1 VIC hydrological model

The basis of the VIC-WUR model is the Variable Infiltration Capacity model version 5 (VIC-5) [Hamman et al., 2018; Liang et al., 1994]. VIC-5 is an open-source marcoscale hydrological model that simulates the full water and energy balance on a (latitude – longitude) grid. Each grid cell accounts for sub-grid variability in land cover and topography as well as allowing for variable saturation across the grid cell. For each sub-grid the water and energy balance is computed individually (i.e. sub-grids do not exchange water or energy with one another). The methods used to calculate the water and energy balance are summarized in Supplementary Section A.1 and are mainly based on the work of Liang et al. [1994]. For a description of the global calibration and validation of the water balance, the reader is referred to Nijssen et al. [2001a].

VIC version 5 [Hamman et al., 2018] upgrades did not change the model representation of physical processes, but they improved the model infrastructure. Improvements include the use of network common data form (NetCDF) for input/output and the implementation of parallelization through message passing interface (MPI). These changes increase computational speed and make VIC-5 better suited for (computationally expensive) global simulations. The most significant modification that enables new model applications is that VIC-5 also changed the processing order of the model. In previous versions, all time steps were processed for a single grid cell before continuing to the next cell (time before space). In VIC-5 all grid cells are processed before continuing to the next time step (space before time). This development allows for interaction between grid cells every time step, which is important for full integration of the anthropogenic impact modules, especially water withdrawals and dam operation.

For example, surface and subsurface runoff routing to produce river streamflow was typically done as a post-processing operation [Hamman et al., 2017; Lohmann et al., 1996], due to the time-before-space processing order of previous versions. In order for reservoirs to account for downstream water demand, an irrigation demand initialization was required. This initialization could either be an independent offline dataset [Voisin et al., 2013] or multiple successive model runs [Haddeland et al., 2006b]. As VIC-5 uses the space-before-time processing order, irrigation water demands and runoff routing could be simulated each time step. The routing post-process was replaced by our newly developed routing module, which simulates routing sequentially (upstream to downstream) based on the Lohmann et al. [1996] equations.

2.2.2 Anthropogenic impact modules

VIC-WUR extends the existing VIC-5 through the addition of several newly implemented anthropogenic impact modules (Figure 2.1). These modules include sector-specific water withdrawal and consumption, environmental flow requirements for both surface and groundwater systems and dam operation for large and small (within-grid) dams.

2.2.2.1 Water withdrawal and consumption

In VIC-WUR, sectoral water demands need to be specified for each grid cell. To meet water demands, water can be withdrawn from river streamflow, small (within-grid) reservoirs and groundwater resources. Streamflow withdrawals are abstracted from the grid cell discharge (as generated by the routing module) and reservoir withdrawals are abstracted from small dam reservoirs (located in the cell). Groundwater withdrawals are abstracted from the third-layer soil moisture and an (unlimited) aquifer below the soil column. Aquifer abstractions represent renewable and non-renewable abstractions from deep groundwater resources. Subsurface runoff is used to fill the aquifer if there is a deficit.

The partitioning of water withdrawals between surface and ground water resources is data driven (similar to e.g. Döll et al. [2012], Voisin et al. [2017] and Hanasaki et al. [2018]). Partitioning was based on the study by Döll et al. [2012], who estimated groundwater withdrawal fractions for each sector in around 15.000 national and subnational administrative units. These groundwater fractions were mainly based on

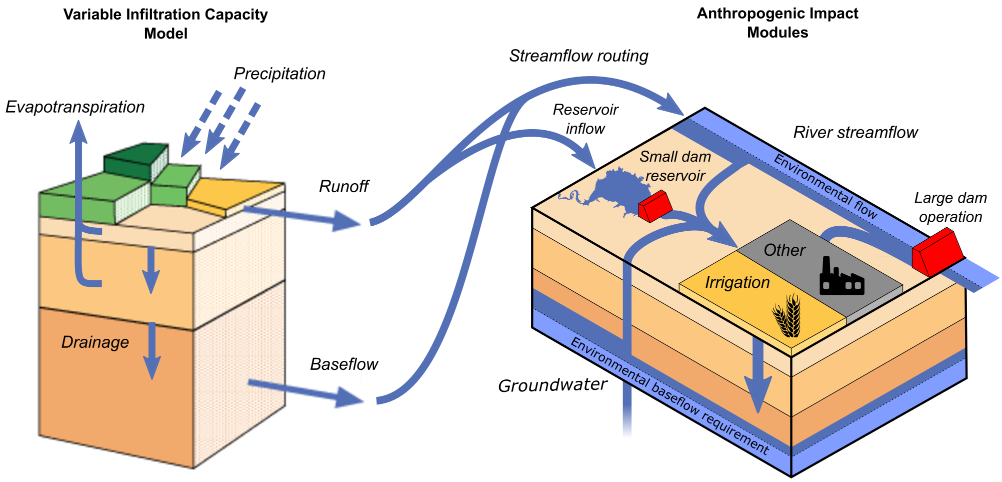

Figure 2.1: Schematic overview of the VIC-WUR model that includes the VIC-5 model (left) and several anthropogenic impact modules (right). Water from river streamflow, groundwater and small (within-grid) reservoirs is available for withdrawal. Surface and groundwater withdrawals are constrained by environmental flow requirements. Withdrawn water is available for irrigation, domestic, industrial, energy and livestock use. Unconsumed irrigation water is returned to the soil column of the hydrological model. Unconsumed water for the other sectors is returned to the river streamflow. Small reservoirs fill using surface runoff from the cell that they are located in, whereas large dam reservoirs operate solely on rivers streamflow.

information from the International Groundwater Resources Assessment Centre (IGRAC; www.un-igrac.org) database. Surface water withdrawals were partitioned between river streamflow and small reservoirs relative to water availability. Groundwater withdrawals were first withdrawn from the third soil layer, then from the (remaining) river streamflow resources and, finally, from the groundwater aquifer. This order was implemented to avoid an overestimation of non-renewable groundwater withdrawals as a result of errors in the partitioning data. Aquifer withdrawals are additionally limited by the pumping capacity from Sutanudjaja et al. [2018], who estimated regional pumping capacities based on information from IGRAC.

Water can also be withdrawn from the river streamflow of other 'remote' cells in delta areas. As rivers cannot split in the routing module, the model is unable to simulate the redistribution of water resources in dendritic deltas. Therefore, streamflow at the river mouth is available for use in delta areas (partitioned based on demand) to simulate the actual water availability. Delta areas were delineated by the global delta map from Tessler et al. [2015].

In terms of water allocation, under conditions where water demands cannot be met, water withdrawals are allocated to the domestic, energy, manufacturing, livestock and irrigation sectors in that order. Withdrawn water is partly consumed, meaning the water evaporates and does not return to the hydrological model. Consumption rates were set at 0.15 for the domestic sector and 0.10 for the industrial sector, based on data from of Shiklomanov [2000]. The water consumption in the energy sector was based on Goldstein & Smith [2002] and varies per thermoelectric plant based on the fuel type and cooling system. For the livestock sector the assumption was made that all withdrawn water is consumed. Unconsumed water withdrawals for these sectors are returned as river streamflow. For the irrigation sector, consumption was determined by the calculated evapotranspiration. Unconsumed irrigation water remains in the soil column and eventually returns as subsurface runoff.

2.2.2.2 Environmental flow requirements

Water withdrawals can be constrained by environmental flow requirements (EFRs). These EFRs specify the timing and quantity of water needed to support terrestrial river ecosystems [Pastor et al., 2019; Smakhtin et al., 2004]. Surface and groundwater withdrawals are constrained separately in VIC-WUR, based on the EFRs for streamflow and baseflow respectively. EFRs for streamflow specify the minimum river streamflow requirements, whereas EFRs for baseflow specify the minimum subsurface runoff requirements (from groundwater to surface water). As baseflow is a function groundwater availability, baseflow requirements are used to constrain groundwater (including aquifer) withdrawals.

Various EFR methods are available [Pastor et al., 2014; Richter et al., 2012; Smakhtin et al., 2004]. Our study used the variable monthly flow (VMF) method [Pastor et al., 2014] to calculate the EFRs for streamflows. VMF calculates the required streamflow as a fraction of the natural flow during high (30%), intermediate (45%) and low (60%) flow periods, as described in Supplementary Section A.2. The VMF method performed favourably compared with other hydrological methods, in 11 case studies where EFRs were calculated locally [Pastor et al., 2014]. The advantage of the VMF method is that the method accounts for the natural flow variability, which is essential to support freshwater ecosystems [Poff et al., 2010].

EFR methods for baseflow have been rather underdeveloped compared with EFR methods for streamflow. However, a presumptive standard of 90% of the natural subsurface runoff through time was proposed by Gleeson & Richter [2018], as described in Supplementary Section A.2. This standard should provide high levels of ecological protection, especially for groundwater-dependent ecosystems. Note that part of the EFRs for baseflow are already captured in the EFRs for streamflow, especially during low-flow periods that are usually dominated by baseflows. However, the EFRs for baseflow specifically limit local groundwater withdrawals, whereas EFRs for streamflow include the accumulated runoff from upstream areas. Moreover, the chemical composition of groundwater-derived flows is inherently different, making them a non-substitutable water flow for environmental purposes [Gleeson & Richter, 2018].

2.2.2.3 Dam operation

Due to the lack of globally available information on local dam operations, several generic dam operation schemes have been developed for marcoscale hydrological models to reproduce the effect of dams on natural streamflow [Haddeland et al., 2006a; Hanasaki et al., 2006; Rougé et al., 2021; Yassin et al., 2019; Zhao et al., 2016]. In VIC-WUR a distinction is made between ‘small’ dam reservoirs (with an upstream area smaller than the cell area) and ‘large’ dam reservoirs, similar to Hanasaki et al. [2018], Wisser et al. [2010b] and Döll et al. [2009]. Small dam reservoirs act as buckets that fill using surface runoff from the grid cell they are located in, and reservoirs storage can be used for water withdrawals in the same cell. Large dam reservoirs are located in the main river and use the operation scheme of Hanasaki et al. [2006], as described in Supplementary Section A.3.

The scheme distinguishes between two dam types: (1) dams that do not account for water demands downstream (e.g. hydropower dams or flood protection dams) and (2) dams that do account for water demand downstream (e.g. irrigation dams). For dams that do not account for demands, dam release is aimed at reducing annual fluctuations in discharge. For dams that do account for demands, dam release is additionally adjusted to provide more water during periods of high demand. The operation scheme was validated by Hanasaki et al. [2006] for 28 reservoirs and has been used in various other studies [Döll et al., 2009; Hanasaki et al., 2008b, 2018; Pokhrel et al., 2012; Voisin et al., 2013]. Here, the scheme was adjusted slightly to account for monthly varying EFRs and to reduce overflow releases, which is described in Supplementary Section A.3. The Global Reservoir and Dam (GRanD) database [Lehner et al., 2011] was used to specify location, capacity, function (purpose) and construction year of each dam. The capacity of multiple (small and large) dams located in the same cell were combined.

2.3 Sectoral water demands

VIC-WUR water withdrawals are based on the irrigation, domestic, industry, energy and livestock water demand in each grid cell. Water demands represent the potential water withdrawal, which is reduced when insufficient water is available. Irrigation demands were estimated based on the hydrological model, whereas water demands for other sectors were provided to the model as an input. Domestic and industrial water demands were estimated based on several socioeconomic predictors, whereas energy and livestock water demands were derived from power plant and livestock distribution data. Due to data limitations, the energy sector was incomplete, and energy water demands were partly included in the industrial water demands (which combined the remaining energy and manufacturing water demands). For more details concerning sectoral water demand calculations the reader is referred to Supplementary Section A.4.

2.3.1 Irrigation demands

Irrigation demands were set to increase soil moisture in the root zone so that water availability was not limiting crop evapotranspiration and growth. The exception is paddy rice irrigation [Brouwer et al., 1989], where irrigation was also supplied to keep the upper soil layer saturated. Water demands for paddy irrigation practices are relatively high compared with conventional irrigation practices due to increased evaporation and percolation. Therefore, the crop irrigation demands for these two irrigation practices were calculated and applied separately (i.e. in different sub-grids). Note that multiple cropping seasons are included based on the MIRCA2000 land use dataset [Portmann et al., 2010] (see Section 2.4.1).

Total irrigation demands also included transportation and application losses. Note that transportation and application losses are not 'lost' but rather returned to the soil column without being used by the crop. The water loss fraction was based on Frenken & Gillet [2012], who estimated the aggregated irrigation efficiency for 22 United Nations subregions. Irrigation efficiencies were estimated based on the difference between AQUASTAT-reported irrigation water withdrawals and calculated irrigation water requirements [Allen et al., 1998], using data on crop information (e.g. growing season and harvest area) from AQUASTAT [Food and Agricultural Organization, 2020].

2.3.2 Domestic and industrial demands

Domestic and industrial water withdrawals were estimated based on gross domestic product (GDP) per capita and gross value added (GVA) by industries respectively [Bolt et al., 2018; Feenstra et al., 2015; World Bank, 2020] (see Supplementary Section A.4.3). These drivers do not fully capture the multitude of socioeconomic factors that influence water demands [Babel et al., 2007]. However, the wide availability of data allows for the extrapolation of water demands to data-scarce regions and future scenarios (using studies such as Chateau et al. [2014]).

Domestic water demands per capita (used for drinking, sanitation, hygiene and amenity uses) were estimated in similar fashion to Alcamo et al. [2003]. Demands increased non-linearly with the GDP per capita due to the acquisition of water-using appliances as households become richer. A minimum water supply is needed for survival, and the saturation of water-using appliances sets a maximum on domestic water demands. Industrial water demands (used for cooling, transportation and manufacturing) were estimated in similar fashion to Flörke et al. [2013] and Voß & Flörke [2010]. Industrial demands increased linearly with the GVA (as an indicator of industrial production). As industrial water intensities (i.e. the water use per production unit) vary widely between different industries [Flörke & Alcamo, 2004; Vassolo & Döll, 2005; Voß & Flörke, 2010], the average water intensity was estimated for each country. Both domestic and industrial water demands were also influenced by technological developments that increase water use efficiency over time, as in Flörke et al. [2013].

Domestic water demands varied monthly based on air temperature variability as in Huang et al. [2018] (based on Wada et al. [2011b]). Using this approach, water demands were higher in summer than in winter, especially for counties with strong seasonal temperature differences. Domestic water demand per capita was downscaled using the HYDE3.2 gridded population maps [Goldewijk et al., 2017]. Industrial water demands were kept constant throughout the year. Industrial demands were downscaled from national to grid cell values using the NASA Back Marble night-time light intensity map [National Aeronautics and Space Administration, 2016; Roman et al., 2018]. National industrial water demands were allocated based on the relative light intensity per grid cell for each country.

2.3.3 Energy and livestock demands

Energy water demands (used for cooling thermoelectric plants) were estimated using data from van Vliet et al. [2016]. Water use intensity for generation (i.e. the water use per generation unit) was estimated based on the fuel and cooling system type [Goldstein & Smith, 2002], which was combined with the generation capacity. Note that the data only covered a selection of the total number of thermoelectric power plants worldwide. Around 27% of the total (non-renewable) global installed capacity between 1980 and 2011 was included in the dataset due to lack of information on cooling system types for the majority of thermoelectric plants. To avoid double counting, energy water demands were subtracted from the industrial water demands.

Livestock water demands (used for drinking and animal servicing) were estimated by combining the Gridded Livestock of the World (GLW3) map [Gilbert et al., 2018] with the livestock water requirement reported by Steinfeld et al. [2006]. Eight varieties of livestock were considered: cattle, buffaloes, horses, sheep, goats, pigs, chicken and ducks. Drinking water demands varied monthly based on temperature as described by Steinfeld et al. [2006] - drinking water requirements were higher during higher temperatures.

2.4 Model application

2.4.1 Set-up

VIC-WUR results were generated between 1979 and 2016, excluding a spin-up period of 1 year (analysis period from 1980 to 2016). The model used a daily time step (with a 6-hourly time step for snow processes) and simulations were executed on a 0.5° by 0.5° grid (around 55 km at the Equator) with three soil layers per grid cell. Soil and (natural) vegetation parameters were the same as in Nijssen et al. [2001c] (disaggregated to 0.5°), who used various sources to determine the soil [Carter & Scholes, 1999; Cosby et al., 1984] and vegetation parameters [Calder, 1993; Ducoudré et al., 1993; Myneni et al., 1997; Sellers et al., 1994].

Nijssen et al. [2001c] used the Advanced Very High Resolution Radiometer (AVHRR) vegetation type database [Hansen et al., 2000] to spatially distinguish 13 land cover types. The land cover type 'cropland' in the original land cover dataset was replaced by cropland extents from the MIRCA2000 cropland dataset [Portmann et al., 2010]. MIRCA2000 distinguishes the monthly growing area(s) and season(s) of 26 irrigated and rain-fed crop types around the year 2000. Crop types were aggregated into three land cover types: rain-fed, irrigated and paddy rice cropland. The natural vegetation was proportionally rescaled to make up for discrepancies between the natural vegetation and cropland extents.

Cropland coverage (the cropland area actually growing crops) varied monthly based on the crop growing areas of MIRCA2000. The remainder was treated as bare soil. Cropland vegetation parameters (e.g. leaf area index (LAI), displacement, vegetation roughness and albedo) vary monthly based on the crop growing seasons and the development-stage crop coefficients of the Food and Agricultural Organization [Allen et al., 1998].

The latest WATCH forcing data ERA-Interim (aggregated to a 6 hourly temporal resolution), developed by the EU Water and Global Change (WATCH) [Harding et al., 2011] project, was used as climate forcing (WFDEI) [Weedon et al., 2014]. The dataset provides gridded historical climatic variables of minimum and maximum air temperature, precipitation (as the sum of snowfall and rainfall, GPCC bias corrected), relative humidity, pressure and incoming shortwave and longwave radiation.

For naturalized simulations, only the routing module was used. For the anthropogenic impact simulations, the sectoral water withdrawals and dam operation modules were turned on in the model simulations. For the EFR-limited simulations, water withdrawals and dam operations were constrained as described.

2.4.2 Validation and evaluation

In order to validate the VIC-WUR anthropogenic impact modules, water withdrawal, terrestrial total water storage anomalies and streamflow and reservoir operation simulations were compared with observations. The validation specifically focused on the effects of the newly included anthropogenic impact modules, meaning that streamflow and total water storage anomaly results are shown for river basins that are strongly influenced by human activities. A general validation for streamflow and terrestrial total water storage anomalies (including basins with limited human activities) is shown in Supplementary Section A.5.

2.4.3 Sectoral water withdrawals

Simulated global domestic, industrial, livestock and irrigation mean water withdrawals were 310, 771, 36 and 2202 km^3 y^{-1} respectively for the period from 1980 to 2016. Sectoral water withdrawals were compared with FAO national annual water withdrawals [Food and Agricultural Organization, 2020], monthly withdrawal data from Huang et al. [2018] and annual withdrawal data from Shiklomanov [2000] and Steinfeld et al. [2006]. For the latter studies, water withdrawals were aggregated by region (world, Africa, Asia, Americas, Europe and Oceania). Note that Huang et al. [2018] irrigation water withdrawals integrate the results of four other marcoscale hydrological models (WaterGAP, H08, LPJmL, PCR-GLOBWB), using the same land use and climate set-up as our study. Results from individual marcoscale hydrological models are also shown.

Simulated domestic, industrial and irrigation water withdrawals correlated well with

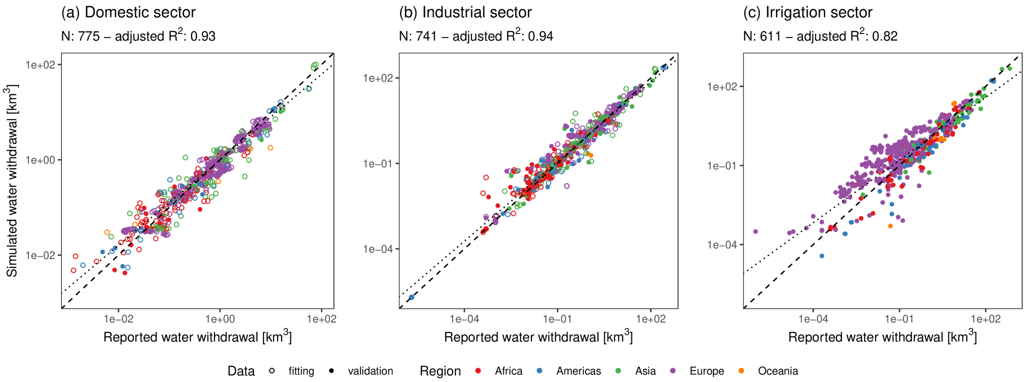

Figure 2.2: Comparison between the simulated national annual water withdrawals and FAO reported values for the (a) domestic, (b) industrial and (c) irrigation sectors. Colours distinguish between regions. Open circles were also used in the calibration of the water withdrawal demands. The dashed line indicates the 1:1 ratio, and the dotted line indicates the simulated best linear fit. Note the log-log axis which is used to display the wide range of water withdrawals. The adjusted R^2 is also based on the log values.

reported national water withdrawals, with an adjusted R^2 of 0.93, 0.94 and 0.82 for domestic, industrial and irrigation water withdrawals respectively (Figure 2.2). Generally, smaller water withdrawals were overestimated and larger water withdrawals were underestimated. Differences for the domestic and industrial sector were small and probably related to the fact that smaller countries were poorly delineated on a 0.5° by 0.5° grid. However, irrigation differences were larger with overestimations of the irrigation water withdrawals in (mostly) Europe. As irrigation water demands are the result of the simulated water balance, overestimations would indicate a regional underestimation of the water availability for Europe or differences in irrigation efficiency.

When domestic, industrial and livestock water withdrawals were compared with other studies, results were mixed (Figure 2.3a-c). Simulated domestic withdrawals followed a similar trend in time. However, simulated domestic water withdrawal trends were somewhat underestimated overall, with a mean bias of 54 km^3 y^{-1} compared with Huang et al. [2018]. Asia is the main contributor to the global underestimation, but results are similar in most regions. The simulated industrial water withdrawal was (mostly) higher in our study with a mean bias of 107 km^3 y^{-1} compared with Huang et al. [2018] but only a mean bias of 5 km^3 y^{-1} compared with Shiklomanov [2000]. Moreover, industrial water withdrawal trends in time were less consistent.

Withdrawal differences for the domestic and industrial sector are probably due to the limited data availability. Our approach to compute water demands was data-driven

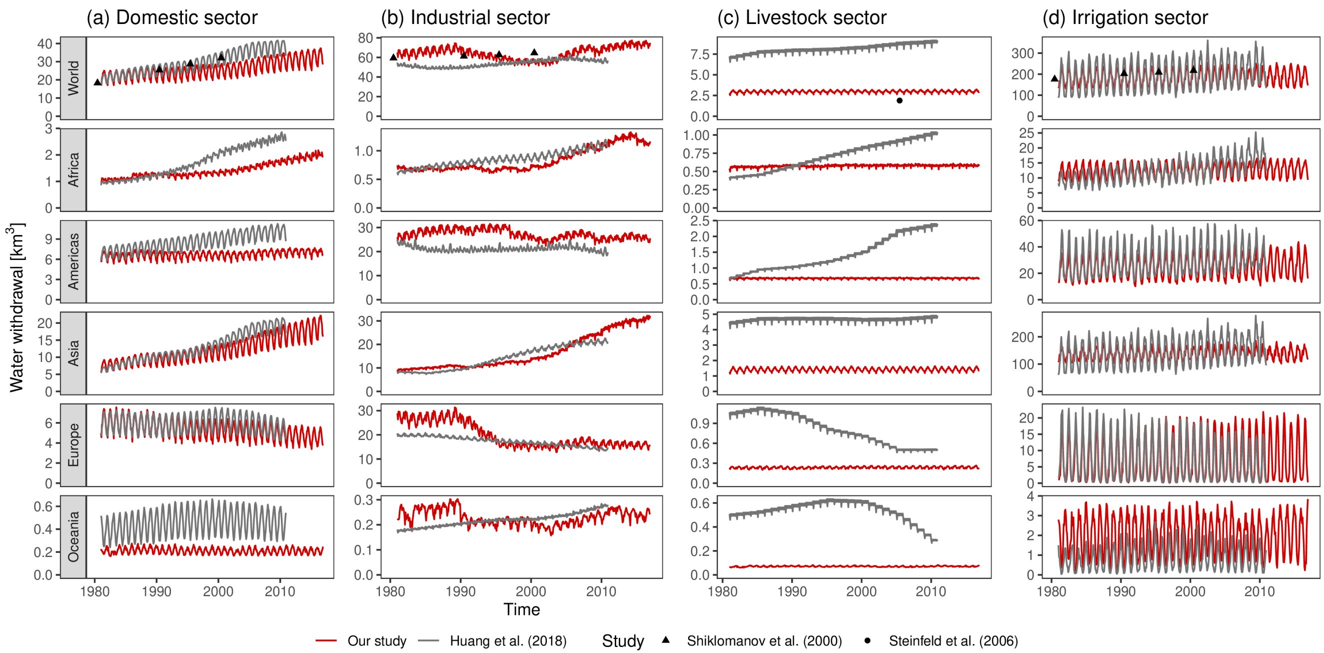

Figure 2.3: Comparison between the simulated compiled monthly and annual regional water withdrawal values and values from Huang et al. [2018], Shiklomanov [2000] and Steinfeld et al. [2006] for the (a) domestic, (b) industrial, (c) livestock and (d) irrigation sectors. Colours and shapes distinguish between studies. Note that the jitter in livestock withdrawals is due to the different days per month.

Table 2.1: Average annual global irrigation water withdrawals as calculated by several global hydrological models.

Model	Irrigation withdrawal (km^3 y^{-1})	Representative years	Reference
VIC-WUR	2202	1980-2016	Our study
H08	2810	1995	Hanasaki et al. [2008a]
	2544	1984 - 2013	Hanasaki et al. [2018]
MATSIRO	2158	1983 - 2007	Pokhrel et al. [2012]
	3028	1998 - 2002	Pokhrel et al. [2015]
LPJmL	2555	1971 - 2000	Rost et al. [2008]
PCR-GLOB	2644	2010	Wada & Bierkens [2014]
	2309[a]	2000 - 2015	Sutanudjaja et al. [2018]
WaterGAP	3185	1998-2002	Döll et al. [2012]
	2400	2003 - 2009	Döll et al. [2014]
WBM	2997	2002	Wisser et al. [2010a]

[a] Includes livestock withdrawals

and sensitive to data gaps (as opposed to Huang et al. [2018], who also combined model results). For example, domestic withdrawal data for China were not available before 2007, and industrial withdrawal data were limited before 1990. Moreover, data on the disaggregation of industrial sectors (e.g. energy and mining), which can be important sectors in the water-food-energy nexus, were limited.

For livestock water withdrawals there is a large discrepancy between Huang et al. [2018] and Steinfeld et al. [2006]. Both studies used similar livestock maps, but there was large differences in livestock water intensity (in units of litres per animal per year). As our study used values from Steinfeld et al. [2006] to estimate livestock water intensity, our results were closer to their values (slightly higher due to the inclusion of buffaloes, horses and ducks). Note that Huang et al. [2018] shows trends in livestock water withdrawals, whereas our study uses static livestock maps.

Simulated irrigation water withdrawals were within the range of other marcoscale hydrological model estimates (Table 2.1). Simulated monthly variability in irrigation water withdrawals is reduced compared with the compiled results of Huang et al. [2018] (Figure 2.3d), especially in Asia. Moreover, trends in time are less pronounced, as can be seen in Africa. These differences may indicate a relative low weather/climate sensitivity of evapotranspiration in VIC-WUR, as annual and interannual weather changes affect irrigation water demands to a lesser degree.

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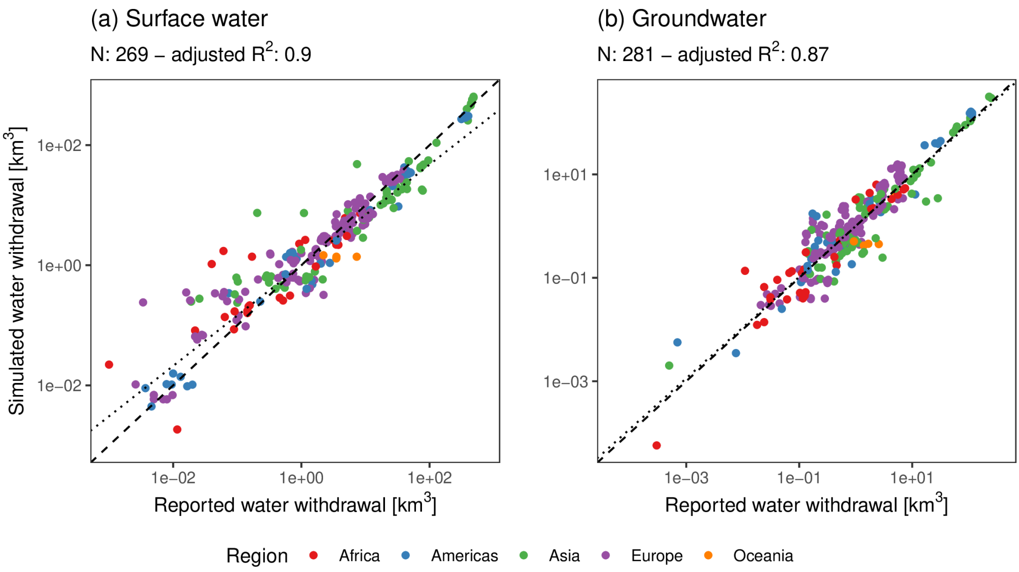

Figure 2.4: Comparison between simulated national annual water withdrawals and FAO reported values from (a) surface water and (b) groundwater. Colours distinguish between regions. The dashed line indicates the 1:1 ratio, and the dotted line indicates the simulated best linear fit. Note the log-log axis which is used to display the wide range of water withdrawals. The adjusted R^2 is also based on the log values.

2.4.4 Groundwater withdrawals and depletion

Simulated global mean withdrawals were 2327 and 992 km^3 y^{-1} for surface and groundwater respectively for the period from 1980 to 2016. Of the global groundwater withdrawals, 334 km^3 y^{-1} contributed to groundwater depletion. Simulated ground and surface water withdrawals and terrestrial total water storage anomalies were compared with FAO national annual water withdrawals [Food and Agricultural Organization, 2020] and monthly storage anomaly data from the GRACE satellite [National Aeronautics and Space Administration, 2017]. GRACE satellite total water storage anomalies were used to validate total water storage dynamics as well as groundwater exploitation contributing to downward trends in total water storage. Groundwater depletion results from other marcoscale hydrological models are shown as well. In order to compare the simulation results to the GRACE dataset, a 300km Gaussian filter was applied to the simulated data (similar to Long et al. [2015]).

Simulated surface and groundwater withdrawals correlated well with the reported national water withdrawals, with an adjusted R^2 of 0.90 and 0.87 for surface and

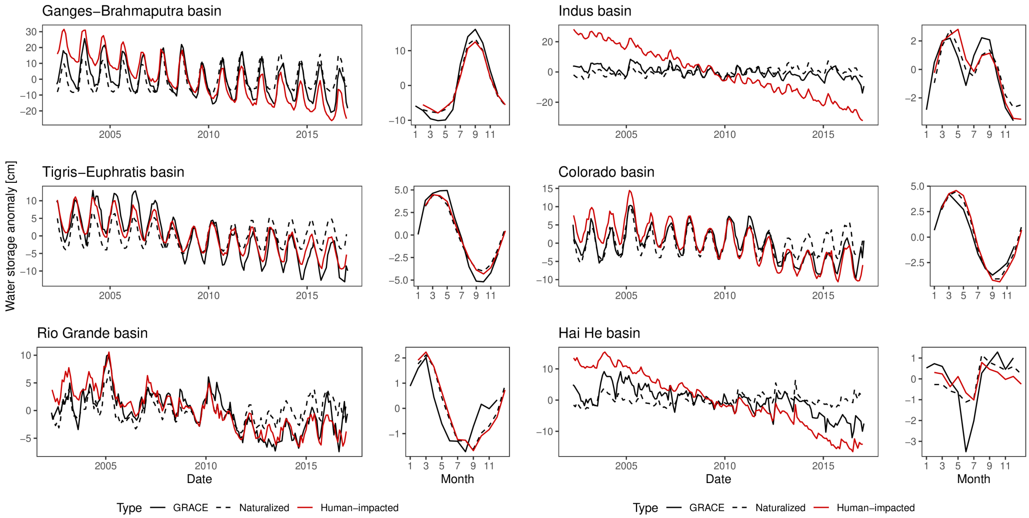

Figure 2.5: Comparison between the simulated monthly terrestrial total water storage anomalies and GRACE observed values. Panels indicate the time series and multiyear mean averages for naturalized simulations (dashed), anthropogenically impacted simulations (red), and observed (black) terrestrial total water storage anomalies.

groundwater respectively (Figure 2.4). Surface water withdrawals were overestimated for low withdrawals and underestimated for large withdrawals. There is a weak correlation (-0.35) between the underestimations in surface water withdrawals and the overestimation in groundwater withdrawals, meaning water withdrawal differences could be related to the partitioning between surface and groundwater resources. Furthermore, it is likely that low water demands are overestimated (see Section 2.4.3), resulting in an overestimation of low surface water withdrawals.

Simulated monthly terrestrial water storage anomalies correlated well with the GRACE observations, with mean annual and interannual root-mean-squared error (RMSE) of 1.9mm and 3.5mm respectively. The difference between annual and inter annual performance was primarily due to the groundwater depletion process (Figure 2.5). Simulated groundwater depletion was (mostly) overestimated (e.g. Indus and Hai He basins), with higher declining trends in terrestrial total water storage for most basins. However, the simulated groundwater withdrawal and exploitation was within range compared with other marcoscale hydrological models (Table 2.2), even though total groundwater withdrawals were relatively high.

As with the FAO comparison, these results seems to indicate that withdrawal partitioning towards groundwater is overestimated. However, conclusions regarding

Table 2.2: Average annual global groundwater withdrawals and depletion as calculated by several global hydrological models.

Model	Groundwater withdrawal (km^3 y^{-1})	Groundwater depletion (km^3 y^{-1})	Representative years	Reference
VIC-WUR	992	316	1980-2016	Our study
H08	789	182	1984 - 2013	Hanasaki et al. [2018]
MATSIRO	570	330	1998 - 2002	Pokhrel et al. [2015]
GCAM		600	2005	Kim et al. [2016]
		550	2000	Turner et al. [2019]
PCR-GLOB	952	304	2010	Wada & Bierkens [2014]
	632	171	2000 - 2015	Sutanudjaja et al. [2018]
WaterGAP	1519	250	1998-2002	Döll et al. [2012]
	888	113	2003 - 2009	Döll et al. [2014]

groundwater depletion are limited by the relatively simplistic approach to groundwater used in our study (as discussed by Konikow [2011] and de Graaf et al. [2017]). For example, processes such as wetland recharge and groundwater flows between cells are not simulated, even though these could decrease groundwater depletion.

2.4.5 Discharge modification

Simulated discharge was compared with GRDC station data [Bundesanstalt für Gewässerkunde, 2020] for various anthropogenically impacted rivers. Stations were selected if the upstream area was larger than 20,000 km^2, matched the simulated upstream area at the station location, and the available data spanned more than 2 years. Subsequently, stations where the anthropogenic impact modules insufficiently affected discharge were omitted. In order validate the reservoir operation more thoroughly, simulated reservoir inflow, storage and release were compared with operation data from Hanasaki et al. [2006] and Yassin et al. [2019]. Reservoirs were included if the simulated storage capacity (which is the combined storage capacity of all large dams in a grid) was similar to the observed storage capacity.

The inclusion of the anthropogenic impact modules improved discharge performance, measured in RMSE, for 370 of the 462 stations (80%; Figures 2.6 and 2.7). Improvements were mainly due to the effects of reservoir operation on discharges (e.g.

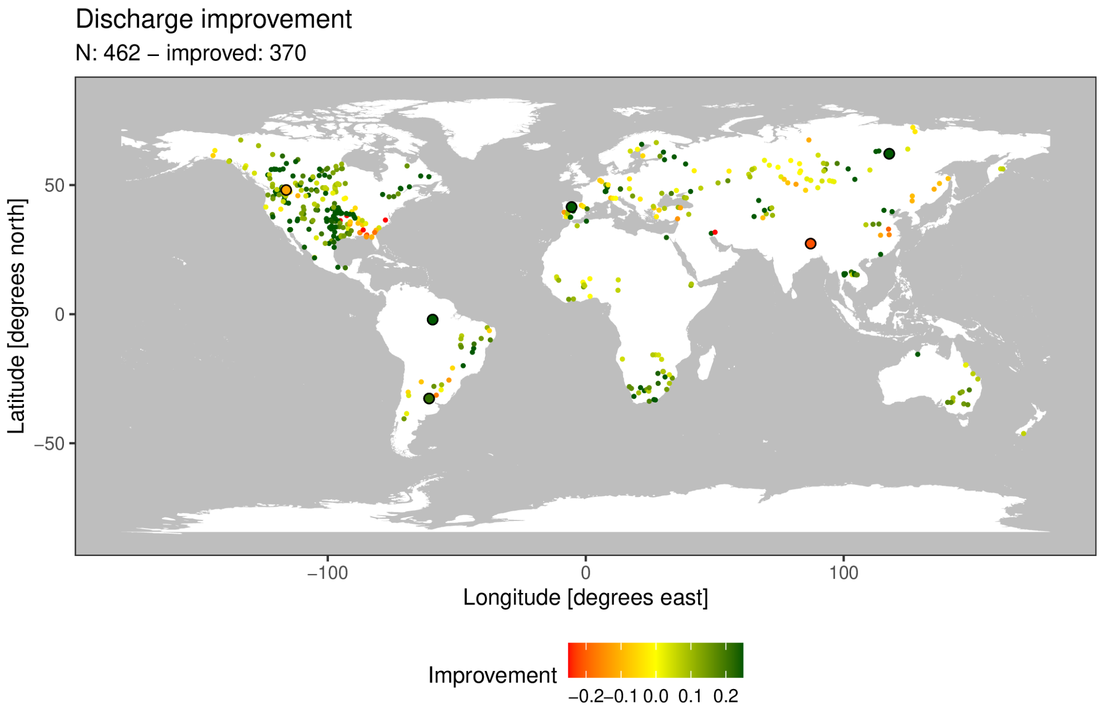

Figure 2.6: Discharge improvement from naturalized to antrhopogenically impacted simulations (as a fraction of the naturalized RMSE). Circled larger stations are shown in Figure 2.7

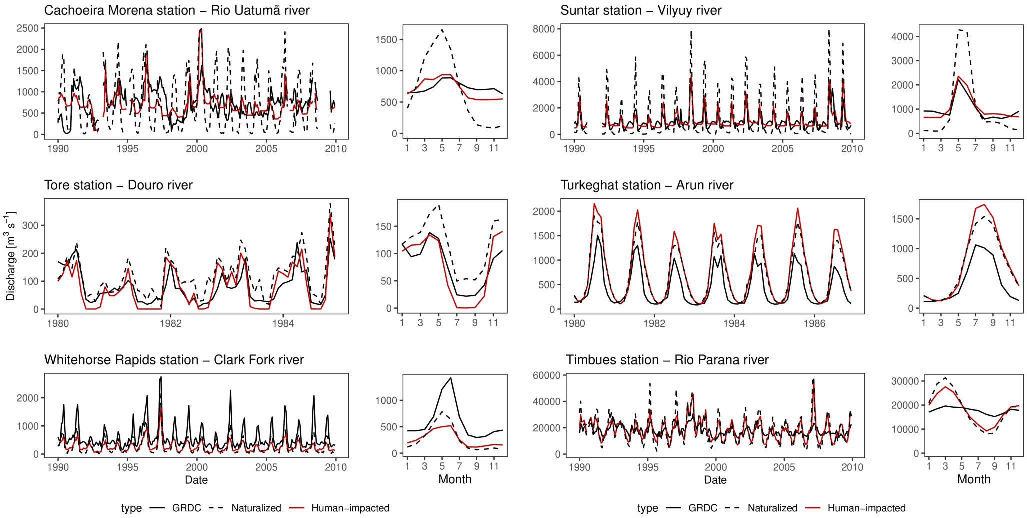

Figure 2.7: Comparison between the simulated discharge and GRDC observed values. Panels indicate the time series and multiyear averages for naturalized simulations (dashed), antrhopogenically impacted simulations (red), and observed (black) discharge.

