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Sensitivity and uncertainty in crop water footprint accounting: a case study for the Yellow River basin

L. Zhuo, M. M. Mekonnen, and A. Y. Hoekstra

Twente Water Centre, University of Twente, Enschede, the Netherlands

Correspondence to: L. Zhuo (l.zhuo@utwente.nl)

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Abstract. Water Footprint Assessment is a fast-growing field of research, but as yet little attention has been paid to the uncertainties involved. This study investigates the sensitivity of and uncertainty in crop water footprint (in $m^3\,t^{-1}$) estimates related to uncertainties in important input variables. The study focuses on the green (from rainfall) and blue (from irrigation) water footprint of producing maize, soybean, rice, and wheat at the scale of the Yellow River basin in the period 1996–2005. A grid-based daily water balance model at a 5 by 5 arcmin resolution was applied to compute green and blue water footprints of the four crops in the Yellow River basin in the period considered. The one-at-a-time method was carried out to analyse the sensitivity of the crop water footprint to fractional changes of seven individual input variables and parameters: precipitation (PR), reference evapotranspiration (ET_0), crop coefficient (K_c), crop calendar (planting date with constant growing degree days), soil water content at field capacity (S_{max}), yield response factor (K_y) and maximum yield (Y_m). Uncertainties in crop water footprint estimates related to uncertainties in four key input variables: PR, ET_0, K_c, and crop calendar were quantified through Monte Carlo simulations.

The results show that the sensitivities and uncertainties differ across crop types. In general, the water footprint of crops is most sensitive to ET_0 and K_c, followed by the crop calendar. Blue water footprints were more sensitive to input variability than green water footprints. The smaller the annual blue water footprint is, the higher its sensitivity to changes in PR, ET_0, and K_c. The uncertainties in the total water footprint of a crop due to combined uncertainties in climatic inputs (PR and ET_0) were about ±20 % (at 95 % confidence interval). The effect of uncertainties in ET_0 was dominant compared to that of PR. The uncertainties in the total water footprint of a crop as a result of combined key input uncertainties were on average ±30 % (at 95 % confidence level).

1 Introduction

More than 2 billion people live in highly water stressed areas (Oki and Kanae, 2006), and the pressure on freshwater will inevitably be intensified by population growth, economic development and climate change in the future (Vörösmarty et al., 2000). The water footprint (Hoekstra, 2003) is increasingly recognized as a suitable indicator of human appropriation of freshwater resources and is becoming widely applied to get better understanding of the sustainability of water use. In the period 1996–2005, agriculture contributed 92 % to the total water footprint of humanity (Hoekstra and Mekonnen, 2012).

Water footprints within the agricultural sector have been extensively studied, mainly focusing on the water footprint of crop production, at scales from a sub-national region (e.g. Aldaya and Llamas, 2008; Zeng et al., 2012; Sun et al., 2013), to a country level (e.g. Ma et al., 2006; Hoekstra and Chapagain, 2007b; Kampman et al., 2008; Liu and Savenije, 2008; Bulsink et al., 2010; Ge et al., 2011) to the global level (Hoekstra and Chapagain, 2007a; Liu et al., 2010; Siebert and Döll, 2010; Mekonnen and Hoekstra, 2011; Hoekstra and Mekonnen, 2012). The green or blue water footprint of a crop is normally expressed by a single volumetric number referring to an average value for a certain area and period. However, the water footprint of a crop is always estimated based on a large set of assumptions with respect to the modelling approach, parameter values, and data sets for input variables used, so that outcomes carry substantial uncertainties (Mekonnen and Hoekstra, 2010; Hoekstra et al., 2011).

Together with the carbon footprint and ecological footprint, the water footprint is part of the "footprint family of indicators" (Galli et al., 2012), a suite of indicators to track human pressure on the surrounding environment. Nowadays, it is not hard to find information in literature on uncertainties in the carbon footprint of food products (Röös et al., 2010, 2011) or uncertainties in the ecological footprint (Parker and Tyedmers, 2012). However, there are hardly any sensitivity or uncertainty studies available in the water footprint field (Hoekstra et al., 2011), while only some subjective approximations and local rough assessments exist (Mekonnen and Hoekstra, 2010, 2011; Hoekstra et al., 2012; Mattila et al., 2012). Bocchiola et al. (2013) assessed the sensitivity of the water footprint of maize to potential changes of certain selected weather variables in northern Italy. Guieysse et al. (2013) assessed the sensitivity of the water footprint of fresh algae cultivation to changes in methods to estimate evaporation.

