Environment International 94 (2016) 211–223

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Full Length Article

Consumptive water footprint and virtual water trade scenarios for China — With a focus on crop production, consumption and trade

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ARTICLE INFO

Article history:
Received 29 February 2016
Received in revised form 20 May 2016
Accepted 20 May 2016
Available online xxxx

Keywords:
Future scenarios
Consumptive water footprint
Virtual water trade
Food consumption
Water consumption
China

ABSTRACT

The study assesses green and blue water footprints (WFs) and virtual water (VW) trade in China under alternative scenarios for 2030 and 2050, with a focus on crop production, consumption and trade. We consider five driving factors of change: climate, harvested crop area, technology, diet, and population. Four scenarios (S1–S4) are constructed by making use of three of IPCC's shared socio-economic pathways (SSP1–SSP3) and two of IPCC's representative concentration pathways (RCP 2.6 and RCP 8.5) and taking 2005 as the baseline year. Results show that, across the four scenarios and for most crops, the green and blue WFs per tonne will decrease compared to the baseline year, due to the projected crop yield increase, which is driven by the higher precipitation and CO_2 concentration under the two RCPs and the foreseen uptake of better technology. The WF per capita related to food consumption decreases in all scenarios. Changing to the less-meat diet can generate a reduction in the WF of food consumption of 44% by 2050. In all scenarios, as a result of the projected increase in crop yields and thus overall growth in crop production, China will reverse its role from net VW importer to net VW exporter. However, China will remain a big net VW importer related to soybean, which accounts for 5% of the WF of Chinese food consumption (in S1) by 2050. All scenarios show that China could attain a high degree of food self-sufficiency while simultaneously reducing water consumption in agriculture. However, the premise of realizing the presented scenarios is smart water and cropland management, effective and coherent policies on water, agriculture and infrastructure, and, as in scenario S1, a shift to a diet containing less meat.

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1. Introduction

Intensified competition for finite water resources among different sectors is challenging the sustainability of human society. Agriculture is the biggest water consumer, accounting for 92% of global water consumption (Hoekstra and Mekonnen, 2012). In China, the world's most populous country, agriculture was responsible for 64% of the total blue water withdrawal in 2014 (MWR, 2015). About 81% of the nation's water resources are located in the south, but 56% of the total harvested crop area is located in the north (Piao et al., 2010; NBSC, 2013; Jiang, 2015). China is a net virtual water importer related to agricultural products (Hoekstra and Mekonnen, 2012). Local overuse of water threatens the sustainability of water resources in China (Hoekstra et al., 2012). China's agricultural water management will be increasingly challenged by climate change, population growth, and socio-economic development (NDRC, 2007; Piao et al., 2010; Jiang, 2015).

The Chinese government pursues self-sufficiency in major staple foods (wheat, rice and maize) (NDRC, 2008; SCPRC, 2014) and has set the 'three red lines' policy on sustainable agricultural blue water use, which sets targets regarding total maximum national blue water consumption (670 billion $m^3\ y^{-1}$), improving irrigation efficiency (aiming at 55% at least) and improving water quality (SCPRC, 2010). However, risks to water security arise not only from blue water scarcity, but also from scarcity of green water (rainwater stored in soil), which limits the national food production potential (Falkenmark, 2013). An important question is whether China can pull off the political plan to attain water, food as well as energy security (Vanham, 2016) under climate change combined with population growth and socio-economic development. A question relevant for the world as a whole is how the development of Chinese food consumption and production, given future socio-economic changes and climate change, will impact on the country's net crop trade and related net virtual water trade.

This study assesses green and blue water footprints (WFs) and virtual water (VW) trade in China under alternative scenarios for 2030 and 2050, with a focus on crop production, consumption and trade. We consider five driving factors of change: climate, harvested crop area, technology, diet, and population. We consider 22 primary crops (Table 5), covering 83% of national harvested crop area (2009) (NBSC, 2013) and 97% and 78% of China's total blue and green WFs of crop production (1996–2005), respectively (Mekonnen and Hoekstra, 2011). We take

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http://dx.doi.org/10.1016/j.envint.2016.05.019
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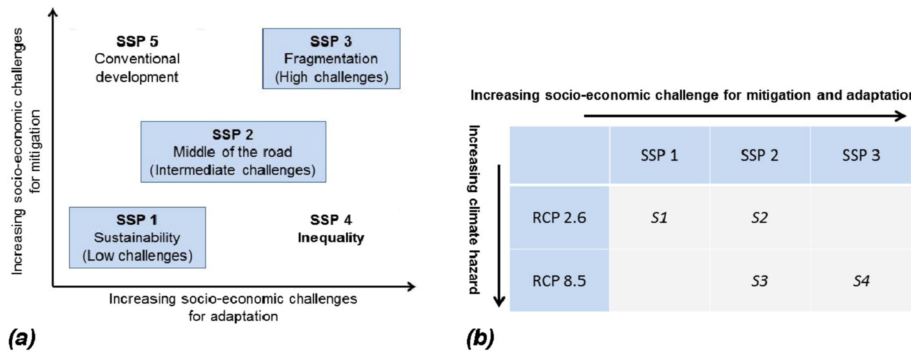


Fig. 1. (a) SSPs in the conceptual space of socio-economic challenges for mitigation and adaptation. Source: O'Neill et al. (2012). (b) Definition of scenarios S1–S4 used in the current study in the matrix of SSPs and RCPs.

the year 2005 as the baseline. The spatial resolution of estimating the WF of crop production is 5 by 5 arc min.

WF is an indicator of water use in relation to production or consumption in the economy (Hoekstra, 2003). In the agricultural sector, the WF of crop production measures the consumption of rainfall at croplands over the crop growing period (the green WF), the consumption of groundwater and surface water as a result of irrigation (the blue WF), and the water pollution that results from the leaching and runoff of fertilizers and pesticides from croplands (the grey WF) (Hoekstra et al., 2011; Hoekstra, 2013). The green and blue WFs together are called the consumptive WF, while the grey WF is also called the degradative WF (Hoekstra, 2013). In the current study, we focus on analysing the consumptive WF. The WF of the consumption in a country consists of an internal and external component. The internal WF refers to the WF within the country itself for making products that are consumed within the country. The external WF of national consumption refers to the WF in other areas for making products that are imported by and consumed within the country (Hoekstra et al., 2011).

A number of WF and VW trade scenario studies are available, some at global level (Fader et al., 2010; Pfister et al., 2011; Hanasaki et al., 2013a, 2013b; Konar et al., 2013; Liu et al., 2013; Ercin and Hoekstra, 2014; Haddeland et al., 2014; Wada and Bierkens, 2014), others focussing on China (Thomas, 2008; Mu and Khan, 2009; Xiong et al., 2010; Dalin et al., 2015; Zhu et al., 2015). Several studies suggest that blue water scarcity in China will increase as a result of a growing blue WF of crop production and a decreasing blue water availability in the course of the 21st century (Mu and Khan, 2009; Xiong et al., 2010; Pfister et al., 2011; Hanasaki et al., 2013a; Hanasaki et al., 2013b; Haddeland et al., 2014; Wada and Bierkens, 2014). However, the scenario analyses generally exclude the potential decrease of consumptive WFs per unit of crop under the combined effect of climate and technological progress. Besides, regarding the consumptive WF of crop production in climate change scenarios, the findings of several studies contradict each other. Zhu et al. (2015) find a significant increased total blue WF for croplands in northwest, southeast and southwest China as a result of climate change under IPCC SRES *B*1, A1B and A2 scenarios by 2046–2065. On the contrary, Liu et al. (2013) find that both blue and total consumptive WFs will decrease in the North China Plain and southern parts of China and increase in the other parts of the country under the IPCC SRES A1FI and B2 scenarios. Thomas (2008) finds a decreased blue WF in north and northwest China by 2030, based on a climate change scenario extrapolated from a regression trend derived from the time series for 1951–1990. Fader et al. (2010) and Zhao et al. (2014) project a decline in consumptive WF per tonne of crops in China as a result of climate change under the IPCC SRES A2 scenario, owing to increased crop yields because of increased CO_2 fertilization. By considering five socio-economic driving factors for 2050, Ercin and Hoekstra (2014) developed four global WF scenarios from both production and consumption perspectives. Under two of the global WF scenarios, China's WF of agricultural production will increase, while it will decrease in the other two WF scenarios. Dalin et al. (2015) assess future VW trade of China related to four major crops and three livestock products by 2030 under socio-economic development scenarios. They find that the VW import of China related to major agricultural products tends to increase given socio-economic growth by 2030. Konar et al. (2013) assess future global VW trade driven by both climate change and socio-economic developments for 2030, and find that China will remain the dominant importer of soybean. But they consider only three crops (rice, wheat and soybean) and neglected changes in crop yield to climate changes. By taking a more comprehensive approach – studying 22 crops (Table 5), looking at production, consumption as well as trade, and considering climate change as well as socio-economic driving factors – the current study aims to achieve a broader understanding of how the different driving forces of change may play out.