Cachoeira Morena and Suntar stations), but also due to withdrawal reductions (e.g. Tore station). However, reservoir effects on discharge were sometimes underestimated (e.g. Timbues station). Decreased performance was mostly related to under- or overestimations of (calibrated) natural streamflow which was subsequently exacerbated by reservoir operation and water withdrawals. For example, the Clark Fork River naturalized streamflow was underestimated, which was subsequently further underestimated by the anthropogenic impact modules (Whitehorse Rapids station). Moreover, increases in discharge due to groundwater withdrawals could increase naturalized streamflow (e.g. Turkeghat station). Further improvements to discharge performance would most likely require a recalibration of the VIC model parameters.

For individual reservoirs, operational characteristics were generally well simulated (Figure 2.8), with reductions in annual discharge variations (e.g. Flaming Gorge and Garrison dams) and increased water release for irrigation (e.g. Seminoe Dam). However, due to changes in locally simulated and actual inflow, dam operation can take on different characteristics (e.g. Toktogul Dam). Furthermore, peak discharge events caused by reservoir overflow (as also described by Masaki et al. [2018]) were not always sufficiently represented in the observations (e.g. Garrison Dam). These differences indicate locally varying reservoir operation strategies. Several studies have developed reservoir operation schemes that can be calibrated to the local situation [Rougé et al.,

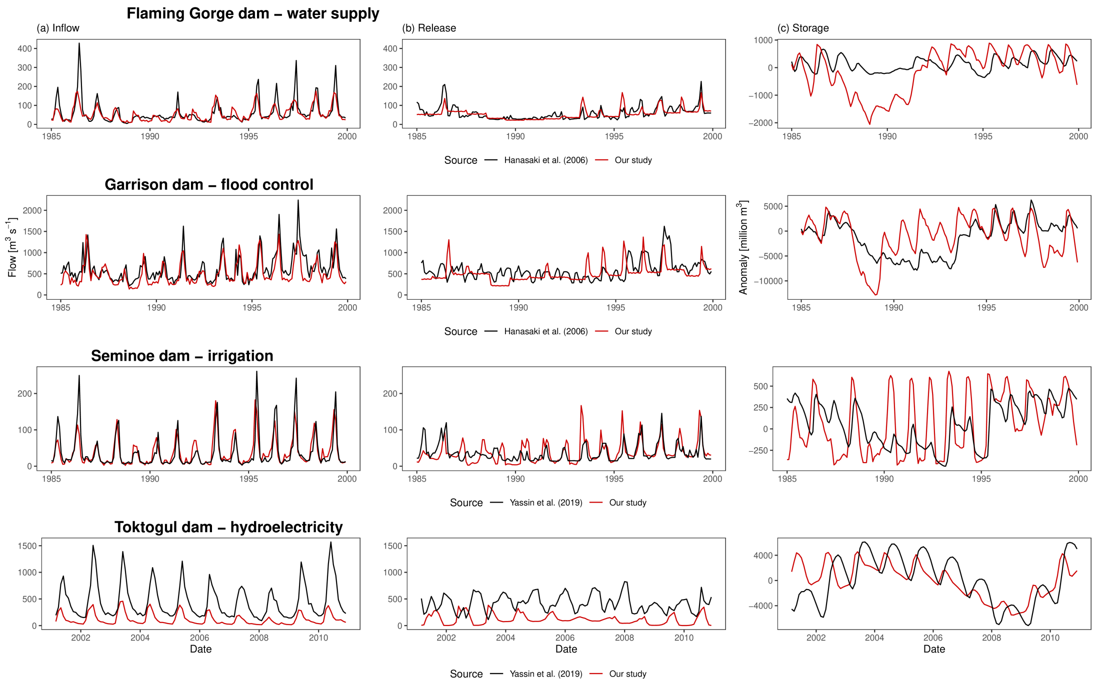

Figure 2.8: Comparison between the simulated reservoir operation and values observed by Hanasaki et al. [2006] and Yassin et al. [2019]. Panels indicate time series and multiyear averages of (a) inflow, (b) release and (c) storage anomalies for antrhopogenically impacted simulations (red) and observations (black).

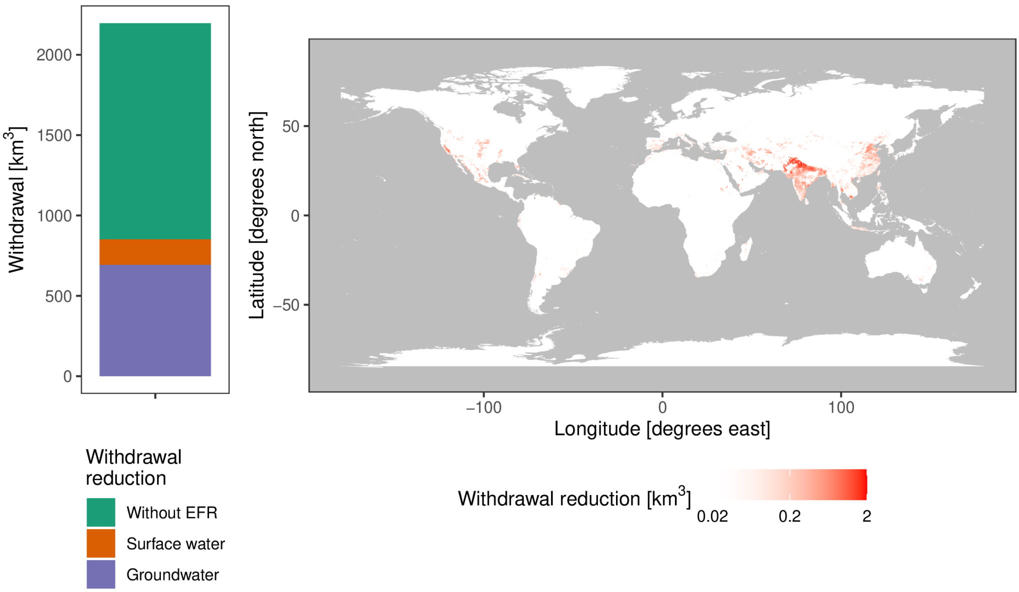

Figure 2.9: Average annual irrigation water withdrawal reductions when adhering to EFRs as a global gross total (left) and as spatially distributed values (right). Global gross totals are separated into withdrawals without any reduction (green), surface water withdrawal reductions (orange) and groundwater withdrawal reductions (purple). Note the log axis for the spatially distributed withdrawal reductions to better display the spatial distribution of the reductions.

2021; Yassin et al., 2019]. However, worldwide implementation of these operation schemes remains limited by data availability.

2.4.6 Integrated environmental flow requirements

In order to assess the impact and capabilities of the newly integrated environmental flow requirements (EFRs) module, simulated water withdrawals with and without adhering to EFRs were compared.

If water use was limited to EFRs, irrigation withdrawals would need to be reduced by about 39% (851 km^3 y^{-1}; Figure 2.9). Under the strict requirements used in our study, 81% (693 km^3 y^{-1}) of the reduction could be attributed to limitations imposed on groundwater withdrawals. Subsequently, the impact of the environmental flow requirements (if adhered to) would be largest in groundwater-dependent regions (Figure 2.9b). Note that, due to the full integration of EFRs, downstream surface water withdrawals increased by 98 km^3

y^{-1} when limiting groundwater withdrawals on top of limiting surface water withdrawals, due to increased subsurface runoff.

Reductions due to EFRs were similar to Jägermeyr et al. [2017], who calculated irrigation withdrawal reductions of 41% (997 km^3 y^{-1}) assuming only surface water abstractions. In our study, surface water reductions were smaller, as the strict groundwater requirements increase subsurface runoff to surface waters. To what extent the EFRs for baseflow were overly constrictive can be discussed, as they were based on the relatively stringent EFR for streamflow from Richter et al. [2012] - 10% of the natural streamflow. However, in the absence of any other standards, this baseflow standard remains the best available. Note that, even when accounting for EFRs for baseflow on a grid scale, withdrawals could still have local and long-term impacts that are not captured by the model. The timing, location and depth of groundwater withdrawals are important factors due to their interactions with the local geohydrology, as discussed by Gleeson & Richter [2018].

2.5 Conclusion

The VIC-WUR model introduced in this paper aims to provide new opportunities for global water resource assessments using the VIC model. Accordingly, several anthropogenic impact modules, based on previous major works, were integrated into the VIC-5 marcoscale hydrological model: domestic, industrial, energy, livestock and irrigation water withdrawals from both surface water and groundwater as well as an integrated environmental flow requirement module and a dam operation module. Global gridded datasets on domestic, industrial, energy and livestock demand were developed separately and used to force the VIC-WUR model.

Simulated national water withdrawals were in line with reported national annual withdrawals (adjusted $R^2 > 0.8$; both per sector and per source). However, the data-oriented methodology used to derive sectoral water demands resulted in different withdrawal trends over time compared with other studies [Huang et al., 2018; Shiklomanov, 2000]. While the current set-up to estimate sectoral water demands is well suited for future water withdrawal estimations, there are various other approaches (e.g. Alcamo et al. [2003]; Hanasaki et al. [2013]; Shen et al. [2008]; Vassolo & Döll [2005]; Wada & Bierkens [2014]). As the model set-up of VIC-WUR allows for the evaluation of other sectoral water demand inputs (on various temporal aggregations), several different approaches can be used depending on the focus region and data availability for calibration. Terrestrial water storage anomaly trends were well simulated (mean annual and interannual RMSE of 1.9 mm and 3.6 mm respectively), whereas groundwater exploitation was overestimated. Overestimated groundwater depletion rates are likely related to an over-partitioning of water withdrawals to groundwater. The implemented anthropogenic impact modules increased simulated discharge performance (at 370 of the 462 stations), mostly due to the effects of reservoir operation.

An assessment of the effect of EFRs shows that (when one would adhere to these requirements) global water withdrawals would be severely limited (39%). This limitation is especially notable for groundwater withdrawals, which, under the strict requirements used in our study, need to be reduced by 81%.

VIC-WUR has potential for studying impacts of climate change and anthropogenic developments on current and future water resources and sector-specific water scarcity. The additions presented here make the VIC model more suited for fully integrated worldwide water resource assessments and substantially decrease computation times compared with Haddeland et al. [2006a].

2

Chapter 3

Worldwide water constraints on attainable irrigated production for major crops

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Abstract

In order to achieve worldwide food security, there is a focus on sustainable intensification of crop production. This requires sustainable irrigation water use for irrigated croplands, as irrigation withdrawals are already resulting in groundwater exploitation and unmet ecosystem water requirements. Our study aims to quantify attainable wheat, maize, rice and soybean production on currently irrigated cropland under sustainable water use. Attainable production accounts for increases in nutrient application, while limiting irrigation withdrawals to renewable water availability and without compromising river ecosystem water requirements. Attainable production was quantified using a newly developed two-way coupled hydrological model and crop model. This model framework could comprehensively simulate biophysical processes related to water availability and crop growth under water and nutrient limitations. Our results indicate worldwide crop nitrogen uptake should increase by 20%, to achieve production gap closure. However, worldwide irrigation withdrawals should decrease by more than a third in order to ensure sustainable water use. Under these constraints, a total (all crops) production decrease of 5% was estimated, compared to currently achievable production. Moreover, achievable irrigated crop production in the extensively irrigated croplands of northeastern China, Pakistan and northwestern India would be reduced by up to a third. On the other hand, increases in achievable irrigated crop production may be possible in regions such as southern America, eastern Europe and central Africa. However, in these regions currently only a small fraction of crops is irrigated. Our results imply that intensification on currently irrigated croplands is at odds with sustainable water management, and further locally-oriented research is needed to assess suitable water management options and solutions.

3.1 Introduction

In order to achieve worldwide food security (sustainable development goal 2 [United Nations, 2015]), sufficient food should be available all year round. Up to double of the 2005 worldwide crop production is needed to satisfy the food demands of a growing and more prosperous population by 2050 [Alexandratos & Bruinsma, 2012; Tilman et al., 2011; Valin et al., 2014]. To achieve these goals, many studies have focused on (sustainably) intensifying agriculture in order to increase crop production [Baulcombe et al., 2009; Foley et al., 2011; Godfray et al., 2010]. In general, intensification is favored over expansion since intensification reduces competition for land with other anthropocentric activities, ecosystems and conservation [Foley et al., 2005]. Several studies have indicated that there is still a large gap between actual and potential crop production (the production gap). This gap could be closed through improved water and nutrient management [Mueller et al., 2012; Rockström et al., 2010; van Bussel et al., 2015].

Production gaps can be divided into several stages [Lobell et al., 2009; van Ittersum et al., 2013]: Potential production (no stress), water limited production (limited by water stress) and actual production (limited by water, nutrient, and biotic stress). Rainfed crops can attain water-limited production through increased nutrient application, while irrigated crops are assumed to be able to attain potential production due to increased water availability. However, it is important to consider sustainable water use when addressing attainable irrigated crop production. The present day agriculture sector is the largest water user worldwide [Shiklomanov, 2000], and is reaching the planetary limits of sustainable water use [Rockström et al., 2009; Steffen et al., 2015]. In many regions unsustainable irrigation withdrawals already result in groundwater-exploitation [Famiglietti, 2014; Gleeson et al., 2012; Rodell et al., 2018] and unmet ecosystem water requirements [Gerten et al., 2013; Pastor et al., 2014; Vörösmarty et al., 2010]. Moreover, competition with other water users is increasing due to socioeconomic developments and climate change [Flörke et al., 2018].

Previous studies have addressed these water management issues from either a water availability perspective [Pokhrel et al., 2015; Vörösmarty et al., 2000; Wada et al., 2011b] or a crop production perspective [Licker et al., 2010; Mueller et al., 2012; van Ittersum et al., 2013]. However, only a few studies have addressed the impacts of sustainable water management on worldwide irrigated crop production. Jägermeyr et al. [2017] estimated the attainable irrigated crop production under sustainable water management using an dynamic vegetation model (LPJmL). However, in their study changes in nutrient application that would occur under production gap closure were unaccounted for. Rosa et al. [2018] estimated sustainable and unsustainable irrigation consumption under production gap closure, by combining simulations of potential crop water requirement and accumulated water runoff. Based on worldwide yield data [Mueller et al., 2012] they estimated the potential production resulting from sustainable and unsustainable irrigation. However, their study did not estimate attainable crop production under water constraints as they did not model crop growth. Therefore, a knowledge gap remains in quantifying the combined effect of increased nutrient application (up to production gap closure requirements) and water constraints (under sustainable water management) on attainable irrigated crop production.

Our study aims to quantify worldwide attainable irrigated production for wheat, rice, maize and soybean. These four crops together cover 44% and 68% of worldwide rainfed and irrigated cropland respectively [Portmann et al., 2010], and account for around 60% of worldwide calorie production [Tilman et al., 2011]. Our study will answer the following question: Where is irrigated crop production constrained by sustainable water use, and what is the attainable production under these constraints while accounting for increases in nutrient application? To quantify attainable irrigated crop production, the variable infiltration capacity hydrological model (VIC) [Droppers et al., 2020; Hamman et al., 2018; Liang et al., 1994], was integrated with the world food studies crop model (WOFOST) [de Wit et al., 2019; Supit et al., 1994]. This two-way coupled framework, called VIC-WOFOST henceforth, is able to comprehensively simulate biophysical processes related to water availability and crop growth under water and nutrient limitations. Further details regarding the VIC and WOFOST model integration is given in section 3.2.1, while simulation details are found in section 3.2.2. In sections 3.3.1 to 3.3.3 the results of our research are presented. These results are followed by a discussion and the main conclusions in sections 3.4 and 3.5 respectively. Note that a model performance and sensitivity analysis is included in Supplementary Sections B.3 and B.4 respectively.

3.2 Methods

3.2.1 The VIC-WOFOST model framework

This study was performed using the newly-developed VIC-WOFOST model framework. VIC is a macro-scale hydrological model that simulates the sub-daily water and energy balance (e.g. interception, evapotranspiration, percolation, and surface and subsurface runoff) [Hamman et al., 2018; Liang et al., 1994] and anthropogenic water-use (i.e. domestic, industrial, energy, livestock and irrigation withdrawal and consumption) [Droppers et al., 2020]. VIC has been used extensively in studies ranging from global streamflow simulations and hydrological climate sensitivity [Chegwidden et al., 2019; Pan et al., 2012; van Vliet et al., 2013] to anthropogenic impacts of irrigation and dam

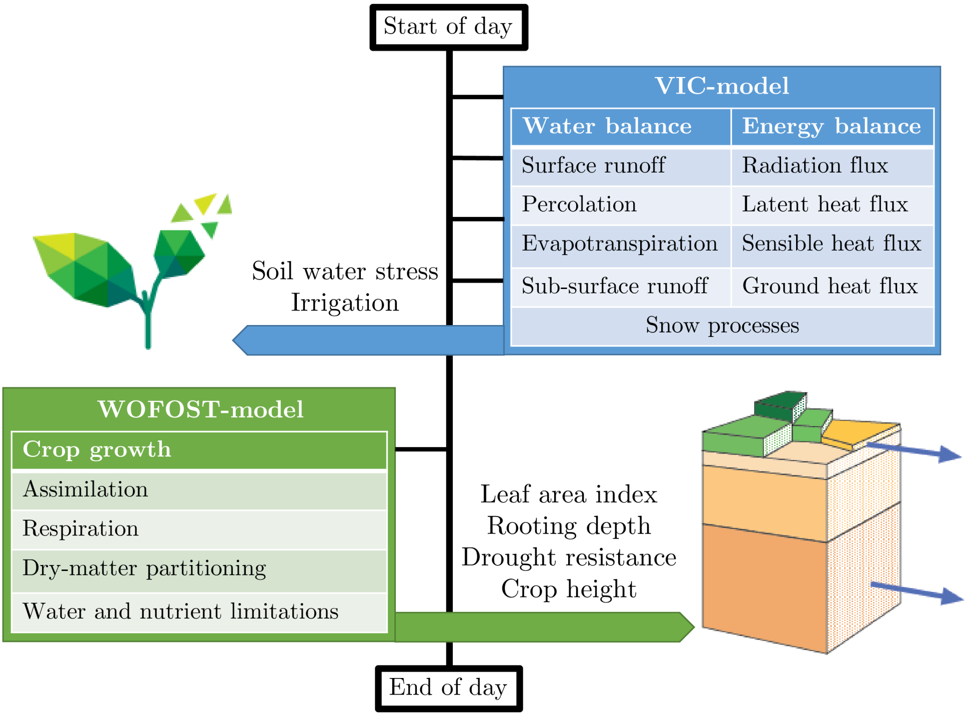

Figure 3.1: The two-way coupled VIC-WOFOST model framework. VIC computes soil water stress and irrigation that is used by WOFOST to compute crop leaf area index, rooting depth, drought resistance and crop height. Since VIC snow simulations are run on a 6 hourly timestep, WOFOST simulations are executed at the end of the day based on input from the previous 24 hours. The VIC model figure was obtained from vic.readthedocs.org and the WOFOST model figure was obtained from wur.nl

operation on water resources [Droppers et al., 2020; Haddeland et al., 2006b; Voisin et al., 2013; Zhou et al., 2016a,b]. WOFOST is a field-scale crop model that simulates daily crop growth (e.g. phenological development and biomass assimilation and partitioning) [de Wit et al., 2020; Supit et al., 1994] and the effect of nutrient limitations [Shibu et al., 2010]. WOFOST has been used extensively in studies ranging from monitoring and predicting yields [Boogaard et al., 2013; Hooijer & Wal, 1994; Supit et al., 2010; van Lanen et al., 1992; Wolf et al., 1989] to estimating the effects of climate change and management strategies on crop growth [Amiri et al., 2009; Mellaart, 1989; Wolf & Van Diepen, 1991, 1995]. The VIC-WOFOST model framework integrated the hydrological model and crop model using a two-way coupling (Figure 3.1). Hydrological simulations were computed on a 0.5° grid, each containing various land-cover classes [Hansen et al., 2000; Portmann et al., 2010]. For each wheat, maize, rice and soybean land-cover class, crop growht was simulated using the crop model. Crop water availability (soil and evapotranspiration components) is directly derived from the hydrological simulation, while hydrological land-cover characteristics (leaf area index, drought resistance, rooting depth and crop height) are directly derived from the crop simulation.

Simulated crop production was, among other factors, affected by soil moisture availability (i.e. crop water stress) and nutrient availability (i.e. crop nutrient stress). In case of crop stress, several crop growth processes are affected in the model: (1) biomass assimilation (i.e. growth) decreases, (2) leaf growth reduces, (3) biomass partitioning changes to favour root growth, and (4) senescence (i.e. aging processes) of various plant organs increases. Where soil water availability was simulated by the hydrological model, soil nutrient availability were based on (organic and mineral) fertilization application [Hurtt et al., 2020; Mueller et al., 2012; Zhang et al., 2017] and mineralization rates [Sattari et al., 2014], which were given as input. In our study only nitrogen availability was accounted for, as our model could not account for phosphorus and potassium legacy effects.

Anthropogenic water use (as discussed below) was simulated following Droppers et al. [2020]. Surface and subsurface runoff was routed using a routing scheme [Lohmann et al., 1996] and a reservoir operation scheme [Hanasaki et al., 2006]. Under sustainable water management, part of the river streamflow was allocated to satisfy the water requirements for river ecosystems (environmental flow requirements), following the variable monthly flow method (60, 45 and 30 % of streamflow during the dry, intermediate and wet season respectively) [Pastor et al., 2014]. Remaining river streamflow was available for anthropogenic use in the domestic, industrial, energy, livestock and irrigation sector (in that order). Note that all other sectors were prioritized over irrigation, meaning irrigation would be constrained first. Irrigation

Table 3.1: Model simulation setup used in our study. Nutrient limitations were based on contemporary fertilizer and mineralization rates. Non-renewable water withdrawals enable (unlimited) irrigation when renewable water resources were insufficient. Environmental requirements constrain irrigation withdrawals to guarantee water availability for river ecosystems.

Simulation	Nutrient limitations	Non-renewable withdrawals	Environmental requirements
Potential		x	
Baseline	x	x	
Restricted	x		x
Attainable			x

demands were calculated based on the soil moisture content (see also Supplementary Figures B.3 and B.4). During periods of water stress, irrigation demands were set to fill soil moisture up to saturation (for paddy rice) or field capacity (for other crops). When anthropogenic water demands exceeded available river streamflow and local dam reservoir storage, water demands could be withdrawn from non-renewable water resources (e.g. groundwater aquifers). The exception was energy water demands, which were exclusively withdrawn from river streamflow. Non-renewable water withdrawal contributed to a water deficit, which subsequently reduced subsurface runoff until the deficit was fulfilled. Non-consumed anthropogenic water withdrawals were returned to the river streamflow. Further model information is given in Supplementary Section B.1.

3.2.2 Simulations and setup

In order to investigate attainable irrigated production, four simulations were run: (1) a *potential simulation*, (2) a *baseline simulation*, (3) a *restricted simulation*, and (4) a *attainable simulation* (Table 3.1). The *potential simulation* estimated the upper crop production under current climate conditions. As such, crop growth was unlimited by nutrient and water availability. The *baseline simulation* was used to simulate crop production under contemporary nutrient limitations and water limitations for rainfed croplands. For both potential and baseline simulations, irrigation withdrawals were unrestricted, such that water is first withdrawn from renewable streamflow resources and subsequently from non-renewable water resources. Crop production gaps, resulting from water limitations (for rainfed crops) and nutrient limitations (for rainfed and irrigated crops), were estimated based on the difference between potential and baseline production. The *attainable* and *restricted simulations* are used to explored crop production when limiting irrigation withdrawals to renewable water availability (i.e. river streamflow and groundwater recharge) and guaranteeing environmental flows. The *restricted simulation* accounted for contemporary nutrient limitations, while the *attainable simulation* explored irrigated crop production under increased nutrient application, where nutrients are no longer limiting crop growth. Attainable and restricted simulations were compared to indicate the extent that nutrient application increases may help offset the effects of water constraints under sustainable water management.

Sub-optimal production, related to for example fertilizer use efficiency, seed selection, farming technologies, labor, biotic stressors (e.g. pests, weeds), and other management aspects [Fader et al., 2010] are not accounted for (i.e. no calibration has taken place). While these elements play a role in determining actual crop production [Beza et al., 2017], they do not limit attainable crop production. As such, our simulations represent the upper production limit under the given water and nutrient availability, which is an optimistic assessment. Simulations were not calibrated for sub-optimal crop production practices. As such, our simulations represent the upper production limit under the given water and nutrient availability, which is an optimistic assessment.

Simulations were run between 1981 and 2016 with a daily timestep (and a 6 hourly snow timestep). However, results were analyzed for the years 1990 to 2010, as this period covers the land-use reference period [Portmann et al., 2010]. Weather variables (air temperature, radiation, precipitation, pressure, humidity and wind speed; aggregated to 6 hourly) were derived from the water and global change forcing data era-interim (WFDEI) [Weedon et al., 2014]. Atmospheric CO_2 concentrations were kept at the current level (i.e. 370 ppm) to avoid CO_2 fertilization effects. Cropland areas and growing seasons were derived from the monthly irrigated and rainfed crop areas around the year 2000 (MIRCA2000) [Portmann et al., 2010], and included up to three crop growing seasons. Crop growing season onset and length were subsequently calibrated (within the limits of MIRCA2000) to ensure optimal crop production. Several adjustments were made to the reported growing seasons. The second season rainfed rice in China and Japan were omitted, as rice was grown during months where crop growth could not occur due to low temperatures. The first irrigated wheat season in China was extended, as other sources [Li et al., 2005; Lv et al., 2013] reported longer growing seasons that were more in line with the reported national crop production. Further setup information is given in Supplementary Section B.2.

3

3.3 Results

3.3.1 Production gaps

First total (rainfed plus irrigated) production gaps were analyzed, to put irrigated production gaps into context. Potential worldwide total (rainfed and irrigated) wheat, maize, rice and soybean production was estimated at 1 228 (±34; detrended interannual standard deviation), 1 257 (±35), 664 (±17), and 188 (±3) Mt y^{-1}. However, due to water and nutrient limitations, wheat, maize, rice and soybean can achieve only 54, 63, 93, and 95% of their potential production under baseline conditions (Figure 3.2). Also, under baseline conditions the detrended interannual standard deviations of wheat, maize, rice and soybean increase to 3, 3, 2, and 8% of their production respectively, resulting from increased year-to-year variability in rainfed water availability. To quantify the limitation from water and nutrients for these production gaps, we compared various simulations. Rainfed crop water limitations were assessed by comparing the potential and attainable simulations, and nutrient limitations were assessed by comparing the attainable and baseline simulations. Irrigated crop nutrient limitations were assessed by comparing the potential and baseline simulations (irrigated crops were assumed not water limited). 86% of simulated baseline wheat production gaps were limited by water (483 Mt), while 68% of maize production gaps were limited by nutrients (315 Mt). Rice is mostly nutrient limited due to the extensive paddy rice irrigation, and soybean is mostly water limited due to its ability to fix nitrogen.

3.3.2 Irrigation constraints

Irrigated production gaps are notably smaller due to increased crop water availability through irrigation. Simulations indicate irrigated wheat, maize, rice and soybean can achieve 89, 80, 95, and 100% of their potential production under baseline conditions (Table 3.2). Hence, opportunities to increase worldwide irrigated crop production through increased nutrients supply are relatively limited, and would require a 20% nitrogen uptake increase (from baseline 19 Mt y^{-1} to a potential 22 Mt y^{-1}).

Accompanying baseline worldwide irrigation withdrawals were estimated at 2881 (±84; interannual standard deviation) km^3 y^{-1}. Under nutrient gap closure, for the irrigated crops considered here, irrigation withdrawals would increase by only 3% (to 2 969 km^3 y^{-1}). However, more than one third (34% or 987 km^3 y^{-1}) of the baseline irrigation withdrawals is considered to be unsustainable. These withdrawals come at the expense of environmental flows or from non-renewable water resources (Figure 3.3). Unsustainable water withdrawals are mostly concentrated in several regions such as: Pakistan and northwestern India (combined 32% of total), southern United States and

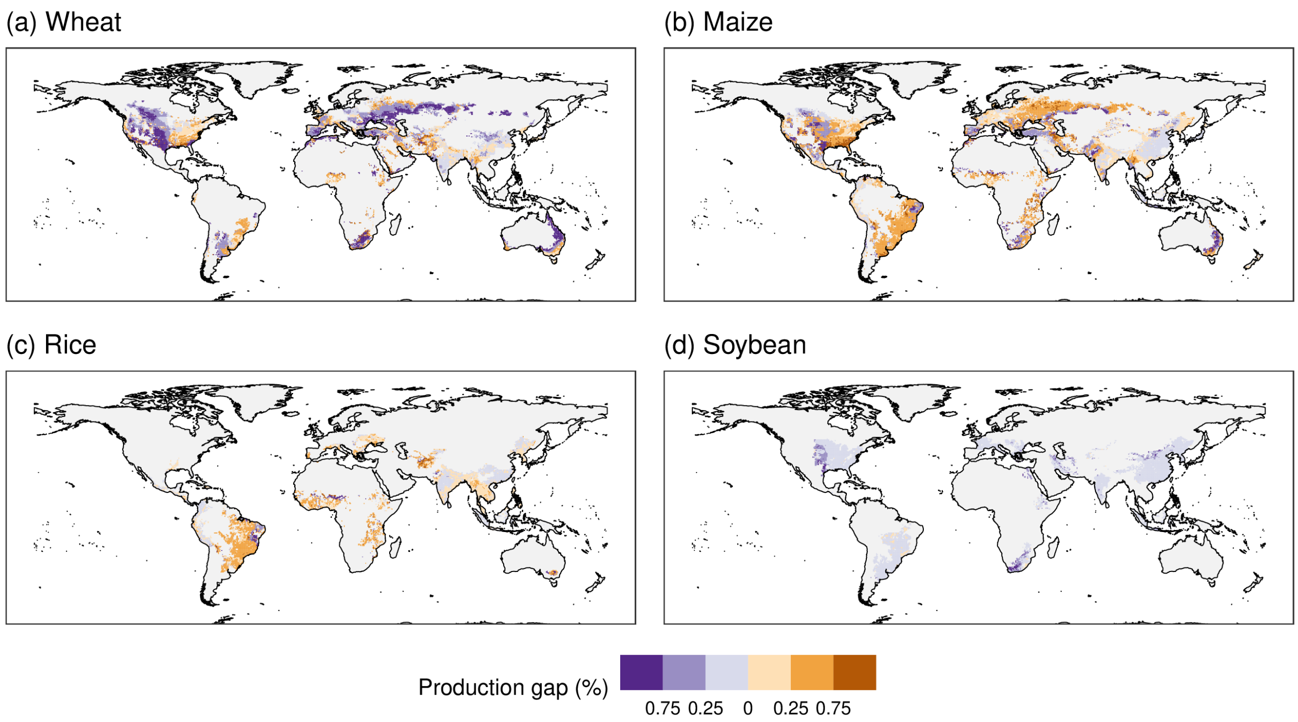

Figure 3.2: Production gap (potential minus baseline production; % of potential production) for total (rainfed plus irrigated) (a) wheat, (b) maize, (c) rice, and (d) soybeans. Colors indicate whether production gaps are mainly limited by nutrients (orange) or water (purple).

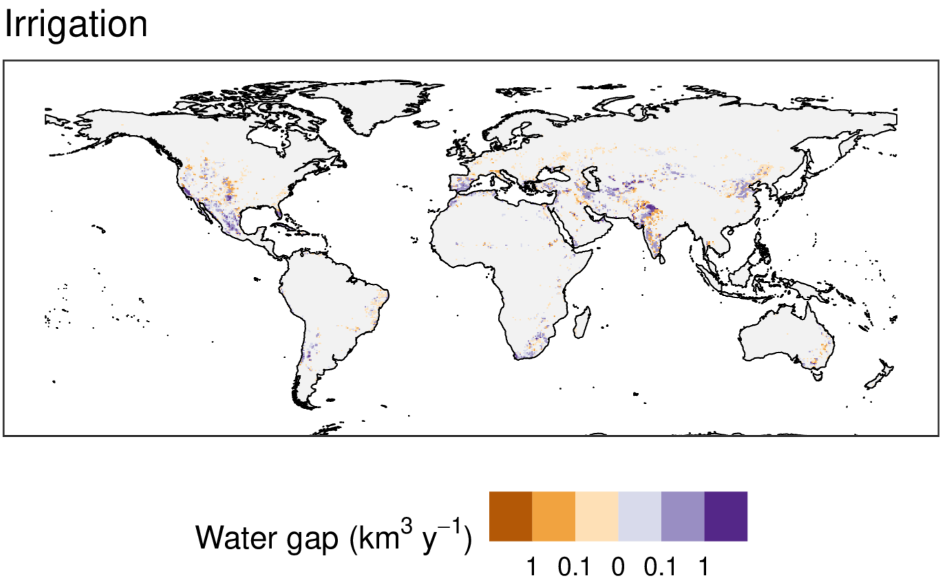

Figure 3.3: Water gap (unsustainable withdrawals) for irrigation under production gap closure. Colors indicate whether water gaps are mainly at the expense of environmental flows (orange) or environmental flows and non-renewable water resources (purple).

Table 3.2: Worldwide irrigated wheat, maize, rice and soybean crop production for potential, baseline, attainable and restricted simulations.

Crop production	Potential ($Mt\ y^{-1}$)	Baseline ($Mt\ y^{-1}$) (% of potential)	Attainable ($Mt\ y^{-1}$) (% of potential)	Restricted ($Mt\ y^{-1}$) (% of potential)
Wheat	268	238 (89)	208 (78)	190 (71)
Maize	242	193 (80)	194 (80)	162 (67)
Rice	436	412 (95)	399 (91)	381 (87)
Soybean	15	15 (100)	14 (94)	14 (94)
Total	961	858	815	747

Mexico (combined 24% of total), and Spain, Iraq, Iran and northeastern China (combined 12% of total). These regions are well-known for their groundwater exploitation [Famiglietti et al., 2011; Gleeson et al., 2012; Qureshi et al., 2010; Rodell et al., 2018, 2009; Shen et al., 2015; Steward et al., 2013], and environmental flow transgression [Gerten et al., 2013; Jägermeyr et al., 2017; Smakhtin, 2008].

3.3.3 Attainable irrigated crop production

Attainable irrigated crop production was estimated by constraining unsustainable irrigation withdrawals and at the same time increasing nutrient application up to nutrient gap closure requirements. Under these conditions, worldwide irrigated wheat, maize, rice and soybean production was estimated to change by -12.6, +0.3, -3.3, and -6.2% (-30, +1, -14 and -1 Mt y^{-1}) compared to the baseline (Table 3.2). This decrease can be divided into a total (all crops) 13% decrease in production due to decreased water availability (baseline to restricted production), and a 8% increase due to increased nutrient application (restricted to attainable production). Worldwide maize and rice production was reduced the least, as the increase in nutrient application offset their baseline nutrient limitations (section 3.3.1). Worldwide wheat and soybean production was reduced more substantial.

The previously mentioned regions with high levels of unsustainable water withdrawals (section 3.3.2) would show also large crop production reductions, when comparing the attainable production to the baseline (Figure 3.4 and figure 3.5). Estimated maize and wheat production reductions would be mostly concentrated in the irrigated croplands of northeastern China (Hai, Huai and Yellow river basin). This region would cover 44% of both worldwide maize and wheat reductions. Furthermore, these reductions constitute to almost a quarter of the region's baseline production. Reduced rice production would

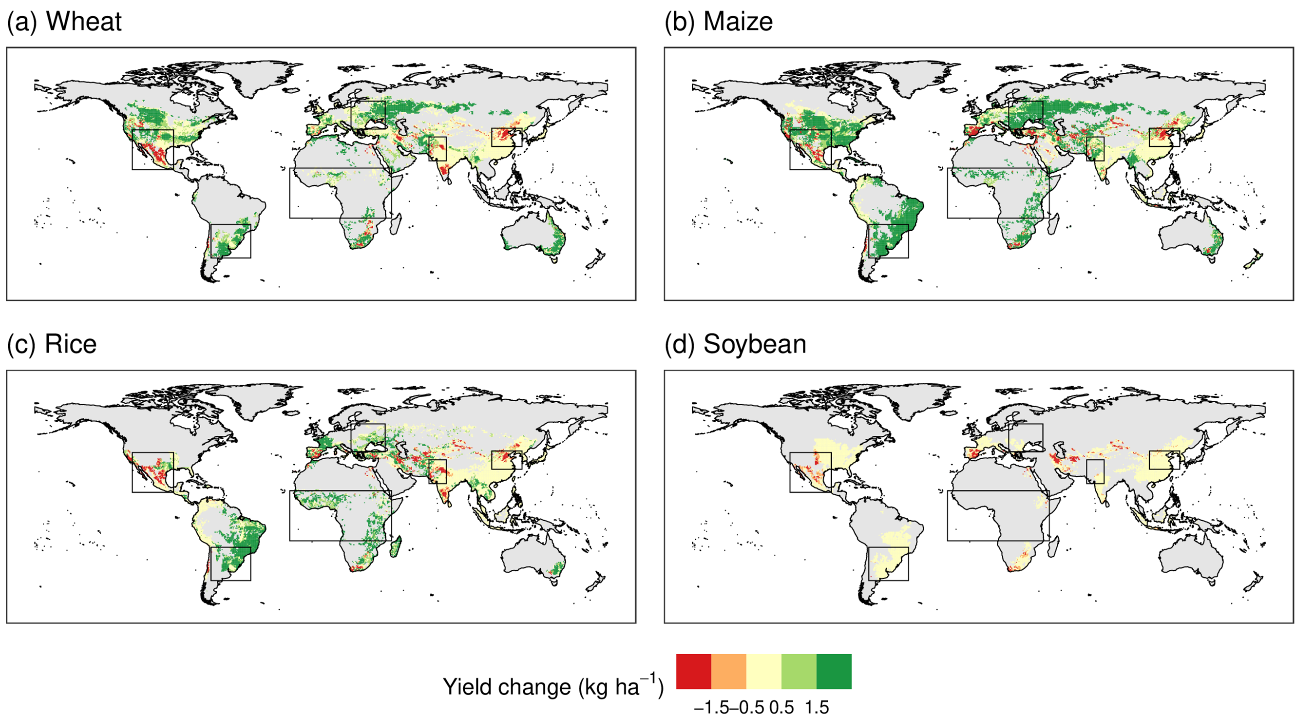

Figure 3.4: Crop yield changes for irrigated (a) wheat, (b) maize, (c) rice and (d) soybeans between baseline and attainable simulations. Boxes indicate the areas used in Figure 3.5.

