The impacts of future climate change on land and water productivity of staple crops: a case study for China Marcel Muller, s0199907

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Summary

Fresh water and arable land are scarce resources in China. Because of China's growing population and therefore food requirements, it is of great importance to have a high land and water productivity (LP and WP). Climate change could have a significant effect on the LP and WP of China. Therefore we investigated the effects on the land and water productivity of staple crops (rice, maize and wheat) in China as a result of climate changes from 2005 (the baseline year) to 2050 at the spatial resolution of 5 by 5 arc min. In order to do this, the downscaled climate data for 2050 in China of two global climate models (GCMs) under two representative concentration pathways (RCPs) have been used as input for the AquaCrop model. From its outputs, the future LP and WP of the considered crops were calculated. According to the climate scenarios, the future climate will be wetter (+8% precipitation) and warmer (+1.5 °C to +2.8 °C). These climate changes lead to increases in both LP and WP in 2050 for all crops except maize, which suffers from a decrease in precipitation, causing the rainfed maize to fail with severe water stress. The sources of the water used to grow the crops were investigated by calculating the blue (originating from ground and surface water), and green (originating from precipitation) water footprints (WFs) for all crops. The green WF of crops is higher than the blue WF and both decrease in the future for rice and wheat. For maize both green and blue WFs increase due to the lowered LP. Beside the increase in precipitation the main reason for the increase in LP is increased CO_2 fertilization, which has a smaller effect on maize than on the other crops. All in all, the possible future climate changes seem to have positive effects for China, increasing the food production while decreasing the water use. However, there is also a warning to be found in the maize results: a spatial redistribution of precipitation can have devastating effects, even if the total precipitation over the crop area increases.

Keywords

Land productivity, water productivity, water footprint, climate change, AquaCrop

1. Introduction

1.1 Background

China has the world's largest population of 1.380 billion people (19% of the world population) and, with 9.6 million km², the third largest land area, of which only 11.3% is arable (1.1 million km², 7% of the arable land in the world). Only 0.08 ha of arable land is available per capita, which is much lower than the level of, for example, the US (0.49 ha/cap) or the global average level (0.2 ha/cap) (The World Bank, 2015b). The relatively small agricultural area used to feed the inhabitants of China can be compensated by creating high crop land productivity (LP), i.e. high crop production per unit area (key definitions can be found in Appendix A). For decades, the developments in agricultural technology have significantly improved crop LP (e.g., the Chinese average grain LP has doubled from 2.5 to 5.5 ton/ha for 1978-2015) (NBSC, 2015). The LP of crops can be improved by developing agricultural technology. In the meantime, however, the crop LP is also constrained by key environmental factors that cannot be controlled by humans, including the effects of climate variability on water stress in the crop root zone and the water availability for crop growth (Kang, Khan and Ma, 2009; Reddy and Pachepsky, 2000; Zwart et al., 2010).

Agriculture accounts for the largest use of freshwater, accounting for 92% of the global water consumption (Hoekstra and Mekonnen, 2012). This is especially of concern to China, as the country is facing increasingly severe water scarcity caused by high water use demands (61-69%) by the agricultural sector and a rising competition on water use among different sectors (Postel, Daily and Ehrlich, 1996; Vörösmarty et al., 2000; Alcamo et al., 2003; Oki and Kanae, 2006; Yang et al., 2008; Jiang, 2009; Jiang, 2015). Moreover, China's spatial water distribution is unbalanced: Northern China only has 17% of China's water resources, but 60% of the cultivated land (Ge et al., 2011; Ministry of Water Resources of China, 2011). Therefore, an important question is if, in the future, China can still ensure food and water security for its increasing population. Raising crop LP can be done, for example, by increasing the irrigation area or by fertilization. The downside of these measures, however, is that they increase the use of water, a scarce resource in China. Therefore, besides relying on increasing technology, it is necessary to gain a better understanding of the effect of possible climate changes on LP and crop water productivity (the "crop per drop) in order to ensure both a sufficient LP and water security in future China.

The crop water productivity (WP, tonne/m³) expresses the amount of crops produced (LP, tonne/ha) by a unit volume of water consumed at crop field over the cropping period (Appendix A). The total crop water use (CWU, m³/ha) that is needed to produce a crop is measured by the evapotranspiration (ET) of the crop over its growing period (Wang et al., 2014).

The WP of a crop shows the crop per consumptive drop, but it is also necessary to know how many drops are consumed to produce a unit mass of the crop and where these 'drops' come from, which is measured by the water footprint (WF) of crop growth (in l/kg) (Hoekstra, 2003a). There are three components in the total WF of a crop: green, blue and grey WF. The *green* WF is the volume of rainwater consumed by the crops during its growth process, the *blue* WF refers to the volume of surface and groundwater consumed and the *grey* WF is the volume required to reduce the concentration of pollutants created in the process to existing water quality standards (Hoekstra, 2003a). In this study, we only consider the *consumptive* (green and blue) WF of crops.

Several researches on the effects of climate change on water scarcity problems and crop production in China have been conducted. These studies show that the projected future climate

changes in China are heterogeneous (Xu and Long, 2004; Piao et al., 2010; Ge et al., 2011; Zhuo, Gao and Liu, 2014). This means that, when analysing climate change, China can be divided into several climate regions.

Partly due to this heterogeneity and partly due to a lack of understanding of responses of crops to climate changes, current understanding does not allow a clear assessment of the impact of anthropogenic climate change on the total of China's water resources and agriculture (Piao et al., 2010). However, according to Zhao et al. (2014), it is likely that the crop WP will increase due to the increased crop LP for the whole of China by 2050, under the Intergovernmental Panel on Climate Change (IPCC) 4th report 'Special Report on Emissions Scenarios' (SRES) A2 emission scenario. An important reason for the increase in crop LP is called "CO₂ fertilization". Several studies have shown that an increase in CO_2 concentration in the atmosphere has a positive influence on LP of wheat, rice and maize (Erda et al., 2005a; Lobell and Field, 2007; Guo et al., 2010; Wiegel and manderscheid, 2012). This means that future climate change with increasing CO_2 concentration will likely have a positive effect on food security and the reduction of water scarcity in China. The positive effects might also be caused by the results found by Xiao et al. (2013), who have studied the historical impact of climate change (precipitation and temperature) on the WP of wheat, potato and corn in semi-arid areas of China from 1960 to 2009. They concluded that, compared to 1960-1969, a temperature rise and reduced rainfall have led to an increased WP of wheat, potatoes and corn, so future climate change might also have a positive effect on the WP.

However, other studies show that a possible future decrease of precipitation and an increase in temperature (under the SRES A2, A1B and B1 emission scenarios), which is likely to occur in some areas of China, will lead to a severe drop in crop LP, even with increased CO_2 levels, by 2041-2070 (Valverde et al., 2015). On the other hand, increase of CO_2 possibly increases the crop WP (Piao et al., 2010), although this increase is non-uniform globally and there are also many regions that are projected to have a decreased WP (Fader et al., 2010; Bocchiola, Nana and Soncini, 2013).

Most of the studies mentioned in the previous section either focussed on global changes (Fader et al., 2010), changes in countries other than China (Bocchiola, Nana and Soncini, 2013; Valverde et al., 2015), or changes in a specific part of China (Guo et al., 2010; Tao and Zhang, 2013a; Tao and Zhang, 2013b; Xiao et al., 2013). The studies that did focus on the whole of China (Piao et al., 2010; Zhuo, Gao and Liu, 2014) concluded that there was high spatial variability in the effects of climate changes over the entire country and that global models with a low spatial resolution cannot cope well with this variability. Because of this, such a study for China should be conducted at a high spatial resolution in order to capture the heterogeneity.

There have been a substantial number of studies incorporating future climate change scenarios using the SRES storylines from the IPCC's 3rd and 4th assessment report to look into responses in water stress (Vörösmarty et al., 2000; Alcamo and Henrichs, 2002; Alcamo et al., 2003; Arnell, 2004; Alcamo, Flörke and Marker, 2007; Shen et al., 2008) and the effects of the climate changes on crop LP or crop consumptive (green and blue) WFs (Fader et al., 2010; Bocchiola, Nana and Soncini, 2013; Zhao et al., 2014).

Since 2013/2014, the latest, 5th IPCC report (IPCC, 2014a) is available. This latest version of the IPCC report could be a vital reference for policy makers for future plans to adapt to climate changes, but there are few studies available on the response of LP, WP and WF of crops under the

climate scenarios approved in the IPCC 5th assessment report and, to our knowledge, none yet for the whole of China. In the summary for policymakers (IPCC, 2014b), it is stated that there will be: *"Negative impacts on aggregate wheat and maize yields in China, beyond increase due to improved technology"*, but this statement has a low confidence level.