2. Method and data

2.1. Scenario set-up

Scenarios are sets of plausible stories, supported with data and simulations, about how the future might unfold from current conditions under alternative human choices (Polasky et al., 2011). In the current study we build on the 5th IPCC Assessment Report (IPCC, 2014), which employs a new generation of scenarios (Moss et al., 2010), including socio-economic narratives named shared socio-economic pathways (SSPs) (O'Neill et al., 2012) and emission scenarios named representative concentration pathways (RCPs) (van Vuuren et al., 2011).

Table 1
Summary of the four scenarios S1–S4 in the current study.

	S1	*S2*	*S3*	*S4*
Shared socio-economic pathway (SSP)	*SSP1*	*SSP2*	*SSP2*	*SSP3*
Population growth	Relatively low	Medium	Medium	Relatively high
Diet	Less meat	Current trend	Current trend	Current trend
Yield increase through technology development	High	Medium	Medium	Low
Representative concentration pathway (RCP)	*RCP 2.6*	*RCP 2.6*	*RCP 8.5*	*RCP 8.5*
Climate outcomes (GCMs)	CanESM2, GFDL-CM3, GISS-E2-R and MPI-ESM-MR			
Harvested crop area (IAM)	IMAGE	IMAGE	MESSAGE	MESSAGE

Table 2
Population projections for China under SSP1 to SSP3.
Source: IIASA (2013).

	2005	2030			2050		
		SSP 1	*SSP 2*	*SSP 3*	*SSP 1*	*SSP 2*	*SSP 3*
Population (million)	1307.59	1359.51	1380.65	1398.88	1224.52	1263.14	1307.47

Five SSPs (SSP1–SSP5) were developed within a two-dimensional space of socio-economic challenges to mitigation and adaptation outcomes (O'Neill et al., 2012) (Fig. 1a). In sustainability scenario SSP1, the world makes relatively good progress towards sustainability: developing countries have relatively low population growth as well as rapid economic growth; increasingly developed technology is put towards environmentally friendly processes including yield-enhancing technologies for land; the consumption level of animal products is low. In middle-of-the-road scenario SSP2, the typical trends of recent decades continue, with a relatively moderate growth in population; most economics are stable with partially functioning and globally connected markets. In fragmentation scenario SSP3, the world is separated into regions characterized by extreme poverty, pockets of moderate wealth and a bulk of countries that struggle to maintain living standards for a strongly growing population, and slow technology development. In inequality scenario SSP4, mitigation challenges are low due to some combination of low reference emissions and/or high latent capacity to mitigate. While challenges to adaptation are high due to relatively low income and low human capital among the poorer population and ineffective institutions. In conventional development scenario SSP5, the world suffers high greenhouse gas emissions and challenges to mitigation from fossil dominated rapid conventional development. While lower socio-environmental challenges to adaptation are due to robust economic growth, highly engineered infrastructure and highly managed ecosystems. From SSP1 to SSP3, socio-economic conditions increasingly pose challenges and difficulties to mitigate and adapt to climate change. In order to cover the full range from the best to the worst possible future conditions of China, we choose to consider the two extreme scenarios SSP1 and SSP3. SSP1 represents a world with relatively low challenges to both climate change mitigation and adaptation, and SSP3 represents a world with relatively large challenges in both respects. In addition, we consider the middle of the road scenario SSP2 with an intermediate level of challenges.

The IPCC distinguishes four RCPs (RCP 2.6, 4.5, 6 and 8.5) based on different radiative forcing levels by 2100 (from 2.6 to 8.5 W/m^2) (van Vuuren et al., 2011). In this study, we consider the two climate change scenarios RCP2.6 (also called RCP 3PD) (van Vuuren et al., 2007) and RCP8.5 (Riahi et al., 2007). RCP2.6 represents pathways below the 10th percentile and RCP8.5 pathways below the 90th percentile of the reference emissions range (Moss et al., 2010). By combining the RCPs and SSPs, a matrix framework was proposed showing that an increased level of mitigation efforts corresponds to a decreased level of climate hazard (Kriegler et al., 2010). For the purpose of our study we constructed two scenarios S1 and S2 by combining climate scenarios forced by RCP2.6 with socio-economic scenarios SSP1 and SSP2, respectively. In addition, we constructed two scenarios S3 and S4 that combine climate outcomes forced by RCP8.5 with SSP2 and SSP3, respectively (Fig. 1b).

Table 4
Two diet scenarios for China.

Consumption per capita in kcal/day per category	2005[a]	2050	
		Current-trend scenario[b]	Less-meat scenario
Cereal	1458	1552 (6.4%)	1709 (17.2%)
Roots	187	149 (−20.6%)	201 (7.6%)
Sugar crops	60	85 (41.7%)	124 (106.7%)
Oil crops	246	288 (17.1%)	265 (7.8%)
Vegetables and fruits	247	205 (−16.9%)	219 (−11.2%)
Other crops	95	66 (−30.4%)	82 (−13.5%)
Animal products	586	612 (4.4%)	372 (−36.5%)
Total	2879	2956 (2.8%)	2973 (3.3%)

[a] Source: FAO (2014);
[b] Values were generated according to the scenarios for East Asia by Erb et al. (2009), with relative changes from 2005 level in brackets.

The assumptions for the four scenarios S1–S4 are summarised in Table 1. The five driving factors of change considered in this study have been quantified per scenario as will be discussed below.

2.2. Population

The SSPs of the IPCC consist of quantitative projections of population growth as given by IIASA (2013) (Table 2).

2.3. Climate

Climate change projections by four Global Climate Models (GCMs) within the Coupled Model Intercomparison Project (CMIP5) (Taylor et al., 2012) were used: CanESM2 (Canadian Centre for Climate Modelling and Analysis), GFDL-CM3 (NOAA Geophysical Fluid Dynamics Laboratory), GISS-E2-R (NASA Goddard Institute for Space Studies), and MPI-ESM-MR (Max Planck Institute for Meteorology). The models were selected from nineteen GCMs in such a way that the outcomes of the selected GCMs span the full range of projections for China on precipitation (mm) for spring and summer (March to July), when most crops grow. The projections by CanESM2 and GFDL-CM3 represent relatively wet conditions and the projections by GISS-E2-R and MPI-ESM-MR relatively dry conditions (Table 3).

Table 3
Projected changes in national average precipitation (PR), maximum temperature (T_{max}), minimum temperature (T_{min}), reference evapotranspiration (ET_0) and CO_2 concentration in China for the four selected GCMs for RCP2.6 and RCP8.5 by the years 2030 and 2050 compared to 2005.