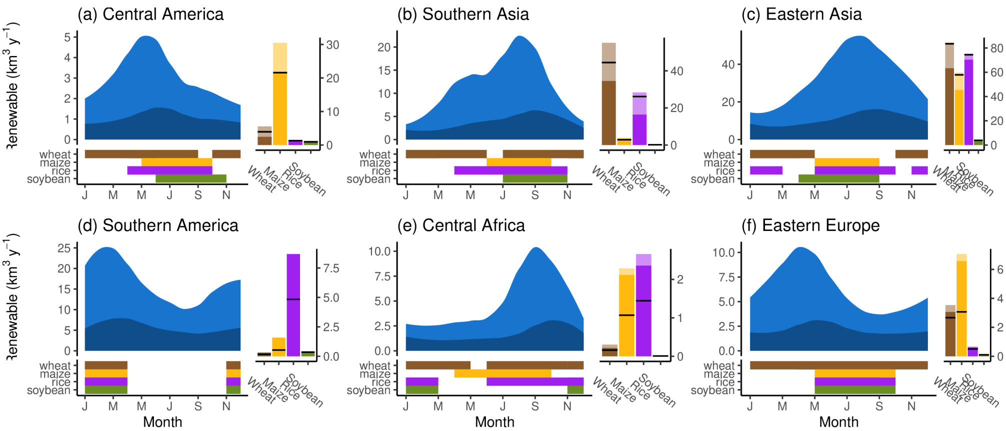

Figure 3.5: Regional irrigated crop production, crop growing season and renewable water resources. Left top is the smoothed monthly total renewable water availability (light-blue) and environmental flow requirements (dark-blue). Left bottom is the major crop growing season per crop. Right is the total attainable (dark), potential (light) and baseline (black line) production per crop. Note the difference in y scales among plots.

mainly occur in the irrigated croplands of Pakistan and northwestern India (Indus and Ganges river basins). These reductions would cover an estimated 32% of worldwide rice reductions and more than a third of the region's baseline production. The southern United States and Mexico (Mississippi, Colorado and Rio river basins) would be responsible for 24% of worldwide soybean reductions (23% of its baseline soybean production).

On the other hand, regions such as southern America, eastern Europe, and central Africa may sustainably increase their baseline irrigated crop production. These regions still have a nutrient gap to exploit and, especially for southern America, irrigated crops were mostly cultivated during periods of high renewable water availability. As such, sustainable intensification on irrigated croplands may achieve increases of 79% for rice in southern America, 97% and 63% for maize and rice respectively in central Africa, and 114% for maize in eastern Europe. However, currently these regions contribute only little to the worldwide irrigated crop production, as their irrigated area is limited. These results indicate possibilities to sustainably expand irrigation in these areas. However, quantifying the sustainable expansion extent lies outside of the scope of our study.

3.4 Discussion

Our study aims to quantify the impact of worldwide water constraints on attainable irrigated crop production. Attainable production accounted for increases in nutrient application, while limiting irrigation withdrawals to renewable water availability and without compromising river ecosystem water requirements. The quantification of attainable irrigated production was made possible by our newly developed model framework, which fully (two-sided) couples the VIC hydrological model and the WOFOST crop model. This model framework is the first to simulate daily biophysical processes related to worldwide water availability and crop growth under various water and nutrient limitations. This framework enabled our study to comprehensively simulate attainable irrigated crop production under sustainable intensification. Our simulations demonstrate limited possibilities to increase irrigated crop production through additional nutrient application. However, at least one third of current irrigated water withdrawals need to be reduced in order to account for environmental flow requirements and renewable water availability. Under these water constraints, substantial increases in worldwide irrigated production cannot be achieved.

Our study examined attainable irrigated crop production in terms of water quantity constraints. However, other considerations regarding sustainable intensification fell outside our study scope. Increasing production and optimizing management may not be viable due to socioeconomic constraints such as marginal investments returns, poor access to markets, and increased labor requirements [Giller et al., 2009; Godfray et al., 2010]. Also, increasing nutrient application rates without improving nutrient management practices have adverse side effects such as increased greenhouse gas emissions, river eutrophication, and coastal hypoxia [Bennett et al., 2001; Burney et al., 2010; Canfield et al., 2010; Diaz & Rosenberg, 2008]. The quantification of attainable irrigated production was affected by several limitations. Most importantly, the worldwide extent of our study required the use of coarse and aggregated input data (e.g. weather, soil, land-use, and fertilizer). These inputs hide the inherent local variation of agricultural processes which may interact non-linearly with crop growth [de Wit & van Keulen, 1987; Giller et al., 2011; Grassini et al., 2015]. These datasets also carry their own uncertainties due to data limitations [Frenken & Gillet, 2012; Hurtt et al., 2020; Mueller et al., 2012; Portmann et al., 2010; Zhang et al., 2017]. Sensitivity analysis (Supplementary Section B.4) indicated that, at our resolution, production was most sensitive to the timing and length of the growing season. The growing season was subsequently calibrated. However, at higher resolutions other aspects such as geohydrology, soil quality, fertilizer gradients and cropping patterns may become more apparent. Also, crop cultivar parameters other than phenology parameters (e.g. distribution of dry matter, optimum nutrient content, and translocation fractions) were kept constant for each crop. Therefore they do not comprehensively reflect the crop varieties cultivated worldwide [Gilardelli et al., 2018]. Further locally-oriented research (using locally relevant and high resolution observations) is needed to address these limitations and confirm the results of our study.

Our simulated worldwide crop production falls within the range of other studies (Supplementary Table B.4) [Alexandratos & Bruinsma, 2012; Iizumi et al., 2014; Mueller et al., 2012; Ray et al., 2013]. This is also the case for simulated irrigation withdrawals (Supplementary Table B.5) [Döll et al., 2014; Hanasaki et al., 2018; Pokhrel et al., 2015; Rost et al., 2008; Sutanudjaja et al., 2018; Wisser et al., 2010a]. The delineation and quantification of unsustainable irrigation withdrawals is similar to Rosa et al. [2018] and Jägermeyr et al. [2017], who also explored possibilities for irrigation intensification. In line with our work, both studies also show that sustainable intensification of crop production on currently irrigated croplands is limited. However, our study indicates that the decrease in crop production under sustainable irrigation management can be offset by increased nutrient application. Substantial increases in irrigated crop production can be achieved locally through the increased availability of nutrients. Nevertheless, even when accounting for increased nutrient application, water constraints resulting from sustainable irrigation management would result in a net decrease in worldwide crop production by 5%. This decrease is largely due to reduced water availability in some of the largest irrigated cropland areas worldwide, which currently use unsustainable irrigation practices.

It is important to acknowledge that some of the areas with unsustainable irrigation practices (e.g. Pakistan, India, and China) have large populations and are striving to achieve food security through various degrees of self-sufficient agricultural production [Clapp, 2017; Hussain & Routray, 2012; Soltani et al., 2020]. To achieve sustainable crop production increases for these irrigated croplands, options other than intensification should be explored such as: reducing irrigation demands by changing to less water intensive crops and developing water efficient crop varieties [Godfray et al., 2010; Morison et al., 2008], reducing irrigation withdrawals by increasing the irrigation efficiencies [Jägermeyr et al., 2016, 2017], increasing irrigation availability through inter-basin water transfers [Liu et al., 2017], and reallocating and expanding irrigation use in areas where sufficient water is available [Pastor et al., 2019; Rosa et al., 2019, 2018]. Moreover, climate change and socio-economic developments should be considered, as they will affect agricultural production through agricultural adaptation and COCO$_2$ fertilization [Challinor et al., 2014; McGrath & Lobell, 2013; Olesen & Bindi, 2002; Smith et al., 2014], and available water resources through precipitation and sectoral water demand changes [Bijl et al., 2018; Elliott et al., 2014; Flörke et al., 2018; Hejazi et al., 2014].

Ultimately, nutrient and water limitations are not the only factors influencing food security, as food security is a complex combination of biophysical factors, access, economics, and consumption and production patterns [Foley et al., 2011; Kastner et al., 2012; Rosegrant & Cline, 2003; Schmidhuber & Tubiello, 2007; Valin et al., 2014].

However, our results imply that intensification of currently irrigated croplands is at odds with sustainable water management. The question remains how long current unsustainable practices (e.g. groundwater exploitation) will remain physically, economically and environmentally feasible to support irrigated crop production [Aeschbach-Hertig & Gleeson, 2012; Gleeson et al., 2010; Rosegrant et al., 2009; Turner et al., 2019].

3.5 Conclusion

Irrigated wheat, maize, rice and soybean production gaps on currently irrigated croplands range from 83 to 100% of their potential. Achieving potential production would require an estimated 20% increase of crop nitrogen uptake. However, in order to satisfy environmental flow requirements and avoid non-renewable water withdrawals, current irrigation withdrawals should be reduced by at least one third according to our simulations. Under these water constraints, substantial increases in achievable irrigated production cannot be attained, even when considering increases in nutrient application. On the contrary, a change of -30, +1, -14 and -1 Mt y^{-1} is estimated for achievable irrigated wheat, maize, rice and soybean production respectively. The majority of these losses are concentrated in extensively irrigated cropland areas (e.g. northeastern China, Pakistan, and northwestern India). Sustainable intensification is possible on irrigated croplands in regions such as southern America, central Africa and eastern Europe. However, in these regions only a small fraction of crop is irrigated, and thus their contribution to worldwide irrigated crop production is limited. In sum, attainable irrigated production under worldwide water constrains is 78, 80, 91, and 94% of the potential wheat, maize, rice and soybean production respectively.

Chapter 4

Limits to management adaptation for the Indus' irrigated agriculture

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Abstract

Future irrigated agriculture will be strongly affected by climate change and agricultural management. However, the extent that agricultural management adaptation can counterbalance negative climate-change impacts and achieve sustainable agricultural production remains poorly quantified. Such quantification is especially important for the Indus basin, as irrigated agriculture is essential for its food security and will be highly affected by increasing temperatures and changing water availability. Our study quantified these effects for several climate-change mitigation scenarios and agricultural management-adaptation strategies using the state-of-the-art VIC-WOFOST hydrology–crop model. Our results show that by the 2030s, management adaptation through improved nutrient availability and constrained irrigation will be sufficient to achieve sustainable and increased agricultural production. However, by the 2080s agricultural productivity will strongly depend on worldwide climate-change mitigation efforts. Especially under limited climate-change mitigation, management adaptation will be insufficient to compensate the severe production losses due to heat stress. Our study clearly indicates the limits to management adaptation in the Indus basin, and only further adaptation or strong worldwide climate-change mitigation will secure the Indus' food productivity.

4.1 Introduction

Irrigated agriculture is essential for worldwide food security. By supplementing rainfall deficits with other water resources, irrigation enables agriculture in arid regions and dry periods that would otherwise not support crop cultivation. Moreover, agricultural intensification and yield-gap closure through, among others, irrigation expansion is likely needed to maintain sufficient food production for a growing and developing population [Foley et al., 2011; Godfray et al., 2010; Mueller et al., 2012].

However, irrigated agriculture is threatened by climate-change and its two fold impacts on crop growth and water availability. Temperature increases under climate change will reduce crop productivity and cropland suitability, especially in lower latitudes, as crop development and stress is strongly linked to growing season temperatures [Ortiz et al., 2008; Pugh et al., 2016; Tan et al., 2021]. In addition, changing precipitation, evaporation and snow melt patterns under climate change will affect the timing and distribution of surface and groundwater availability [Haddeland et al., 2014; Immerzeel et al., 2010]. Contrary to these negative climate impacts, elevated atmospheric carbon dioxide concentrations ($[CO_2]$) will positively affect irrigated agriculture through increased crop productivity and water-use efficiency (especially for C_3 crops) [Ainsworth & Long, 2021; Toreti et al., 2020].

These climate-change impacts on irrigated agriculture is especially important for the Indus basin. Agriculture in the Indus basin supports the livelihoods of more than half of its 240 million inhabitants and is a key component of the local government's food self-sufficiency strategy [Government of India, 2015; Government of Pakistan, 2018a, 2020b]. To enable agriculture in the arid Indus basin, croplands are extensively irrigated with water from the mountainous upper Indus region in combination with large scale groundwater extractions, redistributed through the world's largest contiguous irrigation system [Food and Agricultural Organization, 2011]. However, agricultural productivity is well below its potential and barely able to sustain the food requirements of the rapidly developing population [Ahmad & Farooq, 2010; Khan et al., 2021a; Shapouri et al., 2010]. Moreover, excessive water withdrawals threaten the long-term viability of irrigated agriculture. Groundwater depletion and associated salinity problems are prevalent [Qureshi, 2018; Qureshi et al., 2010; Sidhu et al., 2021; Watto & Mugera, 2016] and water withdrawals and reservoir construction are endangering the integrity of the riverine ecosystem [de Graaf et al., 2019; Irfan et al., 2019; Salik et al., 2016].

To achieve sufficient and sustainable agricultural productivity in the Indus basin, the possibilities and limitation of management adaptation under climate change need to be addressed. While the impact of climate-change on crop heat stress [Ali & Erenstein, 2017; Arshad et al., 2017] and water availability [Dahri et al., 2021; Wijngaard et al., 2017] in the Indus basin is well studied, their combined impact on irrigated agriculture is often poorly understood and quantified. Moreover, the possibilities and limitations of agricultural management adaptation to increase productivity and constrain excessive water withdrawals is hardly ever considered, while recognizing these limitations is essential to determine the need for more drastic interventions and plan for those appropriately.

Our study therefore quantifies the effects of agricultural management adaptation in the Indus basin under various climate-change mitigation scenarios. To this end, the effects of projected climate change and elevated [CO_2] on the productivity of primary food crops, wheat and rice (Section 4.3.1), and the availability of and demand for water (Section 4.3.2) are quantified. Subsequently, the extent to which agricultural management adaptation can enhance agricultural productivity and achieve sustainable water use is explored (Section 4.3.3). Lastly, the implications of these results for the Indus basin food security are examined (Section 4.4).

We use the state-of-the-art process-based hydrology–crop model VIC-WOFOST [Droppers et al., 2021] to estimate crop growth, water availability and their two-sided interactions (Section 4.2.1). Three climate-change mitigation scenarios were included [Lange, 2019]: high mitigation (+2°C by 2100), medium-low mitigation (+4°C by 2100) and low mitigation (+5°C by 2100). Furthermore, three periods are assessed: the 1980s (1970-2000), the 2030s (2020-2050) and the 2080s (2070-2100), representing the historical, mid-century and end-of-the-century periods, respectively. Considered management-adaptation options are: (1) reduced crop nutrient limitations (i.e. improved soil and fertilizer management) to increase crop productivity and (2) constrained irrigation withdrawals to avoid unsustainable water use (i.e. avoiding non-renewable water withdrawals and protecting riverine ecosystems). The model is specifically setup for the Indus basin, and thoroughly calibrated and validated for the elevated [CO_2] effects on crop growth and for the Indus' agriculture and hydrology (Supplementary Sections C.1 and C.2).

4.2 Methods

4.2.1 Model description

VIC-WOFOST [Droppers et al., 2021] is a two-way coupling between the variable infiltration capacity (VIC) hydrological model [Droppers et al., 2020; Hamman et al., 2018; Liang et al., 1994] and the world food studies (WOFOST) crop model [de Wit et al., 2019, 2020; Supit et al., 1994] (Figure 4.1). In the coupled model framework, the VIC hydrological model is used to estimate water availability while the WOFOST crop model is used to estimate crop growth. The hydrological model simulates the gridded

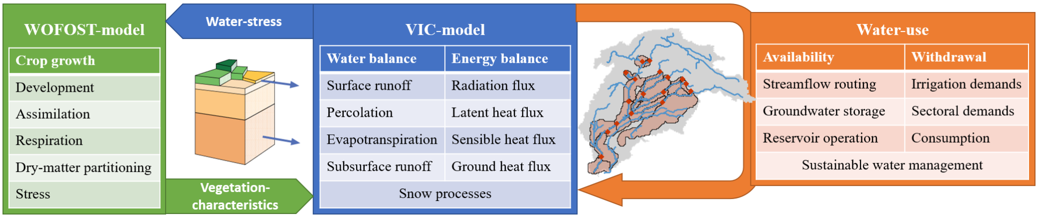

Figure 4.1: Conceptualization of the VIC-WOFOST model implementation. The VIC hydrological simulates the water and energy balance for various land-cover tiles and the WOFOST crop model simulates crop growth for wheat and rice land-cover tiles. Water use is based on the simulated water availability and withdrawal. For croplands in an irrigation scheme (orange regions on map), irrigation can be withdrawn from the irrigation scheme inlet (orange points on map).

(5-arcminute resolution) spatially distributed water and energy balance for various land-cover tiles (e.g. forests, grasslands, rainfed agriculture, irrigated agriculture and bare soil). Evapotranpsiration and latent heat fluxes are governed by the Penman-Monteith equation [Shuttleworth, 1993], where energy and water balance components meet. Each land-cover tile is simulated separately, meaning there is no interaction between the water and energy balance of each tile. The crop model simulates crop growth for each wheat and rice land-cover tile over the growing season. The crop model subsequently informs the hydrological model regarding changes in vegetation characteristics (e.g. LAI, rooting depth and height), thereby affecting water and energy fluxes. Further information on the model setup is given in Supplementary Section C.1.

4.2.2 Water use

Water demands originate from several sectors: irrigation, domestic, industrial (i.e. manufacturing and thermoelectric energy) and livestock. Irrigation water demands are determined by model simulation [Droppers et al., 2020]. For wheat, and other crops except rice, irrigation is required when crop water stress would occur (see Section 4.2.3). Irrigation demands are subsequently set to fill the soil moisture up to field capacity. For paddy rice, irrigation is required when the upper soil layer becomes dry. Irrigation demands are subsequently set to fill the upper soil layer. Domestic, industrial and livestock water demands are given as an input to the model, and are estimated based on reported values for Pakistan and estimates of population growth (see Supplementary Section C.1). These sectors combined constitute only between 6% and 17% of the total water demands.

Simulated surface and subsurface runoff is routed along flow paths to simulate river streamflow [Lohmann et al., 1996; Watt & Chow, 1985] (Figure 4.1). River streamflow is further modified by reservoir storage and release, which operates according to the reservoir's main purpose [Hanasaki et al., 2006]. For example, reservoirs with an irrigation purpose will increase river streamflow when needed for irrigation. Water demands are subsequently withdrawn from local (i.e. within grid) river streamflow. For irrigation areas that are part of a centralized irrigation scheme, water can additionally be withdrawn from remote river streamflow at the irrigation scheme inlet [Biemans et al., 2019]. If rivers streamflow is insufficient to supply these water demands, water is withdrawn from a local (i.e. within grid) unconfined groundwater aquifer. Groundwater aquifer withdrawals are unrestricted. However, if the aquifer storage has been reduced, subsurface runoff will be redirected to recharge the aquifer, instead of contributing to river discharge.

Only part of the withdrawn water resources actually evaporates, referred to as 'consumed', while the rest is returned to the water system. These return flows play an important role in the Indus basin irrigation efficiency, as the contribute significantly to groundwater recharge [Laghari et al., 2012]. Irrigation efficiency is separated into conveyance and application efficiency. Conveyance efficiency refers to percolation losses during transport from inlet to field and is set to 0.6 [Hussain et al., 2011]. Application efficiency refers to evaporation and percolation losses during field irrigation, which is assumed to occur via surface application [Hussain et al., 2011]. As such irrigation is applied continuously to the upper soil layer and may subsequently increase evaporation and percolation. Percolation from both conveyance and application are eventually returned to the groundwater aquifer or, if there is no aquifer deficit, to the river streamflow. These return flows are again available for withdrawal. Therefore, the overall irrigation efficiency changes based on the spatial extent of the analysis. For example, our simulations indicate the consumption efficiency for an individual field (irrigation water transpiration per withdrawal) is only 0.29, while the consumption efficiency for the whole region (irrigation water transpiration per evapotranspiration) is 0.63.

4.2.3 Crop growth

Crop growth results from carbon assimilation and nutrient uptake during the growing season. Crop growing seasons follow reported planting and harvesting dates [Portmann et al., 2010], including one wheat and two rice seasons, and crop phenology (i.e. the temperature requirements for crop development) is adjusted accordingly.

Growth is affected by several stress factors that reduce productivity and yield. The most important stress factors in our study are heat, water and nutrient stress. Heat stress occurs when daily air temperatures exceed suitable crop growing temperatures. Suitable growing temperatures were based on detailed field experiments [Boons-Prins et al., 1993], and are further adjusted in our study to match regional wheat varieties [Government of Pakistan, 2015] (rice suitable growing temperatures were deemed sufficient [Hussain et al., 2019]). Water stress occurs when soil moisture drops below the critical moisture point [Keulen & Wolf, 1986; van Diepen et al., 1988] and restricts water uptake. In order to avoid water stress, irrigation may be used to increase the soil moisture content, as described in Section 4.2.2. Lastly, nutrient stress occurs when nutrient supply is insufficient to meet nutrient demands, and crop nutrient concentrations drop below their critical nutrient concentration [Shibu et al., 2010].

Nutrient supply is determined by soil mineralization and fertilizer application. Mineralization rates were estimated based on the soil pH, soil carbon content and air temperature [Batjes, 2016; Sattari et al., 2014]. Organic and inorganic fertilizer application rates between 1850 and 2015 were derived from various studies [Hurtt et al., 2020; Mueller et al., 2012; Zhang et al., 2017]. Mineralization rates and fertilizer efficiencies were scaled to match observed yields under minimal fertilizer application and observed yield trends respectively (Supplementary Section C.2). Only nitrogen fertilization data was available and accounted for in our study.

Several crop responses to elevated [CO_2] were simulated: increased maximum carbon assimilation rates, increased light-use efficiency and increased stomatal resistance. Increased maximum assimilation and light-use efficiency increases the potential crop productivity while increased stomatal resistance decreases crop water demands. Increases in maximum assimilation rates and light-use efficiency were based on values from WOFOST [Wolf et al., 2012]. However, increases in maximum assimilation rates were reduced compared to the default values because they overestimated field conditions [Long et al., 2006; Wolf et al., 2010], as confirmed by our validation (see Supplementary Section C.2.1). Stomatal resistance increases were based on a meta-analysis of a multitude of free air concentration enrichment (FACE) experiments [Ainsworth & Rogers, 2007], and were applied appropriately to each land-cover tile. Stomatal resistance hyperbolically increases with increases in [CO_2] (i.e. strong increase at the start that levels-off at higher [CO_2]) [Li et al., 2019].

4.2.4 Agricultural management-adaptation strategies

Apart from contemporary agricultural management practices, referred to as the 'baseline', two agricultural management-adaptation strategies were explored: production-focused and sustainability-focused management. Production-focused management aims to maximize crop productivity by closing crop yield gaps (i.e. the gap between the potential and actual yield) resulting from water and nutrient limitations. This is done by improving nutrient supply (e.g. through increased fertilizer application or improved soil management) compared to the baseline, and by allowing irrigation withdrawals from surface and groundwater resources.

Contrastingly, sustainability-focused management aims for sustainable water management by avoiding non-renewable groundwater withdrawals and protecting stream flow requirements for riverine ecosystems. Following the variable monthly flow method [Pastor et al., 2014], 60%, 45% and 30% of the historical naturalized river stream flow is allocated for river ecosystems during low, medium and high flows respectively. Note that these allocations are also accounted for during reservoir operation [Droppers et al., 2020]. In addition, groundwater withdrawals cannot exceed long-term groundwater recharge. Temporary storage deficits were allowed, to account for interannual variation in groundwater withdrawal and recharge. As a result, irrigation withdrawals for agriculture are constrained compared to the baseline. However, within these irrigation constraints, sustainable crop production increases are still possible through improved nutrient supply.

4.2.5 Climate-change mitigation scenarios

Climate inputs are derived from the inter sectoral impact model intercomparison project phase 3b (ISIMIP3b), which includes three of the newest United Nations intergovernmental panel on climate change (IPCC) mitigation scenarios: high mitigation (radiative forcing of 2.6 W m^{-2}), medium-low mitigation (radiative forcing of 7.0 W m^{-2}), and low mitigation (radiative forcing of 8.5 W m^{-2}). These scenarios result in average temperature increases of 2°C, 4°C and 5°C by 2100 in the Indus basin for each mitigation scenario respectively. Meteorological inputs (daily precipitation, air temperature, surface pressure, wind speed, long and shortwave radiation and vapor pressure) at 30-minute resolution are based on five models from the coupled model intercomparison project phase 6 [Eyring et al., 2016] (CMIP6) climate models: GFDL-ESM4 [Dunne et al., 2020], IPSL-CM6A-LR [Boucher et al., 2020], MPI-ESM1-2-HR [Müller et al., 2018], MRI-ESM2-0 [Yukimoto et al., 2019] and UKESM1-0-LL [Sellar et al., 2020]. These models were selected in ISIMIP3b based on their performance during the historical period, and represent the CMIP6 ensemble spread in climate sensitivity. For ISIMIP3b, these inputs were bias-adjusted and statistically downscaled [Lange, 2019] based on the water and global change (WATCH) forcing data methodology applied to ERA5 data (WFDE5) [Cucchi et al., 2020].

However, bias-adjustments often provide poor results in the upper Indus, as meteorological observations, especially at greater altitudes, are lacking and suffer from gauge under-catch corrections [Dahri et al., 2018; Immerzeel et al., 2015]. Therefore, the upper Indus was further corrected based on meteorological inputs, at 15-minute resolution, from the European centre for medium-range weather forecasts reanalysis 5th data (ERA5) [European Centre for Medium-range Weather Forecasts, 2021], which compares favorably to other dataset in the upper Indus region [Dahri et al., 2018]. Monthly correction factors (one for each month of the year) were calculated for each model, such that the multi-year monthly average temperature, total precipitation and average short and longwave radiation would match ERA5 in the overlap period (1979-2015). These monthly correction factors were subsequently applied for all years (historical and future). Simulations were run for three periods: the 1980s (1970-2000), the 2030s (2020-2050) and the 2080s (2070-2100).

4.3 Results

4.3.1 Climate-change mitigation and crop productivity

Climate and [CO_2] changes have a diverging impact on the Indus' crop production. Elevated [CO_2] will increase crop carbon assimilation and final yields. On the other hand, higher temperatures contribute to increased crop heat stress and decrease final yields. Both these processes become stronger under lower climate-change mitigation due to a higher increase in [CO_2] and temperature.

For wheat, with optimal growing temperatures between 15°C and 30°C [Government of Pakistan, 2015], heat stress dominates. Wheat production is estimated to decrease by 16% and 38% by the 2080s under high and low mitigation scenarios respectively (Figure 4.2a). For rice, with optimal growing temperatures between 25°C and 35°C [Hussain et al., 2019], heat stress is likely to be less important. Rice production is estimated to decrease 5% and 12% by the 2080s under high and low mitigation scenarios respectively (Figure 4.2b). However, these results are highly uncertain due to the large spread in climate-model sensitivities. Under some climate models with a lower climate sensitivity (GFDL-ESM4 and MPI-ESM1-2-HR) temperature increases are lower and rice production is actually expected to increase (Figure 4.2b).

Note that a turning point for wheat and rice yields exists. During the 2030s productivity remains relatively similar to the historical production because the positive impacts of elevated [CO_2] compensates for the negative impacts of higher temperatures. However, towards the 2080s temperature increases clearly offsets the elevated [CO_2] benefits. Climate-change impacts are unevenly distributed across the Indus basin (Figure 4.2c and d). In the north-eastern region yields tend to increase, while decreases are prevalent in the south-western region. These geographic differences can largely be

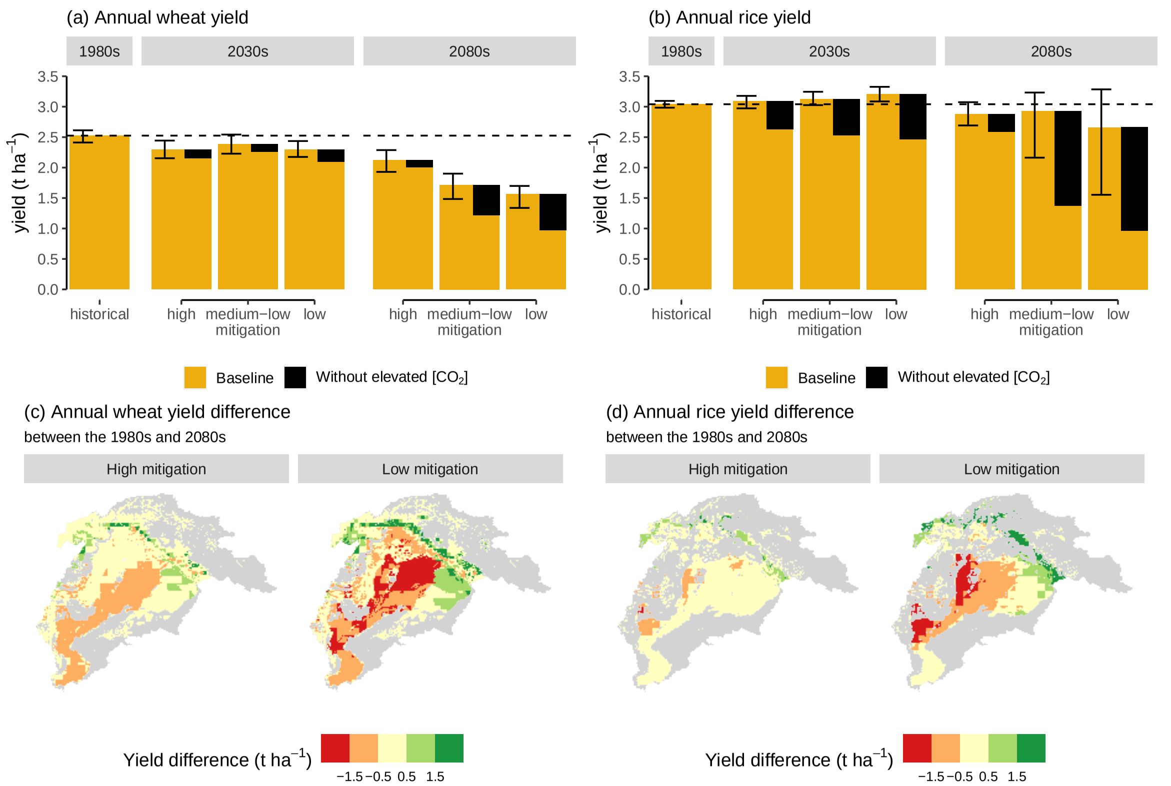

Figure 4.2: Simulated baseline (i.e. no management adaptation) annual median (a) wheat and (b) rice yield, and spatially distributed annual median (c) wheat and (d) rice yield differences between the 1980s (historical) and 2080s. Black bars indicate the annual median yield difference (bar height) between simulations with and without elevated [CO_2]. Error bars denote interannual and intermodel variability (1st to 3rd quartile).

4

attributed to elevation (i.e. temperatures in the higher northern regions actually become more suitable under climate change), growing seasons (i.e. eastern Indus wheat harvest occur earlier, thereby avoiding temperature increases), and spatial distribution of temperature increases (i.e. western Indus temperatures increase relatively further). Furthermore, the effects of elevated [CO_2] are smaller for wheat than rice, with a 2080s average increase of 12% and 22% for wheat and rice respectively (average of all mitigation scenarios). These effects are smaller because heat stress and nutrient limitations are larger for wheat than rice, thus decreasing the effectiveness of the elevated [CO_2] on wheat carbon assimilation.

4.3.2 Climate-change mitigation and water availability

As the Indus' agriculture is mostly irrigated, precipitation changes will not directly affect crop production. Rather, changes in precipitation and [CO_2] will affect water availability and irrigation water demands.

Increases in renewable surface water availability (i.e. the pristine river streamflow) are expected for all mitigation scenarios, mostly due to projected precipitation increases (Figure 4.3a). Water availability increases between 11% and 25% by the 2080s for high and low mitigation scenarios respectively. Relative water availability increases are largest during the dry season of October to February, while absolute increases are largest during the early wet season of March to May (Figure 4.3c). Note that these results indicate a shift to an earlier start of the wet season.

At the same time, irrigation demands are expected to continuously and substantially reduce towards the 2080s, mostly due to the crop [CO_2] response (Figure 4.3b). This response is largest under low mitigation scenarios, with demand reductions of 28%. Moreover, decrease in groundwater irrigation demands of up to 58% are expected under low mitigation scenarios (Figure 4.3d). These reductions are larger than the total reductions as, besides the crop [CO_2] response, they also account for the increase in available river streamflow.

4.3.3 Management adaptation

Management decisions are a major factor determining future crop production. Under production-focused management, agricultural production increases between 10 Mt (2080s low mitigation) and 19 Mt (2030s low mitigation) are possible compared to the baseline (Figure 4.4). Especially during the 2030s, production increases between 38% and 45% of the historical (1980s) production are possible. Larger crop production increases are expected for wheat as compared to rice, as wheat has a higher nutrient deficit than rice.

However, the high irrigation withdrawals that accompany production-focused

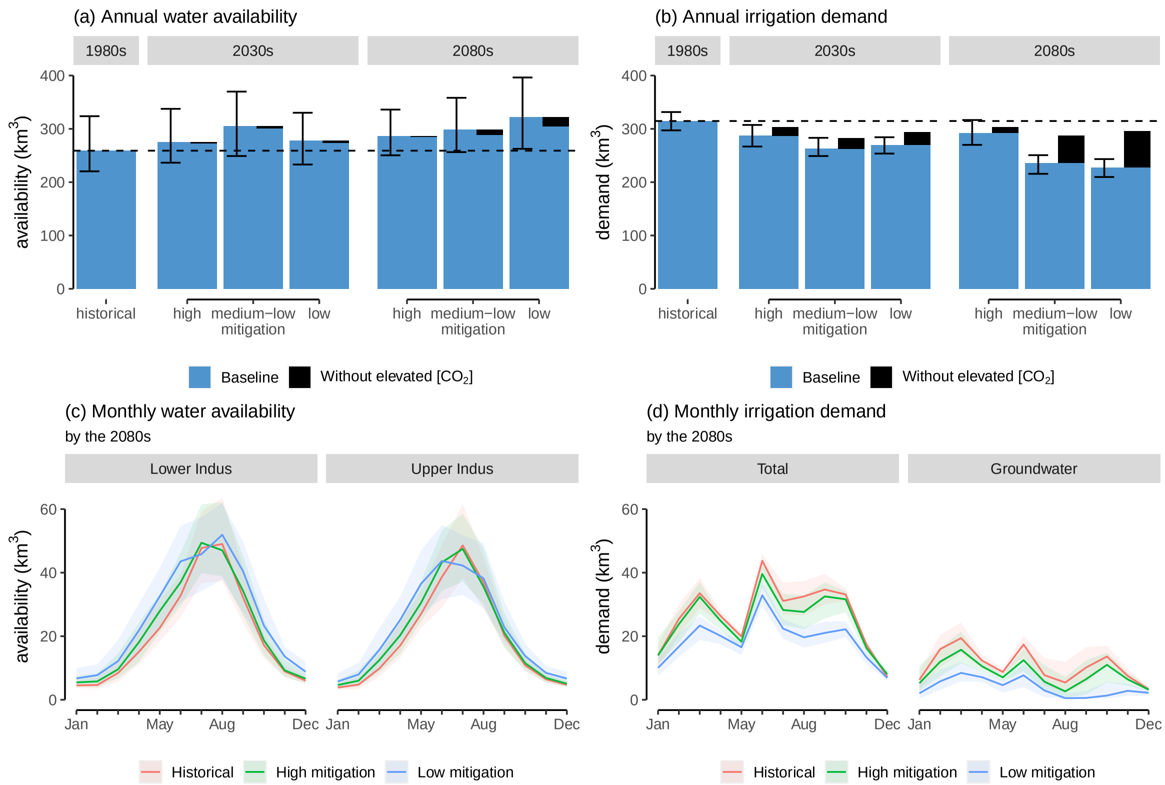

Figure 4.3: Simulated baseline (i.e. no management adaptation) annual median (a) water availability and (b) irrigation demand, and temporally distributed 2080s annual median (c) water availability by location and (d) irrigation demand by source. Water availability is estimated based on pristine river streamflow without water withdrawals and reservoir operation. Black bars indicate the annual median availability and withdrawal difference (bar height) between simulations with and without elevated [CO_2]. Error bars and shaded areas denote interannual and intermodel variability (1st to 3rd quartile).

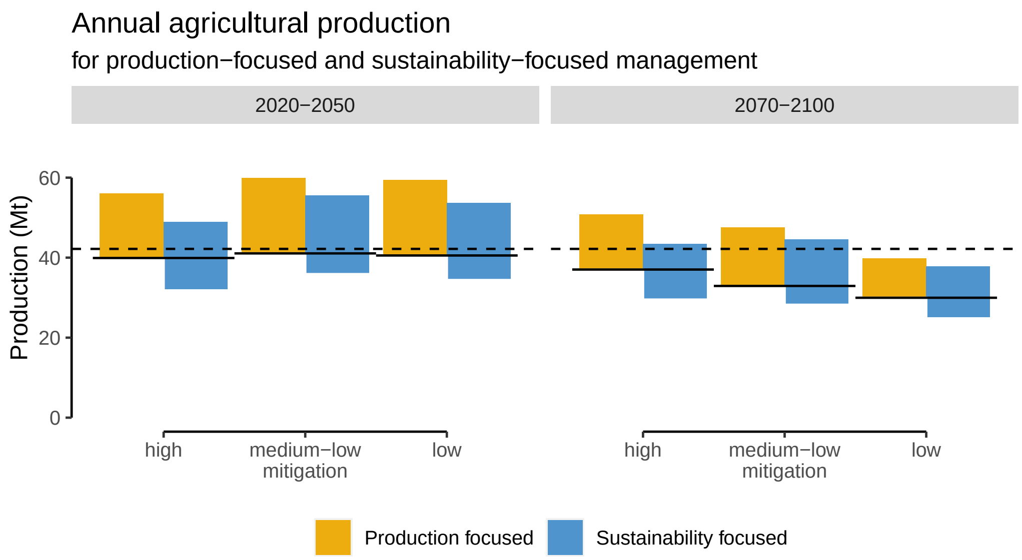

Figure 4.4: Simulated possibilities and limitations of management adaptation, in annual median agricultural production, for (yellow) production focused and (blue) sustainability focused management. The solid lines indicate baseline production without management adaptation, while bar heights indicates the production range under management adaptation. Production focused management starts at the baseline and ends at the maximum production possible under improved nutrient supply. Sustainability focus management start below the baseline, due to irrigation constraints, and end at the maximum production possible under both improved nutrient supply and irrigation constraints. The dashed line indicates the historical production.

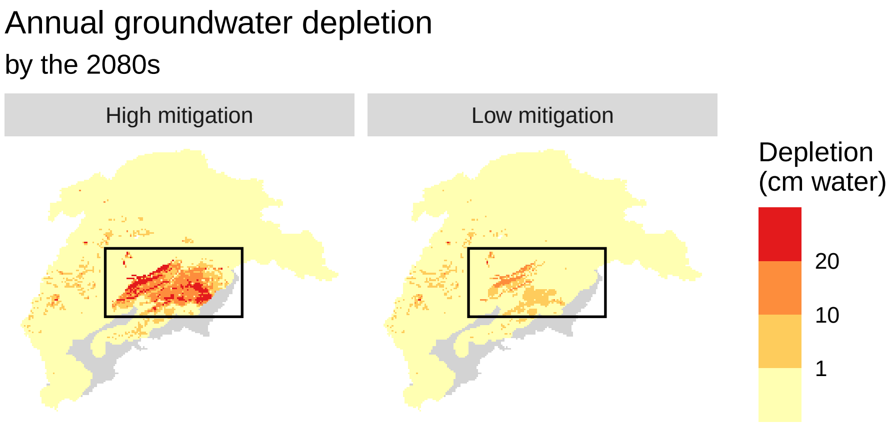

Figure 4.5: Simulated 2080s annual median groundwater depletion for production focus management. Eastern Indus area is indicated with a rectangle.

management would be hard to maintain due to continuing groundwater depletion (Figure 4.5). Average groundwater depletion rates of 7cm and 2cm water are estimated in the Indus' eastern region during the 2080s for high and low mitigation scenarios respectively. Assuming a soil porosity of 0.13 [Jabeen et al., 2020], these rates are equivalent to a groundwater table drop of at least 58m and 12m respectively between 2000 and 2100 (accumulated depletion over time).