In the 5th report, the 'Representative Concentration Pathways' (RCPs) replaced the SRES scenarios. The SRES scenarios included and combined emissions and socio-economic scenarios, while RCPs are newly developed independent emission scenarios, approved by the IPCC 5th report. The RCPs (RCP2.6, 4.5, 6 and 8.5) describe four 21st century pathways of greenhouse gas emissions and atmospheric concentrations, air pollutant emissions and land use based on different radiative forcing levels by the year 2100 (from 2.6 to 8.5 W/m²) (van Vuuren et al., 2011a). The RCPs cover a wider range than the SRES, as the RCPs also represent scenarios with climate policy (IPCC, 2014a).

1.2 Research Goal

The research goal of this study is to assess the relative changes in the land and water productivity of three main staple crops (wheat, maize and rice) in China as a result of climate changes over the period 2005-2050, at a high spatial resolution, forced by the new RCPs, and to describe the effects and possible risks of these changes on the food and fresh water security of China. The main research question is:

What are the effects on the land and water productivity of staple crops in China as a result of climate changes over the period 2005-2050?

We aim to find the responses in:

- 1. Land productivity (crop per unit land)
- 2. water productivity (crop per drop)
- 3. Green and blue water consumption in crop production (drop per crop, indicated by green and blue WFs)

This study will be one of the first to use the new RCP forced climate change scenarios, considering the impacts of temperature, precipitation and CO_2 changes. This will be done for the whole of China, divided in a grid with a high spatial resolution. This will also be one of the first times the crop land and water productivity of China and the trade-offs between the two are researched, given that previous studies have always focussed on one of them. It is important to consider both, because water and land are both scarce resources in China.

1.3 Outline of the Report (Research Questions)

In order to fulfil the research goal and the answer the main research question, the report is divided into four parts for the following four sub-research questions:

Sub Question 1, Climate Change: How will the climate change in China until 2050?

- What are the possible changes in *temperature*, *precipitation*, *reference evapotranspiration* (*ET*₀) and *CO*₂ *concentration* in China over the periods 2005-2050 due to climate change?
- What are the latest projections of future climate for China?
 - Which climate simulations (models/scenarios) are available?
 - Which combinations of climate models and scenarios are the best choices for this exploratory study?

Sub Question 2, Responses in Crop Land Productivity: What are the responses to future climate changes of the *land productivity* of staple crops (wheat, maize and rice) from both irrigated and rainfed systems in China?

• What are the effects of the changes in ET₀, precipitation and CO₂ on the crop *land productivity* (crop yield)?

Sub Question 3, Responses in Crop Water Productivity: What are the responses to future climate changes of the *water productivity* of staple crops (wheat, maize and rice) from both irrigated and rainfed systems in China?

- What are the effects of the changes in ET₀, precipitation and CO₂ on the crop WP?
- What are the differences in reaction between crop *land* and *water productivity*?
 If there are differences, what are the reasons for this?

Sub Question 4, Responses in Green and Blue Water Footprints of Crop Production: What are the responses in the *green and blue WFs* of staple crops (wheat, maize and rice) from both irrigated and rainfed systems to future climate changes in China?

After answering the research questions, the implications of these answers will be discussed. The bottlenecks in future crop production due to climate changes, as well as the possible effects of these bottlenecks on China's food security will be identified, and discussed. The change in WFs will be used to discuss the effects on China's water scarcity.

2. Method and data

This section describes the method used to answer the research questions. The main research question is answered by combining the answers to the three sub questions.



2.1 Study area

Figure 1. The provinces of China, the study area of this study

The current study area is mainland China, which consists of 31 of Chinas provinces, as shown in Figure 1. The current study is conducted at a spatial resolution of 5 by 5 arc min grid level¹.

The climate of the study area in the baseline 2005 year is as follows:

Maximum temperatures are the average of the daily maximum temperatures for each month, they range from -2.1 °C in January up to 25.7 °C in July in the baseline situation (2005). In the winter months (December, January and February), the national average maximum temperature is below the freezing point.

Minimum temperatures are the averages of the daily minimum temperatures for each month. In the baseline year, the highest minimum temperature is in July, with 14.8 °C. The lowest

 $^{^{1}}$ At sea level one minute of arc along the equator or a meridian equals approximately one Nautical mile (1.852 km or 1.151 mi), so 5 arc-minutes equal approximately 9.26 km. For China, a 5 arc-minute grid cell ranges from 5.52 x 9.27 km in the North to 8.81 x 9.22 km in the South.

temperature is reached in January, with an average of -13.5 $^{\circ}$ C. From November to March, temperatures are below zero.

Precipitation in this study is the nationwide average of the monthly precipitation. In the baseline situation, the wettest months are from May until September, so an extended summer period. The highest monthly precipitation is in July, with 106 mm/month. The winter months are driest, with only 8 mm/month in December.

Potential evapotranspiration (ET_0) in this study is the average daily ET_0 for each month. In the baseline situation, the potential evapotranspiration ranges from 2.3 mm/day in the winter period, after which it gradually increases up to 6.8 mm/day in June and then decreases again.

The *CO*² *concentration* in the 2005 baseline situation is 379.75 ppm by volume.

2.2 Climate Scenarios and Models

In order to study climate change, the future climate has to be compared to the present climate (baseline). The conditions of the year 2005 are chosen as the baseline of this study because this year is a good average (not too wet, dry, hot or cold) of the current climate (Jones and Harris, 2015). The reason a single year is chosen over an historical average is because, over the last decades, China's crop LP has increased a lot due to improved technologies (NBSC, 2015).

The future climate conditions are determined using the RCP emission scenarios from the IPCC 5th assessment report, as this is the most recent data. These RCP scenarios have been used to run several Global Climate Models (GCMs) (Flato et al., 2013).

The first step in determining which GCMs to use will be to choose how many and which RCPs will be used. There are four RCPs in total, ranging in radiative forcing² from 2.6 to 8.5 W/m², with two pathways in-between with a forcing of 4.5 and 6 W/m² (Appendix B). We choose to focus on the RCP 2.6 and 8.5, because the two most extreme RCPs envelop the entire RCP spectrum.

The second step is to determine how many and which GCMs' outputs for each RCP will be implemented. There are fourteen GCMs' outputs available that have used all four RCPs as input at 5 by 5 arc min grid level (Appendix C). Under each RCP, different GCMs generate climate changes scenarios in different degrees. Choosing the GCMs that produce the most extreme changes in precipitation and temperature provides the widest and most complete spectrum of possible future climates. The changes in water availability are the most important for crop production, so both the driest and wettest models are chosen. The climates produced under RCP8.5 are compared, because this RCP will give the most extreme results.

This comparison can be seen in Appendix E. The 'driest' climate is the one with the highest temperature and the lowest precipitation; the opposite (low temperature and high precipitation) gives the 'wettest' climate. These two climates account for the broadest spectrum of results for RCP 8.5.

As compared to the baseline year 2005, the lowest projection of annual mean precipitation across China is found in the Csiro Mk360 Model climate scenarios. This GCM also has a relatively high temperature increase (5th place out of 14), making it the 'driest' climate (Figure 2a and 2c). The

² Radiative Forcing (RF) is the measurement of the capacity of a gas or other forcing agents to affect the earth's energy balance, thereby contributing to climate change. Put more simply, RF expresses the change in energy in the atmosphere due to emissions.

'wettest' climate scenario is generated through Miroc-Miroc5, which has the highest annual mean precipitation and a mediocre temperature (Figure 2b and 2d). The full ranking of GCMs' outputs can be found in Appendix E. The spatial distribution of changes in average monthly temperature and precipitation from 2005 to 2050, calculated by these two models for RCP 8.5 can be seen in Figure 2.



a. Csiro Mk 3.6.0 (D85) mean temperature changes (2005-2050). Minimum: -17.4 °C, Mean: +2.7 °C, Maximum: +16.9 °C.



b. Miroc Miroc5 (W85) mean temperature changes (2005-2050). Minimum: -17.9 °C, Mean: +2.8 °C, Maximum: +15.0 °C.

Changes in °C *10

<-30	-10 - 0	20 - 30	50 - 60
-3020	010	30 - 40	60 - 70
-2010	10 - 20	40 - 50	>70



c. Csiro Mk 3.6.0 (D85) monthly precipitation changes (2005-2050). Minimum: -137 mm, Mean: +0.8 mm, Maximum: +219 mm.



d. Miroc Miroc5 (W85) monthly precipitation changes (2005-2050). Minimum: -120 mm, Mean: +8.3 mm, Maximum: +237 mm.

Changes in mm/month

	<-100	-2510	0 - 5	25 - 50
	-10050	-105	5 - 10	50 - 100
	-5025	-5 - 0	10 - 25	>100

Figure 2. Changes in mean temperature and monthly precipitation under climate scenarios generated by Csiro Mk 3.6.0 (a, c) and Miroc Miroc5 (b, d) for RCP 8.5, respectively, by 2050 as compared to 2005.