Changes in climate variables	*RCP2.6*				*RCP8.5*			
	CanESM2	GFDL-CM3	GISS-E2-R	MPI-ESM-MR	CanESM2	GFDL-CM3	GISS-E2-R	MPI-ESM-MR
Year: 2030								
Relative changes in annual PR	15%	12%	1%	4%	16%	8%	2%	7%
Increase in T_{max} (°C)	1.9	2.4	0.9	1.2	2.2	2.6	1.4	1.6
Increase in T_{min} (°C)	1.7	2.0	0.5	0.9	2.1	2.2	1.1	1.4
Relative changes in annual ET_0	3%	5%	2%	2%	3%	5%	3%	2%
Relative changes in CO_2 concentration	13%				18%			
Year: 2050								
Relative changes in annual PR	19%	20%	3%	5%	24%	20%	6%	7%
Increase in T_{max} (°C)	2.2	3.1	0.9	1.3	3.5	4.3	2.2	2.7
Increase in T_{min} (°C)	2.1	2.5	0.5	1.0	3.5	3.7	1.8	2.6
Relative changes in annual ET_0	3%	8%	2%	2%	6%	11%	5%	5%
Relative changes in CO_2 concentration	17%				42%			

2.4. Harvested crop area

We use the harmonized land use (HLU) scenarios provided at a resolution of 30 by 30 arc min from Hurtt et al., 2011. We downscale the original data to a 5 by 5 arc min resolution. The changes in cropland area, provided as a fraction of each grid cell, were obtained from the IMAGE model (van Vuuren et al., 2007) for the RCP2.6 pathway and the MESSAGE model (Rao and Riahi, 2006; Riahi et al., 2007) for the

Table 5
Relative changes in the green, blue and total consumptive water footprint ($m^3\ t^{-1}$) of the 22 considered crops in China across scenarios, compared to the baseline year 2005.

Crop		Baseline 2005		Relative changes in consumptive WF per tonne of crops compared to baseline level (%)							
				2030				2050			
		Consumptive WF ($m^3\ t^{-1}$)	Yield ($t\ ha^{-1}$)	S1	S2	S3	S4	S1	S2	S3	S4
Wheat	Green	nnnnnnnnnnnnk990	4.28	−20	−12	−18	−9	−31	−21	−35	−23
	Blue	713		−31	−24	−23	−15	−43	−34	−44	−33
	Total	1703		−25	−17	−20	−11	−36	−27	−38	−27
Rice	Green	948	6.26	−33	−26	−28	−20	−44	−36	−42	−31
	Blue	280		−38	−32	−30	−22	−48	−40	−44	−33
	Total	1229		−34	−27	−28	−20	−45	−37	−42	−31
Maize	Green	736	5.29	−37	−30	−4	6	−49	−42	−17	−2
	Blue	161		−45	−40	−35	−28	−57	−51	−46	−36
	Total	898		−38	−32	−10	0	−51	−43	−22	−8
Sorghum	Green	914	4.47	−34	−28	−22	−14	−44	−36	−32	−19
	Blue	58		−18	−10	−12	−2	−33	−24	−25	−11
	Total	972		−33	−27	−22	−13	−43	−35	−32	−19
Millet	Green	1374	2.10	−43	−37	−41	−34	−52	−46	−50	−41
	Blue	47		−37	−30	−37	−30	−50	−43	−50	−41
	Total	1422		−42	−37	−41	−34	−52	−45	−50	−41
Barley	Green	727	4.14	−9	0	−21	−13	−25	−15	−39	−27
	Blue	60		−34	−28	−35	−28	−46	−39	−52	−43
	Total	787		−11	−2	−22	−14	−27	−16	−40	−28
Soybean	Green	2517	1.71	−33	−26	−28	−21	−45	−37	−42	−32
	Blue	142		−47	−41	−35	−28	−60	−54	−50	−40
	Total	2659		−33	−27	−29	−21	−46	−38	−43	−32
Sweet potato	Green	236	22.18	7	17	−26	−18	−9	3	−41	−30
	Blue	11		−31	−24	−34	−26	−42	−34	−52	−43
	Total	247		5	15	−27	−19	−11	2	−42	−31
Potato	Green	192	14.52	29	42	−19	−10	−13	−1	−36	−24
	Blue	7		−27	−20	−27	−19	−44	−35	−46	−35
	Total	199		27	40	−19	−11	−14	−2	−36	−24
Cotton	Green	1404	3.92	−26	−18	−28	−20	−38	−29	−43	−32
	Blue	244		−20	−12	−28	−20	−36	−27	−46	−36
	Total	1648		−25	−17	−28	−20	−37	−28	−43	−33
Sugar cane	Green	120	63.97	47	62	−15	−6	−6	7	−27	−13
	Blue	1		12	23	−45	−39	−9	4	−57	−49
	Total	121		47	61	−15	−6	−6	7	−27	−14
Sugar beet	Green	100	37.51	−66	−62	−67	−63	−72	−68	−73	−68
	Blue	0		13	24	−69	−66	−10	3	−75	−70
	Total	100		−66	−62	−67	−63	−72	−68	−73	−68
Groundnut	Green	1616	3.08	−16	−8	−25	−17	−33	−23	−41	−30
	Blue	133		−25	−17	−26	−18	−41	−32	−46	−36
	Total	1749		−17	−9	−25	−17	−34	−24	−41	−31
Sunflower	Green	896	1.89	−46	−41	−39	−32	−55	−49	−52	−43
	Blue	79		−38	−32	−38	−31	−51	−43	−53	−44
	Total	976		−46	−40	−39	−32	−55	−49	−52	−43
Rape seed	Green	1416	1.79	3	13	−13	−4	−9	4	−31	−19
	Total	1416		3	13	−13	−4	−9	4	−31	−19
Tomato	Green	66	35.00	40	54	−3	8	49	71	−19	−4
	Blue	1		−21	−14	−42	−36	−26	−16	−62	−55
	Total	67		39	53	−4	7	48	69	−20	−5
Cabbage	Green	129	33.68	−20	−13	−26	−18	−30	−20	−41	−29
	Blue	7		−38	−32	−32	−25	−75	−71	−44	−33
	Total	135		−21	−14	−26	−18	−32	−23	−41	−30
Spinach	Green	96	19.35	−36	−29	−39	−33	−43	−35	−41	−30
	Blue	24		−47	−42	−43	−37	−56	−50	−58	−51
	Total	120		−38	−32	−40	−33	−46	−38	−44	−34
Grape	Green	346	14.19	−31	−24	−29	−21	−42	−33	−43	−33
	Blue	134		−29	−22	−24	−16	−42	−33	−41	−30
	Total	479		−30	−23	−28	−20	−42	−33	−43	−32
Apple	Green	374	12.70	−31	−24	−33	−26	−41	−32	−48	−38
	Blue	27		−46	−40	−43	−37	−55	−49	−59	−52
	Total	401		−32	−25	−34	−27	−42	−34	−49	−39
Tea	Green	9178	0.89	−27	−20	−24	−16	−42	−34	−34	−21
	Blue	142		−51	−46	−52	−46	−65	−60	−57	−49
	Total	9320		−27	−20	−25	−17	−42	−34	−34	−22
Tobacco	Green	1831	1.97	−34	−27	−28	−20	−45	−37	−42	−31
	Blue	53		−39	−32	−31	−23	−53	−47	−48	−38
	Total	1884		−34	−27	−28	−20	−45	−37	−42	−31

RCP8.5 pathway. We apply the projected relative changes in the cropland area per crop and grid cell to the current cropland area per crop and grid cell as provided by Portmann et al. (2010) and Monfreda et al. (2008). The total harvested crop area for the selected crops in China was 124.9 million ha in the baseline year 2005, and is projected to increase by 19% from 2005 to 2050 in RCP2.6 and by 4% in RCP8.5, on the expense of forest and pasture land uses (Hurtt et al., 2011).