Under sustainability-focused management, irrigation withdrawals will have to be constrained by 20% and 15% (57 and 36 km^3 y^{-1}) for the 2030s and by 19% and 7% (55 and 16 km^3 y^{-1}) for the 2080s high and low mitigation respectively. Note that these constraints are less under low mitigation scenarios, due to increased water availability and decreased irrigation demands (Section 4.3.2). As a result of these constraints, the upper and lower bounds of the sustainability-focused production is decreased as compared to production-focused management (Figure 4.4). Under improved fertilizer application, sustainability-focused production can achieve 68% (between 6 Mt and 14 Mt) of the production-focused production increases (average of all periods and mitigation scenarios).

Even so, whether production increases are possible by the 2080s strongly depends on the climate-change mitigation scenario. Although baseline production is expected to decrease under all climate-change scenarios, management adaptation can compensate for these decreases under high climate-change mitigation. However, management adaptation

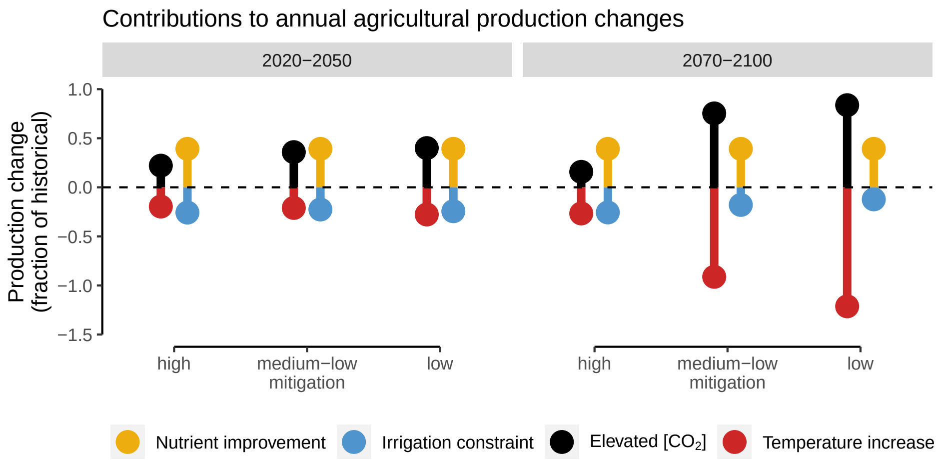

Figure 4.6: Simulated annual median agricultural (wheat plus rice) production changes due to climate change and management adaptation. Colors indicate the individual contributions of (black) elevated [CO_2], (red) temperature increases, (yellow) nutrient improvements and (blue) water constraints. Contributions are given as a fraction of the 1980s (historical) production.

will be insufficient to maintain production under low mitigation. This discrepancy is due to the relative contributions of management adaptation, elevated [CO_2] and temperature increases in these scenarios (Figure 4.6). While reduced management adaptation and elevated [CO_2] will contribute positively to sustainable agricultural productivity, the negative contribution of temperature increases outweighs these factors under low climate-change mitigation by the 2080s.

4.4 Discussion

Our study comprehensively assessed the possibilities and limitation of management adaptation in the Indus' agriculture under various climate-change scenarios. Our results indicate that the relative contributions of climate change and management adaptation to the Indus' future irrigated agriculture are markedly different in time and per climate-change mitigation scenario. During the 2030s, management adaptation will be sufficient to achieve sustainable and increased agricultural productivity. Although irrigation constraints are necessary to avoid unsustainable water withdrawals, nutrient management improvements can increase agriculture productivity and compensate for these irritation constraints. Note that implementing these management adaptations will require substantial investments in agricultural inputs (e.g. fertilizers) and organization (e.g. water policies) that may be economically or practically difficult or environmentally unsustainable [Chang et al., 2021; Giller et al., 2009; Godfray et al., 2010; Qureshi, 2020; van Steenbergen & Oliemans, 2002].

However, towards the 2080s, agricultural production in the current agricultural landscape (e.g. land use and growing seasons) will strongly depend on worldwide climate-change mitigation efforts. Especially under low climate-change mitigation scenarios, temperature increases and associated crop heat stress will result in substantial reductions in agricultural productivity that cannot be compensated by elevated [CO_2] or management adaptation. Moreover, additional canopy temperature increases resulting from reduced transpiration cooling under elevated [CO_2], not included in our study, will further increase heat stress severity [Kimball, 2016]. Nevertheless, climate-change will positively affect water abundance (i.e. the difference between water demands and availability). Crop water-use efficiency will increase due elevated [CO_2], and precipitation increases will enhance water availability. In addition, permanent glacier melting, not included in our study, will temporarily increase summer streamflows even further [Immerzeel et al., 2013; Lutz et al., 2016].

While our study shows that heat stress impacts outweigh the elevated [CO_2] benefits in the Indus basin, this net effect varies worldwide. In particular in regions where temperature increases do not exceed optimal crop growing temperatures, generally higher latitude regions, agricultural productivity increases can be expected under climate change [Deryng et al., 2014; Ortiz et al., 2008; Wassmann et al., 2009]. Furthermore, changes in water abundance will depend on the net effect of water demand decreases and water availability changes [Elliott et al., 2014]. For example, water abundance increases have been reported for Morocco where crop water-use efficiency increases counterbalance precipitation decreases [Bouras et al., 2019], while crop water-use efficiency increases insufficiently compensate for precipitation decreases and water demand shifts in the Colorado basin [Rajagopalan et al., 2018]. However, few studies fully consider changes in both river-basin water availability and irrigated crop productivity under climate change and management adaptation, as in our study.

In order to achieve sustainable food security the Indus basin, further agricultural adaptation is needed. Under high mitigation scenarios, water management improvements should be prioritized to achieve sustainable water use. Irrigation withdrawals should be constrained to enable long term sustainable agricultural production and avoid transgressing environmental streamflow requirements for riverine ecosystems. Practices such as enhanced groundwater recharge during the wet season, when water is abundant, may provide renewable groundwater storage that can be withdrawn during the dry season, when irrigation demands are high [Khan et al., 2008].

Importantly, improving the region's irrigation efficiency may not always be beneficial, as unused irrigation withdrawals are partially reused later [Grafton et al., 2018; Simons et al., 2020] (Section 4.2.2). Care should be taken to increase irrigation efficiency through reductions in evaporation losses, while accounting for return flows that contribute to groundwater recharge and dry season water availability.

Under low mitigation scenarios, agricultural changes are required to avoid production decreases. A transition to shorter growing seasons or other, more heat resistant, crops should be considered to cope with the temperature increases [Davis et al., 2018; Teixeira et al., 2013], especially for wheat. Development of heat resistant and high yielding crop varieties will also reduce production diminution [Bita & Gerats, 2013; Bustos et al., 2013; Gulnaz et al., 2019; Wu et al., 2019]. Note that crop transitions would be highly transformative to the Indus' food system, as wheat and rice are currently important in both agricultural exports and local dietary preferences [Ahmad & Farooq, 2010]. Therefore, such transitions would need thorough corroboration of the suitability and productivity of these new agricultural production systems.

If these agricultural changes are planned appropriately, and increases in heat stress can be avoided, the Indus agriculture could also benefit from climate-change. Elevated [CO_2] will increase agricultural productivity, while water abundance increases will enable sustainable intensification and expansion of irrigation systems. Note that groundwater pumping intensification and expansion should be considered carefully. While our simulations are in range of the reported gross groundwater depletion rates (Supplementary Section C.2), the effect of groundwater depletion on local river streamflow and groundwater tables may be more severe than appears in our simulations. Depending on the pumping approach and the surrounding geohydrology, river streamflow depletion and groundwater table lowering patterns may differ substantially in time and space [de Graaf et al., 2019; Gleeson & Richter, 2018].

Whether or not the Indus region can attain future food security remains ambiguous. Food demands are rising rapidly due to population growth and socioeconomic developments [Beltran-Peña et al., 2020; Fader et al., 2013; Zulfiqar & Hussain, 2014], and outweigh the possible production increases presented here. Further cropland intensification and expansion are likely possible but should confirm to the above-mentioned sustainable water use and crop transitions to enable food security. A greater dependence on food imports, with its political and economic challenges, seems unavoidable [Clapp, 2017; D'Odorico et al., 2014; Porkka et al., 2013].

4.5 Conclusions

By the 2030s, elevated [CO_2] and nutrient and water management adaptation will be able to achieve increased and sustainable agricultural production in the Indus basin. Production increases up to 14 Mt (or 35% of the historical production) are possible, even when considering sustainable water use. Achieving sustainable water management would require a substantial reduction in irrigation withdrawals between 15% and 20%. However, due to increases in precipitation and decreases in crop water demands, irrigation constraints resulting from sustainable water management will be reduced compared to the historical context.

However, towards the 2080s climate-change effects will decrease agricultural production between 11% and 30% compared to the 2030s values. This decrease is due to increased crop heat stress that outweighs the benefits of elevated [CO_2] on crop productivity and water demands. Especially under limited worldwide mitigation efforts, agricultural productivity will drop below its historical value, regardless of management-adaptation strategies. These results clearly show the limits to agricultural management adaptation, and only of further adaptation or strong worldwide mitigation will secure the Indus' food productivity.

4.6 Acknowledgments

The authors express their gratitude to the Arizona and Wuxi FACE teams for sharing their data on the wheat and rice FACE experiments, with special mention to Bruce Kimball and Toshihiro Hasegawa who provided valuable insight on these experiments. The authors also express their gratitude to WADPA and GRDC for sharing their discharge data, with special mention and thanks to Zakir Hussain Dahri who provided valuable insight on the Indus basin hydrology.

Chapter 5

Agricultural adaptation to provide sustainable self-sufficiency in Pakistan

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Abstract

One of this century's most important challenges is to provide food security for a growing and developing population. Agriculture is threatened by climate change and excessive water withdrawals, and must therefore urgently adapt to meet rising food demands. However, the extent to which adaptation helps to achieve sufficient agricultural production is poorly quantified for climate-sensitive and rapidly-growing countries such as Pakistan. Our study quantifies the opportunities and limitations of agricultural adaptation to provide cereal self-sufficiency in Pakistan under sustainable water management and several climate-change mitigation and population-growth scenarios. Without adaptation, end-of-this-century (2071-2100) wheat and rice production decreases up to 52% and 28% respectively, due to increasing temperatures and associated heat stress. However, climate-change adaptation (i.e. growing-season adjustments and substitution of current crops by maize) mostly avoids these adverse temperature impacts, whereas climate-change benefit of increased water availability and the elevated [CO_2] effect on crop water use efficiency and productivity remain. In combination with management adaptation (i.e. nutrient-gap closure and irrigated cropland expansion), three-fold end-of-this-century production increases are possible, even when conforming to sustainable water management. This production increase provides sustainable cereal self-sufficiency for up to 400 million people, supports cereal requirements for low to moderate population-growth scenarios but not for high population-growth scenario. Our results clearly show that climate-change adaptation plays a pivotal role in providing food security in a changing climate. Therefore, a greater focus on climate-change adaptation is needed.

5.1 Introduction

One of this century's most important challenges is to provide worldwide food security for a growing and developing population in a changing climate. Food demands are expected to increase due to population growth and dietary changes associated with socioeconomic development [Alexandratos & Bruinsma, 2012; Kearney, 2010; Valin et al., 2014]. To meet these demands, worldwide agricultural production should substantially increase [Foley et al., 2011; Pardey et al., 2014; Ray et al., 2013; Tilman et al., 2011]. Moreover, agriculture is strongly affected by climate change. Although crop production will benefit from elevated atmospheric carbon dioxide concentrations ([CO_2]) [Ainsworth & Long, 2021; Toreti et al., 2020], it will be adversely affected by increasing temperatures and intensifying droughts [Battisti & Naylor, 2009; Lesk et al., 2016]. Agricultural production and variability is likely already affected by climate change [Iizumi & Ramankutty, 2016; Ray et al., 2019] and further agricultural productivity losses are estimated, especially at lower latitudes [Jägermeyr et al., 2021; Rosenzweig et al., 2014].

One of the countries that is severely threatened in its food security is Pakistan. Food security in Pakistan is not only susceptible to rapid population growth [Ahmad & Farooq, 2010; Smolenaars et al., 2021] and climate change [Ali & Erenstein, 2017; Ortiz et al., 2008] but also to unsustainable water use [Government of Pakistan, 2018b]. To meet the food demands of its 220 million inhabitants, Pakistan's arid croplands are extensively irrigated with water from the Indus river and groundwater aquifers [Food and Agricultural Organization, 2011]. In addition to agriculture, these water resources are essential for a range of domestic [Smolenaars et al., 2022] and industrial [Mirza et al., 2008; van Vliet et al., 2016] purposes. However, irrigation continues to exceed renewable water availability and uses non-renewable groundwater storage to meet water demands [Gleeson et al., 2012]. These non-renewable withdrawals result in groundwater table lowering, groundwater quality deterioration and soil salinization [MacDonald et al., 2016; Rodell et al., 2018], thereby threatening agricultural sustainability [Qureshi et al., 2010]. In addition, renewable irrigation withdrawals reduce river streamflow, even though sufficient streamflow should be maintained to support river ecosystems [Archer et al., 2010; Poff et al., 1997, 2010].

Although the impacts of climate change and unsustainable water management are well understood, the extent to which agricultural adaptation helps address these impacts and contributes to providing food security remains poorly quantified. Improved understanding of adaptation opportunities and limitations is essential to inform investments, policy decisions and planning [Anderson et al., 2020; Cradock-Henry et al., 2020; Howden et al., 2007; Lobell & Burke, 2008], especially for climate-sensitive and rapidly-growing countries such as Pakistan. In these countries, agriculture should adapt to changing temperature and precipitation patterns under climate change [Lipper et al., 2014; Vermeulen et al., 2012] while improving nutrient and water management to meet their growing food demands [Godfray et al., 2010].

Our study quantifies the opportunities and limitations of several agricultural adaptation options to achieve Pakistan's food security under sustainable water management. We specifically focus on the primary cereal crops, wheat and rice, as food security strongly depends on these crops. Wheat and rice cover almost half of Pakistan's food consumption [Hussain & Routray, 2012] and the government specifically aims to achieve self-sufficiency in these food grains [Government of Pakistan, 2018a]. Together these crops cover a harvest area of more than 10 million hectares and are grown in rotation [Portmann et al., 2010]. Wheat is cultivated during the cold dry season (called 'Rabi') from November to May and rice is cultivated during the hot wet season (called 'Kharif') from June to October.

Two adaptation types are distinguished: *climate-change adaptation*, which aims to avoid adverse climate-change impacts, and *management adaptation*, which aims to increase agricultural productivity. We first investigate two climate-change adaptation options that are locally employed or recommended [Ali et al., 2017; Gupta et al., 2002]: (1) *growing-season adjustments* and (2) *substitution of current crops by maize (maize-crop substitution)* (Section 5.3.1). We subsequently investigate two management adaptation options to improve nutrient and water management [Mueller et al., 2012]: (1) *cropland nutrient-gap closure* and (2) *irrigated cropland expansion* (Section 5.3.2). Note that irrigation withdrawals are constraint to conform to sustainable water management. Lastly, the impact of these options on Pakistan's self-sufficiency is assessed (Section 5.3.3). This assessment includes two climate-change mitigation scenarios following the representative concentration pathways (RCPs) [van Vuuren et al., 2011], high (RCP2.6) and low (RCP8.5) mitigation, and three population-growth scenarios following the shared socioeconomic pathways (SSPs) [Jones & O'Neill, 2016], low (SSP1), moderate (SSP2) and high (SSP3) growth.

Water resources and agricultural productivity are quantified using the process-based hydrology-crop model VIC-WOFOST [Droppers et al., 2021]. VIC-WOFOST dynamically simulates water availability, crop growth, the effects of elevated [CO_2] and their interactions. Moreover, the model was already successfully setup, calibrated and validated for Pakistan's agriculture, the Indus' hydrology and the elevated [CO_2] effects on crop growth [Droppers et al., 2022].

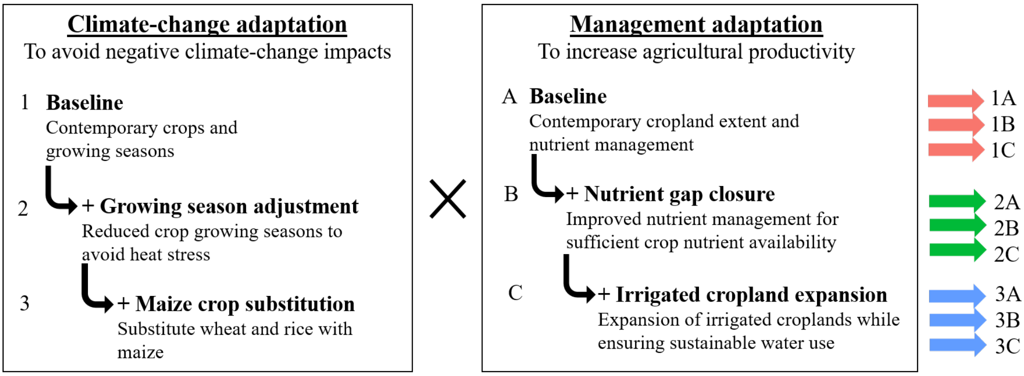

Figure 5.1: Agricultural adaptation options. Each climate-change adaptation option is combined with each management adaptation option to assess the opportunities and limitations of agricultural adaptation. Note that climate-change and management adaptation options are cumulative (i.e. stacking)

5.2 Methods

Here, first the agricultural climate-change and management adaptation options and their implementation are described (Section 5.2.1). Subsequently a description of the climate-change and population growth inputs (Section 5.2.2) and a description of the VIC-WOFOST model is given (Section 5.2.3).

5.2.1 Agricultural adaptation options

Cimate-change and management adaptation options represent deviations from current agricultural practices, the so-called 'baseline' (Figure 5.1). Baseline simulations include contemporary crops, cropland extent, growing seasons and nutrient management [Hurtt et al., 2020; Mueller et al., 2012; Portmann et al., 2010; Zhang et al., 2017]. Nutrient mineralization rates and fertilizer application efficiency were scaled to match observed agricultural productivity, while sub-monthly (5^{th}, 15^{th} or 25^{th} month day) planting and harvesting dates were determined from their contemporary monthly values based on historical (1971-2000) crop productivity simulations (see [Droppers et al., 2022]).

Growing-season adjustment (Figure 5.1 - option 2) represents changes in planting dates and crop varieties to avoid productivity losses resulting from increased temperatures and heat stress under climate change. Note that shorter growing seasons are a trade-off between avoiding heat stress and increasing the carbon assimilation period. Optimal planting and harvesting dates were determined based on end-of-this-century (2071-2100) crop productivity simulations for the two climate-change mitigation scenarios. Contrary to baseline simulations, adjusted planting and harvesting dates could be up to two months later or earlier than their contemporary values respectively. *Maize-crop substitution* (Figure 5.1 - option 3) represents the shift from wheat and rice to maize cultivation. Maize has been indicated as a suitable replacement for wheat and rice [Davis et al., 2018], as it is more tolerant to high temperatures and droughts. Note that maize, as a C4 crop, is also relatively insensitive to the elevated [CO_2] effects on crop carbon assimilation and thus limits potential climate-change benefits. Moreover, maize generally has higher water requirements than wheat and thus increases irrigation demands. To simulate the effect of maize-crop substitution, both wheat and rice are fully replaced by maize during their respective growing seasons.

Nutrient-gap closure (Figure 5.1 - option B) represents a multitude of soil and fertilizer management options (e.g. fertilizer application, precision agriculture and conservation tillage) that avoid productivity decreases due to nutrient limitations [Cassman et al., 2002; Oenema & Pietrzak, 2002]. Nutrient-gap closure is simulated by enabling unlimited nutrients for crop growth. However, achieving full nutrient-gap closure is practically unfeasible due to factors such as pests, diseases and management limitations [van Ittersum et al., 2013]. Therefore, nutrient-gap closure productivity is taken as 90% of the simulated potential productivity. *Irrigated cropland expansion* (Figure 5.1 - option C) represents cropland expansion into uncultivated lands, harvest-area expansion into temporary fallow croplands and irrigation expansion into rain-fed croplands. Cropland and harvest-area expansion was implemented by taking bare soil areas into cultivation, throughout the year, for all grid cells with croplands. Irrigation expansion was implemented by allowing irrigation for all rain-fed crop in Pakistan's Indus basin irrigation system (i.e. within irrigation command areas; Section 5.2.3). Following this implementation crop harvesting area increased by approximately 70%, with 55% for wheat (during Rabi; November to May) and 90% for rice (during Kharif; June to October).

Irrigation withdrawals are constrained to conform to sustainable water management. Only part of the river flow was available for irritation. River flow is first allocated to meet river ecosystem flow requirements (30%, 45% and 60% of the historical pristine low, moderate and high flow respectively [Pastor et al., 2014]), subsequently to meet domestic, industrial and livestock water demands and lastly to meet irrigation demands. Moreover, groundwater withdrawals were constrained to equal groundwater recharge to avoid groundwater depletion (again irrigation withdrawals were constrained first). Some groundwater depletion (50cm) was allowed to compensate for inter annual difference in withdrawal and recharge. These irrigation constraints subsequently reduce crop production in croplands were sustainable irrigated agriculture cannot be supported. Therefore, these constraints also limit the benefits of irrigated cropland expansion.

5.2.2 Climate-change mitigation and population-growth scenarios

Two climate-change mitigation and three population-growth scenarios were used. The selected climate-change mitigation scenarios comprise high (RCP 2.6) and low (RCP 8.5) mitigation, with temperature increases for Pakistan of +2°C and +6°C respectively between historical (1971-2000) and the end-of-this-century (2071-2100) climates. The selected population-growth scenarios comprise high (SSP 3), moderate (SSP 2) and low (SSP 1) growth, with approximately 2.5, 3.3 and 4.8 times Pakistan's historical (1971-2000) population respectively by the end of this century (2071-2100).

Climate inputs were derived from the latest Inter Sectoral Impact Model Intercomparison Project (ISIMIP3b) [ISIMIP, 2020]. ISIMIP3b provides corrected historical and future climate inputs from five climate models (GFDL-ESM4 [Dunne et al., 2020], IPSL-CM6A-LR [Boucher et al., 2020], MPI-ESM1-2-HR [Müller et al., 2018], MRI-ESM2-0 [Yukimoto et al., 2019] and UKESM1-0-LL [Sellar et al., 2020]) of the latest Coupled Model Intercomparison Project (CMIP6) [Eyring et al., 2016]. These inputs were bias-corrected and statistical downscaled [Lange, 2019] based on a historical climate reference (WFDE5 [Cucchi et al., 2020]). However, due to insufficient observations and precipitation gauge under-catch at high altitudes, bias-correction performs poorly in the upper Indus basin [Dahri et al., 2018; Immerzeel et al., 2015]. Therefore, ISIMIP3b climate inputs for the upper Indus basin were further corrected [Droppers et al., 2022] based on the European Centre for Medium-range Weather Forecasts reanalysis (ERA5) [European Centre for Medium-range Weather Forecasts, 2021], which performs better in this region [Dahri et al., 2018].

Population inputs were acquired from a recent regionalized and spatialized population assessment [Smolenaars et al., 2021]. This assessment spatially downscaled national population projections [Dellink et al., 2017; Klein Goldewijk et al., 2017; Samir & Lutz, 2017] for the Indus basin (at 5 arc-minute resolution), based on regional development narratives that were determined in collaboration with stakeholders [Roy et al., 2019; Siddiqui et al., 2019].

5.2.3 Model description

VIC-WOFOST [Droppers et al., 2021] is a two-way coupling of the variable infiltration capacity (VIC) hydrological model [Hamman et al., 2018; Liang et al., 1994], which was modified to account for human impacts on the water system [Droppers et al., 2020], and the world food studies (WOFOST) crop model [de Wit et al., 2019, 2020; Supit et al., 1994]. Simulations were executed with a daily time step and on a 5 arc-minute resolution grid.

VIC simulates water fluxes for various land-cover types in each grid cell based on climate, soil and vegetation inputs. Incoming precipitation is partitioned into canopy interception, surface runoff and infiltration [Dickinson, 1984; Wood et al., 1992], the latter of which is available for transpiration. Potential transpiration is based on the Penman-Monteith equation [Shuttleworth, 1993], and is adjusted based on several resistance factors (e.g. aerodynamic, architectural and stomatal) [Ducoudré et al., 1993; Louis, 1979]. Below the root zone, soil water is added to subsurface runoff [Franchini & Pacciani, 1991].

Grid cell surface and subsurface runoff is routed along river flow paths [Lohmann et al., 1996], and is further modified by dam reservoir operation [Hanasaki et al., 2006; Lehner et al., 2011] and water withdrawals. Within irrigation command areas [Biemans et al., 2019] (i.e. major irrigation canal systems), withdrawals originate from river streamflow at the command area inlet, while for other areas water is withdrawn from within-grid rivers streamflow. Additional groundwater withdrawals supplement water demands if river streamflow is insufficient, creating a local groundwater deficit. Subsurface runoff is redirected to recharge groundwater storage until this deficit is fulfilled.

For each wheat, rice and maize land-cover type WOFOST simulates crop growth based on the climate and water and nutrient availability. During the growing season incoming direct and diffuse radiation is used for crop carbon assimilation [Goudriaan, 1986; Spitters et al., 1986]. Assimilates are allocated to different crop organs (roots, stems, leaves and storage organs) based on the crop development stage. Both assimilation and allocation is affected by crop stress, including heat, water and nutrient stress.

Elevated [CO_2] affects transpiration, through increased stomatal resistance, and crop productivity, through increased maximum carbon assimilation. Stomatal resistance increases were derived from a meta-analysis of multiple Free Air Carbon dioxide Enrichment (FACE) experiments [Ainsworth & Rogers, 2007], and increases hyperbolically with elevated [CO_2] [Li et al., 2019]. Maximum carbon assimilation increases were derived from our comparison [Droppers et al., 2022] of simulated and observed wheat and rice productivity for several FACE experiments [Bloom et al., 2014; Hasegawa et al., 2017; Kimball et al., 2017; Yang et al., 2006]. For a full description on the setup, calibration and validation of VIC-WOFOST the reader is referred to our previous study [Droppers et al., 2022].

5.3 Results

5.3.1 Agricultural climate-change adaptation

To assess the potential benefits of climate-change adaptation for wheat and rice productivity, end-of-this-century (2071-2100) yields for each climate-change adaptation option are compared to the historical (1971-2000) yields under high (RCP2.6) and low

(RCP8.5) climate-change mitigation scenarios (using the model ensemble median). This comparison ignores agricultural management adaptation and sustainable water use, as these are discussed in the next section.

For wheat, increasing temperatures during the growing season and subsequent heat stress reduce yields towards the end of this century (Figure 5.2a - baseline). Simulated annual historical baseline yields of 9.3 million kcal ha^{-1} (harvest-area weighted) will decrease by 21% and 52% by the end of this century under high and low climate-change mitigation respectively. However, major losses are potentially avoided by adjusting growing seasons (Figure 5.2a - growing-season adjustment). Heat stress impacts are minimized by avoiding detrimental temperatures during the start and end of the growing season (Figure 5.3 - wheat). Moreover, elevated [CO_2] positively affects productivity. Therefore, simulated end-of-this-century growing-season adjusted yields are actually 82% and 215% higher than end-of-this-century baseline yields under high and low climate-change mitigation respectively.

For rice, increasing temperatures will mostly affect productivity under the low climate-change mitigation scenario as temperature increases under high climate-change mitigation are insufficient to increase heat stress (Figure 5.2b - baseline). Simulated annual historical baseline yields of 8.6 million kcal ha^{-1} y^{-1} (area weighted) will increase by 2% and decrease by 36% under high and low climate-change mitigation respectively. Moreover, limited rice yield losses are potentially avoided by adjusting growing seasons (Figure 5.2b - growing-season adjustment), as growing seasons between June and October coincide with Pakistan's hot season (Figure 5.3 - rice). Therefore, simulated growing-season adjusted yields are only 3% and 13% higher than baseline yields for the end-of-this-century under high and low climate-change mitigation respectively.

For both wheat and rice, maize-crop substitution is potentially beneficial to raise productivity under climate change (Figure 5.2 - maize-crop substitution). This productivity increase reflects maize's larger energy content (3560 kg^{-1}) compared to wheat (3340 kg^{-1}) and rice (2800 kg^{-1}) [Food and Agricultural Organization, 1991], and higher maximum growing temperatures (42°C) compared to wheat (30°C) and rice (35°C) [de Wit, 2020]. Full transition to maize cultivation increases end-of-this-century yields by up to 15% and 66% compared to end-of-this-century growing-season adjusted wheat and rice respectively.

5.3.2 Agricultural management adaptation

To assess the benefits of management adaptation for Pakistan's total wheat and rice production, production for each management adaptation option is compared with the baseline production by the end of this century (2071-2100) under high (RCP2.6) and

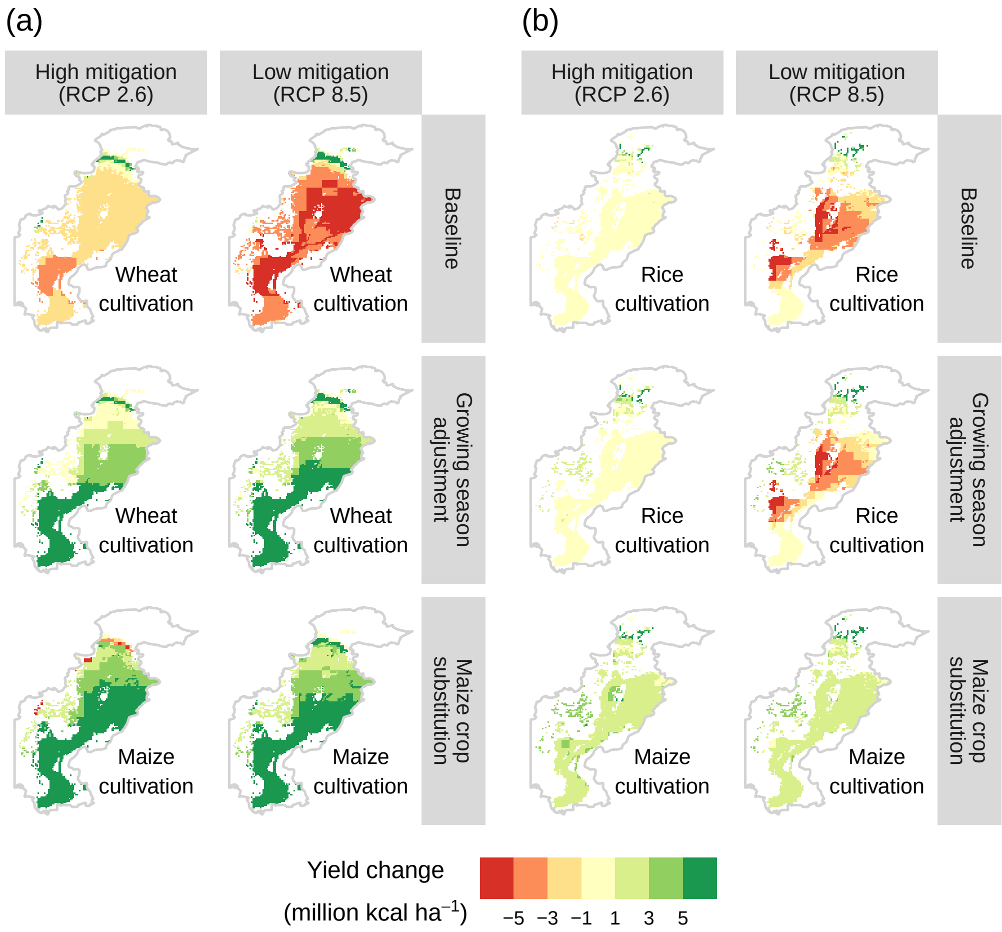

Figure 5.2: Simulated average annual yield change for (a) wheat and (b) rice for each climate-change adaptation option. Note that for the maize-crop substitution adaptation option both rice and wheat are replaced with maize. Changes are shown between historical (1971-2000) yields and end-of-this-century (2071-2100) yields. To increase readability, Pakistan's south-western country borders are trimmed as croplands in this region are negligible.

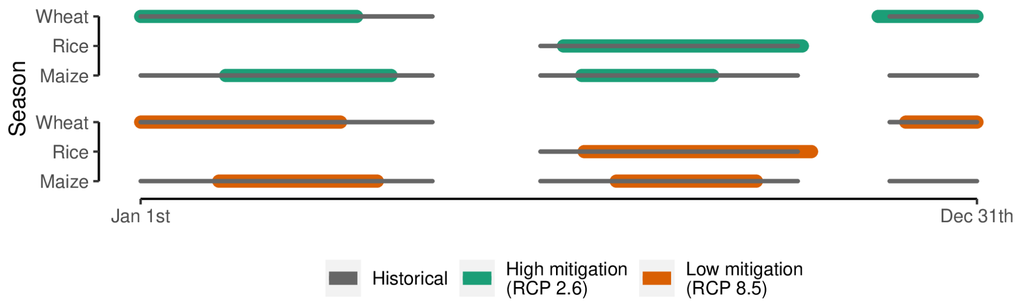

Figure 5.3: Simulated optimal growing seasons (harvest-area weighted) for two climate-change mitigation scenarios. Grey lines indicate baseline historical (1971-2000) growing seasons and colored lines indicate end-of-this-century (2071-2100) growing seasons.

low (RCP8.5) climate-change mitigation scenarios (using the model ensemble median). However, irrigation is constrained to conform to sustainable water management for each management adaptation option. This thus limits agricultural production in regions with excessive irrigation withdrawals. Results are shown with the growing-season adjustment climate-change adaptation option as an example, as combinations with other climate-change adaptation options show similar patterns (Supplementary Figures D.1 and D.2).

The effect of irrigation constraints under sustainable water management on agricultural production is markedly different for high and low climate-change mitigation scenarios (Figure 5.4a - baseline). Under high climate-change mitigation, production substantially decreases due to irrigation constraints in Pakistan's eastern croplands. This region is well known for its unsustainable water management and groundwater depletion [Watto & Mugera, 2016]. Annual end-of-this-century production of 135 billion kcal decreases by 8% when conforming to sustainable water management under baseline conditions. Conversely, under low climate-change mitigation, irrigation constraints are reduced. This reduction results from increased precipitation, which enlarges water availability (precipitation minus evaporation), and elevated [CO_2], which reduces irrigation demands, under climate change (Figure 5.5). Therefore, agricultural productivity in Pakistan's eastern croplands is affected less by sustainable water management under low climate-change mitigation.

Substantial production increases under sustainable water management are possible through management adaptation (Figure 5.4a - nutrient-gap closure and cropland expansion). Under nutrient-gap closure, annual production increases by 8% and 10% compared to sustainable baseline production under high and low climate-change mitigation respectively. Under additional cropland expansion, production increases by

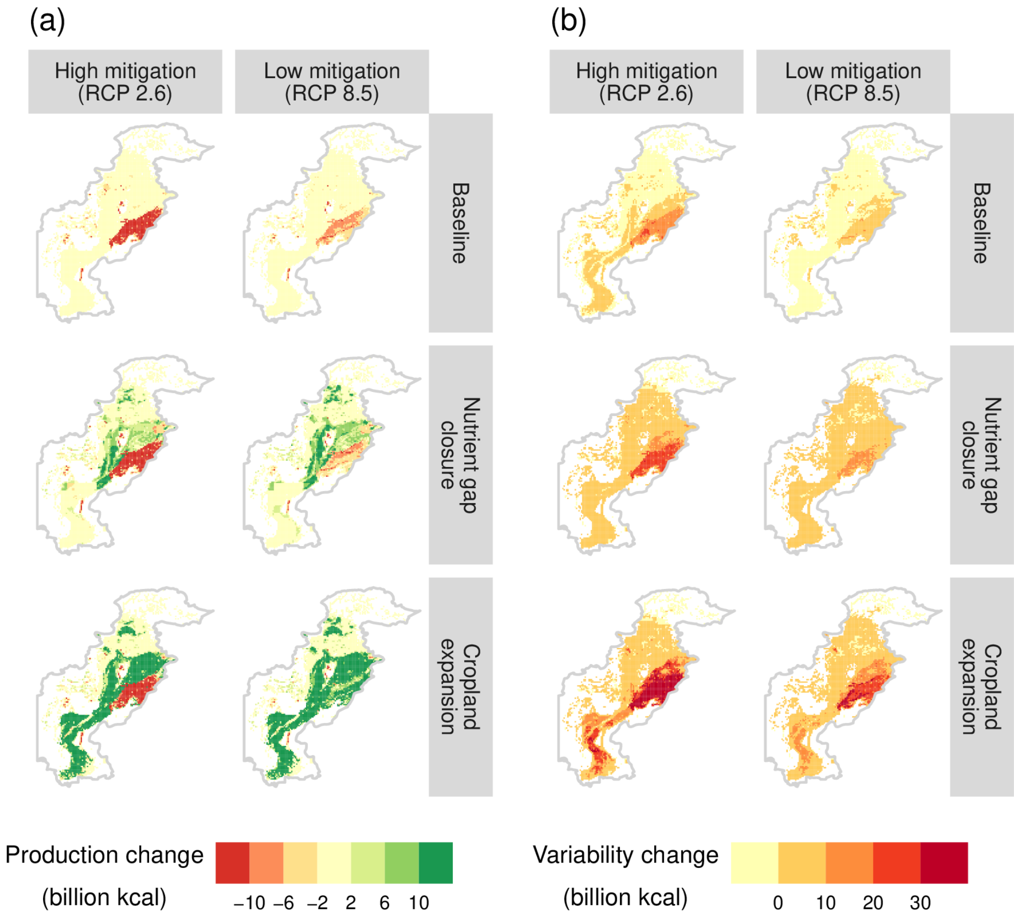

Figure 5.4: Simulated average annual total (wheat plus rice) (a) production change and (b) inter-annual variability increase (1^{th} to 3^{rd} quartile) for each management adaptation option. Changes are shown between end-of-this-century (2071-2100) unsustainable production and sustainable production.

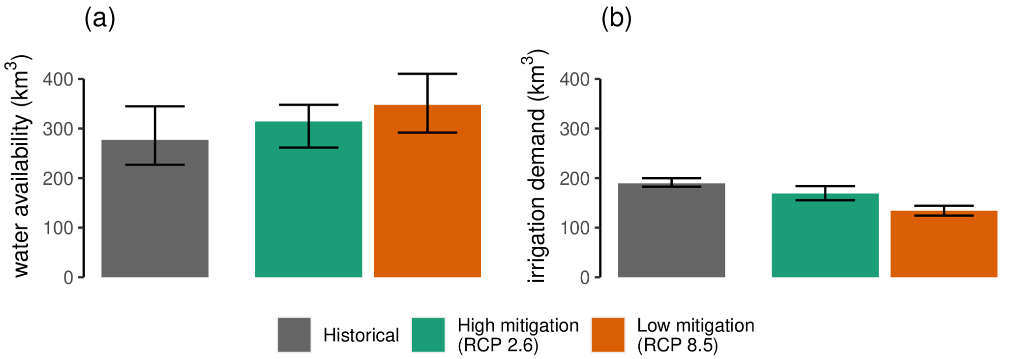

Figure 5.5: Simulated average annual (a) water availability (precipitation minus evaporation) and (b) irrigation demand for two climate-change mitigation scenarios. Note that part of the available water is shared with India. Error bars indicate the availability and demand variability (1^{th} to 3^{rd} quartile). Grey bars indicate baseline historical (1971-2000) availability and demand and colored bars indicate end-of-this-century (2071-2100) availability and demand.

51% and 58% compared to sustainable baseline production under high and low climate-change mitigation respectively. However, with these production increases, inter-annual production variability also increases (Figure 5.4b). These variability increases result from a greater production dependence on year-to-year water availability, especially under cropland expansion. Therefore, to avoid major variability increases, expansion should favor Pakistan's southern and eastern croplands (i.e. along the left-most Indus branch).