Therefore, the current study is carried out under four (2RCPs ×2GCMs) climate scenarios and takes 2005 as the baseline year, giving the following model runs:

Baselir	Baseline 2005							
"Dry" ("Dry" GCM: Csiro MK360							
0	Low radiative forcing: RCP 2.6	Code: D26						
0	High radiative forcing: RCP 8.5	Code: D85						
"Wet"	GCM: Miroc Miroc5							
0	Low radiative forcing: RCP 2.6	Code: W26						
0	High radiative forcing: RCP 8.5	Code: W85						

For practical purposes, each model run has a code by which it will be referred to in the rest of the report.

The changes of climatic variables considered in the current study are minimum and maximum temperature (T_{max} and T_{min}), precipitation, ET_0 and CO_2 concentration in which only ET_0 is not

directly available in the GCM output database for 2050. In order to generate ET_0 in future climate scenarios, both the current and the future monthly average ET_0 values per grid cell are estimated using the Penman-Monteith method with the limited input data of temperature (Allen et al., 1998). Next, the absolute changes of ET_0 in mm are calculated as the difference between the future and the current simulated values. Finally, the gridded monthly average ET_0 for each climate scenario is generated by adding the gridded relative changes to the baseline monthly ET_0 values of 2005.

2.3 Estimating Responses in LP, WP and Consumptive WFs of Crops

The study includes the three major staple crops in China: rice, maize and wheat. These three crops are divided into sub groups because of their different growth periods. This gives the following crop types and areas (Figure 3):



Figure 3. The planted areas for the investigated crops. The crop types are specified in the left column, the middle column shows the planted area for irrigated crops and the right column shows the planted area for rainfed crops.

The FAO (Food and Agriculture Organisation of the United Nations)'s AquaCrop (version 4.0), a crop WP model used to simulate yield responses to water (Raes et al., 2011) (Appendix D), is used at each grid cell to simulate the actual evapotranspiration (ET) over the cropping period and crop LP (yield) in both the current (2005) and considered future (2050) situations. The required input parameters are: monthly precipitation, ET_0 , and the atmospheric CO_2 concentration. These input parameters are found answering the first research question. The data is in the form of 5 by 5 arc min grids of China, containing the input parameter values that will be converted to climate input files for AquaCrop using Python scripts.

The irrigation is defined as a 'net irrigation'. The irrigation technologies are not considered; water is simply added whenever it is required. Only water stress impacts are considered. Impacts from fertilizer, temperature stress and salinity are ignored.

Each GCM/RCP combination for 2005 and 2050 simulation contains the following areas:

• Irrigated areas: Irrigation whenever there is water required

There is no water stress over the cropping period. The crop growth is mainly affected by the changes in evapotranspiration requirement and CO_2 concentration.

• Rain fed areas: Zero irrigation

Different from irrigated crops, the growth of rainfed crops is also strained by the water stress given a certain precipitation level over the cropping period. The situation without irrigation can be used to show the effects of irrigation on crop LP and to determine which areas are the most susceptible to (current and future) water scarcity.

2.3.1 Crop Land Productivity (LP) Responses

The Aquacrop results for crop LP give the results for each grid-cell. To compare the future results to the baseline, the relative changes are calculated:

$$\Delta LP = \frac{LP_{future} - LP_{baseline}}{LP_{baseline}} * 100\%$$
(1)

These relative changes are analysed and the reasons for extreme or unusual changes are researched.

To calculate the absolute changes, the crop LP of the baseline year (2005) is calibrated by provincial statistics. This gives a scaling factor:

$$LP calibrated = LP simulated * sf$$
(2)

$$sf = \frac{LPstatistic}{LPsimulated} \tag{3}$$

This scaling factor is then applied to the simulated future crop LP to calibrate it. For relative changes, this scaling procedure is not necessary.

2.3.2 Crop Water Productivity (WP) Responses

Aquacrop gives the CWU per grid-cell as a result. The crop WP is calculated by dividing crop LP by the CWU (m3/ha):

$$WP = \frac{LP}{ET * 10} \tag{4}$$

To compare the future results to the baseline, the relative changes are calculated:

$$\Delta WP = \frac{WP_{future} - WP_{baseline}}{WP_{baseline}} * 100\%$$
⁽⁵⁾

These relative changes are analysed and the reasons for extreme or unusual changes are researched.

2.3.3 Crop Consumptive Water Footprint (WF) Responses

The WF (m3/tonne) of a crop is the inverse of the WP, so it is calculated by dividing CWU by LP of the crop.

$$WF = \frac{CWU}{LP} \tag{6}$$

$$\Delta WF = \frac{WF_{future} - WF_{baseline}}{WF_{baseline}} * 100\%$$
(7)

The green WF (kg/l) and blue WF (kg/l) of the crops are obtained following the framework defined by Hoekstra et al. (2011). They are calculated by dividing the green CWU (m³/ha) and blue CWU (m^3/ha) per grid cell over the growing season by the scaled crop LP (t/ha). These CWUs can be calculated from the AquaCrop output. AquaCrop is a water driven crop water productivity model with a dynamic soil water balance, which considers the soil water content, the precipitation, the irrigation, the capillary rise from groundwater, the actual evapotranspiration, the surface runoff and the deep percolation for each day. The surface runoff is estimated using the Soil Conservation Service runoff equation (Rallison, 1980). The incoming and outgoing water fluxes at the boundaries of the root zone are tracked in order to separate the green and blue water balances for each day. In this balance, the incoming fluxes are rainfall - which adds to the green water stock, irrigation and capillary rise - which add to the blue water stock. The outgoing fluxes are evaporation, transpiration and drainage and runoff. These outgoing fluxes are partitioned into blue and green water based on the relative green/blue distribution of the water stock on that day (Chukalla, Krol and Hoekstra, 2015; Zhuo et al., 2015). Summarizing these fluxes over the crop lifetime gives the total blue and green CWU, which, divided by the corresponding crop LP, gives the crop blue and green WF. The relative changes are analysed and the reason for extreme or unusual changes are researched.

2.4 Data Sources

- The GIS polygon data for China and its provinces comes from the Surveying and Mapping data sharing network (NASMG, 2010)(available at: http://sms.webmap.cn/default.asp)
- Agriculture statistics on crop harvested area and yield at province level of China at the baseline year (2005) are obtained from national statistics (NBSC, 2013) (available at: http://data.stats.gov.cn/index)
- The data from the baseline year 2005 on precipitation, temperature and ET₀ are extracted from the CRU-TS 3.10 (Jones and Harris, 2015) at a spatial resolution of 30 by 30 arcminute (available at: <u>http://www.cgiar-csi.org/data</u>)

- Data on irrigated and rain-fed area for each crop at a 5x5 arc-minute resolution are obtained from the MIRCA2000 dataset (Portmann, Siebert and Döll, 2010)(available at: http://www.uni-frankfurt.de/45218023/MIRCA)
- The downscaled outputs of GCMs at 5 by 5 arc-minute are obtained from the Climate Change, Agriculture and Food Security (CCAFS) database (available at <u>www.ccafs-climate.org</u>).
- The soil texture data are extracted from the ISRIC Soil and Terrain database for China at a 1:1million resolution (Dijkshoorn, van Engelen and Huting, 2008)(available at: http://www.isric.org/data/soil-and-terrain-database-china)
- The soil water capacity (in %vol.) at 5 by 5 arc-minute resolution is extracted from the ISRIC-WISE version 1.2 dataset (Batjes, 2012)(available at: http://www.isric.org/data/isric-wise-derived-soil-properties-5-5-arc-minutes-global-grid-version-12).
- For the hydraulic characteristics for each type of soil, the indicative values provided by AquaCrop are used.
- The future CO₂ concentration can be extracted from the RCP database (version 2.0.5.)(Available at:

http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=welcome).

- Crop planting dates from Chen et al. (1995)
- Relative crop growing stages and maximum rooting depths from Allen et al. (1998) and Hoekstra and Chapagain (2007)

3. Results

3.1 Climate Changes across China's Crop Lands

The considered climate scenarios for 2050 in China generated significantly different climate change projections. The average annual climate factors (precipitation, T_{max} , T_{min} , and ET_0) in each considered climate scenario for 2050 and their relative changes to the baseline year 2005 across China and cropping fields of three staple crops can be seen in Tables 1-4, respectively.

Table 1. Annual mean precipitation across China and its cropping fields of three staple crops in each climate scenario. The first column represents the country average, the columns titled Rice, Maize and Wheat are the averages for the planted areas of these crops.