2.5. Crop yield increase through technology development

According to a recent global yield gaps analysis for major crops (Mueller et al., 2012), it is possible to increase yields by 45%-70% for most crops. For China's case, studies are available only for wheat, maize and rice. Meng et al. (2013) reported that experimental attainable maize yield was 56% higher than the average farmers' yield (7.9 t ha^{-1}) in China for 2007–2008. Lu and Fan (2013) found that the yield gap for winter wheat is 47% of the actual yield in the North China Plain. Zhang et al. (2014) estimated that the national average yield gap for rice is 26% of the actual yield. With limited land and water resources available to expand the acreage of croplands, the only way to enlarge production is by yield increase (Huang et al., 2002). In a scenario analysis on potential global yield increases, De Fraiture et al. (2007) conclude that yield growth can reach 20–72% for rain-fed cereals and 30–77% for irrigated cereals as compared to the year 2000. Due to a lack of quantitative data on crop yield growth under each SSP, we took the values from De Fraiture et al. (2007) as a starting point by assuming a yield increase of 72% from 2000 to 2050 in SSP1, 46% in SSP2, and 20% in SSP3. Assuming a linear increase in the crop yield over time, corresponding yield increases over the period 2005–2030 are 34% in SSP1, 22% in SSP2, and 10% in SSP3, and corresponding yield increases over the period 2005–2050 are 60% in SSP1, 40% in SSP2, and 18% in SSP3.

2.6. Diet

We make use of the two diet scenarios for East Asia for 2050 by Erb et al. (2009). We assume the less-meat scenario for SSP1 and the current-trend scenario for SSP2 and SSP3. We assume that the conversion factor from the kilocalorie intake to kilogram consumption of each type of crop per capita remains constant over the years. As shown in Table 4, the share of animal products in the Chinese diet will decrease by 37% in the less-meat scenario and increase by 4.4% in the current-trend scenario, compared to baseline year 2005.

2.7. Estimating water footprints and virtual water trade

Following Hoekstra et al. (2011), green and blue WFs of producing a crop ($m^3 t^{-1}$) are calculated by dividing the total green and blue evapotranspiration (ET, $m^3 ha^{-1}$) over the crop growing period, respectively, by the crop yield (Y, t ha^{-1}). Daily ET and Y were simulated, at a resolution level of 5 by 5 arc min, with the FAO crop water productivity model AquaCrop (Hsiao et al., 2009; Raes et al., 2009; Steduto et al., 2009). Following Zhuo et al. (2016a), the daily green and blue ET were derived based on the relative contribution of precipitation and irrigation to the daily green and blue soil water balance of the root zone, respectively. In AquaCrop, the daily crop transpiration (Tr, mm) is used to derive the daily gain in above-ground biomass (B) via the normalized biomass water productivity of the crop, which is normalized for the CO_2 concentration of the bulk atmosphere, the evaporative demand of the atmosphere (ET_0) and crop classes. The harvestable portion (the crop yield) of B at the end of the growing period is determined as product of B and the harvest index. Harvest index is adjusted to water stress depending on the timing and extent of the stress (Hsiao et al., 2009; Raes et al., 2009; Steduto et al., 2009). Therefore, changes of crop yield to climate changes were simulated through AquaCrop modelling by taking consideration of effects of changes in precipitation, ET_0 and CO_2 concentration. We considered multi-cropping of rice (i.e. twice a year in southern China) and assumed single cropping for other crops. The simulated Y of each crop for the baseline year was scaled to match provincial statistics (NBSC, 2013). The projected Y under climate scenarios was obtained by multiplying the scaled baseline Y by the ratio of the simulated future Y to the simulated baseline Y, corrected for the assumed Y increases per scenario.

The water footprint of food consumption ($WF_{cons,\ food}$, $m^3 y^{-1}$) includes the WF related to the consumption of crops and crop products as well as the WF related to the consumption of animal products. The WF related to crop consumption ($m^3 y^{-1}$) under each scenario was obtained, per crop, by multiplying the crop consumption volume ($C_{crop,\ food}$, t y^{-1}) by the WF per tonne of the crop ($WF_{cons,\ unit\ crop}$, $m^3 t^{-1}$). The WF related to the consumption of animal products ($m^3 y^{-1}$) was estimated by multiplying total animal products consumption ($C_{animal,\ food}$, kcal y^{-1}) by the WF per kilocalorie of animal products ($WF_{cons,\ unit\ animal}$, m^3 $kcal^{-1}$).

$C_{crop,\ food}$ was calculated, per crop, as the crop consumption per capita (in kg $cap^{-1} y^{-1}$) times the projected population (Table 2). We consider the seed and waste as part of the food consumption. The fraction of seed and waste in the crop consumption is assumed to be constant in the coming decades and calculated as the ratio of total waste

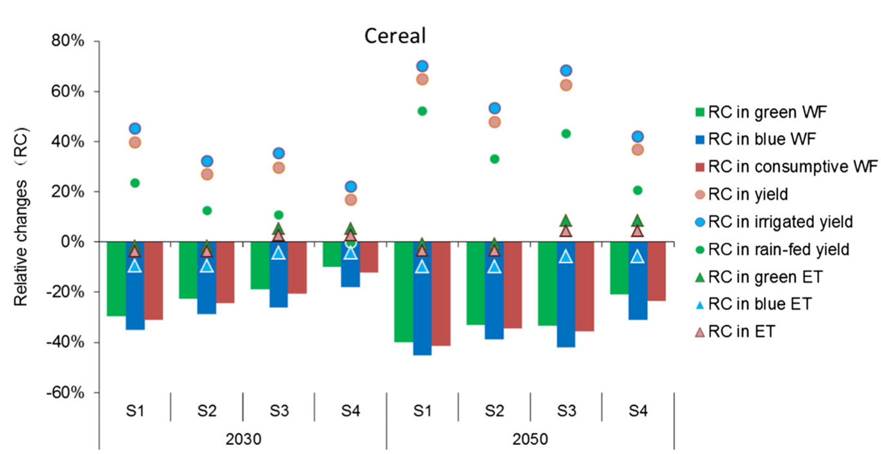
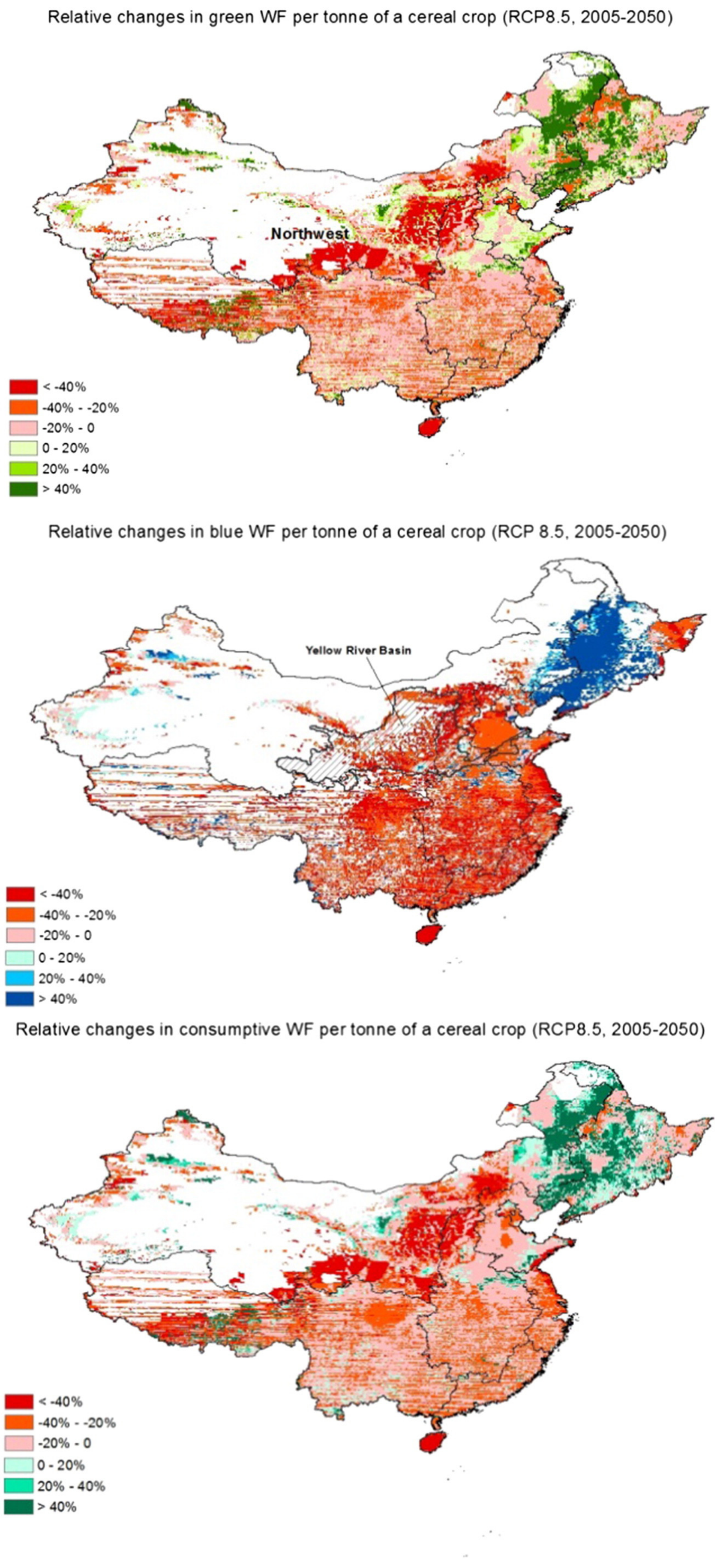


Fig. 2. Relative changes (RC) in water footprint (WF) per tonne of a cereal crop, cereal yield and average ET at cereal croplands in China across scenarios as compared to the baseline year 2005.