5.3.3 Sustainable self-sufficiency

By combining both climate-change and management-adaptation options, the opportunities and limitations of achieving self-sufficiency are quantified for Pakistan. Here self-sufficiency is defined as producing the annual historical wheat and rice consumption requirements of approximately 1600 kcal cap^{-1} [Food and Agricultural Organization, 2021]. Note that these requirements are a conservative estimate, as food demands likely increase with socioeconomic development [Hayat et al., 2016].

Without climate-change adaptation, sustainable agricultural productivity would be insufficient to provide for Pakistan's rapidly growing population (Figure 5.6 - baseline). Even considering management adaptation, the end-of-this-century (2071-2100) self-sufficient population will remain similar or decrease compared to the historical (1970-2000) self-sufficient population under high and low climate-change mitigation

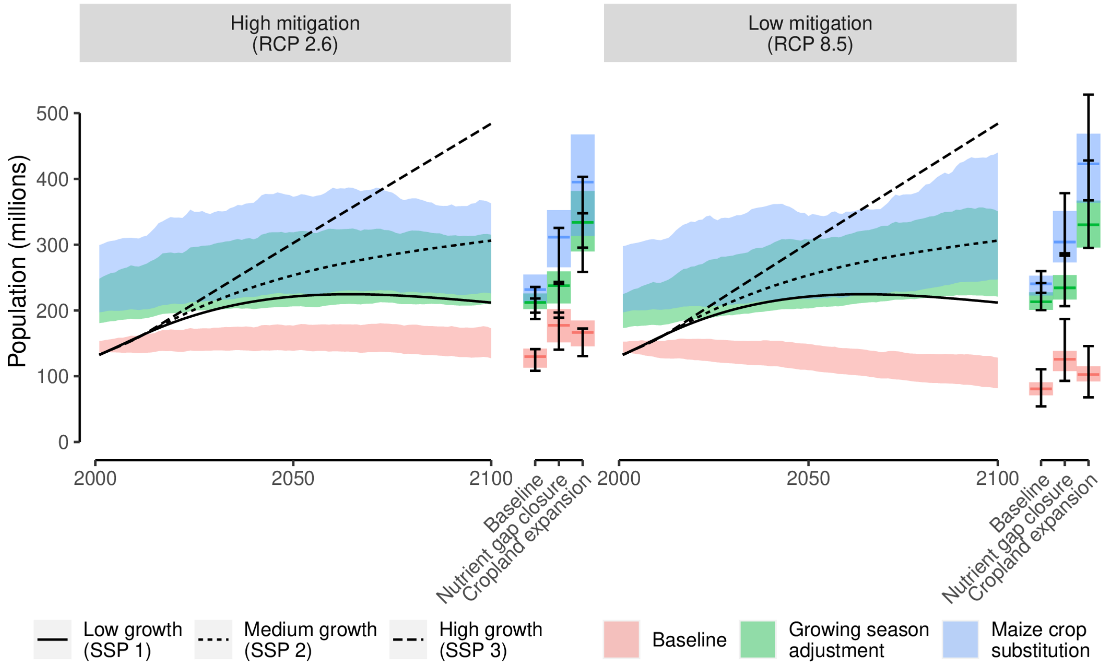

Figure 5.6: Simulated 30-year moving average annual self-sufficient population (assuming 1600 kcal cap^{-1}). Black lines indicate population under various population-growth scenarios. Colored bars at the end indicate end-of-this-century (2071-2100) average inter-annual production variability (1$^{\text{th}}$ to 3$^{\text{rd}}$ quartile) while black error bars at the end indicate end-of-this-century (2071-2100) average production uncertainty (represented by the minimum to maximum of all climate models).

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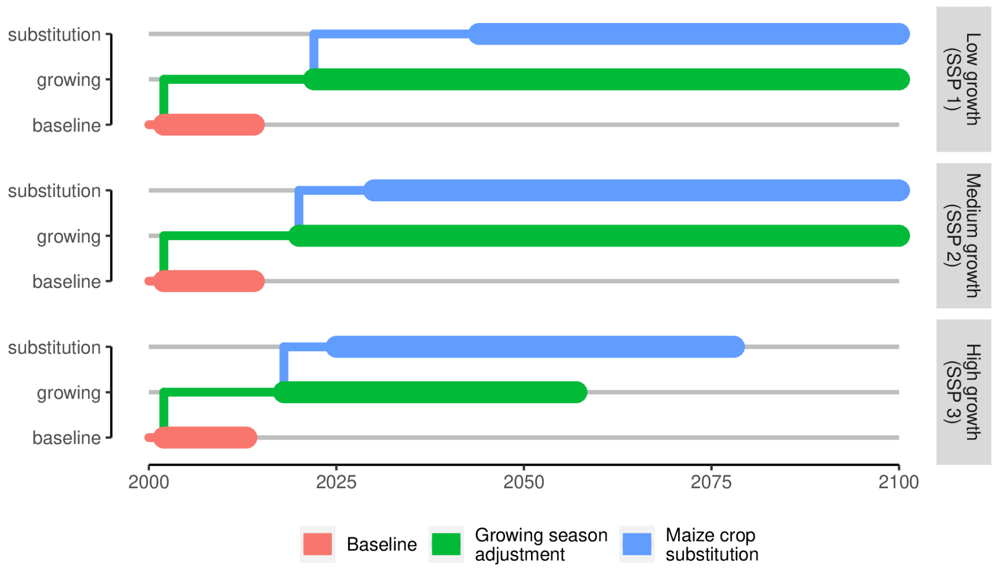

Figure 5.7: Pathways to achieve agricultural self-sufficiency. Colored thin lines indicate self-sufficiency without management adaptation, while colored thick lines indicate the self-sufficiency range under management adaptation. Lines between climate-change adaptation options indicate the earliest moment (i.e. no management adaptation) during which a change in adaptation is required in order to maintain self-sufficiency.

respectively. Conversely, climate-change adaptation in combination with management adaptation options have the possibility to support all but the highest population-growth scenario (Figure 5.6 - growing-season adjustment and maize-crop substitution). Growing-season adjustment could support a self-sufficient population of between 210 and 330 million people by the end of this century, while full transition to maize cultivation could support between 230 and 420 million people by the end of this century, depending on the climate-change scenario and management adaptation. However, note that for low climate-change mitigation scenarios, the end-of-this-century self-sufficient population is highly uncertain due to varying climate-model temperature responses under increases greenhouse gas emissions.

Timely adaptation is necessary to achieve sustainable self-sufficiency as indicated by the explored pathways to achieve agricultural self-sufficiency (Figure 5.7). Agricultural productivity under sustainable water management is already insufficient to meet historical cereal requirements. These results confirm the currently strong dependence of Pakistan's agriculture on unsustainable irrigation. Under low (SSP1) to moderate (SSP2) population-growth scenarios, growing-season adjustment and a combination of nutrient-gap closure and cropland expansion will be sufficient to meet historical cereal requirements. However, under the high population-growth scenario (SSP3), a transition to maize cultivation will be necessary by during the middle of this century, and would be insufficient by the end of this century.

5.4 Discussion

Our study quantifies the opportunities and limitations of agricultural adaptation to provide cereal self-sufficiency in Pakistan under various climate-change mitigation and population-growth scenarios. Our results show that, climate change potentially strongly affects agricultural productivity and that climate-change adaptation is important to maintain and improve productivity. However, substantial cereal production increases are possible by combining climate-change adaptation with improved agricultural management, even when conforming to sustainable water management.

Our cereal production estimate under climate change and agricultural management is sensitive to the parameterization of Pakistan's crop varieties, especially to parameters that reflect optimal growing temperatures. Although our parameters may not fully reflect local crops, they are based on extensive field studies [de Wit, 2020; van Diepen et al., 1988; Wolf et al., 2012]. Additionally, wheat optimal growing temperatures were adjusted to better reflect Pakistan's heat-tolerant varieties [Government of Pakistan, 2015]. The impacts of temperature increases on productivity shown in our study are in line with several other studies [Ali & Erenstein, 2017; Sultana et al., 2009], thereby giving confidence in our parameterization. Besides crop parameterization sensitivities, water availability estimates are sensitive to irrigation efficiency uncertainties. Substantial shares of irrigation withdrawals are reused, as inefficient irrigation contributes to return flows to the (ground) water system [Simons et al., 2020]. Although we explicitly model these return flows, our irrigation efficiency is based on an aggregated basin-scale factor [Hussain et al., 2011]. Although this limits the applicability of our results to field-scale conditions, our groundwater withdrawal and depletion validation [Droppers et al., 2022] confirms they accurately reflect basin-scale water (re)use, which is important for sustainable water management [Grafton et al., 2018].

Contrary to several worldwide agricultural [Jägermeyr et al., 2021; Rosenzweig et al., 2014] and hydrological [Haddeland et al., 2014; Hanasaki et al., 2013; Schewe et al., 2014] studies, we show that climate change is potentially beneficial for Pakistan's irrigated agriculture. This difference is due to the explicit representation of elevated [CO_2] effects and the incorporation of growing-season adjustments in our assessment. Many worldwide hydrological studies ignore transpiration decreases under elevated [CO_2] [Elliott et al., 2014]. We show that these decreases substantially increase water abundance (i.e. the difference in water availability and demand), and reduce irrigation constraints for sustainable water management. In addition, worldwide agricultural studies often assume fixed crop phenologies or planting dates [Elliott et al., 2015], resulting in shorter or unsuitable growing seasons [Asseng et al., 2013]. However, ignoring changes in growing seasons is arguably unrealistic, as these adjustments are generally autonomously performed by farmers [Esham & Garforth, 2013; Khan et al., 2021b; Khanal et al., 2019]. We show that growing-seasons adjustments avoids adverse temperature impacts while benefiting from elevated [CO_2] effects on carbon assimilation.

However, the extent to which adaptation benefits shown here for Pakistan are generalizable to other regions depends on local conditions. Changes in water abundance are determined by both precipitation and evapotranspiration trends under climate change. Although these trends are beneficial for Pakistan, other regions experience decreases in water abundance or a mismatch between water availability and demand timing [Barnett et al., 2005; Haddeland et al., 2014]. Growing-season adjustment effectiveness is based on local temperature regimes and agricultural cultivation systems. Reducing growing seasons leads to reduced productivity if they become too short [Hertel & Lobell, 2014] or if temperature throughout the season are too high, as shown here for rice in Pakistan.

Currently, Pakistan strongly invests in improved agricultural management through domestic fertilizer-production subsidies, reduced farm-machinery import tariffs, irrigation and reservoir development and agricultural loans [Government of Pakistan, 2021]. These investments have supported agricultural management and production improvements over recent decades [Food and Agricultural Organization, 2021; Rehman et al., 2019], and several studies estimate a large potential to further increase agricultural production through improved agricultural management [Akram et al., 2018; Aslam, 2016; Khan et al., 2021a]. However, we show that climate-change impacts will be severe for Pakistan's agriculture and cannot be compensated by only further management improvements. Therefore, greater investments in climate-change adaptation, besides management adaptation, is necessary to secure food productivity throufghout this century.

5.5 Conclusion

Without agricultural adaptation, Pakistan's end-of-this-century (2070-2100) wheat and rice production will decrease up to respectively 52% and 28% due to increased temperatures and associated heat stress. However, climate-change and management adaptation could sustainably increase agricultural productivity to provide end-of-this-century cereal self-sufficiency for approximately 400 million people.

Climate-change adaptation (i.e. growing-season adjustments and substitution of wheat and rice by maize) effectively avoids adverse temperature effects for wheat and rice, with estimated end-of-this-century wheat and rice yield that are 230% and 87% higher than under the baseline respectively. Management adaptation (i.e. nutrient-gap closure and irrigated cropland expansion) additionally increases end-of-this-century production between 27% and 76% depending on climate-change mitigation and adaptation, even under sustainable water management. Together, these increases are sufficient to secure food requirements under low (SSP1) to moderate (SSP2) population-growth scenarios but are insufficient to support self-sufficiency under a high population-growth scenario (SSP3).

Our results clearly show that climate-change adaptation plays a pivotal role in providing Pakistan's food security in a changing climate. Without climate-change adaptation, productivity will be insufficient to meet cereal requirements of the rapidly-growing population, regardless of management improvements. However, with appropriate and timely climate-change adaptation, agriculture will potentially benefit from increased water availability due to enhanced precipitation and increased crop water use efficiency and productivity due to elevated [CO_2] under climate change. Therefore, a greater focus on climate-change adaptation is needed to provide food security in climate-sensitive and rapidly-growing countries such as Pakistan.

Chapter 6

Synthesis

6.1 Main results

Food and water demands of a growing and more prosperous population likely increase in the coming decades [Alcamo et al., 2007; Tilman et al., 2011]. However, developments to achieve sufficient agricultural production and sustainable water management interact through their conjoined used of and competition for water resources [Flörke et al., 2018; Strzepek & Boehlert, 2010]. In addition, climate change alters the distribution of water availability [Oki & Kanae, 2006; Taylor et al., 2013] and affects agricultural productivity [Asseng et al., 2015; Ray et al., 2019; Toreti et al., 2020] in many regions around the world. Such changes need to be accounted for to avoid undesirable development outcomes. As decision making towards for water, agriculture and climate often occurs in isolation, they may adversely affect one another or fail to realize potential benefits [Le Blanc, 2015; Nilsson et al., 2016; Stafford-Smith et al., 2017]. Therefore, quantification of their interactions is needed to support integrated decision making [Bazilian et al., 2011; Hanjra & Qureshi, 2010]. My thesis aimed to **quantify whether sufficient agricultural production is achievable under sustainable water management and climate change**. In line with my thesis' main research objective, four research questions (RQs) were investigated in Chapters 2 to 5. These RQs are answered in Sections 6.1.1 to 6.1.4, with a conclusion with respect to the research objective in Section 6.1.5.

6.1.1 RQ1: To what extent does present-day human water use exceed sustainable water use?

Sustainable water use exceedance is determined by comparing renewable water availability under sustainable water management with human water use. To this end, I extended the Variable Infiltration Capacity (VIC) hydrological model [Hamman et al., 2018; Liang et al., 1994], with modules that integrate river streamflow routing, reservoir operation and water withdrawal and consumption for agricultural, domestic, industrial (i.e. energy and manufacturing) and livestock purposes. Renewable water availability is determined by routing simulated surface and subsurface runoff from the VIC model along river flow paths. River streamflow is further modified by reservoir operation, based on the reservoir's purpose (e.g. irrigation or energy generation). Under sustainable water management, part of the river streamflow is not available for meeting human water demands to allow sufficient streamflow for river and wetland ecosystems. These ecosystem flows are determined following the variable monthly flow (VMF) method [Pastor et al., 2014], which defines environment flow requirements as a monthly varying portion of the historical natural streamflow. Note that this method does not explicitly include the complex relationships between ecosystem functioning and streamflow alterations [Poff et al., 2010]. However, since quantification of these relationships are unavailable at larger scales, the VMF method remains a viable proxy as it compares well with locally determined environmental flow requirements [Pastor et al., 2014]. Irrigation demands are estimated based on the cropland soil-moisture content as simulated by the VIC model, and irrigation is applied to the upper-layer soil-moisture content. Domestic, energy, manufacturing and livestock water demands are calculated separately, based on historical water-demand relations, and are an input to the water withdrawal and consumption modules.

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According to my worldwide assessment, more than a third of worldwide human water use exceed sustainable water use [Chapters 2 and 3]. These water uses result in rapidly lowering groundwater tables and river streamflow reductions below their environmental requirements. Excessive water use is concentrated in some of the world's most extensively irrigated croplands, such as the croplands in Pakistan and northwestern India and Pakistan, northeastern China and the United States high plains and central valley. Although my results compare well with reported water withdrawals and several other studies on worldwide unsustainable water use, worldwide groundwater depletion rates are overestimated [Chapters 2]. As groundwater depletion indicates excessive human water withdrawals, my worldwide assessment thus also overestimates the magnitude of unsustainable water use. This overestimation likely results from a simplified implementation of irrigation return-flows (i.e. return flows during application and transport inefficiencies) and insufficient representation of groundwater processes (i.e. riverbed infiltration and lateral groundwater flows). My regional assessment for the Indus basin explicitly separates irrigation application return-flows that can still be used by crops from irrigation transportation return-flows that contribute to groundwater recharge [Chapter 4]. This separation reduced groundwater depletion to more realistic rates for the Indus basin. Although this reduced groundwater depletion also reduced the magnitude of excessive human water withdrawals, my regional assessment nevertheless showed substantial unsustainable water use. These results clearly indicate that present-day human water use severely exceeds sustainable water use in many regions around the world and in the Indus basin in particular.

6.1.2 RQ2: What is the impact of sustainable water management on agricultural production?

Under sustainable water management, irrigation withdrawals should be constrained in regions where they currently exceed sustainable water use. Due to these constraints, cropland soil-moisture contents would decrease to the point where crops would experience water stress. The impact of this water stress on (irrigated) agricultural production is determined by dynamically coupling the extended VIC hydrological model with the WOrld FOod STudies (WOFOST) crop model [de Wit et al., 2019, 2020]. In this coupled model, called VIC-WOFOST, the WOFOST model estimates crop growth and productivity based on the estimated water stress by VIC. Besides water stress, crop growth and productivity is further affected by nutrient limitations resulting from insufficient mineralization and fertilization [Hurtt et al., 2020; Mueller et al., 2012; Sattari et al., 2014; Zhang et al., 2017]. Productivity is determined for wheat, rice, maize and soybean crops, as they are major contributors to worldwide food production [Tilman et al., 2011]. Crop phenological parameters that determine the growing season length under a given temperature regime are calibrated based on historical observations [Portmann et al., 2010], whereas other crop-specific parameters are constant for each crop [de Wit, 2020]. Under sustainable water management, irrigation withdrawals are constrained first in my assessment. This means that available water resources are first allocated to satisfy water demands for non-agricultural purposes (i.e. domestic, industrial and livestock purposes).

My worldwide assessment shows agricultural productivity reductions up to 13% under sustainable water management [Chapter 3]. Moreover, irrigation constraints reduce the agricultural production attainable under agricultural improvements, thereby limiting it to 85% of its theoretical potential. Reductions are largest for maize and wheat, as these are mostly grown in the dry season of previously identified regions of excessive water use. Conversely croplands in regions such as central Africa and eastern

Europe show potential to expand irrigation under sustainable water use. The robustness of my worldwide assessment is affected by uncertainties in crop parameters (e.g. dry-matter distribution) and management parameters (e.g. fertilizer efficiency). As limited information is available regarding the worldwide distribution of these parameters, generic values are used. These generic parameter values may not fully reflect locally grown crop varieties and agricultural practices and they mostly overestimate worldwide actual productivities (i.e. as limited by water and nutrients) [Chapter 3]. Crop and management parameters are further calibrated and validated for my regional assessment of the Indus basin and Pakistan [Chapters 4 and 5]. This calibration resulted in lower wheat and rice productivities than in my worldwide assessment and these reductions compare well with reported historical productivity and productivity trends. Nevertheless, this regional calibration has little impact on the effects of water stress on (potential) productivity and still shows that sustainable water management will result in substantial reductions in agricultural production, in line with my worldwide assessment.

6.1.3 RQ3: What is the impact of climate change on agricultural production and water use?

Climate-change impacts on agricultural production and water resources are determined for the Indus basin and Pakistan by providing the VIC-WOFOST model with climate inputs. Inputs are provided for three climate-change mitigation scenarios following the representative concentration pathways (RCPs) [van Vuuren et al., 2011]: high (RCP2.6), moderate (RCP7.0) and low (RCP8.5) climate-change mitigation, with temperature increases for the Indus basin of 2°C, 4°C and 5°C respectively between historical (1971-2000) and the end-of-this-century (2071-2100) climates. Climate inputs (e.g. precipitation, temperature and vapor pressure) are based on bias-adjusted general circulation model outputs [Lange, 2019], which are derived from the latest Coupled Model Intercomparison Project (CMIP6) [Eyring et al., 2016]. However, as bias-adjustments often provide poor results in the upper Indus [Immerzeel et al., 2015], climate inputs are further corrected based on the European Centre for Medium-range Weather Forecasts Reanalysis 5th (ERA5) [European Centre for Medium-range Weather Forecasts, 2021], which performs better in this region [Dahri et al., 2018]. Crop planting and harvesting dates are kept constant with respect to their historical dates. This means that crop phenologies are adjusted to future climates to avoid shortening growing seasons. The effect of changing planting and harvesting dates is further explored in Section 6.1.4. VIC-WOFOST is modified to account for the effects of elevated atmospheric carbon dioxide concentrations ([CO_2]) on vegetation transpiration and crop productivity. For transpiration, vegetation stomatal resistance is assumed to increase hyperbolically with elevated [CO_2] [Li et al., 2019], whereas the rate of increase is based on a meta-analysis of Free Air Carbon dioxide Enrichment (FACE) experiments [Ainsworth & Rogers, 2007]. For crop productivity, maximum carbon assimilation increases are reduced compared to their default values as they overestimated field conditions [Long et al., 2006; Wolf et al., 2010], as confirmed by my comparison with several FACE experiments [Bloom et al., 2014; Hasegawa et al., 2017; Kimball et al., 2017; Yang et al., 2006].

Climate-change impacts in the Indus basin and Pakistan are divergent for water use and agricultural production [Chapters 4 and 5]. Renewable water availability increases due to increased precipitation under climate change that outweigh evaporation increases under higher temperatures, whereas irrigation demand decreases due to reduced crop transpiration under elevated [CO_2]. Note that glacier melt processes are not included in VIC-WOFOST and may further increase water availability under climate change [Immerzeel et al., 2013; Lutz et al., 2016]. These changes together reduce irrigation constraints under sustainable water management. However, temperature increases under climate change result in increased crop-heat stress and decreased crop productivity, even when accounting for maximum carbon assimilation increases under elevated [CO_2]. Therefore, end-of-the-century (2071-2100) wheat and rice productivity ultimately decreased up to 35% and 40% for the Indus basin and Pakistan respectively. Wheat productivity is affected most, as temperatures during the start of the growing season exceed those suitable for wheat. Naturally, these production decreases are sensitive to the parameterization of suitable growing temperatures, which are adjusted to match Pakistan's wheat varieties (up to 30 °C) [Government of Pakistan, 2015]. Rice productivity is affected less, as rice suitable growing temperatures (up to 35 °C) are higher than those of wheat. These results show that, although climate change is beneficial for the Indus' water use, it adversely affects its agricultural production.

6.1.4 RQ4: To what extent can agricultural adaptation enable agricultural production increases?

As sustainable water management and climate change are expected to decrease agricultural productivity, agriculture needs to adapt to maintain (and increase) its productivity. To assess the opportunities and limitations of agricultural adaptation, four agricultural adaptation options are implemented in VIC-WOFOST. These options are classified as either management adaptation options that aim to in increase agricultural productivity or climate-change adaptation options that aim to avoid adverse climate-change impacts. Two management adaptation options are implemented: (1) nutrient-gap closure and (2) cropland expansion. Additionally, two climate-change adaptation options are implemented: (1) growing-season adjustments and (2) crop substitution with maize (maize-crop substitution). For my worldwide assessment only the nutrient-gap closure option is evaluated, whereas for my regional assessment in Pakistan all options and their combinations are evaluated. For Pakistan, cereal production is additionally compared with requirements under three population-growth scenarios following the shared socioeconomic pathways (SSPs) [Jones & O'Neill, 2016]. Three population-growth scenarios are included: low (SSP1) moderate (SSP2) and high (SSP3) population growth, with a growth of 250%, 330% and 480% respectively between Pakistan's historical (1971-2000) and the end-of-this-century (2071-2100) populations. Cereal requirements, of approximately 1600 kcal cap^{-1}, are determined based on the historical wheat and rice consumption [Food and Agricultural Organization, 2021]. Note that these requirements are a conservative estimate as demands are likely to increase under socioeconomic growth in this century [Tilman & Clark, 2014].

My worldwide assessment shows that nutrient-gap closure (the first management adaptation option) is insufficient to fully compensate for irrigation constraints under sustainable water management. Wheat, maize, rice and soybean production, in total, still decreases by 5% [Chapter 3]. Moreover, my regional assessment shows that management adaptation alone is insufficient to compensate for climate-change impacts under low climate-change mitigation. Wheat and rice production, in total, still decreases up to 30% [Chapter 4]. However, in Pakistan the impacts of temperature increases under climate-change are potentially strongly reduced by growing-season adjustments and maize-crop substitution, while the climate-change benefits on water use and maximum carbon assimilation remain. Combining climate-change and management adaptation results in substantial agricultural production increases up to 130% and 145% for high and low climate-change mitigation respectively [Chapter 5]. Note that these results only indicate increases in average agricultural production and do not explicitly consider the impacts of greater agricultural variability and volatility [Wheeler & Von Braun, 2013]. Nevertheless, these average production increases potentially support end-of-the-century (2071-2100) cereal requirements for up to 400 million people, which is sufficient under low to moderate population-growth scenarios (SSP1 and SSP2) but is insufficient to support the high population-growth scenario (SSP3).

6.1.5 Conclusion

My thesis aimed to **quantify whether sufficient agricultural production is achievable under sustainable water management and climate change**. My results show that present-day human water use severely exceeds sustainable water use, especially in regions with extensively irrigated croplands (Section 6.1.1). Therefore, irrigation withdrawals in these regions should be constrained under sustainable water management. These irrigation constraints would result in substantial reductions in worldwide agricultural production (Section 6.1.2). In particular croplands in the Indus basin, which contains almost all of Pakistan's agriculture, would be severely affected. Moreover, in these regions, temperature increase under climate change and associated crop-heat stress adversely affects agriculture, even though climate change and elevated [CO_2] benefits water use (Section 6.1.3). However, growing-season adjustments and maize-crop substitution can reduce these adverse climate-change impacts and, in combination with management adaptation, can substantially increase Pakistan's agricultural production (Section 6.1.4). Consequently, if appropriate agricultural adaptation measures are taken, sufficient agricultural production can be achieved for all but the highest population growth scenario in Pakistan, even under sustainable water management and climate change.

6.2 Key strengths and weaknesses

One of the key strengths of my thesis is my development and application of the VIC-WOFOST model, as it has a highly process-based representation of hydrological and agricultural climate-change impacts and agricultural adaptation. The VIC model incorporates both the water and energy balance and uses the Penman-Monteith equation to estimate evapotranspiration [Liang et al., 1994]. This estimation is further improved in my thesis by explicitly including the effect of elevated [CO_2] on stomatal resistance. These elements together facilitate a strong physical basis for the simulation of climate-change impacts [Kingston et al., 2009], including the important effects of vapor pressure, surface temperatures and transpiration changes. In addition, the WOFOST model comprehensively represents the complex effects of water, nutrient and heat stress on crop growth [Supit et al., 1994]. Therefore, agricultural adaptation, and its effects on reducing these stress factors, are directly incorporated in my crop growth simulations. The elevated [CO_2] effects on crop growth also compares well to FACE experiments for wheat and rice. VIC-WOFOST thus provides a robust scientific tool that can be used to assess climate change and agricultural adaptation in the future.

Another key strength of my thesis is my regional adaptation assessment for the Indus basin and Pakistan, as it provides locally relevant information for water and agricultural planning and investments. Although climate-change impacts assessments are essential for guiding worldwide climate-change mitigation efforts, these assessments often provide little actionable information for countries and stakeholders that have little influence over worldwide climate-change mitigation. Especially for Pakistan, which emits less than 1% of worldwide greenhouse gasses [Ritchie et al., 2020] and is highly vulnerable to climate change [Farooqi et al., 2005], adaptation planning and investing is essential [United Nations, 2021]. Moreover, my regional assessment allowed for more robust and accurate results through better implementation and calibration of hydrology (e.g. irrigation return-flows and weather bias-correction) and agriculture (e.g. mineralization rates and fertilizer efficiency). Therefore, my regional assessment compares well with reported historical values.

However, while my thesis's regional adaptation assessment is indicated as a key strength, its worldwide assessment is weaker. My worldwide results of agricultural production and water resources are less accurate (Sections 6.1.1 and 6.1.2) as detailed hydrological and agricultural inputs are generally unavailable worldwide. In addition, the coarse spatial resolution of my worldwide assessment (i.e. 30-arcminute resolution or approximately 55km by 55km at the equator) may obscure the spatial heterogeneity in crop and water processes, and their (non-linear) interaction, in more complex landscapes [Hoffmann et al., 2016]. These limitations are a major reason for the initiation of my regional assessment, which subsequently showed an increase in performance compared to the worldwide assessment. Nevertheless, my regional assessment results for the Indus basin an Pakistan are in line with my worldwide assessment results for those regions. Therefore, although my worldwide results are less accurate, they likely remains robust in identifying hotspots of unsustainable water use and agricultural production trends under sustainable water management.

In addition, a weakness of my thesis is that my adaptation assessment was limited in scope. Especially the exclusion of water-related adaptation options, such as irrigation efficiency improvements (e.g. drip or deficit irrigation) that reduce irrigation demands, may increase agricultural production beyond the limitations indicated in my thesis [Grafton et al., 2018; Jägermeyr et al., 2016]. Such improvements were ignored as the VIC-WOFOST model inadequately represents their underlying processes (e.g. spatial heterogeneity in water application under drip irrigation). Conversely, implementing my thesis' adaptation options to their full extent can be unfeasible or undesirable due to, for example, economic and labor constraints or increased environmental pollution [Chukalla et al., 2020; Tittonell & Giller, 2013]. Therefore, achieving the full benefits of adaptation as indicated in my thesis is unlikely in practice. Nevertheless, my thesis is the first to indicate the potential productivity increases of agricultural adaptation under sustainable water management.

6.3 Preliminary worldwide assessment of climate-change benefits

As described in Section 6.1.3 and 6.1.4, climate change is potentially beneficial for water use and agricultural production in Pakistan. On the one hand, water deficits reduce due to increased water availability under climate change and decreased irrigation demands under elevated [CO_2] (Section 6.1.3). On the other hand, crop productivity increases under elevated [CO_2] if growing-seasons are adjusted to reduce crop-heat stress under climate change (Section 6.1.4). Naturally the question arose to what extent these climate-change benefits could be generalized to other regions. In response, this section provides a brief preliminary worldwide assessment of these climate-change benefits.

Preliminary worldwide results are generated separately for water use and potential irrigated wheat productivity. Water use results are based on the worldwide hydrological setup of Chapter 2 (i.e. soil, vegetation and land-use parameterization) and the elevated [CO_2] effects on transpiration of Chapter 4 (i.e. hyperbolic increase of stomatal resistance with elevated [CO_2]). Potential irrigated wheat productivity results are based on the worldwide crop setup of Chapter 3 (i.e. crop and growing season parameterization), the elevated [CO_2] effects on maximum crop productivity of Chapter 4 (i.e. maximum carbon assimilation increase with elevated [CO_2]) and the growing season optimization of Chapter 5 (i.e. planting and harvesting up to 2 months later and earlier than currently respectively). Results are shown for the end of this century (2071-2100) for low climate-change mitigation (RCP8.5) based on the same bias-corrected climate inputs as in Chapter 4 and 5.

My worldwide results show that, under climate change, irrigation demands mostly decrease due to transpiration decreases under elevated [CO_2] (Figure 6.1b). Only in higher latitude regions (i.e. northern America and Europe), these irrigation demands increase due to temperature increases and subsequent evaporation increases. Water availability changes, resulting from the combined effects of precipitation and evapotranspiration changes, are more spatially distributed (Figure 6.1c). For example, water availability decreases in central America and the Mediterranean, whereas water availability increases in northern America, northeastern Asia and central Africa. These spatial patterns are generally in line with other multi-model ensemble studies [Haddeland et al., 2014]. When combining irrigation demand changes with water availability changes, my results show that climate change is mostly beneficial for irrigation water use, as water deficits generally reduce around the world (Figure 6.1a). However, in regions where irrigation demand increases co-occur with water availability decreases, water deficits increase, which is especially clear in the Mediterranean region.

In addition, my worldwide results show that, under climate change, potential

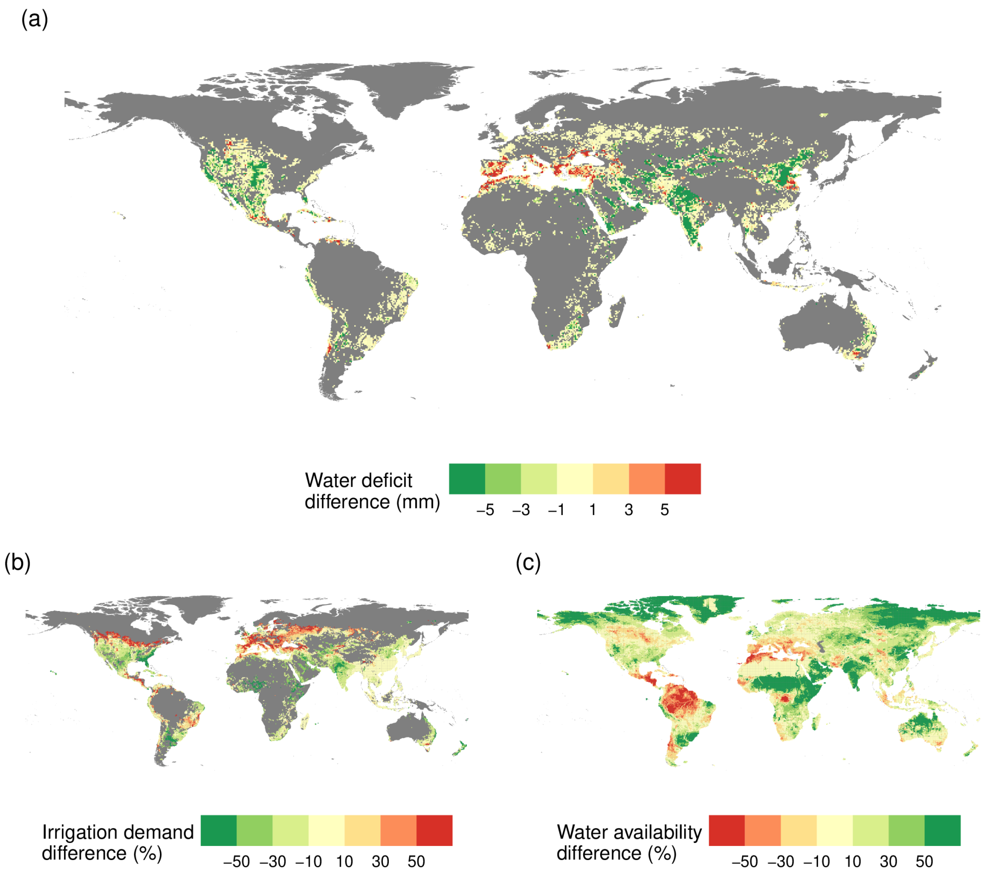

Figure 6.1: Simulated end-of-this-century (2071-2100) annual average difference in (a) water deficit, (b) irrigation demand and (c) water availability under low climate-change mitigation (RCP8.5) compared to 1971-2000. Note that negative water deficit changes do not necessary indicate there no longer is a deficit, only that this deficit decreases.

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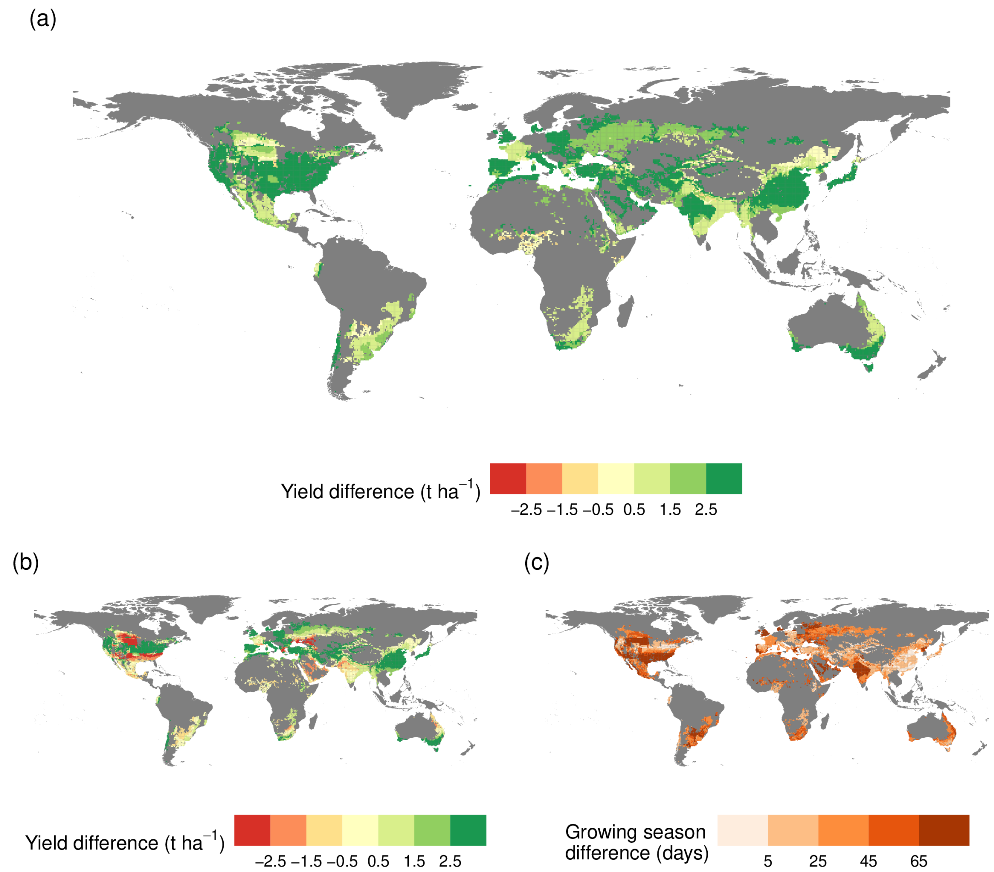

Figure 6.2: Simulated end-of-this-century (2071-2100) annual average difference in irrigated wheat (a) productivity *with* growing-season adjustments, (b) productivity *without* growing-season adjustments and (c) growing seasons under low climate-change mitigation (RCP8.5) compared to 1971-2000.

irrigated wheat productivity generally increases due to maximum productivity increases under elevated [CO_2] (Figure 6.2b). However, temperature increases and associated crop-heat stress potentially reduce irrigated wheat productivity in various croplands throughout Europe, northern America and western and southern Asia. The most severe of these heat-stress impacts can be reduced with appropriate shifts in planting and harvesting (Figure 6.2c). As a result, climate change is mostly beneficial for worldwide irrigated wheat productivity under growing season adaptation (Figure 6.2a). However, few croplands in northern and southern America western Africa and northeastern Asia cannot achieve productivity increases, even under growing-season adjustments.

Note that, in my preliminary assessment, results regarding agricultural water use and productivity are not fully integrated (i.e. agricultural productivity is not limited by water availability), nutrient limitations are ignored and only a single climate-change scenario and crop was included. Nevertheless, this assessment indicates that the climate-change benefits for water availability and agricultural productivity shown for Pakistan in my thesis probably also apply for other croplands around the world.

6.4 Scientific contribution

Although much research has been done into the impacts of climate change on agriculture and water resources separately, these impacts often remain unconnected. Most hydrological modelling studies solely estimate changes in water resources (e.g. Haddeland et al. [2014]; Immerzeel et al. [2020]), ignoring the impacts of these changes on agriculture, whereas agricultural modelling studies often assume unlimited water availability for irrigated crops (e.g. Jägermeyr et al. [2021]; Rosenzweig et al. [2014]). Furthermore, the few models that account for both agriculture and water resources (e.g. Bondeau et al. [2007]) often poorly represent agricultural management, thus limiting quantification of non-water related development strategies.