In order to provide realistic information to stakeholders in water governance, analysing the sensitivity and the magnitude of uncertainties in the results of a Water Footprint Assessment in relation to assumptions and input variables would be useful (Hoekstra et al., 2011; Mekonnen and Hoekstra, 2011). Therefore, the objectives of this study are (1) to investigate the sensitivity of the water footprint of a crop to changes in input variables and parameters, and (2) to quantify the uncertainty in green, blue, and total water footprints of crops due to uncertainties in input variables at the scale of a river basin. The study focuses on the water footprint of producing maize, soybean, rice, and wheat in the Yellow River basin, China, for each separate year in the period 1996–2005. Uncertainty in this study refers to the uncertainty in water footprint that accumulates due to the uncertainties in inputs propagated through the accounting process, which is reflected in the resulting estimates (Walker et al., 2003).

2 Study area

The Yellow River basin (YRB), drained by the Yellow River (*Huang He*), is the second largest river basin in China, with a drainage area of 795×10^3 km^2 (YRCC, 2011). The Yellow River is 5464 km long, originates from the Bayangela Mountains of the Tibetan Plateau, flows through nine provinces (Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan and Shandong), and finally drains into the Bohai Sea (YRCC, 2011). The YRB is usually divided into three reaches: the upper reach (upstream of Hekouzhen, Inner Mongolia), the middle reach (upstream of Taohuayu, Henan province) and the lower reach (draining into the Bohai Sea).

The YRB is vital for food production, natural resources and socioeconomic development of China (Cai et al., 2011). The cultivated area of the YRB accounts for 13 % of the national total (CMWR, 2010). In 2000, the basin accounted for 14 % of the country's crop production, with about 7 million ha of irrigated land in a total cultivated area in the basin of 13 million ha (Ringler et al., 2010). The water of the Yellow River supports 150 million people with a per capita blue water availability of 430 m^3 per year (Falkenmark and Widstrand, 1992; Ringler et al., 2010). The YRB is a net virtual water exporter (Feng et al., 2012) and suffers severe water scarcity. The blue water footprint in the basin is larger than the maximum sustainable blue water footprint (runoff minus environmental flow requirements) 8 months out of the year (Hoekstra et al., 2012).

3 Methods and data

3.1 Crop water footprint accounting

For the period 1996–2005, we calculated annual green and blue water footprints (WF) related to the production of maize, soybean, rice, and wheat in the YRB. The green and blue WF per unit mass of crop (m^3 t^{-1}) were calculated by dividing the green and blue crop water use (CWU, m^3 ha^{-1}) by the crop yield (Y, t ha^{-1}), respectively (Hoekstra et al., 2011). The total WF refers to the sum of green and blue WF.

A grid-based dynamic water balance model, developed by Mekonnen and Hoekstra (2010, 2011), is used to compute different components of CWU according to the daily soil water balance. The model has a spatial resolution of 5 by 5 arcmin (about 7.4 km × 9.3 km at the latitude of the YRB). The daily root zone soil water balance for growing a crop in each grid cell in the model can be expressed in terms of soil moisture ($S_{[t]}$, mm) (Mekonnen and Hoekstra, 2010):

$$S_{[t]}=S_{[t-1]}+I_{[t]}+\mathrm{PR}_{[t]}+\mathrm{CR}_{[t]}-\mathrm{RO}_{[t]}-\mathrm{ET}_{[t]}-\mathrm{DP}_{[t]}, \quad (1)$$

where $S_{[t-1]}$ (mm) refers to the soil water content on day $(t-1)$, $I_{[t]}$ (mm) the irrigation water applied on day t, $\mathrm{PR}_{[t]}$ (mm) precipitation, $\mathrm{CR}_{[t]}$ (mm) the capillary rise from the groundwater, $\mathrm{RO}_{[t]}$ (mm) water runoff, $\mathrm{ET}_{[t]}$ (mm) actual evapotranspiration and $\mathrm{DP}_{[t]}$ (mm) deep percolation on day t.