Relative changes in green WF per tonne of a cereal crop (RCP8.5, 2005-2050)
Northwest
< -40%
-40% - -20%
-20% - 0
0 - 20%
20% - 40%
> 40%
Relative changes in blue WF per tonne of a cereal crop (RCP 8.5, 2005-2050)
Yellow River Basin
< -40%
-40% - -20%
-20% - 0
0 - 20%
20% - 40%
> 40%
Relative changes in consumptive WF per tonne of a cereal crop (RCP8.5, 2005-2050)
< -40%
-40% - -20%
-20% - 0
0 - 20%
20% - 40%
> 40%

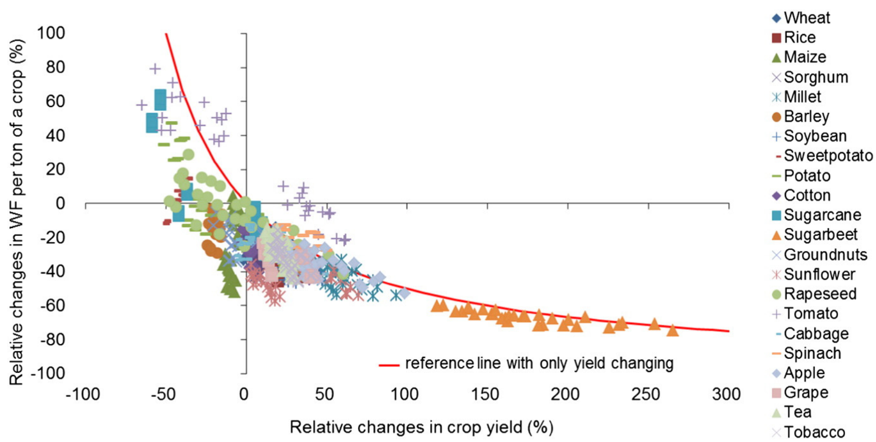


Fig. 4. Relationship between relative changes in crop yields and relative changes in corresponding water footprint per tonne of crop. One dot refers to the projection for one crop under one GCM for one scenario for one year.

and seed to the total crop use in the baseline year (FAO, 2014). $WF_{cons,\ unit\ crop}$ was calculated, per crop, as:

$$WF_{cons,unitcrop} = \frac{P_{crop} \times WF_{prod} + I_{crop} \times WFi_{prod}}{P_{crop} + I_{crop}} \quad (1)$$

where P_{crop} ($t\ y^{-1}$) is the total national production of the crop, I_{crop} ($t\ y^{-1}$) the total import of the crop from outside the country; WF_{prod} ($m^3\ t^{-1}$) the water footprint of the crop produced domestically, and WFi_{prod} ($m^3\ t^{-1}$) the water footprint of the imported crop, taken as the global average WF of the crop as reported by Mekonnen and Hoekstra (2011). Here the possible changes in global average WF of crops to global changes under each scenario were not considered. Under each scenario, I_{crop} equals to the sum of the crop consumption for food ($C_{crop,\ food}$) and the crop consumption for feed ($C_{crop,\ feed}$, $t\ y^{-1}$) minus the national production of the crop (P_{crop}). A negative value for I_{crop} means export. The crop import I_{crop} multiplied with WFi_{prod} refers to the net VW import related to trade in the crop ($m^3\ y^{-1}$).

$C_{crop,\ feed}$ changes with animal products consumption, which is driven by population growth, personal income growth and diet changes (Rosegrant et al., 1999; Du et al., 2004; Bouwman et al., 2005; Keyzer et al., 2005; Liu and Savenije, 2008; Trostle, 2008; Nonhebel and Kastner, 2011; Shiferaw et al., 2011; Hoekstra and Mekonnen, 2012; Hoekstra and Wiedmann, 2014). Here we assume that the relative change in $C_{crop,\ feed}$ under each scenario is the same as the relative changes in the total consumption of animal products, which is driven by corresponding diet changes (Table 4) and population growth. $C_{crop,\ feed}$ in China for the baseline year 2005 was obtained from FAO (2014).

Values for $WF_{cons,\ unit\ animal}$ in China in the baseline year were obtained from Hoekstra and Mekonnen (2012). The WF of animal feed contributes 98% to the WF of animal products (Mekonnen and Hoekstra, 2012). Animal productivity (i.e. animal production output per unit mass of feed) ($\Delta_{productivity}$, %) was assumed to grow in the future as a result of higher offtake rates and higher carcass weights or milk or egg yields (Bruinsma, 2003). We use the projections on $\Delta_{productivity}$ for the various types of animal products by Bouwman et al. (2005) for East Asia from 1995 to 2030, assuming a linear increase. We took a weighted average based on production of each type of animal product in the baseline year (NBSC, 2013), which implies an animal productivity increase of 4% by 2030 and 8% by 2050 compared to the baseline year 2005. Therefore, in each scenario, $WF_{cons,\ unit\ animal}$ was estimated by considering relative changes in the WF of animal feed (ΔWF_{feed}, %) and $\Delta_{productivity}$:

$$WF_{cons,unitanimal} = \frac{WF_{cons,unitanimal[2005]} \times (1 + \Delta WF_{feed})}{(1 + \Delta_{productivity})}. \quad (2)$$

ΔWF_{feed} was calculated as a weighted average of changes in the WF of feed crops ($\Delta WF_{feed\ crops}$, %) and changes in the WF of other feed ingredients (i.e. pasture, crop residues and other roughages) ($\Delta WF_{feed\ other}$, %), given their corresponding shares in the total WF of animal feed in China ($pct_{feed\ crops}$ and $pct_{feed\ other}$, %):

$$\Delta WF_{feed} = \Delta WF_{feedcrops} \times pct_{feedcrops} + \Delta WF_{feedother} \times pct_{feedother}. \quad (3)$$

We assume that the composition of the animal feed in China stays constant. Currently, the 13 selected crops from 22 considered crops (wheat, maize, rice, barley, millet, sorghum, potato, sweet potato, sugar cane, sugar beet, soybean, sunflower seed and rape seed) account for 75% of the total feed crop consumption in quantity (FAO, 2014) and contribute 70% and 86% to the green and blue WFs of feed crops consumed in China, respectively (Hoekstra and Mekonnen, 2012). For the selected crops we account changes in WF by yield increase for each crop under each scenario. For the feed crops that are not included in the current study, the $\Delta WF_{feed\ other}$ was assumed in line with the average level of assessed crop yield increase under each scenario. The values of $pct_{feed\ crops}$ and $pct_{feed\ others}$ for green and blue WFs were obtained from Mekonnen and Hoekstra (2012).

China's international virtual water trade was estimated per crop by considering the difference between the WF of crop production and the WF of crop consumption (in the form of food, feed, seed or waste) within China.