		Annual mean precipitation and relative changes (RC) to baseline across China and its cropping fields								
Year	Scenario	China	RC	Rice	RC	Maize	RC	Wheat	RC	
		(mm/y)	%	(mm/y)	%	(mm/y)	%	(mm/y)	%	
2005	Baseline	572	-	1235	-	727	-	775	-	
2050	D26	591	+3.2	1265	+2.5	729	+0.3	749	-3.3	
	D85	575	+0.5	1222	-1.0	701	-3.6	725	-6.4	
	W26	642	+12.2	1298	+5.1	807	+11	832	+7.3	
	W85	666	+16.3	1276	+3.3	850	+17	863	+11.3	
Average	RCP 2.6	617	+7.7	1282	+3.8	768	+5.7	790	+2.0	
2050	RCP 8.5	621	+8.4	1249	+1.1	775	+6.7	794	+2.5	

In the baseline situation, China's wettest months occurred from May until September, so an extended summer period. The highest monthly precipitation was in July, with 106 mm/month averaged nationwide. The winter months are driest, with only 8 mm/month in December. As shown in Table 1, in all four considered scenarios of 2050, there is an increase in precipitation (for all months except for May and August, which show a decrease). The Csiro Mk3.6.0 model (D26\D85) generated small increases in precipitation for 2050, with only 3.2% and 0.5% for RCP2.6 and RCP 8.5 respectively for the whole of China. The MirocMiroc5 model (W26\W85), on the other hand, shows a significantly higher increase of 12.2% and 16.3% for RCP2.6 and RCP8.5, respectively. When looking at the different staple crop fields, the most notable phenomenon is that rice lands receive a higher annual total precipitation than fields growing the other two crops. All crops have a decrease in precipitation under scenario D85, where wheat has the highest decrease and also has a decrease under scenario D26.

Table 2. Average maximum temperature (T_{max}) across China and the cropping fields of three staple crops in each scenario.
The first column is the country average, the columns titles Rice, Maize and Wheat are the averages for the planted areas of
these crops.

		Annual max	imum temperati	ure and absolu	ute changes	(AC) to basel	ine across (China and its o	cropping
Voar	Scenario								
Tear		China	AC	Rice	AC	Maize	AC	Wheat	AC
		(°C)	°C	(°C)	°C	(°C)	°C	(°C)	°C
2005	Baseline	12.9	-	17.2	-	15.2	-	15.6	-
2050	D26	14.6	+1.7	19.2	+2.0	16.9	+1.7	17.6	+2.0
	D85	15.8	+2.9	20.3	+3.1	18.0	+2.8	18.8	+3.2
	W26	14.6	+1.7	19.0	+1.8	16.8	+1.6	17.5	+1.9
	W85	15.8	+2.9	19.9	+2.7	17.8	+2.6	18.5	+2.9
Average	RCP 2.6	14.6	+1.7	19.1	+1.9	16.85	+1.7	17.55	+2.0
2050	RCP 8.5	15.8	+2.9	20.1	+2.9	17.9	+2.7	18.65	+3.1

In the baseline situation, average T_{max} ranged from -2.1 °C in January up to 25.7 °C in July. In the winter months (December, January and February) the average T_{max} is below the freezing point. As can be seen from Table 2, in the considered future climate scenarios both GCMs estimated increased T_{max} nationwide, where the RCP 2.6 model runs (D26 and W26) had a relatively lower increase of 1.7 °C and the RCP 8.5 model runs (D85 and W85) had a relatively higher increase of 2.9 °C. The changes for the different crop areas have comparable results. The planted area of rice is the warmest, followed by wheat lands and then maize lands.

Table 3. Average minimum Temperature (Tmin) across China and the cropping fields of three staple crops in each scenario. The first column is the country average, the columns titles Rice, Maize and Wheat are the averages for the planted areas of these crops.

		Annual minimum temperature and absolute changes (AC) to baseline across China and its cropping fields								
Year	Scenario	China	AC	Rice	AC	Maize	AC	Wheat	AC	
		(°C)	°C	(°C)	°C	(°C)	°C	(°C)	°C	
2005	Baseline	1.0	-	7.6	-	4.5	-	5.2	-	
2050	D26	2.3	+1.3	9.0	+1.4	5.7	+1.2	6.5	+1.3	
	D85	3.5	+2.5	10.0	+2.4	6.8	+2.3	7.6	+2.4	
	W26	2.5	+1.5	8.9	+1.3	5.7	+1.2	6.5	+1.3	
	W85	3.7	+2.7	9.9	+2.3	6.8	+2.3	7.6	+2.4	
Average	RCP 2.6	2.4	+1.4	8.95	+1.4	5.7	+1.2	6.5	+1.3	
2050	RCP 8.5	3.6	+2.6	9.95	+2.4	6.8	+2.3	7.6	+2.4	

The highest record of the monthly T_{min} in 2005 across China occurred in July, with 14.8 °C. The lowest record was reached in January, with -13.5 °C. From November to March T_{min} is below zero degrees. When looking at Table 3, for all the 2050 scenarios there was an increased average T_{min} in each month as compared to 2005, where D26 had the lowest increase with 1.3 °C, followed by W26 with 1.5 °C, D85 with 2.5 °C and W85 with 2.7 °C. The changes per crop area do not differ

much from the countrywide changes. Rice lands have the highest T_{min} , followed by wheat lands and maize lands.

Table 4. Annual mean potential evapotranspiration across China and the cropping fields of three staple crops in each scenario. The first column is the country average, the columns titled Rice, Maize and Wheat are the averages for the planted areas of these crops.

	Annual mean ET_0 and relative changes (RC) to baseline across China and its cropping fields									
Year	Scenario	China	RC	Rice	RC	Maize	RC	Wheat	RC	
		(mm/y)	%	(mm/y)	%	(mm/y)	%	(mm/y)	%	
2005	Baseline	1693	-	1641	-	1644	-	1664	-	
2050	D26	1764	+4.2	1735	+5.7	1765	+7.3	1787	+7.4	
	D85	1789	+5.6	1776	+8.2	1795	+9.2	1819	+9.3	
	W26	1754	+3.6	1723	+5.0	1746	+6.2	1765	+6.1	
	W85	1771	+4.6	1737	+5.9	1757	+6.9	1781	+7.0	
Average	RCP 2.6	1759	+3.9	1729	+5.4	1756	+6.8	1776	+6.7	
2050	RCP 8.5	1780	+5.1	1757	+7.0	1776	+8.0	1800	+8.2	

In the baseline situation, the ET_0 was the lowest with 70 mm/month in the winter period, after which it gradually increased up to 204 mm/month in June and then decreased again. Increases in total annual ET_0 compared to the baseline level in each of the scenarios can be seen in Table 4. In the 2050 scenarios, there was a projected increase in national average ET_0 for every month - as a result of increased temperature - by 4.2%, 5.6%, 3.6% and 4.6% in W26, D26, W85 and D85 respectively. The table also shows that the increases are higher in the crop areas than for the whole of China. The ET_0 levels increased most for Maize and Wheat and less for Rice.

The CO_2 concentration in the 2005 baseline situation was 379.8 ppm by volume. In the RCP 2.6 (D26 and W26), this was projected to increase to 442.7 ppm. The RCP 8.5 had a projected CO_2 concentration of 540.5 ppm (Riahi, Gruebler and Nakicenovic, 2007; van Vuuren et al., 2007).

3.2 Responses in Crop Land Productivity to Climate Changes

	crop iand productivity and responses in climate									
Cron	2005 Relative changes to baseline in climate									
drop	(kg/ha)	scenarios for 2050 (%)								
	Bacolino	D26	D85	W26	W85	RCP	RCP			
	Dasenne	D20	005	W20	woj	2.6	8.5			
Rice	2894	+17	+26	+15	+27	+16	+26			
Irrigated rice	3031	+11	+23	+11	+23	+11	+23			
Rainfed rice	1926	+106	+80	+83	+96	+94	+88			
Maize	5621	-11	-11	-5	+2	-8	-5			
Irrigated maize	7044	+4	+5	+3	+5	+3	+5			
Rainfed maize	4089	-33	-36	-17	-4	-25	-20			
Wheat	3152	+22	+31	+24	+32	+23	+32			
Irrigated wheat	4266	+12	+24	+12	+24	+12	+24			
Rainfed wheat	565	+157	+125	+183	+153	+170	+139			
Total	3540	+10	+16	+12	+21	+11	+19			
Irrigated	3918	+10	+19	+10	+19	+10	+19			
Rainfed	2386	+11	+1	+22	+31	+17	+16			

Table 5. Responses of land productivity of staple crops to potential climate changes in China by 2050.

The results in Table 5 show that the potential climate changes generally had positive effects on the crop LP (in kg/ha) in China. The climate scenarios under RCP 8.5, which represent a higher increase in CO₂, generated higher increases in crop LP than scenarios under RCP2.6. Among different climates under RCP 8.5, the W85 runs generated higher crop LP increases than the D85 runs. All scenarios generated negative changes for maize for 2050, which occurred in rain-fed area with decreased precipitation (Figure 2c). Although the average precipitation per hectare increased for maize, the severe decrease of precipitation in some areas lead to a large decrease in rainfed LP in these areas, which is not compensated by the increased rainfed LP in other areas. In other words, the decrease of precipitation had a larger effect on rainfed LP than the increase of precipitation. All other runs show increased crop LP for 2050. The increases for irrigated crops, which do not suffer from water stress in crop growth, were mainly caused by increased CO₂ fertilization. This can be concluded from the fact that they are uniform over the entire country and only the CO₂ change is uniform. Increases in rainfed crop LP were mainly affected by changes in precipitation (in combination with CO_2 increase). Another notable result is that the changes in rainfed crop LP are larger than the irrigated changes; which shows that the crops are more sensitive to precipitation changes than to CO_2 and ET_0 changes.