$\mathrm{CWU_{green}}$ and $\mathrm{CWU_{blue}}$ over the crop-growing period (in m^3 ha^{-1}) were calculated from the accumulated corresponding ET (mm day^{-1}) (Hoekstra et al., 2011):

$$\mathrm{CWU_{green}} = 10 \times \sum_{d=1}^{\mathrm{lgp}} \mathrm{ET_{green}} \quad (2)$$

$$\mathrm{CWU_{blue}} = 10 \times \sum_{d=1}^{\mathrm{lgp}} \mathrm{ET_{blue}}. \quad (3)$$

Table 1. Crop characteristics for maize, soybean, rice and wheat in the Yellow River basin.

	Crop coefficients			Planting	Growing	Relative crop-growing stages			
	K_c_ini	K_c_mid	K_c_end	date	period (days)	L_ini	L_dev	L_mid	L_late
Maize	0.70	1.20	0.25	1 Apr	150	0.20	0.27	0.33	0.20
Soybean	0.40	1.15	0.50	1 Jun	150	0.13	0.17	0.50	0.20
Rice	1.05	1.20	0.90	1 May	180	0.17	0.17	0.44	0.22
Wheat	0.70	1.15	0.30	1 Oct	335	0.48	0.22	0.22	0.07

Sources: Allen et al. (1998); Chen et al. (1995); Chapagain and Hoekstra (2004).

The accumulation was done over the growing period from the day of planting ($d = 1$) to the day of harvest (lgp, the length of growing period in days). The factor 10 ($m^3\,mm^{-1}\,ha^{-1}$) is applied to convert the mm to $m^3\,ha^{-1}$. The daily ET ($mm\,day^{-1}$) was computed according to Allen et al. (1998) as

$$\mathrm{ET} = K_\mathrm{s}[t] \times K\mathrm{c}[t] \times \mathrm{ET}_0[t], \tag{4}$$

where $K_\mathrm{c}[t]$ is the crop coefficient, $K_\mathrm{s}[t]$ a dimensionless transpiration-reduction factor dependent on available soil water, and $\mathrm{ET}_0[t]$ the reference evapotranspiration ($mm\,day^{-1}$). The crop calendar and K_c values for each crop were assumed to be constant for the whole basin, as shown in Table 1. $K_\mathrm{s}[t]$ is assessed based on a daily function of the maximum and actual available soil moisture in the root zone (Allen et al., 1998):

$$K_\mathrm{s}[t] = \begin{cases} \frac{s[t]}{(1-p)\times S_\mathrm{max}[t]} & S[t] < (1-p) \times S_\mathrm{max}[t] \\ 1 & \text{otherwise,} \end{cases} \tag{5}$$

where $S_\mathrm{max}[t]$ is the maximum available soil water in the root zone (mm, when soil water content is at field capacity), and p the fraction of S_max that a crop can extract from the root zone without suffering water stress, which is a function of ET_0 and K_c (Allen et al., 1998).

WF of the four crops in the YRB was estimated covering both rain-fed and irrigated agriculture. In the case of rain-fed crop production, blue CWU is zero and green CWU ($m^3\,ha^{-1}$) was calculated by aggregating the daily values of ET over the length of the growing period. In the case of irrigated crop production, green CWU was assumed to be equal to the ET for the case without irrigation. The blue CWU was estimated as the actual ET for the case with sufficient irrigation minus the green CWU (Mekonnen and Hoekstra, 2010, 2011).