2.8. Data

The GIS polygon data for China were obtained from NASMG (2010). Climate data for baseline year 2005 on monthly precipitation (PR), reference evapotranspiration (ET_0), maximum temperature (T_{max}) and minimum temperature (T_{min}) at a resolution of 30 by 30 arc min were taken from Harris et al. (2014). The downscaled GCM outputs at 5 by 5 arc min grid level for China on monthly PR, T_{max} and T_{min} were obtained from Ramirez-Villegas and Jarvis (2010). Since this dataset does not include data on ET_0, we calculated monthly ET_0 with inputs on temperature through the Penman-Monteith method introduced in Allen et al. (1998) for the baseline year 2005 and each climate scenario. Then the monthly ET_0 under each climate scenario was corrected by adding the

Fig. 3. Changes in green, blue and overall consumptive water footprint (WF) per tonne of cereal crop in China over the period 2005–2050 under RCP8.5.

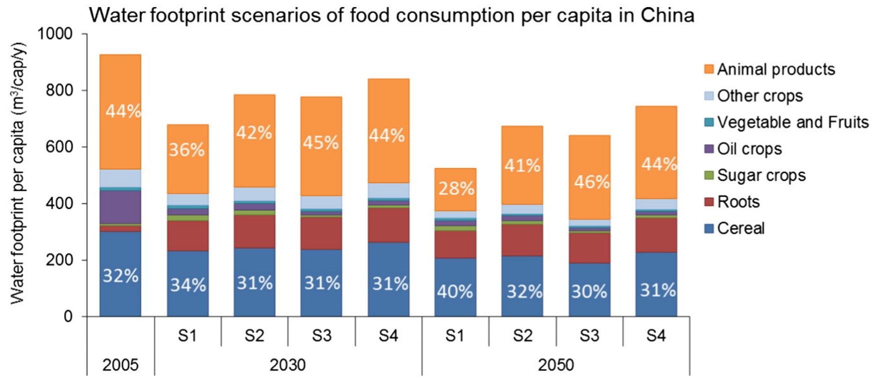


Fig. 5. Water footprint of food consumption per capita under the four scenarios of China.

absolute changes in the calculated ET_0 from 2005 to the values of 2005 in CRU-TS database. The projected CO_2 concentrations (in ppm) under the two RCPs were obtained from IIASA (2009). Data on irrigated and rain-fed areas for each crop at 5 by 5 arc min resolution were obtained from the MIRCA2000 dataset (Portmann et al., 2010). For crops not available in this database, we used the 5 by 5 arc min crop area map by Monfreda et al. (2008). Crop yield statistics at province level for the baseline year were taken from NBSC (2013). For crops not reported in NBSC (2013), we used national average values from FAOSTAT (FAO, 2014). Soil texture data were obtained from the ISRIC Soil and Terrain database for China (Dijkshoorn et al., 2008). Data on total soil water capacity (in % vol) at a spatial resolution of 5 by 5 arc min were obtained from the ISRIC-WISE version1.2 dataset (Batjes, 2012).

3. Results

3.1. Water footprint of crop production

For most of the crops studied, consumptive WFs per tonne of crop were projected to decrease across all scenarios, as shown in Table 5. Taking cereal crops (wheat, rice, maize, sorghum, millet and barley) as an example, compared to the baseline year 2005, the consumptive WF per tonne of cereal crops reduced by 41%, 35%, 36% and 24% till 2050 under S1, S2, S3 and S4, respectively, averaged across the four GCMs. From Fig. 2 we can see that the reductions in the WFs of cereal crops were mainly driven by significant increases in crop yields, which have larger impact than the relatively small changes in ET under each scenario. The effects of climate change on WF of crops can be observed by comparing scenarios S2 and S3 under the same SSP and different RCPs. Positive effects on crop yields by increased CO_2 fertilization have been widely reported (Yao et al., 2007; Tao and Zhang, 2011; Wada et al., 2013; Zhao et al., 2014), which is also shown in the current result. With relatively small differences in ET_0 and precipitation for RCP 2.6 and RCP8.5 (see Table 3), scenario S3 for RCP8.5 with significant higher CO_2 concentration had higher cereal yields than scenario S2 for RCP 2.6 (Fig. 2). The effect of the application of better technology on the WF can be observed by comparing S1 versus S2 (both RCP2.6) and S3 versus S4 (both RCP8.5). The scenarios with a higher level of technology development (S1 and S3) have a higher yield increase and a lower WF per tonne of crop. The increase in irrigated cereal yields is around 20% higher than the increase in rain-fed cereal yields under each scenario, which reflects the limits on yield increases by water stress on rain-fed fields. The reduction of the blue WF per tonne of cereal crop is higher than for the green WF under each scenario. This is because of the decrease in irrigation requirements and thus in blue ET as a result of projected increases in precipitation across the GCM scenarios for both RCP2.6 and RCP 8.5. The relative changes in the national average yield for the selected crops under the four scenarios from 2005 to 2050 are listed in Appendix C.

Fig. 3 shows maps of multi-GCM averaged projected changes in green, blue and total consumptive WF per tonne of cereal crop over the period 2005–2050 under RCP8.5. Under this RCP, the national average green, blue and total consumptive WFs of cereal crops are projected to decrease by 7%, 19% and 10%, respectively. Reductions in both green and blue WFs of cereal crops larger than 40% were mostly located in Northwest China, which includes the upper and middle reaches of the severely water stressed Yellow River Basin, due to the projected increases in annual precipitation by more than 60% across GCM scenarios (see Appendix A). The projected wetter climate in the Northwest helps to reduce the water stress on rain-fed fields and the resulted yield loss. In most areas in the Northeast, the green and blue WF per tonne of crops was projected to increase by more than 40% as a result of the projected increase in ET_0 and decrease in precipitation in the Northeast across the GCM scenarios (Appendices A and B).

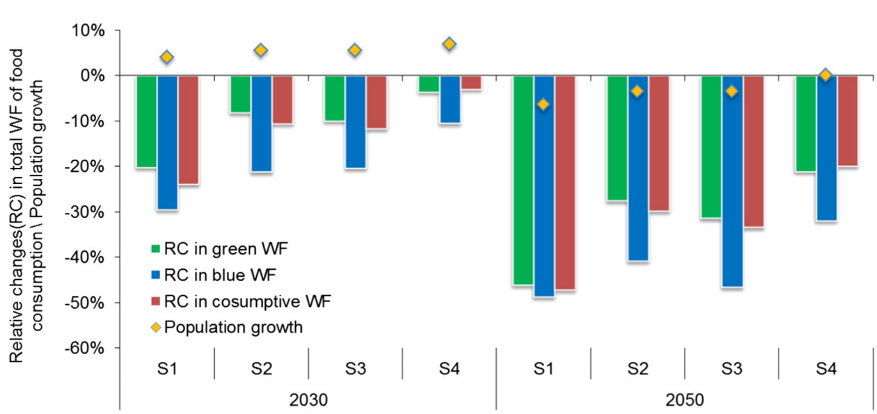


Fig. 6. Changes in China's green, blue and total consumptive water footprint of food consumption across scenarios, as compared to the baseline year 2005. The green, blue and overall consumptive water footprints in 2005 are 1030, 183, and 1212 billion m^3 y^{-1}, respectively.

In Fig. 4 we plotted the relative changes in WF per tonne of the crops studied against the corresponding relative changes in crop yield under each scenario. A reference line indicates the relative changes in WFs when only yields change (thus without the effect of changing ET on WFs). The vertical deviation of the dots from the line shows the impact of changing ET on WFs. The dots below the line, which is the majority, show the positive impact of reduced ET on reducing the WF per unit mass of crops.

Over the period 2005–2050, the total national consumptive WF (in $m^3\ y^{-1}$) of crop production increases by 18% under RCP2.6 (S1 and S2), and by 0.8% under RCP8.5 (S3 and S4), as a result of the combined effect of climate change and projected changes in harvested crop area. The impact of projected changes in harvested crop area under each RCP (19% increase from 2005 to 2050 under RCP2.6 and 4% decrease under RCP8.5) on the total WF was significant, because average ET per hectare over croplands increases by only 3.1% from 2005 to 2050 for RCP2.6 and by 5.6% for RCP8.5. The total green WF of crop production increases under both RCPs (by 21% from 2005 to 2050 under RCP2.6 and by 4% under RCP8.5). The total blue WF increases under RCP2.6 (by 4.3% to 2050) and decreases under RCP8.5 (by 10% to 2050).