LP is the productivity of a crop divided by the planted area. In this study, the planted area remains the same from 2005 to 2050, which means that there are no impacts from land use changes (movements) in terms of location. Crops will grow where they have grown before, so only the

changes in production in these location cause changes in LP. The baseline LP of all considered crops and their future changes under climate scenarios for 2050 are shown in Figures 3-6.



a. Baseline 2005 rice irrigated crop land productivity (tonne/ha)



b. Baseline 2005 rice rainfed crop land productivity (tonne/ha)



c. Baseline 2005 rice total crop land productivity (tonne/ha)



d. Baseline 2005 maize *irrigated* crop land productivity (tonne/ha)



e. Baseline 2005 maize rainfed crop land *productivity (tonne/ha)*



f. Baseline 2005 maize total crop land productivity (tonne/ha)



g. Baseline 2005 wheat irrigated crop land productivity (tonne/ha)



h. Baseline 2005 wheat rainfed crop land productivity (tonne/ha)



i. Baseline 2005 wheat total crop land productivity (tonne/ha)

0	2.0 - 3.0	5.0 - 6.0	8.0 - 9.0
0 - 1.0	3.0 - 4.0	6.0 - 7.0	9.0 - 10.0
1.0 - 2.0	4.0 - 5.0	7.0 - 8.0	>10.0

Figure 4. Land productivity (tonne/ha) of irrigated, rainfed and total rice (a,b,c resp.), maize (d,e,f resp.) and wheat (g,h,i resp.) in the baseline year 2005.

As can be seen in Figure 4, the LP of rice was highest in the North-East of China, up to 8-10 tonne/ha, in the baseline year. The rice LP in irrigated areas is significantly higher than in rainfed areas. This is because the irrigated areas have access to an unlimited water supply (no water stress), whereas the rainfed areas do not. Notable is that the South has a double cropping season, but the corresponding LP is rather low (1-3 tonne/ha). The central provinces of China also have a relatively low LP of rice (0-1 tonne/ha).

Figure 4 d-f show that the LP for maize was more evenly distributed than the LP of the other two crops in 2005. Looking at the irrigated (Figure 4d) and rainfed (Figure 4e) maize fields, it is interesting to note that these have similar LP values, unlike the other crops. This means that compared to rice and wheat, there was less water stress in the 2005 baseline situation for most maize lands.

The LP of wheat in the baseline year 2005 can be seen in Figure 4g-i. The LP of wheat is highest in the central-Eastern provinces of China and is much lower in the other provinces. This is especially clear when looking at the irrigated area. When looking at the rainfed LP, it is clear that only a small part of the planted area is productive. The majority of the 2005 rainfed wheat harvest fails. Although the precipitation over the total crop-growing period decreases (Table 1), the rainfed LP increases (Table 5), which seems odd. The cause for this is that for the entirety of the long growth period of winter wheat (12 months), the precipitation must be sufficient in every month. For winter wheat, the crop requires the most water from May until July, with a peak in June (Yonts et al., 2009). For the areas that fail in the baseline, the precipitation was low in June (Appendix F), which could be a cause for the crops to fail entirely. Among these areas are the Jiangsu province, and the North of Anhui province, which are areas with a high planted area for rainfed wheat.





a. Average relative rice <u>irrigated</u> land productivity changes under <u>RCP 2.6</u> (%)

d. Average relative rice <u>irrigated</u> land productivity changes under <u>RCP 8.5</u> (%) [%]



b. Average relative rice *rainfed* land productivity e. Average relative rice rainfed land productivity changes under <u>RCP 2.6</u> (%) changes under <u>RCP 8.5</u> (%)



changes under <u>RCP 2.6</u> (%)

changes under <u>RCP 8.5</u> (%)

Figure 5. Relative changes in land productivity of irrigated, rainfed and total rice in China from 2005 to 2050 under considered climate scenarios, averages of the two model runs for each RCP (a,b and c resp. for RCP 2.6 and d, e and f resp. for RCP 8.5).

Figure 5 shows the relative changes in LP of irrigated, rainfed and total rice averaged per RCP from 2005 to 2050. The changes in irrigated rice LP are uniform over the entire country for both RCP 2.6 and 8.5 (+15% and +25% respectively), mainly caused by CO_2 fertilization (the only climate change that is also uniform over the whole of China). The changes in rainfed rice LP (Figure 5b and 4e), however, are highly spatially variable, with immense increases in the South but decreases of approximately 20% to 50% in the North. These decreases are caused by a decrease in precipitation in an area that already had low precipitation in 2005, causing low LP. For D85, the precipitation decreases are especially high, causing the rice LP under RCP 8.5 to decrease more than under RCP 2.6. There are even larger decreases in precipitation in the Southern parts of China, but because the 2005 precipitation was sufficient in these locations, this decrease generally does not cause water stress on the rice crops. The increase in ET₀, which occurs in all scenarios (Table 4), also increases the changes of water stress in rainfed crops, because it can increase the crop ET requirement, and therefore also the precipitation requirement.



a. Average relative <u>irrigated</u> maize land productivity changes for RCP 2.6



d. Average relative <u>irrigated</u> maize land productivity changes for RCP 8.5



b. Average relative <u>rainfed</u> maize land productivity changes for RCP 2.6



e. Average relative r<u>ainfed</u> maize land productivity changes for RCP 8.5



c. Average relative total maize land productivity f. Average relative total maize land productivity changes for RCP 2.6 for RCP 8.5

Figure 6. Relative changes in land productivity of irrigated, rainfed and total maize in China from 2005 to 2050 under the considered climate scenarios, averages of the two model runs for each RCP (a,b and c resp for RCP 2.6 and d,e and f resp. for RCP 8.5).

Figure 6 shows the changes in LP of maize for 2050, averaged for each of the considered RCPs. The spatial distribution of the changes is comparable for the two RCPs. Similar as for rice, the

+100 - +400

>+400

changes in irrigated maize LP are mostly uniform over the entire country (+3% for RCP 2.6 and +5% for RCP 8.5) owing to the increased CO₂ fertilization. The increases for maize are lower than the increases in irrigated rice, so this could mean that CO_2 fertilization has a smaller effect on maize than on rice. Also similar to rice, changes in rainfed maize LP (Figure 6b and 5e) are highly spatially variable, with immense increases of over 400% in some small areas and almost all of Hebei province, shown in pink, but decreases of approximately 50% in areas with high LP in the central- and North-East. In 2005, the precipitation varied largely spatially and rainfed maize was mostly planted in areas with high precipitation. In 2050, the precipitation was more uniform over the country, so areas with high precipitation in 2005 received less in 2050 and vice versa. This means that the most densely planted areas received less rain in 2050. As can be seen from Table 1, the precipitation over the total maize area increases for most scenarios. However, as can be seen in Appendix E, there are areas with a significant decrease. Even the W85, the wettest scenario, has a decrease of up to 50% in the central Eastern area, where the planted area per grid cell is high. As can be seen in Figure 6b and 5e, the LP in these areas decreases with 20-50%, while the increases in other areas are not as high. This effect is even stronger for the other scenarios, especially the dry ones. This shows that, although there is an increase in precipitation over the total planted area, the significant decrease in some important areas causes the total LP of rainfed maize to decrease.





a. Average relative <u>irrigated</u> wheat land productivity changes for RCP 2.6

d. Average relative <u>irrigated</u> wheat land productivity changes for RCP 8.5

[%]



b. Average relative <u>rainfed</u> wheat land productivity changes for RCP 2.6

e. Average relative <u>rainfed</u> wheat land productivity changes for RCP 8.5





c. Average relative total wheat land productivity f. Average relative total wheat land productivity changes for RCP 2.6 changes for RCP 8.5

Figure 7. Relative changes in land productivity of irrigated, rainfed and total wheat in China from 2005 to 2050 under the considered climate scenarios, averages of the two model runs for each RCP (a,b and c resp for RCP 2.6 and d,e and f resp. for RCP 8.5).

The most notable results in Figure 7 are the rainfed changes, which cover only a small part of the planted rainfed area. This is because of the massive crop failure of rainfed crops in the baseline, as explained earlier. This is not a good visualization of the real changes in rainfed crop LP. The productive area in 2050 was much larger than in 2005. Only changes for the productive area of 2005 are shown, because relative changes with a base of zero cannot be calculated. This also explains the immense increases in rainfed wheat LP, as shown in Table 5; in 2050 the water stress in June is lower, because the precipitation is higher in that crucial month, leading to less crop failure for rainfed wheat. The irrigated wheat changes are uniform over the country and are larger for RCP 8.5 than for RCP 2.6.