The crop yield is influenced by water stress (Mekonnen and Hoekstra, 2010). The actual harvested yield (Y, $t\,ha^{-1}$) at the end of crop-growing period for each grid cell was estimated using the equation proposed by Doorenbos and Kassam (1979):

$$Y = Y_\mathrm{m} \times \left[1 - K_\mathrm{y}\left(1 - \frac{\sum_{d=1}^{\mathrm{lgp}} \mathrm{ET}}{\mathrm{CWR}}\right)\right], \tag{6}$$

where Y_m is the maximum yield ($t\,ha^{-1}$), obtained by multiplying the corresponding provincial average yield values by a factor of 1.2 (Reynolds et al., 2000). K_y is the yield response factor obtained from Doorenbos and Kassan (1979). CWR refers to the crop water requirement for the whole growing period ($mm\,period^{-1}$) (which is equal to $K_\mathrm{c} \times \mathrm{ET}_0$).

3.2 Sensitivity and uncertainty analysis

The estimation of crop WF requires a number of input variables and parameters to the model, including daily precipitation (PR), daily reference evapotranspiration (ET_0), crop coefficients (K_c) in the different growing stages, crop calendar (planting date and length of the growing period), soil water content at field capacity (S_max), yield response factor (K_y) and maximum yield (Y_m). The one-at-a-time method (see below) was applied to investigate the sensitivity of CWU, Y and WF to changes in these inputs. The uncertainties in WF due to uncertainties in PR, ET_0, K_c, and crop calendar were assessed through Monte Carlo simulations. We assumed that systematic errors in original climate observations at stations had been removed already. Uncertainties in variables PR, ET_0 and K_c were assumed random, independent and close to a normal (Gaussian) distribution (Ahn, 1996; Xu et al., 2006a; Droogers and Allen, 2002; Meyer et al., 1989; Troutman, 1985).

3.2.1 Sensitivity analysis

The "one-at-a-time" or "sensitivity curve" method is a simple but practical way of sensitivity analysis to investigate the response of an output variable to variation of input values (Hamby, 1994; Sun et al., 2012). With its simplicity and intuitionism, the method is popular and has been widely used (Ahn, 1996; Goyal, 2004; Xu et al., 2006a, b; Estévez et al., 2009). The method was performed by introducing fractional changes to one input variable, while keeping other inputs constant. The sensitivity curve of the resultant relative change in the output variable was then plotted against the relative change of the input variable. The sensitivity analysis was carried out for each year in the period 1996–2005. For each cropped grid cell, we varied each input variable within a certain range. Then, the annual average level of the responses in CWU, Y, and (green, blue, and total) WF of the crops for the basin as a whole were recorded. With respect to the input variables PR, ET_0 and K_c, we shifted each within the range of ± 2 SD ($2 \times$ standard deviation of input uncertainties), which represents the 95 % confidence interval for uncertainties in the input variable. In terms of the crop calendar, we varied the planting date (D) within ± 30 days of constant growing degree days (GDD) and relative length of crop-growing stages (Allen et al., 1998) (Table 1). The cumulative GDD (° day), measuring heat units during crop growth, has vastly improved expression and prediction of the crop's phenological cycle compared to other approaches, such as time of the year or number of days (McMaster and Wilhelm, 1997). In the study, a crop's GDD was calculated per year, following the most widely used "Method 1" (McMaster and Wilhelm, 1997), by summing the difference of the daily base temperature and the average air temperature over the reference crop-growing period in days (Table 1). The base temperature is the temperature below which crop growth does not progress. The base temperature of each crop was obtained from FAO (Raes et al., 2012). Parameters S_{max}, K_y and Y_m were varied within the range of ± 20 % of the default value.

3.2.2 Uncertainty analysis

The advantage of uncertainty analysis with the Monte Carlo (MC) simulation is that the model to be tested can be of any complexity (Meyer, 2007). MC simulations were carried out at the basin level to quantify the uncertainties in estimated WF due to uncertainties in individual or multiple input variables. The uncertainty analysis was carried out separately for 3 years within the study period: 1996 (wet year), 2000 (dry year), and 2005 (average year). For each MC simulation, 1000 runs were performed. Based on the set of WF estimates from those runs, the mean (μ) and standard deviation (SD) is calculated; with 95 % confidence, WF falls in the range of $\mu \pm 2$ SD. The SD will be expressed as a percentage of the mean.