3.2. Water footprint of food consumption

The water footprint of food consumption per capita in China decreases across all scenarios as compared to the baseline year (927 $m^3\ cap^{-1}\ y^{-1}$), driven by the decreased WF per tonne of most crops. The largest decrease in the WF of food consumption per capita (by 44% to 2050) is observed under scenario S1 (Fig. 5). This large decrease is due to the less-meat diet combined with the largest decrease in consumptive WF per unit of crops and animal products. S4 shows the most modest decrease in the WF of food consumption per capita (20% to 2050), which is due to diet type (current-trend diet) and a relatively low reduction level in the WFs per unit of crop and animal product compared to the other scenarios. In "current trend" diet scenarios (*S2-S4*), animal product consumption was the largest contributor (~41–46%) to WF of food consumption followed by cereal consumption (~31–32%) and oil crop consumption (~14–18%). In the "less meat" scenario (*S1*), the WF of animal product consumption decreased significantly (by 65% from 2005 to 2050) and became the second largest contributor, after cereal consumption, to total WF of Chinese food consumption. This reduction was driven by decreases in both animal product consumption (by 37% to 2050) and WF per unit calorie of animal products (by 43% to 2050).

The total national consumptive WF of food consumption is projected to decrease across all scenarios, compared to the baseline level of 2005 (1212 billion $m^3\ y^{-1}$) (Fig. 6). Even under an increased population by 2030, we observe a decrease in the total WF of consumption. The main reason for this decrease is the decrease in WF per unit of consumed crop and animal products, and the fact that the population increase to 2030 remains modest. The more significant decrease by 2050 is a combination of the projected declining population and the further decrease in WFs per unit of crops and animal products. In S1, with the smallest population size and the largest decrease in WF per capita, the total WF of food consumption drops most, decreasing on average by 24% and 47% by 2030 and 2050, respectively. With the current-trend diet, the smaller decrease in the WF of food consumption in S4 compared to S2 and S3 results from the relatively large size of the population and the relatively high WFs per unit of crops and animal products.

The reductions in blue WFs are higher than those in green WFs across all scenarios, in line with the higher reductions in the blue WFs per unit of production, which result from climate change and yield improvements through technology. The reduction in the green WF of food consumption in S1 is higher than in the other scenarios, as a result of larger share of roots and sugar crops in the diet and the low fraction of blue WF in the total consumptive WF per unit for roots and sugar crops (~2–3% for root crops and ~0–8% for sugar crops).

Table 6
Net virtual water import of China related to trade in considered crops, for the baseline year 2005 and for 2030 and 2050 in the four scenarios.

Net virtual water import ($10^9\ m^3\ y^{-1}$)	2005	2030				2050			
		S1	S2	S3	S4	S1	S2	S3	S4
Green water	82	−133	−70	−3	65	−267	−192	−139	−40
Blue water	14	−39	−26	−9	9	−71	−59	−48	−23
Total	97	−172	−96	−12	73	−338	−250	−187	−62

3.3. National virtual water trade related to crop products

While in the baseline year 2005 China was a net virtual water importer (with respect to trade in the crops considered in this study), the country will have become net virtual water exporter by 2050, in all scenarios. In scenarios S1–S3 this is already the case in 2030. The potential reversal of China's role in the global VW trade network was also reported by Ercin and Hoekstra (2014), but contradicts the projected increase in net VW import of major agricultural products by Dalin et al. (2015). However, the result of Dalin et al. (2015) was based on a totally different scenario, with decreasing irrigation area and reduced exports of crops. The current result shows an enhanced self-sufficiency in food supply and a potential contribution to the global VW trade network as an exporter. Table 6 presents the multi-GCM averaged net VW import related to crop trade across scenarios. The VW export of China under S1 is larger than in the other scenarios, with the net VW export as high as 38% of the total consumptive WF of crop production. This is the result of the relatively high increase in crop production, by the relatively high crop yield and expansion of harvested crop area, and smaller crop consumption due to the projected population decrease and less-meat diet. In S4, China is still a net VW importer by 2030, due to the VW import related to the large soybean import, which is larger than the total VW export through all exported crops.

Fig. 7 shows the multi-GCM averaged net VW import of China related to different crops under the four scenarios. China's shift from net VW importer to net VW exporter occurs most in particular through the projected export of rice and wheat. In the baseline year, export of maize contributes most to China's virtual water export, responsible for 86% of the crop-related VW exports of China. In the future, rice export is expected to become the biggest contributor to China's virtual water export, accounting for 38% of total VW export in 2050 in S1, 42% in S2, 33% in S3, and 32% in S4. In S1, the net VW export related to rice export even becomes 53% of the total WF of rice production in China by 2050. China will remain a big VW importer related to soybean in all scenarios.

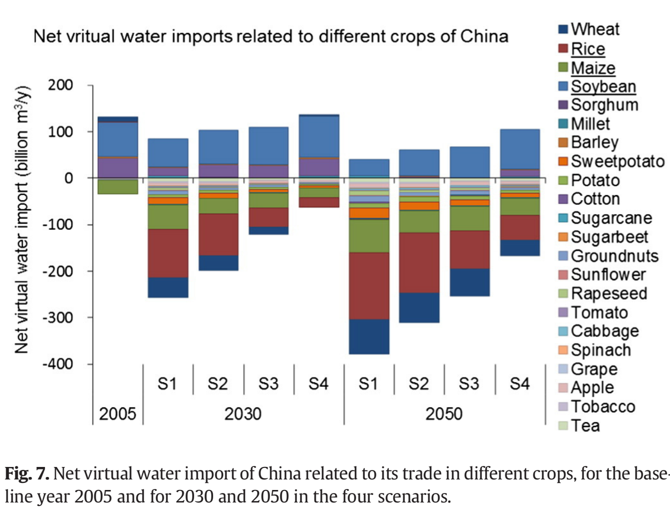


Fig. 7. Net virtual water import of China related to its trade in different crops, for the baseline year 2005 and for 2030 and 2050 in the four scenarios.

Table 7
Fraction of the external water footprint (WF) in the total water footprint of Chinese crop consumption, in the baseline year and in 2030 and 2050 under the four scenarios.

Fraction of external WF in total WF of crop consumption	2005	2030				2050			
		S1	S2	S3	S4	S1	S2	S3	S4
Green WF	17%	10%	12%	15%	17%	5%	8%	10%	14%
Blue WF	11%	6%	7%	8%	11%	1%	2%	1%	6%
Consumptive WF	15%	9%	11%	13%	16%	5%	7%	9%	13%

According to Konar et al. (2013), China could become world's largest VW importer through soybean trade in the future. In the baseline year, 61% of Chinese soybean consumption depends on import. By 2050, the projected dependency on soybean imports is 24%, 37%, 45% and 55% in S1, S2, S3 and S4, respectively.

The fraction of the external WF in the total WF of crop consumption decreases in all scenarios, most in S1 and least in S4 (Table 7).

3.4. Discussion

In Table 8 we compare the current results with the results from earlier studies where possible. The relative changes in WF per tonne of wheat and maize in China in the current study are in the same direction but much larger than the global average values as suggested by (Fader et al., 2010). The differences in magnitude originate from the different geographic scopes of the studies, but also from the fact that different climate scenarios and crop models are used. The relative changes in total blue WF at the current irrigated cropland in China from the current study, which considers the impacts of both changing precipitation and ET_0, are smaller than the estimates for Asia provided by Pfister et al. (2011), who considers the impact of changing precipitation only. The changes in WF of crop production in China found in the current study are much smaller than the figures presented by Ercin and Hoekstra (2014). The decrease in total WF of food consumption in scenario S1 in the current study is greater than the decrease in scenarios S3 and S4 in Ercin and Hoekstra (2014), which are based on the same less-meat diet scenario, but exclude the effect of reduced WFs per unit of food products by climate change that has been included in the current study. The relative changes in VW import related to soybean for S3 in the current study agree best with the result for the low-yield scenario in Konar et al. (2013).