My thesis addresses these knowledge gaps by incorporating the impact and relative contribution of sustainable water management, climate change and agricultural adaptation on both water resources and crop growth. First, irrigation constraints under sustainable water management and nutrient management improvements are translated to production gains or losses for wheat, maize, rice and soybean. Although many studies call for agricultural intensification (e.g. Foley et al. [2011]; Godfray et al. [2010]), my results show that nutrient management improvements alone are likely insufficient to compensate for irrigation constraints under sustainable water management on current croplands. Second, the impacts of sustainable water management and climate change are assessed for water resources, agricultural productivity and their interaction in the Indus basin and Pakistan. Although changes in the Indus' water resources under climate change threaten agricultural productivity (e.g. Immerzeel et al. [2010]; Lutz et al. [2016]), my results show that crop-heat stress is potentially an even larger threat. Lastly, my thesis is the first to comprehensively (i.e. under a range of climate-change and population-growth scenarios) assess agricultural adaptation for self-sufficiency in Pakistan's. This assessment indicates clear opportunities to increase agricultural productivity through climate-change and management adaptation, even under sustainable water management.

My results can further contribute to the advancement of scientific knowledge in several ways. First, my worldwide assessment on unsustainable water use and the impacts of sustainable water management on agriculture clearly identifies regions where water and agricultural management changes are needed. This identification provides opportunities to develop additional case studies that further address strategies to manage agriculture under water scarcity in these regions, such as irrigation efficiency improvements and reservoir operation optimization strategies (e.g. Biemans et al. [2011]; Kahlown et al. [2007]). Moreover, my assessment also quantifies agricultural production under various fertilizer management strategies. These results can be used to explore the side effects of these fertilizer strategies on environmental pollution, using dynamic nutrient models (e.g. Liu et al. [2018]; Strokal et al. [2016]), and the potential economic and environmental benefits of fertilizer efficiency improvements.

Lastly, my thesis also highlights several deficiencies in current macro-scale hydrological and agricultural modelling that likely lead to an overestimation of climate-change impacts. My results show that elevated [CO_2] reduces irrigation demands in many regions, potentially (i.e. without irrigation expansion) also reducing unsustainable agricultural water use. However, most macro-scale hydrological studies ignore the effects of [CO_2], conversely concluding that unsustainable agricultural water use increases (e.g. Haddeland et al. [2014]; Lutz et al. [2022]). As there is a high degree of certainty regarding the benefits of elevated [CO_2] on crop water-use efficiency [Toreti et al., 2020], irrigation demand decreases resulting from these efficiency increases should no longer be ignored. Moreover, my results also show that adjusting planting dates and crop phenologies substantially reduces climate change impacts on agricultural productivity. However, most macro-scale agricultural studies assume planting dates and phenologies remain constant in the future, showing productivity losses due to crop-heat stress or growing season shortening under climate-change (e.g. Schlenker & Lobell [2010]). As growing season adjustments are often autonomously performed by farmers [Ali & Erenstein, 2017; Esham & Garforth, 2013; Khan et al., 2021b; Khanal et al., 2019], their effects should be further explored, for instance using a similar approach as in my thesis.

6.5 Sustainable development contribution

My thesis contributes a considerable step in quantifying the interactions between the Sustainable Development Goals (SDGs). In particular, I assess the interactions between developments to achieve sufficient agricultural production (as part of SDG2), sustainable water management (as part of SDG6) and reduced climate-change impacts (as part of SDG13). Although these interactions constitute only a part of all SDG interactions, the lack of their integrated quantification forms an obstacle to translate these development goals into practice. My quantification reveals several consequences for food, water and climate policies.

My thesis clearly shows a trade-off between developments to achieve sufficient agricultural production and sustainable water management. Irrigation demands needed to maintain agricultural productivity severely exceed sustainable water use, whereas irrigation constraints under sustainable water management would result in substantial agricultural production losses [Chapters 2 and 3]. This trade-off currently strongly favors agricultural productivity, and unsustainable irrigation withdrawals result in groundwater storage depletion and river streamflow reduction around the world. These river streamflow reductions have severe consequences for river and wetland ecosystems that depend on sufficient flows to maintain their functioning and biodiversity [Dudgeon et al., 2006; Vörösmarty et al., 2010]. Moreover, groundwater storage depletion also threatens water and food security, as groundwater reserves are an important resource to temporary meet water demands for agricultural, domestic and industrial purposes in periods of water scarcity [Famiglietti, 2014; Rodell et al., 2018]. This (apparent) contradiction between worthwhile development goals (e.g. sufficient agricultural production) and undesirable outcomes (e.g. freshwater biodiversity loss and threatened water and food security) highlights the need for integrated food and water policies that consider the trade-offs between agricultural production and water management [Liu et al., 2015].

Moreover, my thesis also clearly shows that climate change mitigation and adaptation plays a critical role in agricultural and water developments. Climate change substantially affects agricultural productivity, water resources and their interaction, whereas worldwide climate-change mitigation and regional climate-change adaptation provide opportunities to reduce these adverse climate-change impacts [Chapters 4 and 5]. These interactions confirm the need for coherent implementation of climate, agriculture and water management policies [Beg et al., 2002; Iacobuţă et al., 2021; Srivastava et al., 2022], particularly as agriculture also contributes to greenhouse gas emissions [Hasegawa et al., 2018]. Policy coherency is especially relevant for Pakistan, the focus region of my thesis. Despite several climate-change policies addressing the threat of climate change on agriculture [Government of Pakistan, 2010, 2012], agricultural investments of Pakistan's government mostly focus on agricultural productivity increases through management improvements and crop breeding [Government of Pakistan, 2020a]. My results provide an opportunity to re-emphasize the need for agricultural adaptation policies in Pakistan's new national climate-change adaptation plan [United Nations, 2021] and encourage investments to further develop available climate information services (e.g. World Bank [2018]) to include information on agricultural adaptation.

Navigating the trade-offs and synergies between agriculture, water and climate is a major challenge and likely requires substantial planning and investments to be successful [Hanjra & Qureshi, 2010]. However, the integrated quantification approach in my thesis can be used for the evaluation and prioritization of various development strategies, thereby contributing to sustainable policy and management decision making for a joint implementation of the SDGs at regional, national and worldwide level.

6.6 Outlook

My thesis assesses the impact of sustainable water management, climate change and adaptation on irrigated agriculture. As my climate change and adaptation results were limited to the Indus basin and Pakistan, a next step would be to expand this assessment to the whole world, in line with my preliminary worldwide assessment (Section 6.3). However, as discussed in Section 6.2, worldwide assessments require detailed hydrological and agricultural calibration to achieve better accuracy and model performance. Recent developments in the field of machine learning have shown promising results for process-based model calibration [Tsai et al., 2021], especially in regions where observations are scarce, resulting in strongly improved model accuracy. Machine learning for hydrology and agriculture is still relatively new and I will explore its opportunities in the future.

In addition, the VIC-WOFOST model is highly suited to contribute to worldwide hydrological and agricultural model intercomparison studies, such as the Inter Sectoral Impact Model Intercomparison (ISIMIP) [Warszawski et al., 2014] and the Global Gridded Crop Model Intercomparison (GGCMI) [Franke et al., 2020]. These studies aim to reduce uncertainties related to differences between hydrological or crop models, as these uncertainties are still larger than uncertainties related to climate models [Asseng et al., 2013; Prudhomme et al., 2014; Schewe et al., 2014]. Contribution to agricultural model intercomparison studies is particularly interesting, as these intercomparison studies aim to better integrate water limitations for irrigated agricultural production, thus bridging the gap between hydrology and agriculture.

Besides these worldwide assessments, I believe further efforts should be given to develop reliable and relevant regional adaptation assessments. These regional assessments can make use of regional climate model inputs and local field studies to increase their reliability [van Bussel et al., 2015; van Ittersum et al., 2013]. Moreover, to make these regional assessments more relevant for sustainable development policies, they would benefit from a more transdisciplinary approach. Model simulations should be combined with capacity-based adaptation assessments that consider socioeconomic drivers and limitations for adaptation [Adger et al., 2009; Vermeulen et al., 2013], and adaptation strategies should be designed in co-creation with local stakeholders and policy makers that are able to consider the full range of adaptation challenges in the region [Kanter et al., 2018; Scherr et al., 2012; Wise et al., 2014].

Lastly, water is crucial for human society. Its absence is a major source of conflict and migration [Gleick, 2014; Myers, 2002] and its availability is key for livelihoods and developments in multiple sectors [Cosgrove & Loucks, 2015]. In addition to its relevance for agriculture, water plays an essential role for energy (as part of SDG7), industrial (as part of SDG9) and domestic (as part of SDG11) sectors [Feeley III et al., 2008; Flörke et al., 2013]. Although macro-scale hydrological modelling can still be improved by better representing various hydrological processes, the coupling of these sectors and the inclusion of highly undervalued water quality aspects [Liu et al., 2017; van Vliet et al., 2017] will likely become more important in the coming decade.

Humanity stand at the precipice of uncertain times, with transformative climatic and socioeconomic changes that require the reevaluation of the balance between agriculture and water around the world. My thesis contributes to finding this balance through proper quantification of agriculture, water and climate interactions and the identification of effective adaptation strategies. This information is essential to support integrated policies and decision making towards both sufficient agricultural production and sustainable water management in the epoch of the Anthropocene.

Supplementary material

A Simulating human impacts on global water resources using VIC-5

A.1 VIC water and energy balance

In VIC each sub-grid computes the water and energy balance individually (i.e. sub-grids do not exchange water or energy with one another). For the water balance, incoming precipitation is partitioned between evapotranspiration, surface and subsurface runoff and soil water storage. Potential evapotranspiration is based on the Penman-Monteith equation without the canopy resistance [Shuttleworth, 1993]. The actual evapotranspiration is calculated using two methods, based on whether the land cover is vegetated or not (bare soil). Evapotranspiration of vegetation is constrained by stomatal, architectural and aerodynamic resistances and is partitioned between canopy evaporation and transpiration based on the intercepted water content of the canopy [Deardorff, 1978; Ducoudré et al., 1993]. Bare soil evaporation is constrained by the saturated area of the upper soil layer. The saturated area is variable within the grid, as (as the model name implies) the infiltration capacity of the soil is assumed to be heterogeneous [Franchini & Pacciani, 1991]. Saturated areas evaporate at the potential evaporation rate, whereas evaporation in unsaturated areas is limited. Surface runoff is produced by precipitation over saturated areas. Precipitation over unsaturated areas infiltrates into the upper soil layer and drains through the soil layers based on the gravitational hydraulic conductivity equations of Brooks & Corey [1964]. In the first and second layer, water is available for transpiration, while the third layer is assumed to be below the root zone. From the third layer, baseflow is generated based on the non-linear Arno conceptualization [Franchini & Pacciani, 1991]. Baseflow increases linearly with soil moisture content when the moisture content is low. At higher soil moisture contents, the relation is non-linear, representing subsurface storm flows.

For the energy balance, incoming net radiation is partitioned between sensible, latent and ground heat fluxes as well as energy storage in the air below the canopy. The energy storage below the canopy is omitted if it is considered negligible (e.g. the canopy surface is open or close to the ground). The latent heat flux is determined by the evapotranspiration as calculated in the water balance. The sensible heat flux is calculated based on the difference between the air and surface temperature and the ground heat flux is calculated based on the difference between the soil and surface temperature. As the incoming net radiation is also a function of the surface temperature (specifically the outgoing longwave radiation), the surface temperature is solved iteratively. Subsurface ground heat fluxes are calculated assuming an exponential temperature profile between the surface and the bottom of the soil column, where the bottom temperature is assumed to be constant. Later model developments included options for finite difference solutions of the ground temperature profile [Cherkauer & Lettenmaier, 1999], the spatial distribution of soil temperatures [Cherkauer & Lettenmaier, 2003], a quasi-two-layer snowpack snow model [Andreadis et al., 2009] and blowing snow sublimation [Bowling et al., 2004].

A.2 EFRs for surface and groundwater

VIC-WUR used the variable monthly flow (VMF) method [Pastor et al., 2014] to limit surface water withdrawals. The VMF method calculates the EFRs for streamflow as a fraction of the natural flow during high (Equation A.1), intermediate (Equation A.2) and low (Equation A.3) flow periods. The presumptive standard from Gleeson & Richter [2018] is used to limit groundwater withdrawals (including aquifer groundwater withdrawals). This standard calculates the EFRs for baseflow as 90% of the natural subsurface runoff through time (Equation A.4). Here, daily instead of monthly EFRs were used to better capture the monthly flow variability.

$$EFR_{s,d} = 0.6 \cdot NF_{s,d} \qquad where\ NF_{s,d} \leq 0.4 \cdot NF_{s,y} \tag{A.1}$$

$$EFR_{s,d} = 0.45 \cdot NF_{s,d} \qquad where\ 0.4 \cdot NF_{s,y} < NF_{s,d} \leq 0.8 \cdot NF_{s,y} \tag{A.2}$$

$$EFR_{s,d} = 0.3 \cdot NF_{s,d} \qquad where\ NF_{s,d} > 0.8 \cdot NF_{s,y} \tag{A.3}$$

$$EFR_{b,d} = 0.9 \cdot NF_{b,d} \tag{A.4}$$

Where $EFR_{s,d}$ is the daily EFRs for streamflow ($m^3\ s^{-1}$), $EFR_{b,d}$ the daily EFRs for baseflow ($m^3\ s^{-1}$), $NF_{s,d}$ is the average natural daily streamflow ($m^3\ s^{-1}$), $NF_{s,y}$ is the average natural yearly streamflow ($m^3\ s^{-1}$) and $NF_{b,d}$ is the average natural daily baseflow ($m^3\ s^{-1}$). EFRs for streamflow and baseflow were based on VIC-WUR naturalized simulations between 1980 and 2010. Average natural daily flows were calculated as the interpolated multiyear monthly average flow over the simulation period.

A.3 Dam operation scheme

VIC-WUR used a dam operation scheme based on Hanasaki et al. [2006]. Target release (i.e. the estimated optimal release) was calculated at the start of the operational year. The operational year starts at the month where the inflow drops below the average annual inflow, and, thus the storage should be at its desired maximum. The scheme distinguished between two dam types: (1) dams that did not account for water demands downstream (e.g. hydropower dams or flood control) and (2) dams that did account for water demands downstream (e.g. irrigation dams). The original scheme also accounts for EFRs, which were fixed at half the annual mean inflow. Other studies lowered the requirements to a 10^{th} of the mean annual inflow, increasing irrigation availability and preventing excessive releases [Biemans et al., 2011; Voisin et al., 2013]. In our study the original dam operation scheme was adapted slightly to account for monthly varying EFRs.

For dams that did not account for demands, the initial release was set at the mean annual inflow corrected by the variable EFRs (Equation A.5). For dams that did account for demands, the initial release was increased during periods of higher water demand. If demands were relatively high compared with the annual inflow, the release was corrected by the demand relative to the mean demand (Equation A.6). If demands were relatively low compared with the annual inflow, release was corrected based on the actual water demand (Equation A.7).

A

$$R'_m = EFR_{s,m} + (I_y - EFR_{s,y}) \qquad \textit{where } D_y = 0 \tag{A.5}$$

$$R'_m = EFR_{s,m} + (I_y - EFR_{s,y}) \cdot \frac{D_m}{D_y} \qquad \textit{where } D_y > 0 \textit{ and } D_y > (I_y - EFR_{s,y}) \tag{A.6}$$

$$R'_m = EFR_{s,m} + (I_y - EFR_{s,y}) - D_y + D_m \qquad \textit{where } D_y > 0 \textit{ and } D_y \leq (I_y - EFR_{s,y}) \tag{A.7}$$

Where R'_m is the initial monthly target release (m^3 s^{-1}), $EFR_{s,m}$ is the average monthly EFR for streamflow demand (m^3 s^{-1}), I_y is the average yearly inflow (m^3 s^{-1}), $EFR_{s,y}$ is the average yearly EFR for streamflow (m^3 s^{-1}), D_m is the average monthly water demand (m^3 s^{-1}) and D_y is the average yearly water demand (m^3 s^{-1}).

As in Hanasaki et al. [2006], the initial target release was adjusted based on storage and capacity. Target release was adjusted to compensate for differences between the current storage and the desired maximum storage (Equation A.8). Target release was additionally adjusted if the storage capacity was relatively low compared with the annual inflow, and was unable to store large portions of the inflow for later release (Equation A.9).

$$R_m = k \cdot R_m' \qquad where\ c \geq 0.5 \qquad (A.8)$$

$$R_m = \left(\frac{c}{0.5}\right)^2 \cdot k \cdot R_m' + \left(1 - \left(\frac{c}{0.5}\right)^2\right) \cdot I_m \qquad where\ 0 \leq c < 0.5 \qquad (A.9)$$

Where I_m is the average monthly inflow ($m^3\ s^{-1}$), c the capacity parameter (-) calculated as the storage capacity divided by the mean annual inflow and k the storage parameter (-) calculated as current storage divided by the desired maximum storage.

The desired maximum storage was set at 85% of the storage capacity as recommended by Hanasaki et al. [2006]. Water inflow, demand and EFRs were estimated based on the average of the past 5 years. Water demands were based on the water demands of downstream cells. Only a fraction of water demands were taken into account, based on the fraction of discharge the dam controlled. For example, if a dam controlled 70% of the discharge of a downstream cell, than 70% of its demands were taken into account. Fractions smaller than 25% were ignored.

The original dam operation scheme was shown to produce excessively high discharge events due to overflow releases [Masaki et al., 2018]. These overflow releases occurred due to a mismatch between the expected and actual inflow. In our study, dam release was increased during high-storage events to prevent overflow and the accompanying high discharge events. If dam storage was above the desired maximum storage, target dam release was increased to negate the difference (Equation A.10). If dam storage was below the desired minimum storage, release was decreased (Equation A.11). Dam release was adjusted exponentially based on the relative storage difference: small storage differences were only corrected slightly, but if the dam was close to overflowing or emptying, the difference was corrected strongly.

A

$$R_a = R_m + \frac{S - C \cdot \alpha}{\gamma} \cdot \left(\frac{\frac{S}{C} - \alpha}{1 - a}\right)^b \qquad where\ S > C \cdot \alpha \qquad (A.10)$$

$$R_a = R_m + \frac{S - C \cdot (1 - \alpha)}{\gamma} \cdot \left(\frac{(1 - \alpha) - \frac{S}{C}}{1 - a}\right)^b \qquad where\ S < C \cdot (1 - \alpha) \qquad (A.11)$$

Where R_a is the actual dam release ($m^3\ s^{-1}$), S the dam storage capacity (m^3), α the fraction of the capacity that is the desired maximum (-), β the exponent determining the correction increase (-) and γ the parameter determining the period when the release is corrected (s^{-1}). In testing the exponent and period were tuned to 0.6 and 5 days respectively.

A.4 Water demand

A.4.1 Fitting and validation data

Data on irrigation, domestic and industrial water withdrawals were based on the AQUASTAT database [Food and Agricultural Organization, 2020], the EUROSTAT database [European Commission, 2020] and the United Nations World Water Development Report [Connor, 2015]. Data on GDP per capita and GVA were abstracted from the Maddison Project Database [Bolt et al., 2018], the Penn World Table [Feenstra et al., 2015] and the World Development Indicators [World Bank, 2020].

Available data for domestic and industrial withdrawals were divided into a dataset used for parameter fitting (80%) and a dataset used for validation (20%). Domestic water demands were estimated for each United Nations subregion; thus, the data were divided per subregion to ensure a good global coverage of data. In the same manner industrial water demand was divided per country. In cases where there was only a single data entry, the entry was added to both the fitting and validation data.

A.4.2 Irrigation sector

A

Conventional irrigation demands were calculated when soil moisture contents dropped below the critical threshold where evapotranspiration would be limited. Demands were set to relieve water stress (Equation A.12). Paddy irrigation demands were set to always keep the soil moisture content of the upper soil layer saturated (Equation A.13), similar to Hanasaki et al. [2008b] and Wada & Bierkens [2014]. For paddy irrigation, the saturated hydraulic conductivity of the upper soil layer was reduced by its cubed root to simulate puddling practices, as recommended by the CROPWAT model [Smith, 1996]. Total irrigation demands were adjusted by the irrigation efficiency (Equation A.14). Paddy irrigation used an irrigation efficiency of one, as the water losses were already incorporated in the water demand calculation.

$$ID'_{\text{conventional}} = (w_{cr,1} + W_{cr,2}) - (W_1 + W_2) \quad where\ W_1 + W_2 < W_{cr,1} + W_{cr,2} \tag{A.12}$$

$$ID'_{\text{paddy}} = W_{max,1} - W_1 \quad where\ W_1 < W_{max,1} \tag{A.13}$$

$$ID = ID' \cdot IE \tag{A.14}$$

Where $ID'_{\text{conventional}}$ is the conventional crop irrigation demand (mm), ID'_{paddy} is the paddy crop irrigation demand (mm), ID is the total irrigation demand (mm), W_1 and W_2 are the soil moisture contents of the first and second soil layers respectively (mm), W_{cr} is the critical soil moisture content (mm), W_{max} the maximum soil moisture content (mm) and IE is the irrigation efficiency (mm mm^{-1}).

A.4.3 Domestic sector

Domestic water demands were represented using a sigmoid curve for the calculation of structural domestic water demands (Equation A.15) and an efficiency rate for the calculation of water use efficiency increases (Equation A.16). These equations differ slightly from Alcamo et al. [2003], as our study used the base 10 logarithms of GDP and water withdrawals per capita because they provided a better fit.

$$DSW_y = DSW_{min} + (DSW_{max} - DSW_{min}) \cdot \frac{1}{1 + e^{-f \cdot (GDP_y - o)}} \tag{A.15}$$

$$DW_y = 10^{DSW_y} \cdot TE^{y - y_{base}} \tag{A.16}$$

Where DSW is the yearly structural domestic withdrawal ($\log_{10}$ m^3 per capita), DW is the yearly domestic withdrawal (m^3 per capita), DSW_{min} is the minimum structural domestic withdrawal ($\log_{10}$ m^3 per capita), DSW_{max} is the maximum structural domestic withdrawal without technological improvement ($\log_{10}$ m^3 per capita), GDP is the yearly gross domestic product ($\log_{10}$ $USD_{equivalent}$ per capita), f (-) and o ($\log_{10}$ $USD_{equivalent}$) are the parameters that determine the range and steepness of the sigmoid curve respectively, y the year index, TE is the technological efficiency rate (-) and y_{base} is the base year (taken to be 1980).

DWmin was set at 7.5 L per capita per day based on the World Health Organization standard [Reed & Reed, 2013], DSW_{max} was estimated at around 450 L per capita per year based on a global curve fit, and TE was set at 0.995, 0.99, and 0.98 for developing, transition and developed countries respectively (United Nations development status classification) based on Flörke et al. [2013]. The curve parameters f and o were estimated for the 23 United Nations subregions based on the GDP per capita and domestic water withdrawal data. In cases where insufficient data were available to calculate parameters values, regional (four subregions) or global (four subregions) parameter estimates were used.

A

A.4.4 Industrial sector

Industrial water demands were represented using a linear formula for the calculation of structural industrial water demands (Equation A.17) and an efficiency rate for the calculation of water use efficiency increases (Equation A.18).

$$ISW_y = ISW_{int} \cdot GVA_y \tag{A.17}$$

$$IW_y = ISW_y \cdot TE^{y - y_{base}} \tag{A.18}$$

Where ISW is the yearly structural industrial withdrawal (m^3), ISW_{int} is the country-specific industrial water intensity (m^3 per $USD_{equivalent}$), IW is the yearly industrial withdrawal (m^3), GVA is the yearly gross value added by industry ($USD_{equivalent}$), y is the year index, y_{base} is the base year (taken to be the year when the industrial water intensity is determined) and TE is the technological efficiency rate (-).

TE was set at 0.976 and 1 for Organisation for Economic Co-operation and Development (OECD) and non-OECD countries respectively before the year 1980, 0.976 between the years 1980 and 2000 and 0.99 after the year 2000, based on Flörke et al. [2013]. Industrial water intensities were estimated for the 246 United Nations countries based on the GVA and industrial water withdrawal data. In cases where insufficient data were available to calculate the industrial water intensities, either subregional (56 countries), regional (17 countries) or global (9 countries) intensity estimates were used.

A.4.5 Energy sector

For each thermoelectric power plant the water intensity was combined with their generation to calculate the water demands (Equation A.19). Actual generation is estimated by adjusting the installed generation capacity by 46% for fossil fuel, 72% for nuclear and 56% for biomass power plants based on the U.S. Energy Information Administration (EIA) national annual generation data [Energy Information Administration, 2020].

A

$$EW_y = EW_{int} \cdot G_y \tag{A.19}$$

Where EW is the yearly energy withdrawal (m^3), EW_{int} is the energy water intensity (m^3 MWh^{-1}), G is the yearly generation for each plant (MWh) and y is the year index.

The energy water demands were subtracted from the industrial water demands at the location of each power plant. In cases where the grid cell industrial water demand was less than the energy water demand, national industrial water demands were lowered. In cases where even the national industrial water demands were less than the national energy water demand (three countries), the energy water demands were lowered instead. Energy demands were lowered until 10% of the national industrial water demand remained in order to ensure some spatial coverage of industrial and energy water demands.

A.4.6 Livestock sector

Livestock water demands were estimated by combining the livestock population with the water requirements for each livestock variety (Equation A.20).

$$LW_y = LW_{int} \cdot L \tag{A.20}$$

Where LW is the yearly livestock withdrawal (m^3), LW_{int} is the livestock water intensity (m^3 per livestock) and L is the livestock number for each variety.

A.5 General performance

VIC-WUR monthly discharge and monthly terrestrial total water storage anomalies were compared with observations from the GRDC dataset [Bundesanstalt für Gewässerkunde, 2020] and the GRACE satellite dataset [National Aeronautics and Space Administration, 2017] for eight major river basins not included in the main text (Figure A.1). Discharge stations were selected if the upstream area was larger than 10000 m^2, matched the simulated upstream area at the station location,): Amazon, Congo, Lena, Volga, Yangtze, Danube, Columbia and Mississippi river basins. A 300km Gaussian filter has been applied to the total water storage simulation data (similar to Long et al. [2015]).

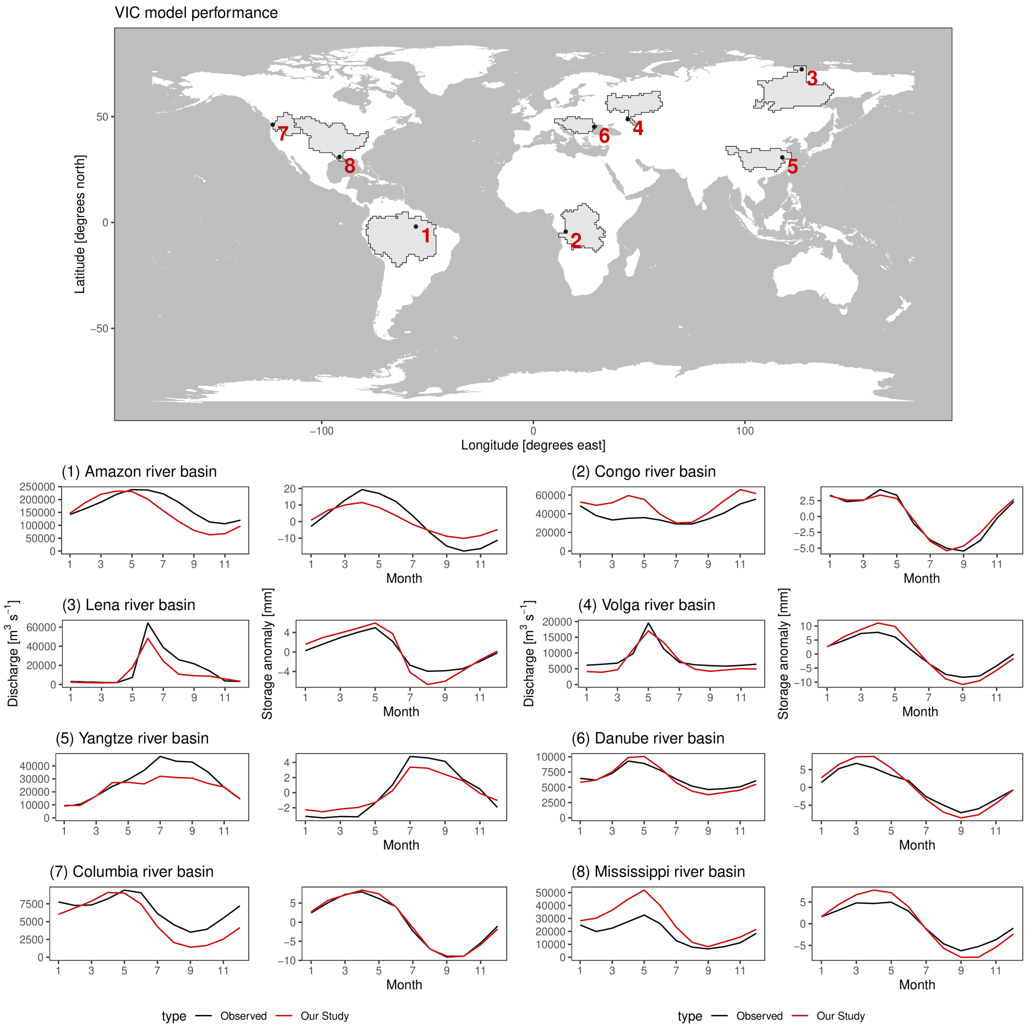

Figure A.1: Comparison between simulated discharge and terrestrial total water storage anomalies and GRDC- and GRACE observed values. Panels indicate the multiyear averages of anthropogenically impacted simulations (red) and observations (black).

A

Supplementary material

B Worldwide water constraints on attainable irrigated production for major crops

B.1 Model description

B.1.1 VIC model description

VIC [Droppers et al., 2020; Hamman et al., 2018; Liang et al., 1994] is a macro-scale hydrological model that simulates the energy and water balance on a spatially distributed grid. Grid cells are defined by their soil characteristics and consist of three soil layers. Each grid cell also contains various land-cover tiles, which define the vegetation characteristics. For each land-cover tile the energy and water balance is simulated, meaning that land-cover tiles do not interact. States, such as soil moisture content, are uniform across the land-cover tile. Here, a short description is given of the processes involved in simulating soil moisture availability, which is the main factor in calculating crop water stress.

B

Soil moisture availability is the result of the processes of infiltration, evapotranspiration and percolation. The soil infiltration capacity is assumed heterogeneous [Franchini & Pacciani, 1991]. Therefore, the saturated area is a non-linear function of the upper layer soil saturation. Infiltrated water percolates through the soil following the hydraulic conductivity equations of Brooks and Corey [Brooks & Corey, 1964]. Bare soil evaporation originates from the upper layer saturated areas and vegetation transpiration originates from the upper two layers containing roots. Potential evapotranspiration is based on the Pennman-Monteith equations without the canopy resistance [Shuttleworth, 1993]. Potential evapotranspiration is constrained by stomatal (only for vegetation), architectural and aerodynamic resistances, based on the land-cover class. For vegetation, evapotranspiration is partitioned between canopy evaporation (interception evaporation) and vegetation transpiration [Deardorff, 1978; Ducoudré et al., 1993]. Water stress is calculated following Equation B.1, and can vary between 1 (no water stress) and 0 (wilting) based on the soil moisture content.

$$Wstress = \frac{\sum_0^l (W_l - Wwp_l)}{\sum_0^l (Wcr_l - Wwp_l)} \qquad where\ Wstress \in [0, 1] \tag{B.1}$$

Where Wstress is the crop water stress, W is the soil water content (mm), Wwp is the wilting point water content (mm) (water content at 1 500 m H_2O or pF 4.2), and Wcr is the critical water content (mm) (i.e. water content below which water stress occurs) in each layer l containing roots. For crops, Wcr is calculated between the wilting and field capacity content as a function of potential evapotranspiration and the crop drought resistance [Doorenbos & Kassam, 1979; Keulen & Wolf, 1986; van Diepen et al., 1988]. For other vegetation, Wcr is calculated at 70 % between Wwp and Wfc, which is the field capacity water content (mm) (water content at 33 m H_2O or pF 2.5).

Irrigated crops will demand water when water stress occurs (i.e. water availability is limiting crop transpiration). Water demands are set to fill the soil water content up to saturation (paddy rice; Equation B.2) or field capacity (other crops; Equation B.3).

$$Dirr_{\text{rice}} = \sum_0^l Ws_l - \sum_0^l W_l \tag{B.2}$$

$$Dirr_{\text{other}} = \left(\sum_0^l Wfc_l - \sum_0^l W_l \right) \cdot Eirr \tag{B.3}$$

Where Dirr is the irrigation demand (mm) (for paddy rice and other crops respectively), Eirr is the irrigation efficiency (-), W is the soil water content (mm), Wfc is the field capacity (mm) (water content at 33 m H_2O or pF 2.5) and Ws is the saturated water content (mm) in each layer l containing roots. Irrigation efficiencies were implemented per UN region [Frenken & Gillet, 2012].

B

Water demands can be fulfilled using locally available water resources. These resources come in four forms: (1) local streamflow, (2) small dam storage, (3) remote streamflow, and (4) non-renewable resources. Local (river) streamflow is generated from the simulated runoff using a routing module. Small dam fill using surface runoff, and reservoir storage is available for withdrawal. Small dams are defined as having a catchment area (as derived from the global reservoir and dam database [Lehner et al., 2011]) smaller than the simulated grid. Remote streamflow consists of available river streamflow from other cells, such as deltas and neighbouring cells. Delta cells [Tessler et al., 2015] can withdraw water from the outflow point of the delta in order to simulate water redistribution in deltas. Remote water withdrawals from higher neighbouring cells are used to simulating water canals. Non-renewable water withdrawals contribute to a water deficit, which will subsequently reduce subsurface runoff until the deficit is fulfilled. For sustainable water management non-renewable water withdrawals were limited to 100 mm to account for renewable groundwater recharge. This means that annual and interannual variations in recharge are allowed, as long as the groundwater deficit is compensated later.

B.1.2 WOFOST model description

WOFOST [de Wit et al., 2020; Supit et al., 1994] is a field-scale crop model that simulates crop growth for a single crop variety. Crop varieties are defined by their crop parameters and phenological development length. Phenological development is expressed in two stages: emergence to anthesis and anthesis to maturity. In our study phenological development depends on air temperature only (no vernalization or day-length effects). Here, a short description is given of the processes involved in simulating crop growth, which is the main factor in calculating crop yields.

Crop growth is the results of carbon assimilation and nutrient uptake. Potential carbon assimilation is calculated based on the incoming (direct and diffuse) radiation [Spitters et al., 1986] during three periods of the day and in three depths in the crop canopy [Goudriaan, 1977, 1986]. Assimilation is constrained by suboptimal daytime temperatures, low nighttime temperatures, nutrient stress and water stress. Net carbon assimilation accounts for maintenance respiration, which is a function of the plant biomass, development stage and temperature. Assimilates, after conversion to dry matter, are subsequently partitioned over the crop organs (stems, leaves, roots and storage) as a function of the plant development stage. Crop nutrient demand is based on the difference between the current and maximum crop organ nutrient content as a fraction of the crop organ biomass [Shibu et al., 2010]. Nutrient uptake is limited by nutrient availability from fertilization, mineralization and fixation. Nutrient stress is calculated following Equation B.4 and Equation B.5, and can vary between 1 (no nutrient stress) and 0 (severe nutrient stress) based on nutrient contents in stems and leaves.

B

$$Nstress = 1 - Neff \cdot (1 - Nidx)^2 \qquad where\ Nstress \in [0,1] \qquad (B.4)$$

$$Nidx = \frac{Nveg - Nres}{Nopt - Nres} \qquad where\ Nidx \in [0,1] \qquad (B.5)$$

Where Nstress is the nutrient stress (-), Neff is the crop specific nutrient use efficiency factor due to nutrient stress (-), Nidx is the nutrient index (-), Nveg is the nutrient content in the stems and leaves (kg N kg^{-1} dry mass ha^{-1}), Nres is the residual nutrient content in the stems and leaves (kg N kg^{-1} dry mass ha^{-1}), and Nopt is the optimal nutrient content in the stems and leaves (kg N kg^{-1} dry mass ha^{-1}).

B.2 Model setup

B.2.1 Soil, land-cover, vegetation and crop parameters

Soil parameters (e.g. saturated hydraulic conductivity, porosity and exponent in hydraulic equations) were derived from the international soil reference and information centre world inventory of soil emission potentials pedon database (ISRIC-WISE, aggregated to 0.5° and aggregated to the 3 VIC soil layers) [Batjes, 2016] in combination with the Saxton et al. [1986] pedotransfer functions. Calibrated soil parameters (i.e. variable infiltration curve parameter, second soil layer depth and baseflow parameters) are based on Nijssen et al. [2001b] (aggregated to 0.5°).

The land-cover distribution is a combination between the advanced very high resolution radiometer land-cover classification (AVHRR) [Hansen et al., 2000] for natural vegetation and the monthly irrigated and rainfed cropland areas around the year 2000 land-cover classification (MIRCA2000) [Portmann et al., 2010] for crops. The vegetation extend is fixed in time while the crop extend varies monthly. In cases where the extends between the different products do not match, the MIRCA2000 land-cover classification is prioritized above the AVHRR classification. Several changes were made to the crop growing seasons. The second irrigated rice season in China and Japan takes place between November and March according to the crop calendar. However, during this time temperatures are too low to constitute to significant crop development (the base temperature for rice is at least 10°C), resulting in crop failure. Therefore, in our study, this season has been omitted. Irrigated winter wheat in Northern China takes place between October and May according to the crop calendar. However, several other sources [Li et al., 2005; Lv et al., 2013] indicate that the winter wheat season extends to June, and allows for increase grain filling. As the original season resulted in very low crop yields, our study has extended the season from May to June.

VIC vegetation parameters (e.g. stomatal and architectural resistances) were based on Nijssen et al. [1997], and derived from various sources [Calder, 1993; Ducoudré et al., 1993; Sellers et al., 1996]. Vegetation parameters for wheat, maize, rice and soybean were based on the so-called "cropland" land-cover classification. The architectural resistance of maize and soybean was increased to avoid overestimating evapotranspiration rates.

WOFOST crop parameters (e.g. biomass partitioning and assimilation rates) were based on Boogaard et al. [2014]. Parameters were derived from various field experiments in the European Community [Boons-Prins et al., 1993; Penning de Vries, 1989; van Diepen & De Koning, 1990; van Diepen et al., 1988; van Heemst, 1988; Wolf &

Van Diepen, 1991] and from research executed in the framework of the MARS project [European Commission, 1993; Russell, 1990; Russell et al., 1997; Russell & Wilson, 1994], which is regularly updated. The rice maximum assimilation rate was increased in order to reach the high reported yields in for example China and Egypt (up to 8 tonnes ha^{-1}) under no-stress (potential) conditions. The maize storage organ maximum nitrogen content was decreased and the soybean maximum assimilation rate was increased following observations from Argentina.

B.2.2 Fertilization and mineralization

Fertilizers application is based on the inter-sectoral impact model intercomparison project phase 3 and global gridded crop model intercomparison phase 3 fertilizer dataset (isimip.org; esg.pik-potsdam.de). The dataset compiled reported national and sub-national organic and mineral fertilizer application rates between 1850 and 2015 [Hurtt et al., 2020; Mueller et al., 2012; Zhang et al., 2017]. Fertilizer is applied at the start of the growing season. Fertilizer use efficiency (i.e. the amount of fertilizer applied that is available for the crop) was set to 66%, following observations from well-managed fields [Dobermann, 2005; Ladha et al., 2005; Roberts, 2008]. Note that this is not the nutrient use efficiency of the crop. Crop nutrient use efficiency are lower due to excess fertilizer application and subsequent nutrient losses (e.g. runoff and leaching).

Mineralization rates were estimated based on soil organic nitrogen content, temperature and pH following Equation B.6 to Equation B.8 [Sattari et al., 2014]. Mineralization occurs throughout the growing season and is scaled proportional to the growing period length.