3.2.3 Input uncertainty

Uncertainty in precipitation (PR)

Uncertainties in the Climate Research Unit Time Series (CRU-TS) (Harris et al., 2014) grid precipitation values used for WF accounting in this study come from two sources: the measurement errors inherent in station observations, and errors which occur during the interpolation of station data in constructing the grid database (Zhao and Fu, 2006; Fekete et al., 2004; Phillips and Marks, 1996). Zhao and Fu (2006) compared the spatial distribution of precipitation as in the CRU database with the corresponding observations over China and revealed that the differences between the CRU data and observations vary from −20 to 20 % in the area where the YRB is located. For this study, we assume a ± 20 % range around the CRU precipitation data as the 95 % confidence interval (2 SD = 20 %).

Uncertainty in reference evapotranspiration (ET_0)

The uncertainties in the meteorological data used in estimating ET_0 will be transferred into uncertainties in the ET_0 values. The method used to estimate the CRU-TS ET_0 data set is the Penman–Monteith (PM) method (Allen et al., 1998). The PM method has been recommended (Allen et al., 1998) for its high accuracy at station level within ± 10 % from the actual values under all ranges of climates (Jensen et al., 1990). With respect to the gridded ET_0 calculation, the interpolation may cause additional error (Thomas, 2008; Phillips and Marks, 1996). There is no detailed information on uncertainty in the CRU-TS ET_0 data set. We estimated daily ET_0 values (mm day^{-1}) for the period 1996–2005 from observed climatic data at 24 meteorological stations spread out in the YRB (CMA, 2008) by the PM method. Then we compared, station by station, the monthly averages of those calculated daily ET_0 values to the corresponding monthly ET_0 values in the CRU-TS data set (Fig. 1a). The differences between the station values and CRU-TS values ranged from −0.23 to 0.27 mm day^{-1} with a mean of 0.005 mm day^{-1} (Fig. 1b). The standard deviation (SD) of the differences was 0.08 mm day^{-1}, 5 % from the station values, which implies an uncertainty range of ± 10 % (2 SD) at 95 % confidence interval. The locations of CMA stations were different from the stations used for generating the CRU data set (Harris et al., 2014) (see Fig. 1c), which was one of the sources of the uncertainty. We added the basin level uncertainty in monthly ET_0 values due to uncertainties in interpolation (± 10 % at 95 % confidence level) and the uncertainty related to the application of the PM method (another ± 10 % at 95 % confidence level) to arrive at an overall uncertainty of ± 20 % (2 SD) for the ET_0 data. We acknowledge that this is a crude estimate of uncertainty, but there is no better method.

Uncertainty in crop characteristics

We used the K_c values from Table 1 for the whole basin. According to Jagtap and Jones (1989), the K_c value for a certain crop can vary by 15 %. We adopted this value and assumed the 95 % uncertainty range falls within ± 15 % (2 SD) from the mean K_c values. Referring to the crop calendar, we assumed that the planting date for each crop fluctuated within ± 30 days from the original planting date used, holding the same length of GDD for each year. Table 2 summarises the uncertainty scenarios considered in the study.