3.3 Responses in Crop Water Productivity to Climate Changes

	Crop wate	r produ	ctivity a	nd resp	onses ii	n climate so	cenarios
Crop	2005	Relati	ve chan	ges to b	aseline	in climate	scenarios
Crop	(kg/ha)	for 20	50 (%)				
	Baseline	D26	D85	W26	W85	RCP 2.6	RCP 8.5
Rice	0.403	+16	+28	+19	+32	+17	+30
Irrigated rice	0.411	+13	+26	+16	+29	+14	+28
Rainfed rice	0.382	+77	+65	+66	+81	+71	+73
Maize	0.805	-11	-11	-4	+2	-8	-5
Irrigated maize	0.921	-4	0	0	+4	-2	+2
Rainfed maize	0.653	-26	-32	-13	-2	-20	-17
Wheat	0.389	+13	+23	+15	+24	+14	+24
Irrigated wheat	0.385	+4	+17	+5	+18	+5	+17
Rainfed wheat	0.490	+111	+89	+117	+84	+114	+86
Total	0.480	+7	+15	+11	+21	+8	+17
Irrigated	0.471	+7	+18	+9	+20	+8	+18
Rainfed	0.532	+9	0	+17	+25	+11	+11

Table 6. Responses of crop water productivity of staple crops to potential climate changes in China by 2050

Table 6 lists the WP of the three crops in the baseline and the relative changes from the baseline to the different 2050 scenarios. The WP of a crop is formed by dividing CL of the crop by CWU at crop fields (eq. 4). The CWU of rice decreases (-1.7% to -1.8%), the CWU of maize remains almost equal (-0.15% to +0.08%) and the CWU of wheat increases (+6.8 to +7.1%). The responses in crop WP to potential climate changes for rice and maize are comparable to the changes in crop LP and generally differ solely by a few percentage points, showing that crop LP is the dominant factor in the changes of WP. For wheat, there is a substantial increase in CWU, making the WP increase significantly lower than the LP increase. This also clearly shows that, although the ET_0 increases are uniform and constant over the country, the actual ET (CWU), varies for each crop.

Because there are relatively small changes in the CWU at rice and maize crop fields under the future climate scenarios, most of the changes in crop WP are already explained in the previous section about responses of crop LP. The changes for wheat, unexplained changes, spatial variability and the influence of CWU on the other crops are explained in the following section.



a. Baseline 2005 rice <u>irrigated</u> crop water productivity (kg/m³)



b. Baseline 2005 rice rainfed crop water

productivity (kg/m³)

d. Baseline 2005 maize <u>irrigated</u> crop water productivity (kg/m³)





g. Baseline 2005 wheat irrigated crop water productivity (kg/m^3)

h. Baseline 2005 wheat <u>rainfed</u> crop water productivity (kg/m³)



c. Baseline 2005 rice <u>total</u> crop water productivity (kg/m³)

e. Baseline 2005 maize <u>rainfed</u> crop water productivity (kg/m³)



f. Baseline 2005 maize <u>total</u> crop water productivity (kg/m³)



i. Baseline 2005 wheat <u>total</u> crop water productivity (kg/m³)



Figure 8. Crop water productivity (kg/m^3) of irrigated, rainfed and total rice (a,b,c resp.), maize (d,e,f resp.) and wheat (g,h,i resp.) in the baseline year 2005.

As can be seen in Figure 8a-c, the spatial distribution of the WP of rice is similar to the distribution of the rice LP (Figure 3 a-c): highest in the North-East, lowest along the South and South-East coastline and slightly higher further away from the coast. WP is higher for irrigated rice than rainfed rice. Although the crop LP mainly determines the spatial variability, the CWU distribution at China's rice fields does show in the rice WP figures. The most notable feature of the CWU of rice is that there is a clear division in two areas, the South-East with double season paddy rice, and the rest of the country where single season highland rice is grown. The South-Eastern part of China (paddy rice) uses significantly more water for rice production than the rest of the country, because of the double season, which means double water usage. The double season should also mean double the LP. However the LP is relatively low, giving a low WP.

For Maize (Figure 8 d-f), the WP is highest of all crops. The fact that the WP in the north is high for irrigated maize but smaller for rainfed maize WP proves that the climate in the North has insufficient precipitation for maize without irrigation, causing low LP and WP (except for Jilin and Liaoning provinces, which have high rainfed WP).

For wheat, the central East of China has the highest LP, but also a high irrigated CWU for the whole of China, leading to a low irrigated wheat WP. The rainfed crops mostly fail, but those that do not fail have a high WP, caused by low rainfed wheat CWU. The crops that fail, however, do use water until they fail. The crops mostly fail in June or July, which is near the end of the season, so the CWU of the failing crop is almost as high as a non-failing crop. Because most of the wheat production is irrigated, the total wheat WP is - like the irrigated wheat WP - fairly low.





a. Average relative <u>irrigated</u> rice crop water productivity changes for RCP 2.6



productivity changes for RCP 2.6

d. Average relative <u>irrigated</u> rice crop water productivity changes for RCP 8.5







e. Average relative <u>rainfed</u> rice crop water productivity changes for RCP 8.5



c. Average relative <u>total</u> rice crop water productivity changes for RCP 2.6



ter f. Average relative <u>total</u> rice crop water productivity changes for RCP 8.5

Figure 9. Relative changes in water productivity of irrigated, rainfed and total rice in China from 2005 to 2050 under the considered climate scenarios, averages of the two model runs for each RCP (a,b and c resp for RCP 2.6 and d,e and f resp. for RCP 8.5).

In the four 2050's climate scenarios, the paddy rice had an increased average CWU by 3-7%, while the highland rice had a decreased CWU by 12-19% as compared to the baseline level. This division comes back in Figure 9a (and to a lesser extent in Figure 8f), showing that irrigated highland rice has a higher relative increase in WP than the paddy rice. The Figure 9d for RCP 8.5 shows a less obvious difference between paddy and highland rice because the increase of rice LP is larger for RCP 8.5, while the changes in CWU are similar for both RCPs, making the WP for paddy rice increase more for RCP 8.5 than for RCP 2.6. The changes in rainfed rice WP are mainly caused by changes in the LP, showing the same spatial pattern.





d. Average relative *irrigated* maize crop water

productivity changes for RCP 8.5

<-50

-50 - -20 -20 - -10 -10 - -5 -5 - 0 0 - +5 +5 - +10 +10 - +20 +20 - +50 +50 - +100 +100 - +400

a. Average relative <u>irrigated</u> maize crop water productivity changes for RCP 2.6



b. Average relative <u>rainfed</u> maize crop water productivity changes for RCP 2.6







c. Average relative <u>total</u> maize crop water *f.* Average relative <u>total</u> maize crop water productivity changes for RCP 2.6 productivity changes for RCP 8.5

Figure 10. Relative changes in water productivity of irrigated, rainfed and total maize in China from 2005 to 2050 under the considered climate scenarios, averages of the two model runs for each RCP (a,b and c resp for RCP 2.6 and d,e and f resp. for RCP 8.5).

The LP of irrigated maize increases more than the CWU of maize, causing the CWP to increase. Because the irrigated maize LP changes are uniform over the planted area, the spatial variability of the irrigated maize WP changes is determined by the CWU changes. The CWU for irrigated maize increases for most of the growing area, likely due to the nationwide ET_0 increases. For RCP 2.6, the maize LP increases with 3% while the CWU increases with 5%. For RCP 8.5 these numbers are vice versa. This gives RCP 2.6 a slight overall maize WP decrease and RCP 8.5 a slight increase.

There was no clear spatial pattern for the changes of the CWU at rainfed maize fields across the four scenarios for 2050: some areas have decreases of around 10% while others have similar increases. On a national average, the decrease in CWU is 7% and 4% for RCP 2.6 and RCP 8.5 respectively. Because the changes in LP are almost identical, the average change in the corresponding WP is small (Figure 10). The most extreme changes in the spatial pattern of the total changes of WP mainly consist of the corresponding changes of the rainfed maize LP (Figure 5).





a. Average relative <u>irrigated</u> wheat crop water productivity changes for RCP 2.6



b. Average relative <u>rainfed</u> wheat crop water productivity changes for RCP 2.6



c. Average relative <u>total</u> wheat crop water productivity changes for RCP 2.6

d. Average relative <u>irrigated</u> wheat crop water productivity changes for RCP 8.5





[%]

e. Average relative <u>rainfed</u> wheat crop water productivity changes for RCP 8.5



f. Average relative <u>total</u> wheat crop water productivity changes for RCP 8.5

Figure 11. Relative changes in water productivity of irrigated, rainfed and total wheat in China from 2005 to 2050 under the considered climate scenarios, averages of the two model runs for each RCP (a,b and c resp for RCP 2.6 and d,e and f resp. for RCP 8.5).