B

$$Nmin = Norg \cdot 2 \cdot f(T) \cdot f(pH) \tag{B.6}$$

$$f(T) = 2^{(T-9)/9} \tag{B.7}$$

$$f(pH) = 0.25 \cdot (pH - 3) \qquad where\ f(pH) \in [0.4, 1] \tag{B.8}$$

Where Nmin is the mineralization rate (kg ha^{-1} 120 days^{-1}), Norg is the upper 20 cm organic nitrogen content (g kg^{-1}), T is the air temperature (°C), and pH is the upper 20 cm pH measured in water (-).

B.2.3 Crop phenology and growing season

Crop simulations require information regarding the cumulative Growing Degree Days (cGDD [° C]) needed to reach the anthesis and maturity development stages (Equation B.9). cGDD are a non-linear function of the temperature, typically including a minimum temperature below which crop development is limited. As cGGD are related

Table B.1: Crop information for variety and period estimation

Crop type	Seasons	Area (Mha)
Irrigated wheat	2	66
Rainfed wheat	2	149
Irrigated maize	1	29
Rainfed maize	1	121
Irrigated rice	2	100
Rainfed rice	3	64
Irrigated soybean	1	6
Rainfed soybean	1	67

to temperature, they are inherently related to the crop growing period. In order to estimate cGDD, crop growing periods were derived from the MIRCA2000 land-use dataset, which spatially distributes monthly irrigated and rainfed crop growing areas. Division between cGGD needed to reach flowering and maturity were simplified to equations Equation B.10 to Equation B.13 based phenological parameters determined in the European Community [Boons-Prins et al., 1993].

$$cGDD_{\mathrm{t}} = cGDD_{\mathrm{a}} + cGDD_{\mathrm{m}} \tag{B.9}$$

$$cGDD_{\mathrm{m,maize}} = cGDD_{\mathrm{a,maize}} + 100 \tag{B.10}$$

$$cGDD_{\mathrm{m,wheat}} = \max\left(cGDD_{\mathrm{a,wheat}} - 100, 1\,500\right) \tag{B.11}$$

$$cGDD_{\mathrm{a,rice}} = \max\left(0.33 \cdot cGDD_{\mathrm{m,rice}}, 1000\right) \tag{B.12}$$

$$cGDD_{\mathrm{m,soybean}} = 1.5 \cdot cGDD_{\mathrm{a,soybean}} \tag{B.13}$$

B

where $\mathrm{cGDD_t}$ is the total temperature sum (°C), $\mathrm{cGDD_a}$ is the temperature sum (°C) to reach anthesis and $\mathrm{cGDD_m}$ is the temperature sum (°C) to reach maturity for maize, wheat, rice and soybean respectively.

As the monthly time resolution of the land-use dataset is quite coarse, the optimal crop growing period was calibrated. Both planting and harvesting could occur early (5th month day), intermediate (15th month day), late (25th month day) and very late (4th month day of the next month). For each of the 16 possible growing periods, cGDDs were calculated based on the 1991-2000 (MIRCA2000 reference years) average growing-season air temperature. For each unique cultivated area (each grid, each crop, irrigated or rainfed, and each season; Table B.1) the best performing crop period was selected. Performance was measured by combining both average yield and yield stability using the following setup: (1) find the period with the highest average yield, (2) find the periods within 250 kg ha^{-1} of the highest average yield, and (3) select the period (from previous periods) with the lowest year-to-year variation in yields.

B.2.4 Sectoral water use

Domesic, indutrial, energy and livestock water demands were estimated as described in Droppers et al. [2020], and are shortly described here. Domestic water demands were estimated using calibrated relationships between gross domestic product (GDP) [Bolt et al., 2018; Feenstra et al., 2015; World Bank, 2020] and the domestic water use intensity [Food and Agricultural Organization, 2020; World Bank, 2020] per UN subregion, similar to Alcamo et al. [2003]. Industrial water demands were estimated using calibrated relationships between national gross value added by industry (GVA) [Bolt et al., 2018; Feenstra et al., 2015; World Bank, 2020] and the industrial water use intensity [Food and Agricultural Organization, 2020; World Bank, 2020] per country similar to Flörke et al. [2013]. Domestic and industrial water demands were subsequently spatially disaggregated using population maps [Klein Goldewijk et al., 2017] and light maps [National Aeronautics and Space Administration, 2016] respectively. Domestic water demands were additionally temporally disaggregated based on monthly air temperature [Huang et al., 2018; Wada et al., 2011b] (using the global average variation). Thermoelectric water demands were estimated by combining energy plant details [van Vliet et al., 2016] with cooling water use intensity per cooling method [Goldstein & Smith, 2002] and average global generation capacity (fraction of installed capacity) per fuel type (based on data from the energy information administration (EIA) [Energy Information Administration, 2020]). Livestock water demands were estimated by combining livestock maps [Gilbert et al., 2018] and livestock drinking and servicing water use intensity [Steinfeld et al., 2006]. Domestic and industrial consumption fractions are 0.15 and 0.10 respectively based on data from Shiklomanov [Shiklomanov, 2000]. Energy consumption fractions vary per cooling method [Goldstein & Smith, 2002] and livestock water withdrawals are fully consumed.

B.3 Model performance

To assess our model performance, simulated national annual crop production was compared to food and agricultural organization (FAO) reported values [Food and Agricultural Organization, 2021]. Simulated crop production is well represented over a large range of climate and soil classifications (correlation larger than 0.9 for all crops), as seen in Figure B.1. However, simulated crop production was generally higher than reported (see also Table B.3 and Figure B.2). This was expected since the model was explicitly not calibrated to account for sub-optimal crop production practices.

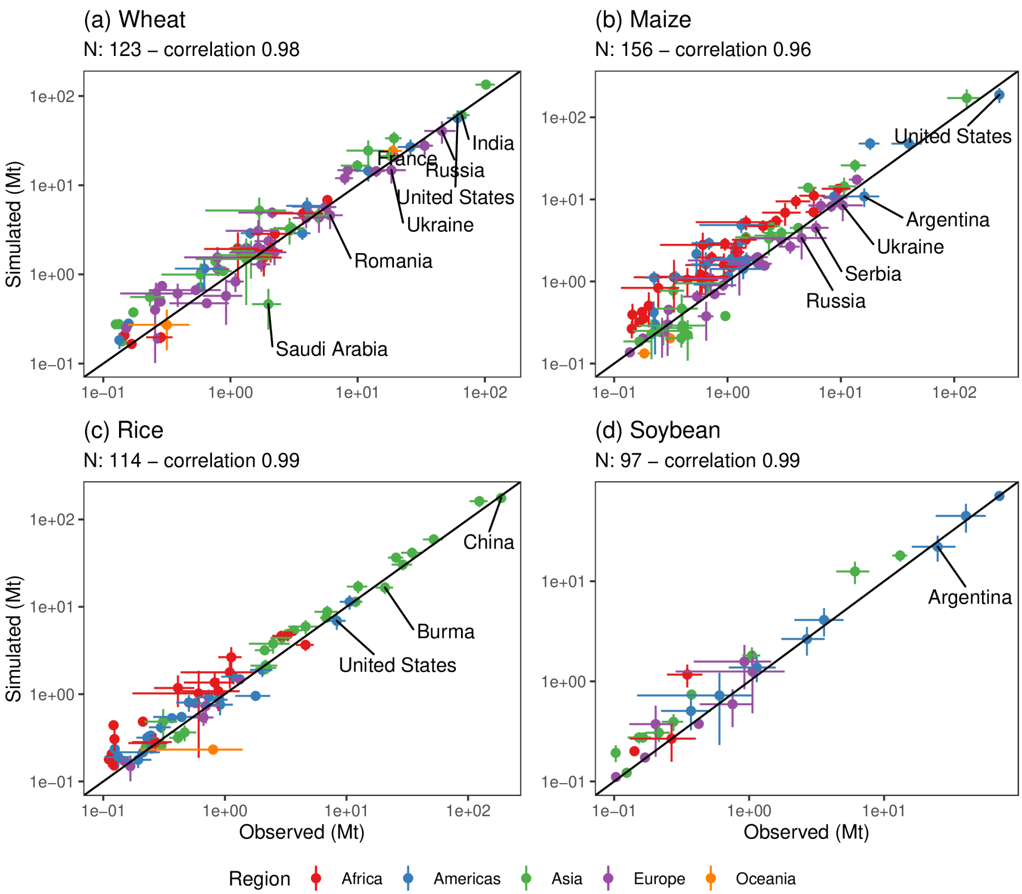

Figure B.1: Comparison between FAO reported [Food and Agricultural Organization, 2021] and simulated national annual total (irrigated and rainfed) (a) wheat, (b) maize, (c) rice and (d) soybeans production. Error lines indicate the detrended interannual variation (one standard deviation). Simulated crop production has been adjusted for differences in harvested area. Note the plots are on a log-log axis to better display the large range of values, and that the plot axis vary for each crop.

B

Table B.2: Simulated crop production variation (% of baseline or attainable production) for changes in growing season length, growing season timing, fertilizer application, mineralization rate, irrigation efficiency, and soil characteristics

Category	Wheat variation (%)	Maize variation (%)	Rice variation (%)	Soybean variation (%)
Season length	34	51	23	13
Season timing	26	37	7	7
Fertilizer application	11	20	6	0
Mineralization rate	6	11	6	0
Irrigation efficiency	2	2	1	1
Soil characteristics	2	4	3	1

Overestimations generally reduce over time as agricultural production is optimized (also called the technological trend [Ramankutty et al., 2018]). On the other hand, underestimations are found in maize production, especially in the Americas (Figure B.1b). Underestimations are mostly related to water stress factors in the Argentinian Pampas and the United States Midwest. Simulated water stress in these areas is probably higher due to shallow groundwater tables in these areas [Kroes et al., 2019; Rizzo et al., 2018] that are not well simulated by our model framework.

B.4 Sensitivity analysis

Simulated worldwide irrigated crop production sensitivity was analyzed for changes in growing season, soil characteristics, and nutrient and water inputs. Crop production was estimated for: (1) short (25th month day of planting to 5th month day of harvest) and long (5th month day of planting to 25th month day of harvest) growing season length, (2) early (5th month day for planting to 5th month day for harvest) and late (25th month day for planting and 25th month day for harvest) growing season timing, (3) high (+25%) and low (-25%) fertilizer application, (4) high (+25%) and low (-25%) mineralization rate, high (+25%) and low (-25%) irrigation efficiency, and high (+25) and low (-25) soil sand percentage (subsequently influencing soil characteristics such as hydraulic conductivity and available water content). Most factors were assessed for the baseline simulation. However, the irrigation efficiency and soil sand content were assessed for the attainable simulation, as this simulation limits water withdrawals (and not nutrient availability). Figure B.5 to B.10 indicate the spatial distribution of the sensitivity.

The growing season length is the dominant factor for changes in simulated crop production (Table B.2). In general, longer growing periods can lead to higher biomass assimilation and thus higher crop production, as is the case for both soybean and rice. However, growing seasons are also determined by the water and nutrient availability during the growing season. Maize is mostly nutrient limited, and shorter growing periods are often preferred to avoid nutrient deficits. This is accompanied by a strong response to fertilizer application and mineralization. Wheat is mostly water limited, and is also sensitive to the timing of the growing period. Shifted growing periods can avoid early or late droughts that may affect crop production. Irrigation efficiencies and soil characteristics mostly affect the irrigation water demands. However, the water constraints imposed in this study are generally larger than the reduction in irrigation water demands. As a results attainable irrigated crop production (i.e. the crop production under constrained water withdrawals) is affected to a lesser extent.

Table B.3: Comparison between FAO reported [Food and Agricultural Organization, 2021] and simulated national annual total (irrigated and rainfed) wheat, maize, rice and soybeans production between 1990 and 2010 (for countries where information was available). Simulated crop production has been adjusted for differences in harvested area.

Crop	Region	Observed production [Mt y^{-1}]	Simulated production [Mt y^{-1}]
Wheat	World	595	684
	Africa	18	21
	Americas	109	113
	Asia	256	326
	Europe	194	199
	Oceania	19	25
Maize	World	638	752
	Africa	45	91
	Americas	344	332
	Asia	174	251
	Europe	74	78
	Oceania	1	0
Rice	World	594	660
	Africa	18	25
	Americas	31	30
	Asia	541	600
	Europe	3	3
	Oceania	1	0
Soybean	World	171	190
	Africa	1	2
	Americas	143	147
	Asia	24	37
	Europe	3	3
	Oceania	0	0

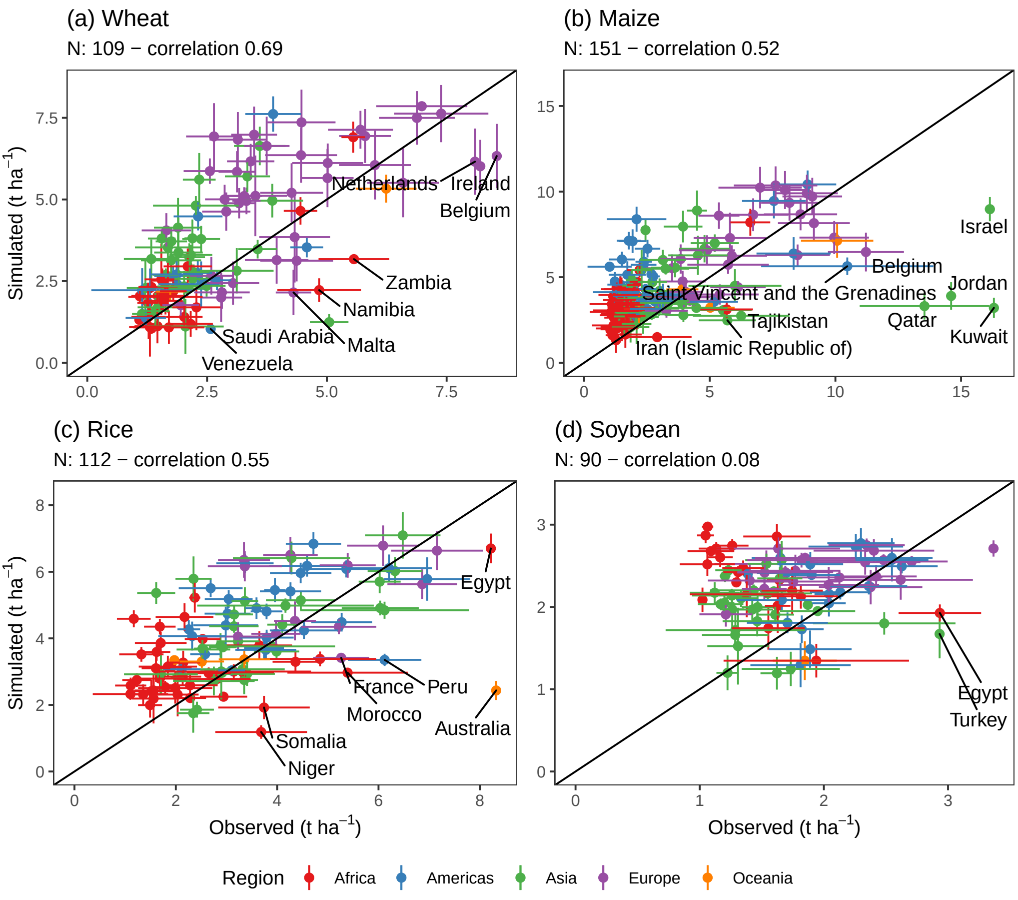

Figure B.2: Comparison between FAO reported [Food and Agricultural Organization, 2021] and simulated national annual total (irrigated and rainfed) (a) wheat, (b) maize, (c) rice and (d) soybeans yield. Error lines indicate the detrended interannual variation (one standard deviation). Note the plot axis vary for each crop.

B

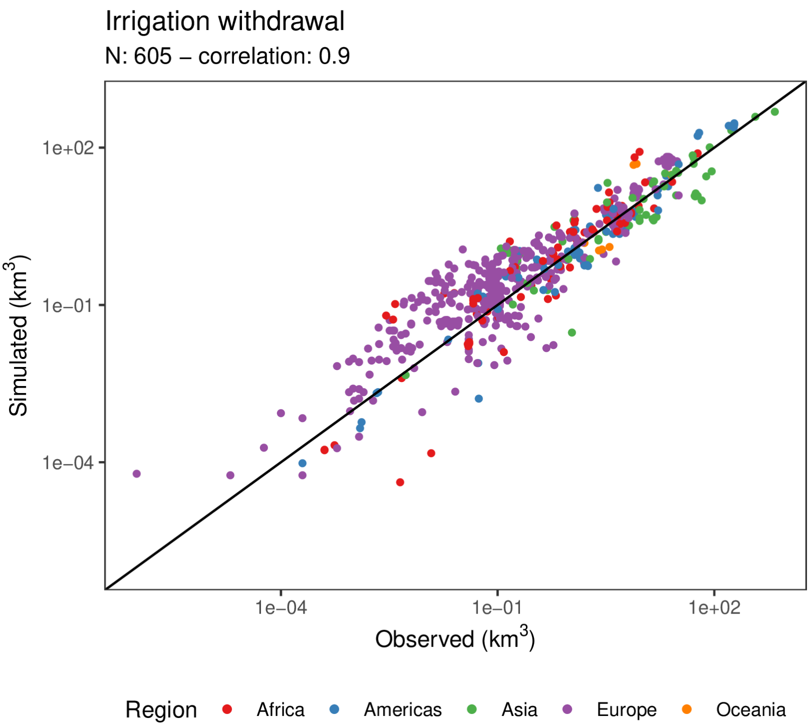

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Figure B.3: Comparison between FAO reported [Food and Agricultural Organization, 2020] and simulated national annual total irrigation water withdrawal. Note the plots are on a log-log axis to better display the large range of values.

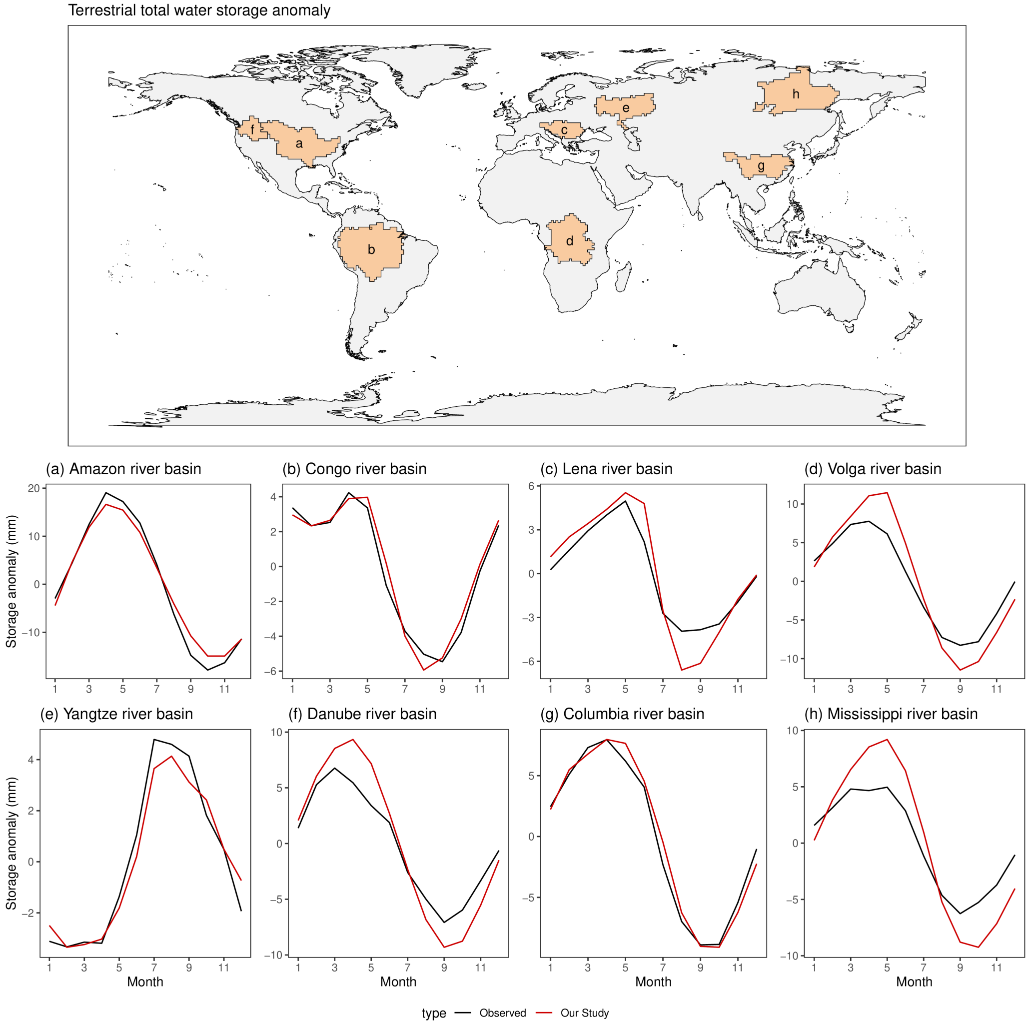

Figure B.4: Comparison between GRACE observed (black) [National Aeronautics and Space Administration, 2017] and simulated (red) multi-year average terrestrial water storage anomalies for several basins (a-h).

B

Table B.4: Comparison between worldwide annual irrigated and rainfed wheat, maize, rice and soybeans production, harvested area and yields from various studies. Values for irrigated crops are shown between brackets. Note the different reference years for each study, which explain some of the differences between the studies.

Study (reference years)	Crop	Production ($Mt\ y^{-1}$)	Area (Mha)	Yield ($t\ ha^{-1}\ y^{-1}$)
Iizumi et al. [2014] (1982 - 2006)	Wheat	563	209	2.7[a]
	Maize	591	136	4.3[a]
	Rice	572	150	3.8[a]
	Soybean	162	74	2.2[a]
Our study (1990 - 2010)	Wheat	665 (238)	209 (65)	3.2 (3.7)
	Maize	791 (193)	147 (29)	5.4 (6.6)
	Rice	617 (412)	142 (82)	4.4 (5)
	Soybean	178 (15)	71 (6)	2.5 (2.5)
Alexandratos & Bruinsma [2012] (2005-2007)	Wheat	614	222	2.8 (3.5)
	Maize	736	155	4.7 (6.8)
	Rice	644	158	4.1 (5.1)
	Soybean	217	94	2.3
Ray et al. [2013] (2008)	Wheat	676[a]	218[a]	3.1
	Maize	811[a]	156[a]	5.2
	Rice	682[a]	155[a]	4.4
	Soybean	221[a]	92[a]	2.4

[a] values were calculated from available data.

B

Table B.5: Comparison between worldwide annual irrigation withdrawal from various studies. Note the different reference years for each study, which explain some of the differences between the studies.

Study	Reference years	Withdrawal ($km^3\ y^{-1}$)
Rost et al. [2008]	1971-2000	2 555
Pokhrel et al. [2015]	1998-2002	3 028
Our study	1990 - 2010	2 881
Hanasaki et al. [2018]	1984-2013	2 544
Döll et al. [2012]	1998-2002	3 185
Sutanudjaja et al. [2018]	2000-2015	2 309

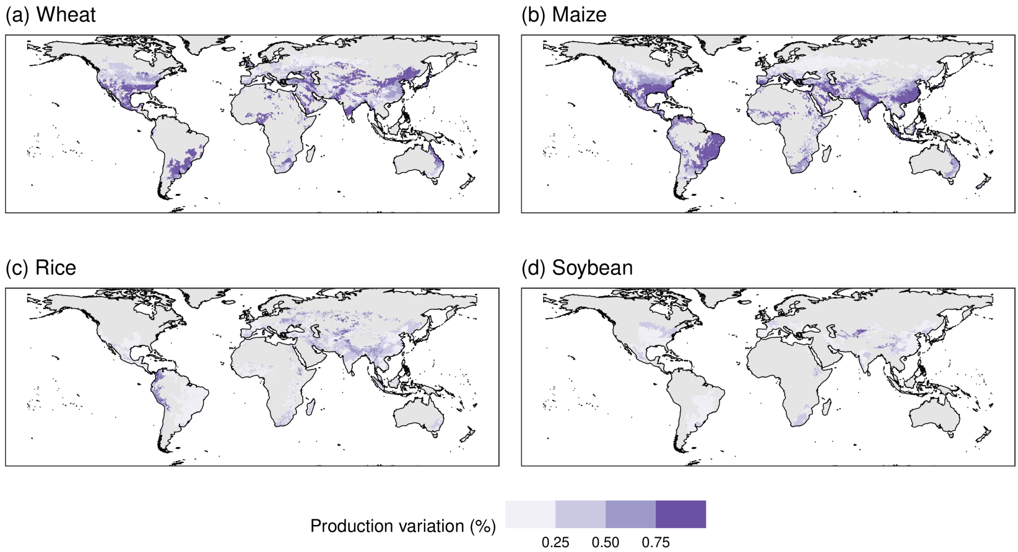

Figure B.5: Simulated yield variation (% of baseline irrigated yields) based on changes in growing period length for (a) wheat, (b) maize, (c) rice, and (d) soybean.

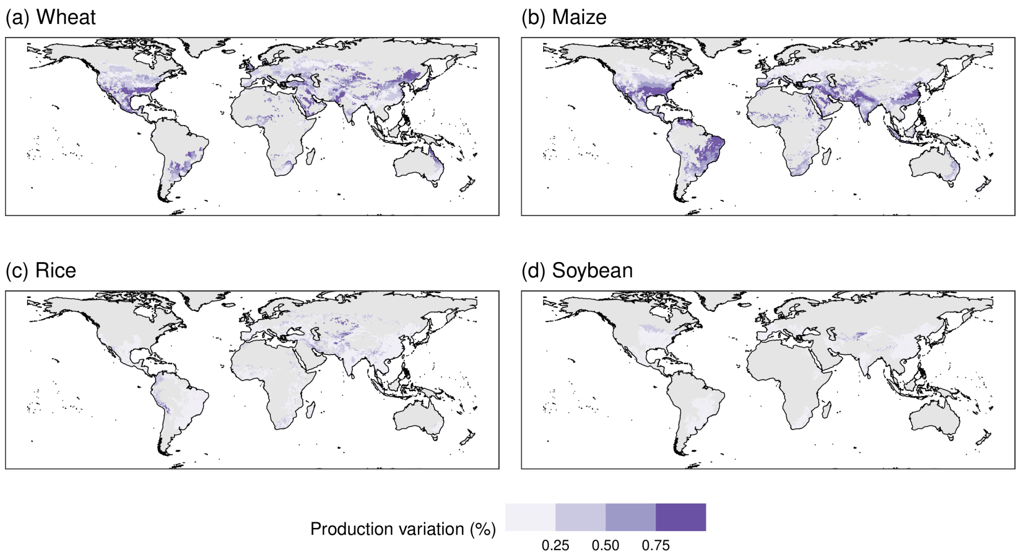

Figure B.6: Simulated yield variation (% of baseline irrigated yields) based on changes in growing period timing for (a) wheat, (b) maize, (c) rice, and (d) soybean.

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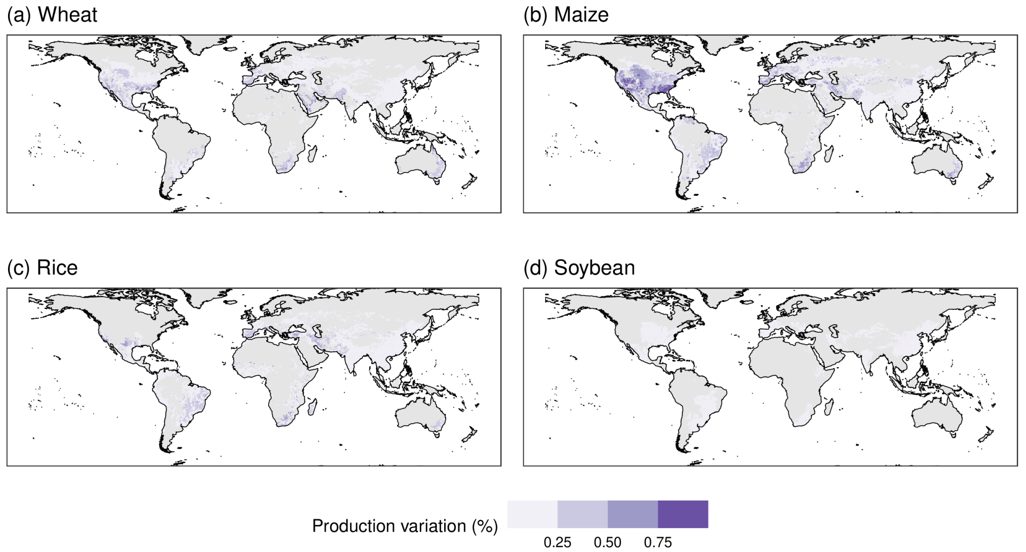

Figure B.7: Simulated yield variation (% of baseline irrigated yields) based on changes in fertilization application for (a) wheat, (b) maize, (c) rice, and (d) soybean.

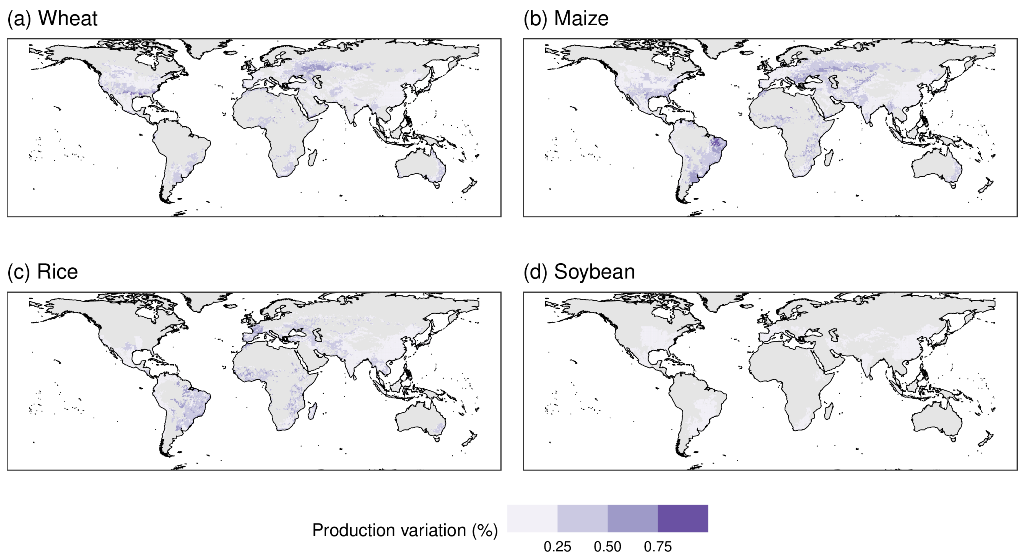

Figure B.8: Simulated yield variation (% of baseline irrigated yields) based on changes in mineralization rate for (a) wheat, (b) maize, (c) rice, and (d) soybean.

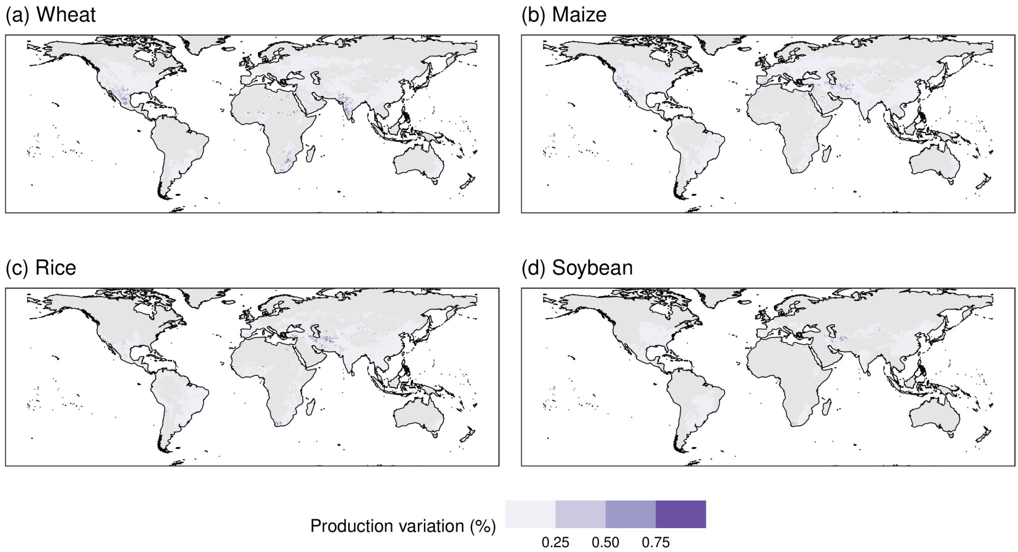

Figure B.9: Simulated yield variation (% of attainable irrigated yields) based on changes in irrigation efficiency for (a) wheat, (b) maize, (c) rice, and (d) soybean.

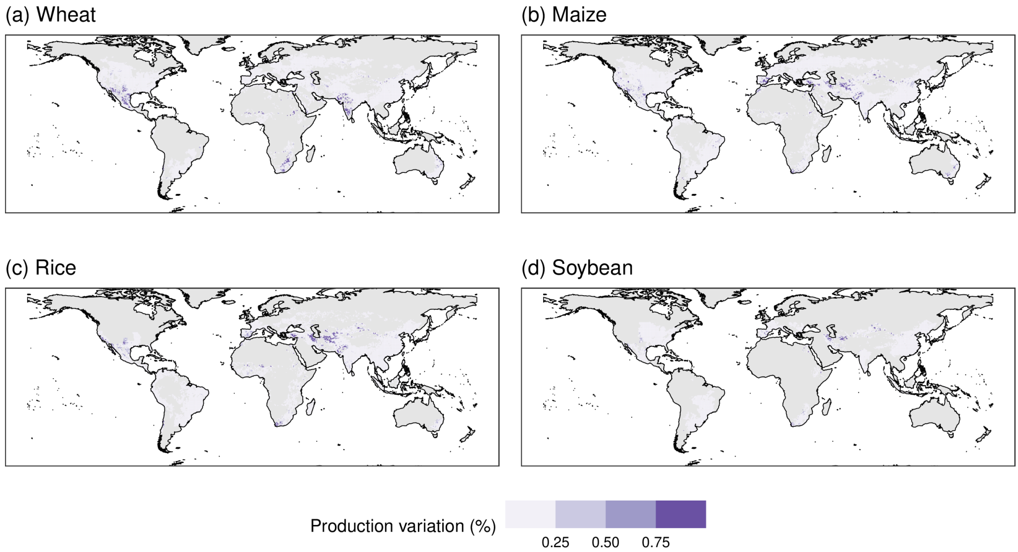

Figure B.10: Simulated yield variation (% of attainable irrigated yields) based on changes in soil characteristics for (a) wheat, (b) maize, (c) rice, and (d) soybean.

B

Supplementary material

C Limits to management adaptation for the Indus' irrigated agriculture

C.1 Model setup

Vegetation parameters and coverage were derived from various sources. Land-cover, normalized difference vegetation index (NDVI), albedo and leaf area index (LAI), at 30m resolution, were derived from the moderate resolution image spectroradiometer satellite (MCD12Q1, MCD15A2H, MCD43A3 and MOD13A1 respectively) [National Aeronautics and Space Administration, 2022a,b,c,d]. Values were aggregated to the model requirements for 5-minute resolution multi-year monthly NDVI, albedo and LAI and multi-yearly land-cover. First temporal and then spatial aggregation and interpolation was performed to fill data-gaps resulting from extensive cloud cover or the satellite trajectory, similar to Bohn *et al* [Bohn & Vivoni, 2019]. Other vegetation parameters (e.g. architectural and stomatal resistance) were assigned to each vegetation type separately [Nijssen et al., 2001b].

C

Monthly crop coverage was derived from the global monthly irrigated and rainfed crop areas around the year 2000 (MIRCA2000) [Portmann et al., 2010]. The primary wheat and primary and secondary rice seasons were assigned to separate land cover tiles. Other rainfed, irrigated and paddy irrigated crops were combined in three more land cover tiles. Crop coverage would vary monthly, and uncultivated areas were treated as bare soil. The crop growing period was optimized, within the observed monthly growing periods, for high and stable yields. Nine different growing periods were simulated (5th, 15th and 25th day of the month for planting and harvest). For each grid cell, crop and crop season the optimal growing period was determined by the growing period with the lowest historical year-to-year yield variability within 0.5 t ha^{-1} of the maximum simulated yield.

Crop parameters were derived from various experiments in the European Community, and are regularly updated [Boogaard et al., 2014; Boons-Prins et al., 1993; European

Commission, 1993; van Diepen & De Koning, 1990; van Diepen et al., 1988; van Heemst, 1988]. Soil inputs were derived from the international soil reference and information centre wold inventory of soil emission potentials (ISRIC-WISE) [Batjes, 2016] in combination with soil texture pedotransfer functions [Saxton et al., 1986]. Elevation inputs were derived from the shuttle radar topography mission (SRTM) [National Aeronautics and Space Administration, 2015]. Routing flow directions were a combination of the upper Indus flow directions of Dahri *et al* [Dahri et al., 2021] and the lower Indus HYDRO1k flow directions [Wu et al., 2012]. Dam inputs were derived from the global reservoir and dam database (GRandD) [Lehner et al., 2011].

Domestic water demands are estimated by multiplying Pakistan's reported domestic water-use intensity [Food and Agricultural Organization, 2020] (52 m^3 cap^{-1} y^{-1}) with historical and future distributed population maps [Klein Goldewijk et al., 2017; Smolenaars et al., 2021]. Domestic water demands vary monthly based on air temperature, whereby months with high temperatures have a higher demand (increased by 45%) and vice versa [Huang et al., 2018]. Industrial water demands are estimated by multiplying Pakistan's reported industrial water use [Food and Agricultural Organization, 2020] (2.3 km^3 y^{-1}) with a distributed historical fractional light-coverage map [National Aeronautics and Space Administration, 2016]. Livestock water demands are estimated by multiplying reported livestock water-use intensity [Steinfeld et al., 2006] with distributed historical livestock population maps [Gilbert et al., 2018]. Both industrial and livestock water demands do not vary within the year (constant demand) or between years (historical estimates are used for future simulations). For domestic, industrial and livestock sectors the consumption fractions are 0.15, 0.10 and 1.00 respectively [Shiklomanov, 2000].

C.2 Validation

The Indus' agricultural yields were validated based on Pakistan's national annual wheat and rice yield data from the food and agriculture organization (FAO) [Food and Agricultural Organization, 2021]. Simulated national annual yields realistically represented the observed yields (Figure C.1a), with a root mean squared error of 0.2 and 0.3 t ha^{-1} for wheat and rice respectively. Also, the simulated yield trend, driven by fertilizer application increases, generally matches the observations. Some deviation from this trend can be observed for rice around 1975, and is attributed to a temporary increase in nutrient-use efficiency [Shahzad et al., 2019]. Moreover, simulated recent interannual variability is larger than observed. This indicates a larger simulated climate sensitivity than observed.