Currently, four billion people live under severe blue water scarcity for at least for one month a year, and 0.9 billion of the four billion live in China (Mekonnen and Hoekstra, 2016). We added the current results on relative changes in national blue WF ($m^3\ y^{-1}$) of crop production in China under each scenario to the context of current China's total water blue WF and compare to the current maximum sustainable blue WF (Mekonnen and Hoekstra, 2016). In scenarios S1and S2 under RCP2.6, the increase of 5% in total blue WF from 2005 to 2050 of crop production will slightly increase current blue water scarcity of China as a whole from 0.49 (low blue water scarcity) (Mekonnen and Hoekstra, 2016) to 0.51 (moderate blue water scarcity). The projected decrease of 9% in total blue WF of China's crop production in S3 and S4 under RCP8.5 will reduce the current blue water scarcity accordingly to 0.45. There have been studies on changes in blue water availability in China to future climate changes (Hanasaki et al., 2013b; Elliott et al., 2014; Santini and di Paola, 2015). The finding on significant decrease in blue water availability in the Yellow River Basin of more than 40% from 2005 to 2050 under RCP 8.5 was unified across these studies. According to the current study, even though the total blue WF of crop production in the Yellow River Basin will decrease by 11% under RCP 8.5 (S3 and S4), the basin could still suffer increasing blue water scarcity from the possible declining runoff. While for other parts of China, the current level of blue water scarcity (Mekonnen and Hoekstra, 2016) will not change significantly for considered scenarios from 2005 to 2050, given the projected slight increase (~10%) in blue water availability (Hanasaki et al., 2013b; Elliott et al., 2014; Santini and di Paola, 2015) and current projected slight increase (~4%) in total blue WF of crop production under RCP2.6 and decreases (~10%) under RCP8.5.

The current study has a number of limitations with regard to assumptions in modelling the WF of crops. First, we assumed a constant cropping calendar (planting date and length of cropping period) for each crop considered, which neglects the potential impact of temperature changes on the crop growing period as reported in previous studies (Yao et al., 2007; Hatfield et al., 2011; Tao and Zhang, 2011). Second, we assumed constant initial soil water content at each grid among different scenarios. Third, we assumed a constant irrigated ratio for each grid cell because of lack of quantitative information in the harmonized land use projections that we used (Hurtt et al., 2011), which may cause over- or

Table 8
Comparison between the current results and previous studies.

Reference	Year	Study case	Scenario	Changes in consumptive WF per tonne of consumed crops (%)
Fader et al. (2010)	2041–70	Global wheat	SRES A2	−0.43/−0.45
		Global maize		−0.35/−0.44
Current study	2005–2050	China wheat	RCP 2.6	−27/−36
			RCP 8.5	−26/−39
		China maize	RCP 2.6	−44/−50
			RCP 8.5	−7/−23
	Year	Study case	Scenario	Changes in total blue WF at current irrigated area (%)
Pfister et al. (2011)	2000–2050	Asia	SRES A1B	−11
Current study	2005–2050	China	RCP 2.6	−8
			RCP 8.5	−2
	Year	Study case	Scenario	Changes in total consumptive WF for crop production (%)
Ercin and Hoekstra (2014)	2000–2050	China	“S1/S2/S3/S4” based on IPCC AR4	89/127/−22/−22
Current study	2005–2050		“S1/S2/S3/S4” based on IPCC AR5	17/17/0.8/0.8
	Year	Study case	Scenario	Changes in total consumptive WF for crop consumption (%)
Ercin and Hoekstra (2014)	2000–2050	China	“S1/S2/S3/S4” based on IPCC AR4	79/117/−29/−25
Current study	2005–2050		“S1/S2/S3/S4” based on IPCC AR5	−47/−30/−33/−20
	Year	Study case	Scenario	Net virtual water import ($10^9\ m^3\ y^{-1}$)
Konar et al. (2013)	2030	Soybean	‘low yield’/‘high yield’ (SRES A2)	25.44/32.44
Ercin and Hoekstra (2014)	2050	Agricultural products	“S1/S2/S3/S4” based on IPCC AR4	−171/−152/−101/−63
Current study	2030	Soybean	“S1/S2/S3/S4” based on IPCC AR5	60(−19%)/71(−3%)/81(11%)/90(21%)
	2050	Crop products		−338/−250/−187/−62

underestimation of the blue WF of crop production in China under different scenarios. Finally, we did not include the impacts of potential changes in fertilizer or pesticide inputs on crop production, neither did we consider water pollution as indicated by the grey WF. By focusing on the impact of water stress on crop growth in modelling, ignoring the potential impact of temperature stress (e.g. cold or heat stress) and biotic stress from weeds, insects and disease, we may overestimate crop production (Hatfield et al., 2011; Mueller et al., 2012). Cropping calendar is one of the fundamental information in crop growing modelling (Waha et al., 2012) as well as one of the impacting factor on crop yield (Dobor et al., 2016; Mekonnen and Hoekstra, 2011) and the initial soil water content defines the level of water stress so that the level of crop yield and water consumption (Lovarelli et al., 2016). For the assumptions on cropping calendar and initial soil water content, a detailed sensitivity analysis to these two variables has been carried out by Zhuo et al. (2014) for the Yellow River basin, the core of Chinese crop production, and by Tuninetti et al. (2015) at global level. By varying the crop planting date by ±30 days with constant growing degree days, Zhuo et al. (2014) found that the consumptive WF of crops generally decreased by less than 10% with late planting date due to decreased crop ET and little change in crop yields. By changing the initial soil water content by ± 1 mm m^{-1}, Tuninetti et al. (2015) showed that the increment in the initial soil water content resulted in decreases in consumptive WF due to higher yield. However, the calibration of yield simulations according to the provincial statistics for the baseline year and implementing the relative changes as simulated for future scenarios minimized the inherent uncertainties in yield outputs, thus in WFs from above assumptions (Zhuo et al., 2016b).

In addition, there are inherent uncertainties in scenario studies. All scenarios are based on assumptions regarding climate change and socio-economic developments like population growth, changes in diets, technological improvements and land use changes. Different GCMs result in different climate projections for a given emission scenario, which can be addressed by using the projections from multiple GCMs (Semenov and Stratonovitch, 2010), as we did in the current study, although we considered four GCMs only. Finally, the crop model used, the Aquacrop model in our study, and parameter values chosen, will inevitably result in different yield predictions when compared to studies based other models and parameter sets (Asseng et al., 2013).

4. Conclusion

The study provides a comprehensive analysis of the consumptive WF and VW trade of China by 2030 and 2050, focusing on the agricultural sector, developing four alternative scenarios forced by different levels of population growth and by changes in production, consumption and climate. The four scenarios differ in assumptions and outcomes, but the projected futures share a few commonalities:

(i) On average, the WF of producing a tonne of crop decreases due to the combined effect of climate change and technology improvements on yield increase. Wetter climate projections in Northwest China potentially reduce the local blue WF of crop production that can help to reduce the high blue water stress from the agriculture sector;
(ii) The WF of food consumption per capita decreases, up to 44% by 2050 if diets change to less meat (scenario S1). The total national WF of food consumption also decreases across all scenarios;
(iii) China will shift from net VW importer through crop trade to net VW exporter. However, China will remain depending on soybean imports.

The results suggest that the target of the Chinese government to achieve higher self-sufficiency in food supply while simultaneously reducing the WF of crop production (SCPRC, 2010; MOA et al., 2015) is feasible. However, the premise of realizing the presented scenarios is smart water and cropland management, effective and coherent policies on water, agriculture and infrastructure, and, in scenario S1, a successful shift to a diet containing less meat.

Acknowledgements

The work was partially developed within the framework of the Panta Rhei Research Initiative of the International Association of Hydrological Sciences (IAHS). Zhuo is grateful for the scholarship under the China Scholarship Council (CSC No. 2011630181).

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.envint.2016.05.019.

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