Under the four climate scenarios, the CWU in the irrigated wheat area increases for most of the country, with an average of 6-7%. For RCP 2.6 the irrigated LP is uniform, so the spatial variability of the CWU changes determines the variability in crop WP changes. The small area of rainfed crop WP changes shown in Figure 11 is mainly determined by the LP of 2005, where most of the rainfed wheat fails. The figure only shows the area with a nonzero LP, but the planted area is much larger. The CWU in the planted area that is not shown here is not zero, leading to a high total CWU compared to the LP in the baseline. In the 2050 scenarios, there is less crop failure, greatly increasing crop LP and also increasing CWU, as the crops continue growing for the entire growing season, instead of dying early. This combination causes the wheat WP to increase less than the wheat LP.

3.4 Responses in Green and Blue Water Footprints of Crops to Climate Changes

	Consumptive water footprint of crop growth											
	Baseline	2005		Responses to climate change scenarios for 2050 (%)								
Crop	(l/kg)			RCP 2.6			RCP 8.5					
	Blue	Green	Total	Blue	Green	Total	Blue	Green	Total			
Rice	567	1913	2480	-36	-9	-15	-39	-19	-23			
Irrigated rice	615	1816	2432	-33	-6	-13	-37	-17	-22			
Rainfed rice	-	3045	3045	-	-42	-42	-	-42	-42			
Maize	202	1040	1242	+26	+5	+8	+15	+3	+5			
Irrigated maize	311	775	1086	+13	-3	+2	+5	-5	-2			
Rainfed maize	-	1531	1531	-	+25	+25	-	+20	+20			
Wheat	939	1631	2570	-21	-7	-12	-23	-17	-19			
Irrigated wheat	993	1607	2600	-13	+1	-4	-18	-13	-15			
Rainfed wheat	-	2041	2041	-	-53	-53	-	-46	-46			
Total	532	1553	2085	-19	-3	-7	-22	-12	-14			
Irrigated	636	1488	2125	-18	-2	-7	-22	-12	-15			
Rainfed	-	1881	1881	-	-10	-10	-	-90	-90			

Table 7. Responses of the blue and green water footprint of staple crops due to potential climate changes by 2050.

Table 7 shows the green and blue WFs (in l/kg) of the crops in the 2005 baseline situation and their responses to the 2050 climate scenarios. Like the responses in LP and WP to climate changes, the results for maize deviate from the other crops. Maize is the only crop with increases in blue WFs in 2050. This only happens for the dry scenarios (D26/ D85). The driving factor was a decrease in rainfed LP, combined with increased irrigation due to lower precipitation in some areas (the blue WF increases significantly).

The WF of wheat is the highest among the considered crops in the baseline year, with 2570 l/kg, followed by rice with 2480 l/kg and finally maize with 1242 l/kg. For all crops, the blue WF is significantly lower than the green WF, accounting for 26% of the consumptive WF when considering the total of the three crops and for 23%, 16% and 37% for rice, maize and wheat respectively. The blue WF of maize is especially low, which means maize uses only a small amount of irrigated water, while the blue WF of wheat is highest, showing that, of the three crops, wheat depends most on irrigation.





a. Rice blue water footprint 2005 (l/kg)



c. Rice blue water footprint changes for 2050, RCP 2.6



e. Rice blue water footprint changes for 2050, RCP 8.5



 0
 2000 - 3000
 5000 - 6000
 8000 - 9000

 0 - 1000
 3000 - 4000
 6000 - 7000
 9000 - 10000

 1000 - 2000
 4000 - 5000
 7000 - 8000
 > 10000

b. Rice green water footprint 2005 (l/kg)



d. Rice green water footprint changes for 2050, RCP 2.6



f. Rice green water footprint changes for 2050, RCP 8.5

<-50	-105	+5 - +10	+50 - +100
-5020	-5 - 0	+10 - +20	+100 - +400
-2010	0 - +5	+20 - +50	>+400

Legend for changes (figures c-f), [%], 100% represents no change

Figure 12. Blue (a) and green (b) water footprints for rice in 2005, and their relative changes to future climate changes for RCP2.6 (c and d for blue and green WF, resp.) and RCP8.5 (e and f for blue and green WF, resp.) (2050).

When looking at the green and blue WFs of rice for the baseline year 2005 (Figure 12 a-b), the most notable result is the high consumptive WFs in and around Hebei province, caused by the low LP (\sim 0.5 kg/ha) of the province compared to the other provinces (\sim 3.8 kg/ha).

Figure 12c-f show the changes of the WF of rice from 2005 to 2050. There are major spatial differences in these changes, especially for the WFs of rainfed rice. Though there is a decreased national average blue WF of rice, some rice lands have significant increases in blue WF. Because the changes in total LP are mostly uniform over these areas, the changes are mainly caused by increased blue CWU in these areas, caused by decreased precipitation in these areas.

Likewise, the changes in green WF of rice are caused by changes in the green CWU. The green CWU increases for paddy rice, generating the WF decreases that can be seen especially in the South-East, as visible from Figure 12d. The North and Central East have decreased precipitation, decreasing the green WFs in these areas (but increasing blue WF). Because the LP of paddy rice also increases, the effect of increasing CWU on WF is cancelled out. The LP increases more under RCP8.5 than RCP 2.6, while the changes in CWU are similar for both RCPs. This results in a decrease in WF for RCP 8.5 and a lower decrease or even an increase in WF in some areas for RCP 2.6.



a. Maize blue water footprint 2005 (l/kg)



c. Maize blue water footprint changes for 2050, RCP 2.6



e. Maize blue water footprint changes for 2050, RCP 8.5



b. Maize green water footprint 2005 (l/kg)



d. Maize green water footprint changes for 2050, RCP 2.6



f. Maize green water footprint changes for 2050, RCP 8.5



Legend for changes (figures c-f), [%], 100% represents no change

Figure 13. Blue (a) and green (b) water footprints for maize in 2005, and their relative changes to future climate changes for RCP2.6 (c and d for blue and green WF, resp.) and RCP8.5 (e and f for blue and green WF, resp.) (2050).

The spatial variability of 2005's blue and green WFs of maize is shown in Figure 13a and 12b, respectively. The relatively high WFs are located in the provinces with relatively low LP (e.g. Jiangsu province).

The figures of the changes in green and blue WFs of maize to climate changes (Figure 13c-f) show that there are areas in which the WF increases with over 400%. Especially the blue water footprints have severe increases. These are caused by a decrease in LP in these areas combined with an increase in blue CWU. Especially in the central-Eastern provinces the blue CWU increases significantly and is the main factor of the increased blue WF. This increase in blue CWU is due to decreased precipitation in those areas. In the baseline year, the precipitation is almost sufficient so there is very little irrigation needed in that year. In the future scenarios, the precipitation decreased, increasing the irrigated water, and therefore the blue WF, from near to zero to a larger value, making for a huge relative change. The results for RCP 2.6 and RCP 8.5 are similar.



Wheat blue water footprint 2005 (l/kg)

0	1000 - 1500	2500 - 3000	4000 - 4500
0 - 500	1500 - 2000	3000 - 3500	4500 - 5000
500 - 1000	2000 - 2500	3500 - 4000	> 5000



Wheat blue water footprint changes for 2050, RCP 2.6



Wheat blue water footprint changes for 2050, RCP 8.5



Wheat green water footprint 2005 (l/kg)

0	2000 - 3000	5000 - 6000	8000 - 9000
0 - 1000	3000 - 4000	6000 - 7000	9000 - 10000
1000 - 2000	4000 - 5000	7000 - 8000	> 10000



Wheat green water footprint changes for 2050, RCP 2.6



Wheat green water footprint changes for 2050, RCP 8.5

<-50	-105	+5 - +10	+50 - +100
-5020	-5 - 0	+10 - +20	+100 - +400
-2010	0 - +5	+20 - +50	>+400

Legend for changes (figures c-f), [%], 100% represents no change

Figure 14. Blue (a) and green (b) water footprints for wheat in 2005, and their relative changes to future climate changes for RCP2.6 (c and d for blue and green WF, resp.) and RCP8.5 (e and f for blue and green WF, resp.) (2050).

The WF of wheat in 2005 is high in the North- and South-East and lower in-between (Figure 14 ab). This is because the LP shows the same pattern (Figure 7). The spatial pattern of the WFs is mainly determined by the 2005 LP, for the same reasons as the pattern of the wheat WP discussed in section 3.3.

The Figure 14c and e show a large increase in blue WF of wheat in the South-east and North. This is caused by a decrease in precipitation during the cropping period in these areas.

4. Discussion

We compared the results of the current simulations to selected previous studies (Ye et al., 2013; Zhao et al., 2014; Zhuo, Gao and Liu, 2014; Mekonnen and Hoekstra, 2015). These studies conclude that CO2 fertilization has a positive effect on the land and water productivity, where the effect on maize is smaller than the effect on rice and wheat, similar to our own results. In these studies the LPs of all three crops increased for the future climate scenarios, especially for the rainfed crop areas. This agrees with the current study for rice and wheat, but differs for maize, according to the current results maize has a decrease in LP for the future climate scenarios. According to Ye et al. (2013), the LP of rice was 6.6 t/ha, for wheat 4.7 t/ha and for maize 5.3 t/ha in 2009. Our results, for 2005, were rice 2.9 t/ha, wheat 3.2 t/ha and maize 5.6 t/ha. So rice and wheat had significantly lower LPs according to our simulation.