The effects of elevated [CO_2] on crop growth were validated based on several free air

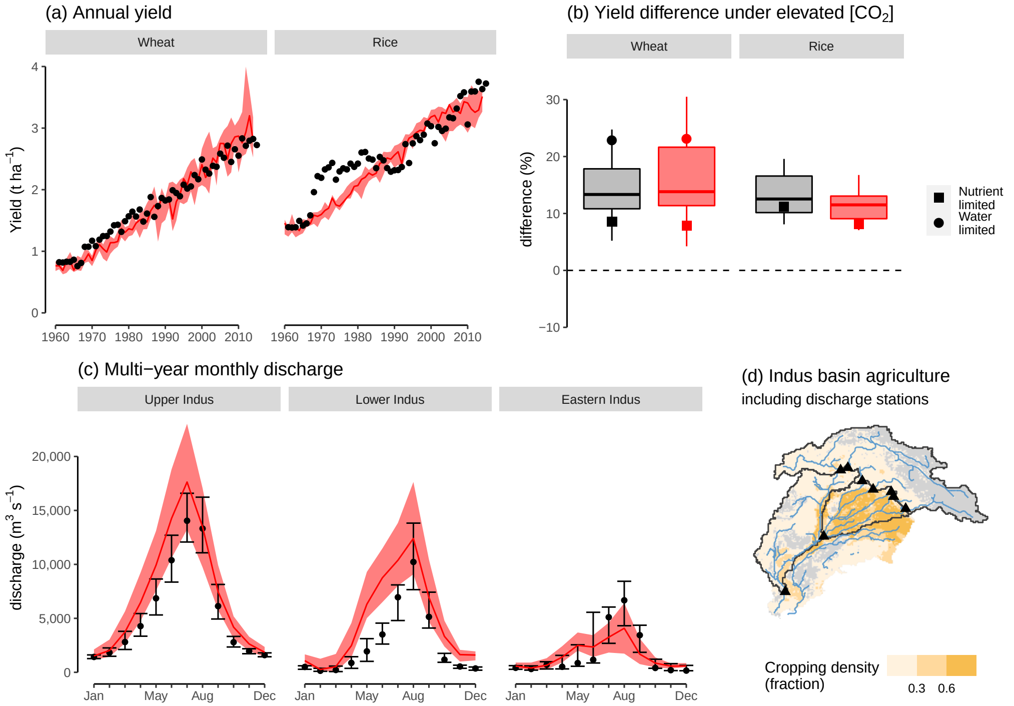

Figure C.1: Comparison between (red) simulations and (black) observations of (a) Pakistan's national annual wheat and rice yields [Food and Agricultural Organization, 2021], (b) yield differences under elevated [CO_2] for wheat and rice free air carbon enrichment (FACE) experiments [Bloom et al., 2014; Hasegawa et al., 2017; Kimball et al., 2017; Yang et al., 2006] and (c) multi-year monthly station discharge [National Aeronautics and Space Administration, 2022c; Water And Power Development Authority, 2022]. Discharge stations, station sub-basins and cropping densities are shown on the bottom right (d). Points in the FACE experiment comparison indicate mean yield differences for (square) nutrient and (circle) water limited experiments. Error bars indicate observed interannual variability (1st to 3rd quartile), while the colored ribbons indicate simulated interannual and intermodel variability (1st to 3rd quartile for discharge and minimum to maximum for yield). Note that discharge observations are a composite of various periods, while simulations cover 1970 to 2000.

carbon enrichment (FACE) experiments: Arizona (united states of America) FACE for wheat [Bloom et al., 2014; Kimball et al., 2017] and Wuxi (people's republic of China) FACE for rice [Hasegawa et al., 2017; Yang et al., 2006]. While the performance of individual experiments varied, the relative effect of elevated [CO_2] on simulated crop growth was adequately captured. Yield differences between ambient and elevated [CO_2] were within range of observed values (Figure C.1b). Moreover, our simulations also captured the effects of irrigation and fertilizer limitations on these differences. Irrigation limitations would increase the relative yield differences, as water demands under elevated [CO_2] were reduced. Contrastingly, fertilizer limitations would decrease the relative yield difference, as increased carbon assimilation under elevated [CO_2] was not possible due to nutrient constraints. Further information on the FACE calibration and validation, including crop growth timeseries, is given in subsection C.2.1 and Figures C.2 and C.3 respectively.

The Indus' hydrology was validated based on station discharge observations from the Pakistan water and power development authority (WAPDA) [Water And Power Development Authority, 2022] in the upper Indus and the global runoff data centre (GRDC) [Bundesanstalt für Gewässerkunde, 2020] in the eastern and lower Indus (Figure C.1d). The upper Indus discharge, which is the sum of 7 discharge stations, is relatively pristine and is the main source of surface water availability for irrigated agriculture (including more than 60% of total rainfall in the basin). The eastern and lower Indus discharge, both consisting of one discharge station, are heavily modified and reduced as a result of reservoir operation and water withdrawals. Simulated upper Indus discharge performance was good (Figure C.1c), with a Nash-Sutcliffe efficiency (NSE) of 0.8. However, water availability during the early wet season is overestimated, mainly due to overestimations in the western upper Indus. This discharge estimate is further exacerbated in the lower Indus, since in the eastern Indus discharge, which is responsible for around two-thirds of all water withdrawals, is heavily reduced. Therefore, while eastern Indus discharge performance was reasonable, with a NSE of 0.6, lower Indus discharge performance was poorer, with a NSE of only 0.3. Note, however, that this streamflow overestimation in the western Indus has little impact on our results, as the majority of agricultural croplands and (unsustainable) water withdrawals are located in the eastern Indus [Ali et al., 2021; Cheema et al., 2014; Government of Pakistan, 2022]. Further information on the hydrological calibration and validation, including discharge timeseries for individual discharge stations, is given in subsection C.2.2 and Figure C.4 respectively.

Simulated water withdrawals, groundwater withdrawals and groundwater depletion rates were compared with various other studies (Table C.1). Our estimated surface and groundwater withdrawals are within range of other studies, except in India where total

Table C.1: Comparison between simulated and reported irrigation water withdrawals, groundwater withdrawals and groundwater depletion rates in the Indus basin. Note that time periods vary between studies.

Region		Our study	reported
Pakistan	Irrigation withdrawal (km^3 y^{-1})	188	173 - 192 [Food and Agricultural Organization, 2020; Hussain et al., 2011; Laghari et al., 2012; Qureshi, 2011; Simons et al., 2020; Young et al., 2019]
	Groundwater withdrawal (km^3 y^{-1})	55	52 - 63 [Food and Agricultural Organization, 2020; Hussain et al., 2011; Laghari et al., 2012; Qureshi, 2011; Watto & Mugera, 2016; Young et al., 2019]
India	Irrigation withdrawal (km^3 y^{-1})	86	94 - 97 [Laghari et al., 2012; Saleth & Amarasinghe, 2010; Sharma et al., 2008]
	Groundwater withdrawal (km^3 y^{-1})	56	27-55 [Laghari et al., 2012; Saleth & Amarasinghe, 2010]
UIP[a]	Groundwater depletion (cm water y^{-1})	9	0.9 - 12 [Cheema et al., 2014; Iqbal et al., 2016; Rodell et al., 2009; Salam et al., 2020; Tiwari et al., 2009]

[a] Upper Indus plains

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irrigation withdrawals were lower and groundwater withdrawals were slightly higher than reported. Note that, while our estimate fits well within the reported range, some uncertainty exists surrounding the Indus' groundwater depletion rates.

C.2.1 Free air carbon enrichment calibration and validation

Free air carbon enrichment (FACE) simulations were set up following soil, weather and crop observations of the Arizona (united states of America) wheat FACE site [Bloom et al., 2014; Kimball et al., 2017] and Wuxi (peoples republic of China) rice FACE site [Hasegawa et al., 2017; Yang et al., 2006]. Missing information, required to run our simulations, was gathered from other appropriate datasets: water and global change (WATCH) forcing data era-interim (WFDEI) [Weedon et al., 2014] for downward longwave radiation and near surface pressure and ISRIC-WISE [Batjes, 2016] for soil pH and organic carbon.

Crop growing degree units were modified for each experiment to match the observed emergence, anthesis and maturity dates. Furthermore, several general crop parameters were adjusted for all experiments (Table C.2). For wheat, specific leaf area was adjusted. For rice, specific leaf area was adjusted, critical leaf area was increased, maximum leaf age was increased and dry matter partitioning was adjusted. Also, for rice the crop development stage had to be adjusted to account for the nursery period. Both crops display late maturity grain filling, which was achieved by simulating dry matter translocation from stems to grains following stem die off. Mineralization rates and the fertilizer efficiency were adjusted based on observations from low and high fertilizer application experiments. Simulations for each location were executing using the same parameters, except for the weather, irrigation application, fertilizer application, crop growing season, initial soil moisture (for wheat only) and initial crop development (for rice only). Simulations were run from crop planting or transplanting, for wheat and rice respectively, to maturity.

C.2.2 Hydrological calibration and validation

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Hydrological calibration was based on observed discharge at several discharge stations (Table C.3). Areas that were not included in the station sub-basins were filled using parameters of their nearest neighbor. Calibration of the hydrological model parameters was done sequentially: first calibrating the baseflow parameters for all 20 discharge stations and second calibrating the infiltration (and runoff) parameter for 15 discharge stations with daily discharge data.

Baseflow calibration was done for all stations, similar to Nijssen *et al* [Nijssen et al., 2001b]. The baseflow parameters (Ds, Dsmax, Ws and c) [Liang et al., 1994] were estimated by analyzing the baseflow recession curves (i.e. periods of continuous

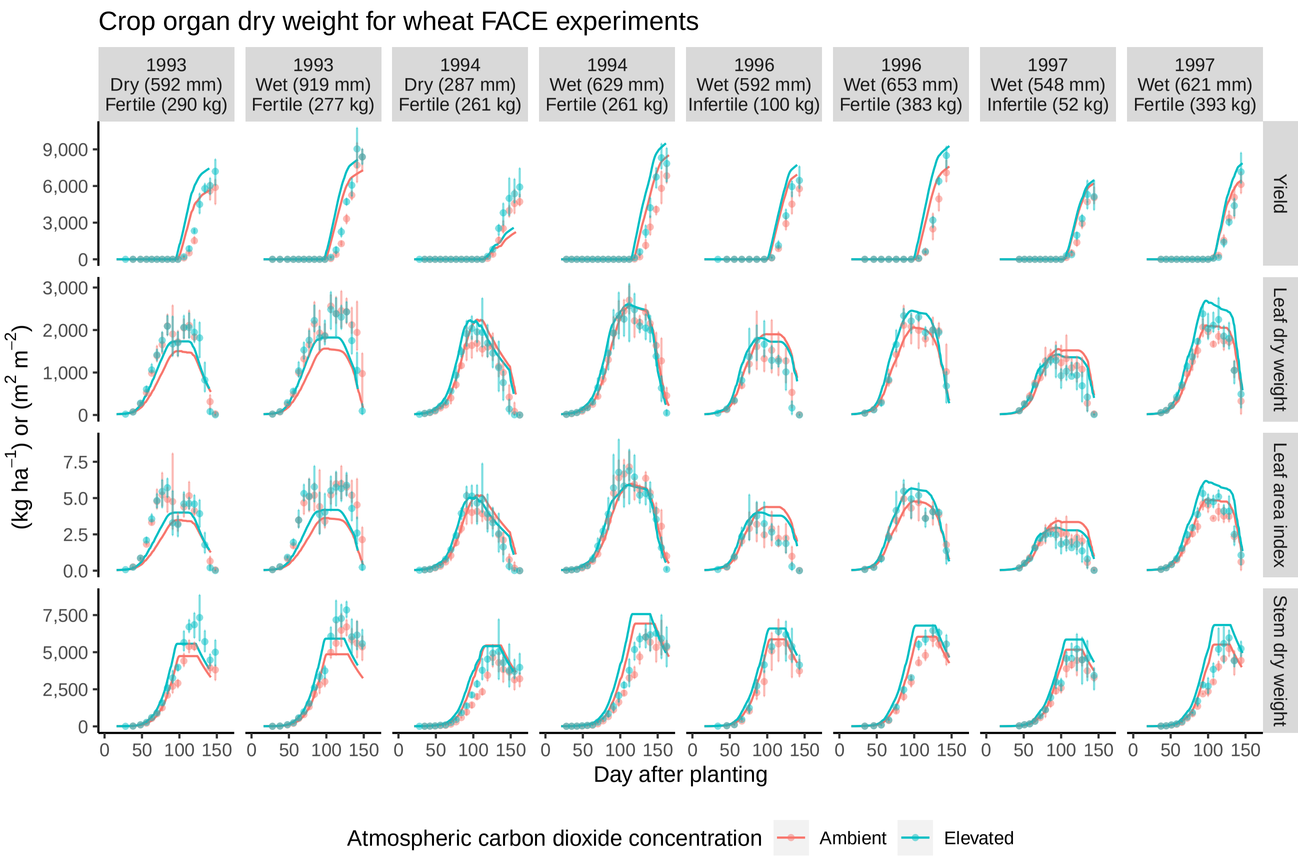

Figure C.2: Comparison between (line) simulated and (points and error bars) observed crop organ dry weight over time, under (red) ambient and (blue) elevated atmospheric carbon dioxide concentrations. Error bars indicate the minimum and maximum of the observations based on 4 measurement repetitions.

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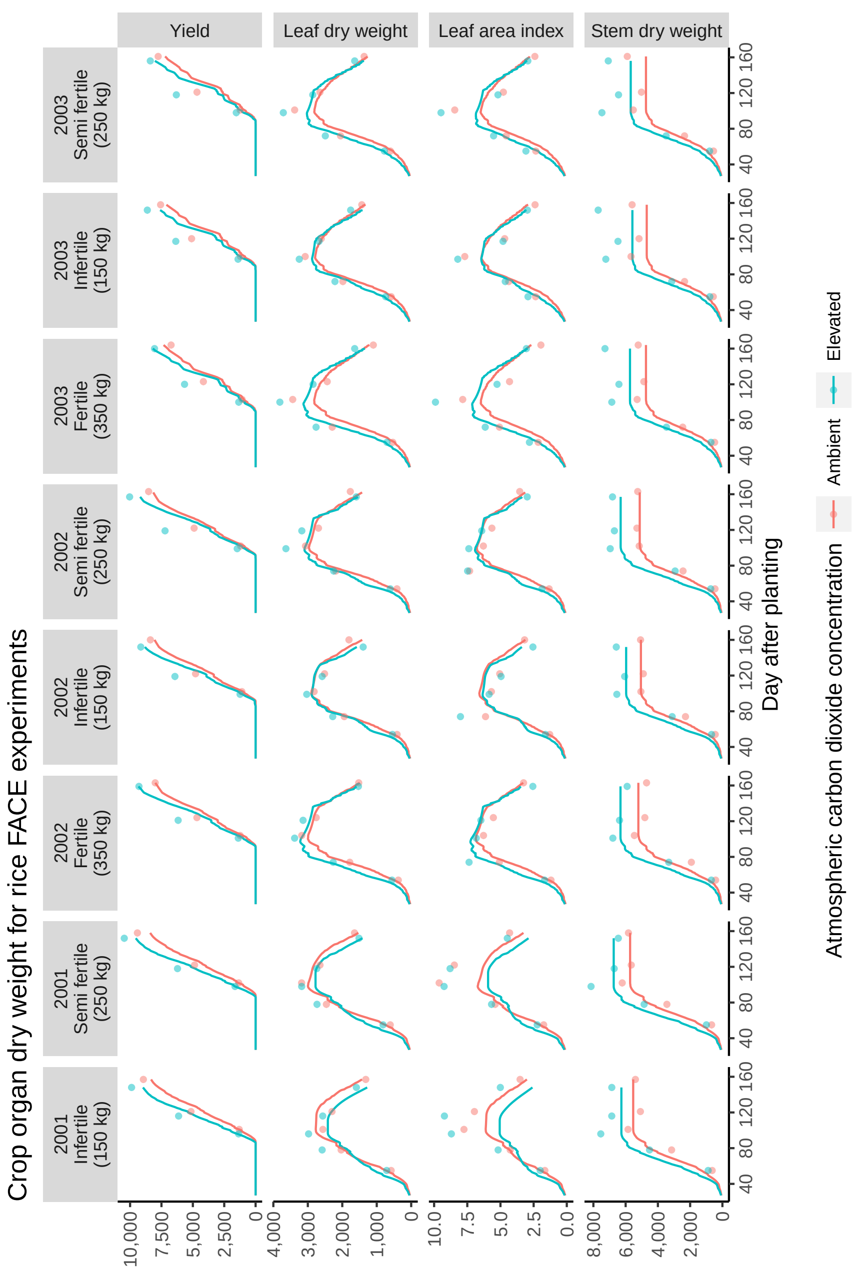

Figure C.3: Comparison between (line) simulated and (points) observed crop organ dry weight over time, under (red) ambient and (blue) elevated atmospheric carbon dioxide concentrations. Note that the observed (and simulated) stem dry matter is the combined living and dead stem dry matter.

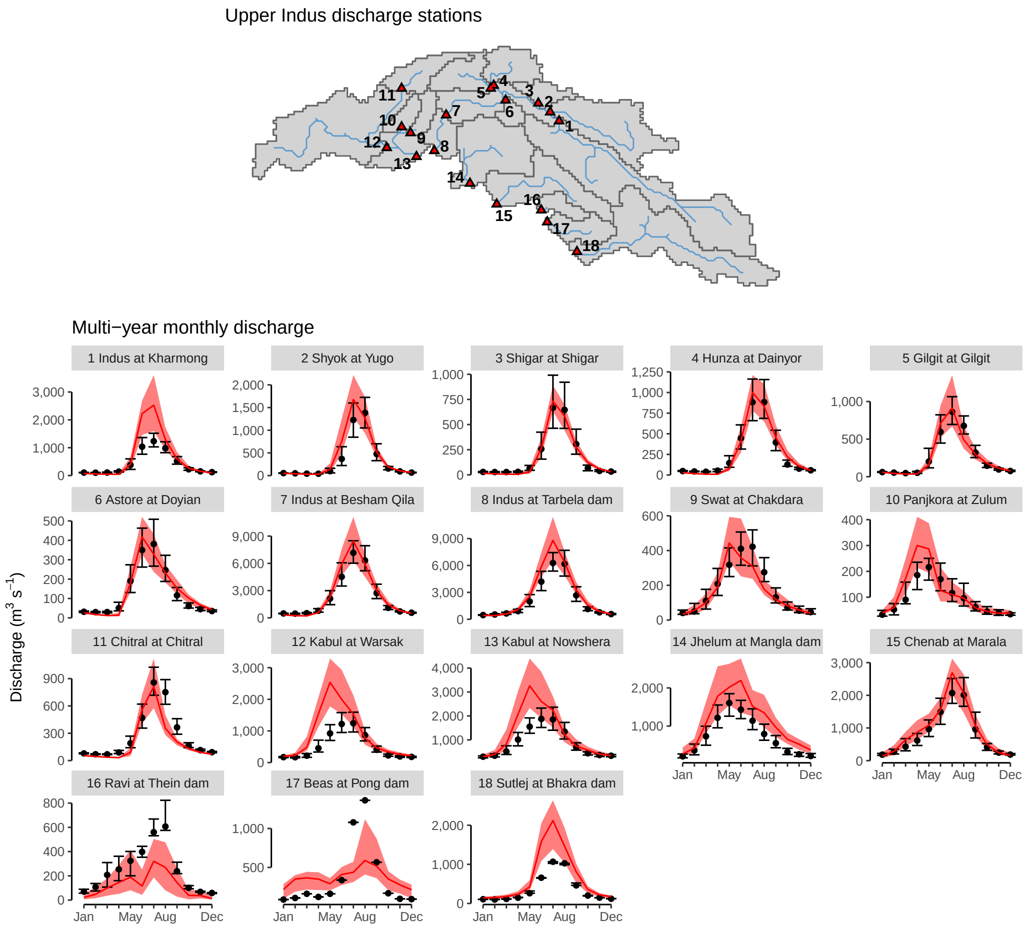

Figure C.4: Comparison between (red) simulations and (black) observations of multi-year monthly upper Indus station discharge [Water And Power Development Authority, 2022]. Discharge stations and their sub-basin are shown on the top. Error bars indicate observed interannual variability (1st to 3rd quartile), while the colored ribbons indicate simulated interannual and intermodel variability (1st to 3rd quartile). Note that discharge observations are a composite of various periods, while simulations cover the 1970 to 2000 period. Stations 1 to 13 are based on daily discharge data, stations 14 to 16 are based on monthly discharge data, stations 17 and 18 are based on multi-year monthly discharge data.

decreases in discharge). Baseflow recession curves were estimated by calculating the 10^{th} percentile multi-year weekly (for daily discharge stations) or monthly (for monthly discharge stations) discharge, which was subsequently smoothed using a three-week moving window (no smoothing for monthly data). Only discharge values below the 90^{th} percentile were used. Subsequently, the period with the longest sequential decrease in discharge was selected as the recession period (in mm s^{-1}). The baseflow parameters were fitted against the baseflow recession curve. The shuffle complex evolution algorithm of the university of Arizona (SCEUA) [Duan et al., 1993] was used to find the optimal baseflow parameters, by minimizing the root mean squared error between the observed and estimated baseflow. In order to estimate the initial soil moisture state at the start of the recession, the soil moisture storage which results in a baseflow which most closely matches the first observed discharge was selected as the initial soil moisture state.

After selecting appropriate baseflow parameters, the infiltration parameter (infilt) [Liang et al., 1994] was calibrated. By adjusting the infiltration, the amount of direct runoff generated by the model is adjusted, which leads to higher or lower discharge peaks after rainfall events. Therefore, the infiltration parameter was calibrated by comparing the 'peakiness' of the simulated and observed discharge. In order to measure the discharge peakiness, our study compared the frequency and magnitude at which the daily discharged deviates from its 30-day average discharge. The optimal parameter was selected based on the minimum root mean squared error between the observed and simulated frequency distribution of these deviations (i.e. the frequency distribution of the difference between the discharge and the 30-day average discharge).

Table C.2: Adjustments made to WOFOST wheat and rice parameters for the FACE experiments.

crop	parameter	old	new
wheat	SLATB	0, 0.00212	*0, 0.00232*
		0.5, 0.00212	*0.5, 0.00232*
		2, 0.00212	*2, 0.00232*
rice	SLATB	0, 0.0022	*0, 0.0038*
		0.6, 0.0022	0.6, 0.0022
		1, 0.0022	1, 0.0022
		1.5, 0.0022	1.5, 0.0022
		2.1, 0.0022	*2.1, 0.0018*
	SPAN	50	60
	FRTB	0, 0.2	0, 0.2
		0.5, 0.2	*0.5, 0.1*
		0.8, 0.15	*0.8, 0.05*
		1, 0.15	*1, 0.05*
		1.1, 0	1.1, 0
	FLTB	0, 0.4	0, 0.4
		0.5, 0.35	0.5, 0.35
		0.85, 0.18	*0.85, 0.35*
		0.9, 0.15	*0.9, 0.25*
		1, 0	1, 0
	FSTB	0, 0.6	0, 0.6
		0.5, 0.65	0.5, 0.65
		0.85, 0.82	*0.85, 0.55*
		0.9, 0.55	*0.9, 0.25*
		1, 0.25	*1, 0*
		1.1, 0.15	*1.1, 0*
		1.2, 0	1.2, 0
	FOTB	0.85, 0	0.85, 0
		0.9, 0.3	*0.9, 0.5*
		1, 0.75	*1, 1*
		1.1, 0.85	*1.1, 1*
		1.2, 1	1.2, 1
	CRITLAI	3.2	*3.6*

Table C.3: Information about discharge stations used for calibration.

No.	Station name	Data reporting frequency	Data availability timeframe
1	Indus at Kharmong	daily	'85-'15
2	Shyok at Yugo	daily	'81-'15
3	Shigar at Shigar	daily	'85-'98
4	Hunza at Dainyor	daily	'81-'12
5	Gilgit at Gilgit	daily	'81-'10
6	Astore at Doyian	daily	'81-'15
7	Indus at Besham Qila	daily	'81-'10
8	Indus at Tarbela dam	daily	'05-'18
9	Swat at Chakdara	daily	'81-'09
10	Panjkora at Zulum	daily	'99-'06
11	Chitral at Chitral	daily	'81-'15
12	Kabul at Warsak	daily	'82-'11
13	Kabul at Nowshera	daily	'96-'18
14	Jhelum at Mangla dam	daily	'01-'18
15	Chenab at Marala	daily	'05-'18
16	Ravi at Thein dam	monthly	'68-'79
17	Beas at Pong dam	multi-year monthly	'00-'08
18	Sutlej at Bhakra dam	multi-year monthly	'60-'00
19	Kotri	monthly	'37-'79
20	Panjnad	monthly	'73-'79

Supplementary material

D Agricultural adaptation to provide sustainable self-sufficiency in Pakistan

D

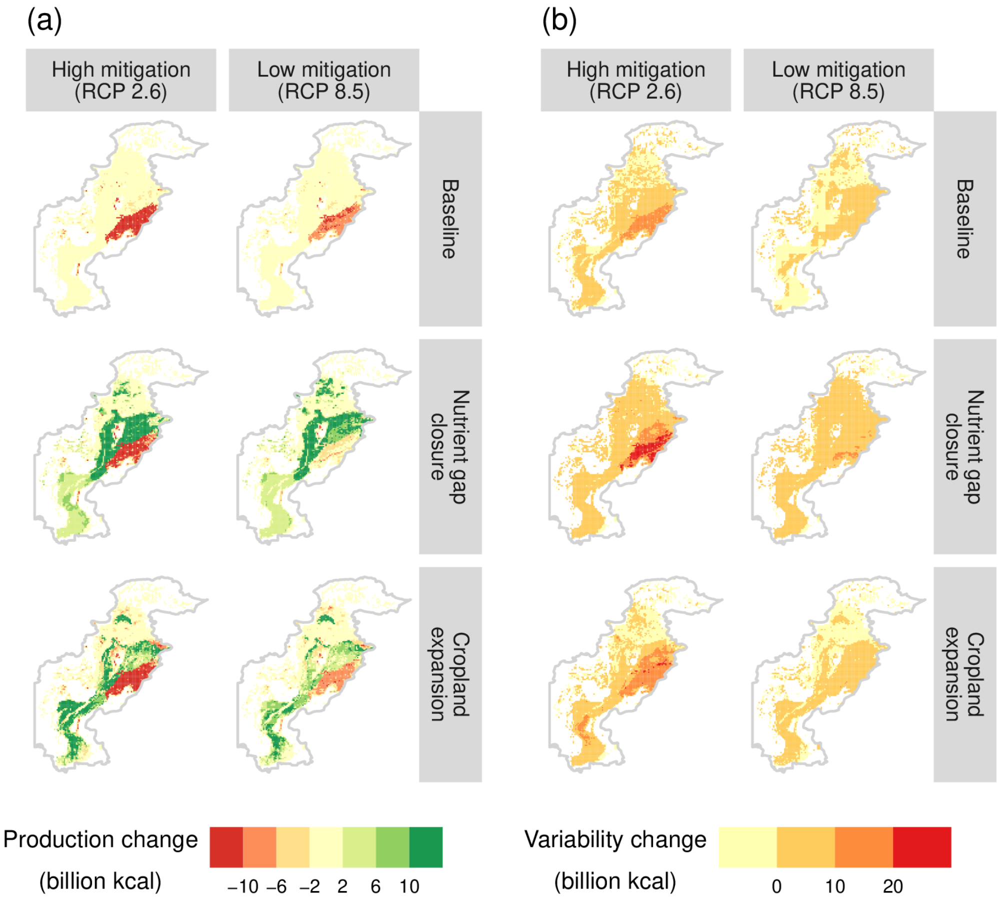

Figure D.1: Simulated (multi-model median) average annual total (wheat plus rice) (a) production change and (b) inter-annual variability increase (1^{th} to 3^{rd} quartile) for each management adaptation option under baseline climate-change adaptation. Changes are shown between end-of-the-century (2071-2100) unsustainable production and sustainable production.

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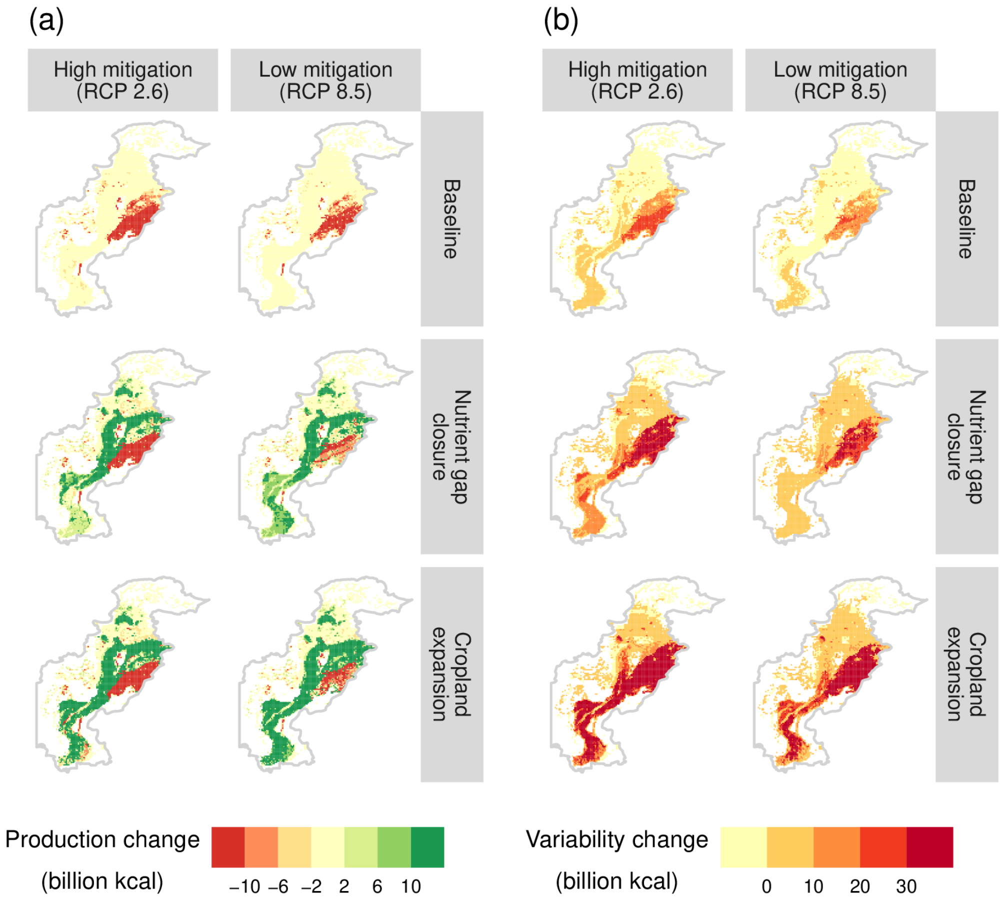

Figure D.2: Simulated (multi-model median) average annual total (wheat plus rice) (a) production change and (b) inter-annual variability increase (1^{th} to 3^{rd} quartile) for each management adaptation option under maize crop substitution climate-change adaptation. Changes are shown between end-of-the-century (2071-2100) unsustainable production and sustainable production.

D

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Summary

In 2015, the United Nations agreed on 17 Sustainable Development Goals (SDGs) that aim to guide human development in the Anthropocene: an epoch where human activities are shaping the local environment as well as the earth system. The SDGs focus on environmentally sustainable and integrated development and thus contain a high number of interlinkages. However, decision making towards different SDGs often still occurs in isolation. As developments towards different SDGs can adversely affect one another, their interactions need to be quantified to inform sustainable decision making towards joint SDG implementation. In particular, developments to achieve sufficient agricultural production (as part of SDG 2), sustainable water management (as part of SDG 6) and reduced climate change impacts (as part of SDG 13) strongly interact.

To meet the food demands of an ever growing and developing population, substantial increases in agricultural production are required. Over the last decades, agriculture has intensified, with widespread adoption of high-yielding crop varieties, fertilizer application, mechanization and, of particular interest to my thesis, irrigation expansion. However, irrigation withdrawals often conflict with sustainable water management, as they threaten river and wetland ecosystems that depend on sufficient water flows and result in major groundwater storage depletion around the world. In addition, agricultural production and water resources are both strongly affected by climate change, as climate change impacts regional cropland suitability and the global water cycle. Therefore, my thesis **quantifies whether sufficient agricultural production can be achieved under sustainable water management and climate change**. To this end, four research questions were defined:

RQ1. To what extent does present-day human water use exceed sustainable water use?

RQ2. What is the impact of sustainable water management on agricultural production?

RQ3. What is the impact of climate change on agricultural production and water use?

RQ4. To what extent can agricultural adaptation enable agricultural production increases?

In Chapter 2, I first show the impact of present-day human water use on worldwide water resources. To this end, I extend the Variable Infiltration Capacity (VIC) hydrological model with several modules that integrate river streamflow routing, reservoir operation and water withdrawal and consumption for agricultural, domestic, industrial (i.e. energy and manufacturing) and livestock purposes. Subsequently I compared water availability under sustainable water management (i.e. renewable water availability minus environmental flow requirements) with these human water uses. My results show that human water use severely exceed water availability under sustainable water management and should be reduced by more than a third. Excessive water uses are mostly concentrated in some of the world's largest irrigated croplands, such as the croplands in Pakistan and northwestern India, northeastern China and the United States high plains and central valley.

In Chapter 3, I subsequently show how the irrigation constraints that are needed to avoid unsustainable water withdrawals would impact worldwide agricultural productivity. The impact of irrigation constraints is determined by dynamically coupling the extended VIC hydrological model with the WOrld FOod STudies (WOFOST) crop model. In this coupled model, called VIC-WOFOST, the WOFOST model estimates agricultural productivity for wheat, maize, rice and soybean based on the estimated irrigation constraints by VIC. Moreover, I explore the impact of improved nutrient management (i.e. nutrient gap closure) on agricultural productivity. My results show that substantial increases in irrigated production cannot be attained under sustainable water management, even when considering improved nutrient management. On the contrary, a change of -30, +1, -14 and -1 Mt y^{-1} is estimated for irrigated wheat, maize, rice and soybean production respectively. The majority of these losses are again concentrated in the extensively irrigated cropland areas of Pakistan and northwestern India and northeastern China.

In Chapter 4, I focus on the Indus basin, which contains almost all the croplands of Pakistan and a part of northwestern India. For this region, I show the impact of climate-change on water resources and cereal (i.e. wheat and rice) productivity in addition to the effects of sustainable water management and improved nutrient management. To this end, I force VIC-WOFOST with bias-corrected climate inputs and atmospheric carbon dioxide concentrations ([CO_2]) under a range of climate-change mitigation scenarios. My results show that cereal productivity increases of a third are possible by the 2030s (2021-2050) due to increased maximum crop productivity and decreased irrigation constraints under climate-change and elevated [CO_2]. However, towards the 2080s (2071-2100) crop-heat stress increases under climate-change ultimately decrease cereal productivity between 10% and 30% compared to the 2030s. Moreover, under limited worldwide climate-change mitigation efforts, agricultural

productivity even drops below Pakistan's historical productivity.

In Chapter 5, I subsequently explore the opportunities and limitations of agricultural adaptation to achieve sufficient cereal (i.e. wheat and rice) production under a range of climate-change and population-growth scenarios. Two management adaptation options, (1) nutrient-gap closure and (2) cropland expansion, and two climate-change adaptation options, (1) growing-season adjustments and (2) crop substitution with maize (maize-crop substitution), are implemented in VIC-WOFOST. My results show that climate-change adaptation is key in reducing crop-heat stress resulting from temperature increases under climate change. Moreover, in combination with improvements in agricultural management, three-fold cereal production increases are possible by the end of this century (2071-2100), even under sustainable water management. These production increases provide cereal self-sufficiency in all but the highest of population growth scenarios.

In short, present-day human water use severely exceeds sustainable water use (Chapter 2) and irrigation constraints under sustainable water management would result in substantial reductions in worldwide agricultural production (Chapter 3), especially in the Indus basin and Pakistan. Moreover, in these regions, temperature increase under climate change adversely affects agriculture, even though climate change and elevated [CO_2] benefits water use (Chapter 4). Nevertheless, agricultural adaptation can achieve sufficient agricultural production for all but the highest of population growth scenarios in Pakistan, even under sustainable water management and climate change (Chapter 5). Although further efforts should be invested in more accurate worldwide and more reliable and relevant regional agro-hydrological assessments, my thesis clearly indicates the strong interactions between agriculture, water and climate and the opportunities of adaptation. This information contributes to integrated policies and decision making for both sufficient agricultural production and sustainable water management in the epoch of the Anthropocene.

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Curriculum vitae

About the author

Bram Droppers was born on February 23rd 1992 in Hengelo (Overijssel), the Netherlands. He started his bachelor *International Land and Water Management* in 2011 at Wageningen University & Research in the Netherlands. This bachelor combines the natural and social sciences for improved (agricultural) land and water management. His BSc thesis focused on *"Assessing the impact of hydropower tunneling on springs and spring-dependent communities in the Himalayas"* and was conducted at Karfectar and Pune in India. Although his social sciences background has been invaluable throughout his career, Bram's interest was mostly in the natural sciences. Therefore, after his BSc graduation in 2014, he started his master *Earth and Environment* with the specialization *Water Systems and Global Change* at Wageningen University & Research in the Netherlands. This master specialization increases understanding of hydrological processes and the impact of climate change on these processes. His MSc thesis focused on *"Modelling the impact of irrigation on the Mekong river streamflow"* by expanding upon and using a macro-scale hydrological model. He graduated his master in 2017.

To continue the work of his MSc thesis, Bram submitted his PhD proposal to an open call of the Wageningen Institute for Environment and Climate Research. He was awarded a PhD grant, and started his PhD at the *Water Sytems and Global Change Group* Wagerningen University & Research in the Netherlands. The next five years were dedicated to his PhD work, which culminates in this PhD thesis titled *"Modelling agricultural production under sustainable water management, climate change and agricultural adaptation"*. In the next few years, Bram will continue working on developing macro-scale hydrological models to more accurately quantify water resources and to better incorporate the impact of hydrological changes on other sectors.

Publications

Published

Droppers, B., Supit, I., Leemans, R., van Vliet, M. T. H., & Ludwig, F. (2022). Limits to management adaptation for the Indus' irrigated agriculture. Agricultural and Forest Meteorology, 321, 108971, DOI: 10.1016/j.agrformet.2022.108971.

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Janssen, A. B. G., **Droppers, B.,** Kong, X., Teurlincx, S., Tong, Y., & Kroeze, C. (2021). Characterizing 19 thousand Chinese lakes, ponds and reservoirs by morphometric, climate and sediment characteristics. Water Research, 202, 117427, DOI: 10.1016/j.watres.2021.117427.

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Droppers, B., Leemans, R., Supit, I., Van Vliet, M. T., & Ludwig, F. (2022). Agricultural adaptation to provide sustainable self-sufficiency in Pakistan. Environmental Research Letters, submitted.

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Droppers, B., Supit, I., Leemans, R., van Vliet, M. T., & Ludwig, F. (2022). Climate-change impacts and adaptation for Pakistan's irrigated agriculture. In *European Geosciences Union Conference*, Vienna, Austria, DOI: 10.5194/egusphere-egu22-9656.

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de Graaf, I., Nauta, L., & **Droppers, B.** (2022). Simulating the contribution of groundwater to crop growth at the global scale. In *European Geosciences Union Conference*, Vienna, Austria, DOI: 10.5194/egusphere-egu22-288.

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SENSE PhD Courses

- Environmental research in context (2017)
- Research in context activity: 'Various Research communication activities', such as a press release and a pitch for popular audiences (2020)

Other PhD and Advanced MSc Courses

- The essentials of scientific writing and presenting, Wageningen graduate schools (2018)
- Competence assessment, Wageningen graduate schools (2018)
- Project and time management, Wageningen graduate schools (2019)
- Career assessment, Wageningen graduate schools (2020)
- Landscape Governance: Collaborating Across Sectors and Scales, Wageningen University (2021)

Management and Didactic Skills Training

- Development of and assisting in practicals of the MSc courses 'Future water stress', 'Climate adaptation in the water sector' and 'Climate smart agriculture' (2017-2021)
- Supervising five MSc student with thesis entitled ' Coupling salinity control and environmental flow requirements', 'The effect of future climate change on thermal lake stratification', 'Tracing the origin of simulation bias', 'Evaluation of perception and trade-offs in adapting climate smart agriculture' and 'An analysis on the simulation and impact of CO2 enrichment on crops' (2018-2022)

Oral Presentations

- *Exploring the impact of environmental (ground)water requirements on irrigation demands in the food sector*. Water Science for Impact, 16-18 October 2018, Wageningen, The Netherlands
- *Worldwide water constrain in closing yield gaps*. EGU, 3-6 May 2020, Online
- *Climate-change impacts and adaptation for Pakistan's irrigated agriculture*. EGU, 23-27 May 2022, Vienna, Austria

SENSE coordinator PhD education

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