		Comp	arison of	WFs for t	he three	e crops found in similar studies					
Study	Year	Rice V	WF		Maize	e WF		Whea	t WF		
		blue	green	total	blue	green	total	blue	green	total	
Muller (2016)	2005	567	1913	2480	202	1040	1242	939	1631	2570	
Muller unscaled	2005	235	794	1029	110	568	678	453	787	1240	
M&H (2011)	1996-2005	246	549	795	74	791	865	466	821	1278	
Shi et. al (2014)	1986-2007	-	-	1333	-	-	850	-	-	1171	
Sun et. al (2013)	2009	492	802	1294	199	631	830	525	546	1071	
Zhuo (2016)	2008	384	961	1345	66	754	819	312	839	1151	

Table 8. Comparison of the WFs of the baseline situation found in this study to the values found in several comparable studies: (Mekonnen and Hoekstra, 2011), (Shi, Liu and Pinter, 2014), (Sun et al., 2013) and (Zhuo, 2016).

When comparing the 2005 WF results to other studies by Mekonnen and Hoekstra (2011), Shi et al. (2014) and Sun et al. (2013), we find that the WFs in this study are well above their values (Table 8). Even when compared to the global average (Mekonnen and Hoekstra, 2015), our results are significantly higher, especially for rice and wheat. A possible reason for this is the scaling of the LP, but not the CWU. By doing this, the LP is lowered because the statistical production is lower than the simulated production. The CWU however remains the same, because there are no statistics to scale them, leading to a possible overestimation of the CWU. As can be seen in Table 8, the unscaled WFs are much closer to the values found in the other studies, which mostly did not use scaling. The scaling factors also were the dominant reason for the spatial variability in the LP, WP and WF distributions, but this is not a limitation according to Tuninetti et al. (2015).

Like all modelling studies, this study has a number of uncertainties. First of all, there are uncertainties based on assumptions in input crop parameters because of a lack of data. In AquaCrop modelling, for each type of crop, we assume constant parameters on the crop calendar, the reference harvested index and the maximum effective root zone across the country.

Taking only water stress into consideration, we monitored some locations which had a simulated LP of zero in the rainfed area, especially for winter wheat (accounting for 76% considered grid cells planting rainfed winter wheat), though has little effect on the overall results given the rainfed crop production accounts for only a small proportion (5% in 2005) of the national total wheat production. The reason behind the failures is severe water stress with a shortage of rainfall during the crop growing period, which resulted in early death. The effects on the LP changes of these

baseline failures is large, because in the 2050 scenarios the amount of failing grid cells is significantly lower, greatly increasing rainfed LP. These failures can be caused by uncertainties in the crop parameters. For places for which this is the case it is necessary to calibrate the parameters using agronomy field experiments. Other reasons could be the uncertainties embodied in the datasets of crop harvested area, or, according to Katerji et al. (2013), the difficulties AquaCrop has simulating LP and ET for areas with water stress.

We did not consider multi-cropping other than paddy rice in the current estimations. Furthermore it is assumed that all the water is used with 100% efficiency, while in reality an increased ET0 will increase evaporation of open water (this especially affects paddy rice), which is now not included in the CWU. The crop LP mostly only increases due to CO_2 fertilization, of which the long term effects are still unsure and it should be noted that some crop simulation models overestimate the impact of CO_2 fertilization. Free Atmosphere Carbon Exchange (FACE) experiments show that measureable CO_2 fertilization effects are typically less than modelled results (Hijioka et al., 2014), and even if the CO_2 fertilization is found to have these positive effects on crop LP, CO_2 concentrations of more than 460ppm can cause more or less deleterious effects on quality of rice, maize and wheat (Erda et al., 2005b).

In reality, water shortages are not the only source of stress on the crops. There are many factors that weren't included in this study that could have major negative effects, like heat stress, extreme weather events (like storms, droughts and flooding) and possible increases in pests and diseases. Therefore, the current results probably give an overly optimistic result.

The above limitations can cause the over- or under- estimates on the absolute values on the studied indicators. However, there is a broad agreement in the results as compared to the previous published studies. The limitations mostly have effect on both the baseline and the 2050 situation. The largest differences in absolute values can be explained by the scaling procedure, and this procedure only has an effect on the absolute values, not the relative changes. Therefore we claim that the current result is still of high validity, especially in the core of the study – the relative responses in crop LP, WP and WFs to climate changes.

Looking at the results, it seems that climate change could provide opportunities for China, since most results show an increase in LP and a decrease in WF.

5. Conclusions

The study aimed to find the effects of climate changes over the period 2005-2050 on the land and water productivity of staple crops in China. There were four climate scenarios for 2050, two under RCP 2.6 (D/W26) and two under RCP 8.5 (D/W85), to cover the widest spectrum of current available GCMs' simulations. These scenarios projected a warmer and wetter China in 2050, compared to the 2005 baseline situation, with increased temperature and precipitation across the country and the planted areas of the crops.

We found that possible future (2050) climate changes mostly have positive results on the land and water productivity of the considered staple crops in China. Rainfed maize is the only crop that had negative results. Contrary to the results for maize, the results for rice and wheat rainfed areas had the largest relative increases. Because the irrigated production is much larger than the rainfed production for all crops, the changes in irrigated productivity have a larger impact on the total productivity changes. The results show that for the rainfed crops, the precipitation is the main driving factor of the changes, while for the irrigated crops the CO_2 increase is the main driving factor, and to a lesser extent the increased ET_0 . The increases in irrigated rice and wheat are stronger than the increases in irrigated maize. This indicates that the CO_2 fertilization effect is stronger on rice and wheat than on maize. Because the CO_2 level increases more for RCP 8.5, the LP also increases more for this RCP.

The changes in LP lead to similar changes in WP for rice and maize, showing that the CWU of these crops remains approximately the same, and that the LP is the dominant factor in the WP changes. For maize there are some differences between the irrigated and rainfed results. The increase of irrigated WP is lower than the increase of irrigated LP, caused by an increase in irrigated CWU. For rainfed maize, the CWU decreases. This shows that a decrease of precipitation in a part of the crop area, even though the total crop area receives more precipitation, can lead to a decrease in rainfed CWU.

When the rainfed CWU decreases, the irrigated CWU increases to compensate for this shortage. For wheat there is a larger increase in CWU, causing the increase in WP to be significantly lower than the increase in LP. Seeing that the ET_0 increases for all crops, it would be logical to suggest that the CWU (measured in ET) also increases for all crops, but looking at the results shows that this is not the case. So, an increase in ET_0 does not necessarily increase the actual ET of a crop. The reasons for this should be investigated further.

So the CWU for rice and maize remains roughly the same while the CWU of wheat increases. To determine the effects on water scarcity, the source of this water was determined by splitting the water use into blue and green water and calculating the blue and green WFs. This shows, that for rice, the increase in LP and the unchanged CWU lead to a decreased blue and green WF. The blue WF decreases most due to the increased precipitation and is roughly equal for both RCPs. This means that the green WF decreases mostly due to the increased LP, so due to the CO₂ fertilization effect. Wheat has approximately the same results as rice, but with slightly smaller decreases due to the increased CWU. For maize, the decrease in LP mostly leads to an increase in WFs. Only the irrigated green WF decreases, because this WF only depends on the irrigated LP, which increases, and the precipitation, which does not change. The rainfed green WF increases due to the decrease in LP, and both blue WFs increase due to increased irrigation.

The results show that there are several places with a significant increase in blue WF, especially for maize, but also for the other crops. These locations are likely to suffer increased water scarcity in the future.

Current findings reveal that the CO_2 fertilization is the dominant factor for irrigated crops' LP, while precipitation changes dominated the changes in rainfed crop's LP, and the blue WF of irrigated crops. The ET increases in all scenarios, which also causes an increase in WF. In order to face climate changes in these locations, it is essential to reduce the blue water use. This can be attempted by introducing new and better technology or cropping techniques, which can possibly increase the LP, reduce the non-beneficial ET or enhance the effective use of precipitation (Mekonnen and Hoekstra, 2015).

This study focuses solely on water demand perspective, and did not analyse the responses in water availability. Especially the blue water availability will probably have changed significantly by 2050. This could be a focus for future studies to complement the picture. Another point of improvement could be the inclusion of heat stress, because the increased temperatures might have negative effects on the crops which are not considered in this study. We focussed only on three staple crops with integrated irrigated and rainfed cropping, while there are also crops in China, like rape seed, which are fully rainfed. The responses of the growth and water use of these other crops to climate changes is still interesting to figure out.

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