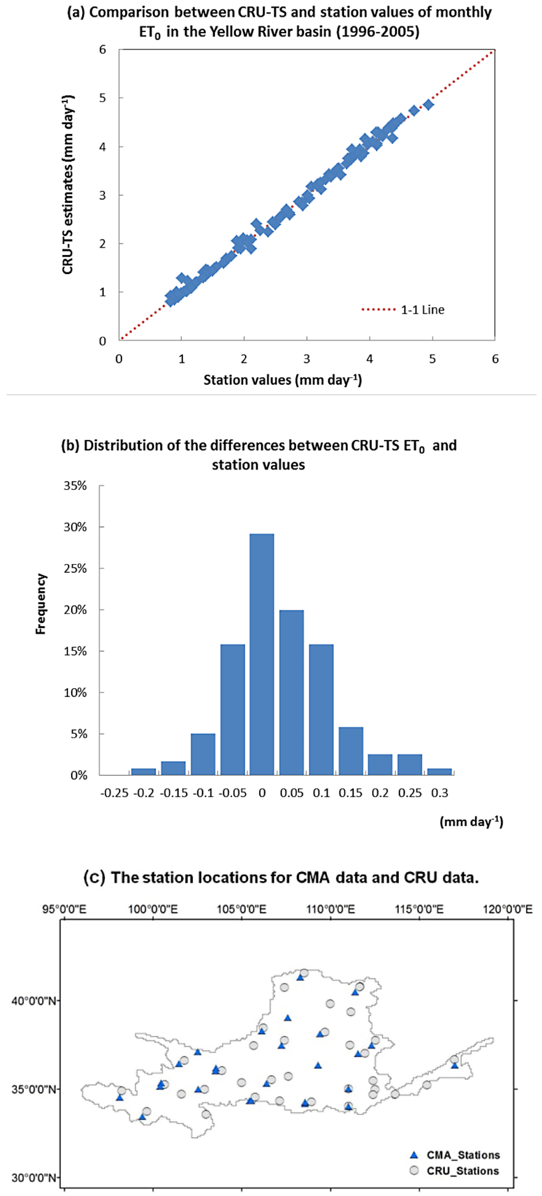

Figure 1. Differences between monthly averages of daily ET_0 data from CRU-TS and station-based values for the Yellow River basin, 1996–2005.

3.3 Data

The GIS polygon data for the YRB were extracted from the HydroSHEDS data set (Lehner et al., 2008). Total monthly PR, monthly averages of daily ET_0, number of wet days, and daily minimum and maximum temperatures at 30 by 30 arcmin resolution for 1996–2005 were extracted from CRU-TS-3.10 and 3.10.01 (Harris et al., 2014). Figure 2 shows PR and ET_0 for the YRB in the study period. Daily values of precipitation were generated from the monthly values using the CRU-dGen daily weather generator model (Schuol and Abbaspour, 2007). Daily ET_0 values were derived from monthly average values by curve fitting to the monthly average through polynomial interpolation (Mekonnen and Hoekstra, 2011). Data on irrigated and rain-fed areas for each crop at a 5 by 5 arcmin resolution were obtained from the MIRCA2000 data set (Portmann et al., 2010). Crop areas and yields within the YRB from MIRCA2000 were scaled to fit yearly agriculture statistics per province of China (MAPRC, 2009; NBSC, 2006, 2007). Total available soil water capacity at a spatial resolution of 5 by 5 arcmin was obtained from the ISRIC-WISE version 1.2 data set (Batjes, 2012).

4 Results

4.1 Sensitivity of CWU, Y, and WF to variability of input variables

4.1.1 Sensitivity to variability of precipitation (PR)

The average sensitivities of CWU, Y, and WF to variability of precipitation for the study period were assessed by varying the precipitation between ±20 % as shown in Fig. 3. An overestimation in precipitation leads to a small overestimation of green WF and a relatively large underestimation of blue WF. A similar result was found for maize in the Po Valley of Italy by Bocchiola et al. (2013). The sensitivity of WF to input variability is defined by the combined effects on the CWU and Y. Figure 3 shows the overall result for the YRB, covering both rain-fed and irrigated cropping.

For irrigated agriculture, a reduction in green CWU due to smaller precipitation will be compensated with an increased blue CWU, keeping total CWU and Y unchanged. Therefore, the changes in Y were due to the changes in the yields in rain-fed agriculture. The relative changes in total WF were always smaller than ±5 % because of the opposite direction of sensitivities of green and blue WF, as well as the domination of green WF in the total. In addition, in terms of wheat only, both Y and total WF decreased with less precipitation. Purposes of modern agriculture are mainly keeping or improving the crop production as well as reducing water use. The instance for wheat indicates that Y (mass of a crop per hectare) might decrease in certain climate situations in practice although the WF (referring to drops of water used per mass of crop) decreased. On the other hand, it can be noted that the sensitivity of CWU, Y, and WF to input variability differs across crop types, especially evident in blue WF. Regarding the four crops considered, blue WF of soybean is most sensitive to variability in precipitation and blue WF of rice is least sensitive. The explanation lies in the share of blue WF in total WF. At basin level, the blue WF of soybean accounted for about 9 % of the total WF, while the blue WF of rice was around 44 % of the total, which is the highest blue water fraction among the four crops. The larger sensitivity of the blue WF of soybean to change in precipitation compared

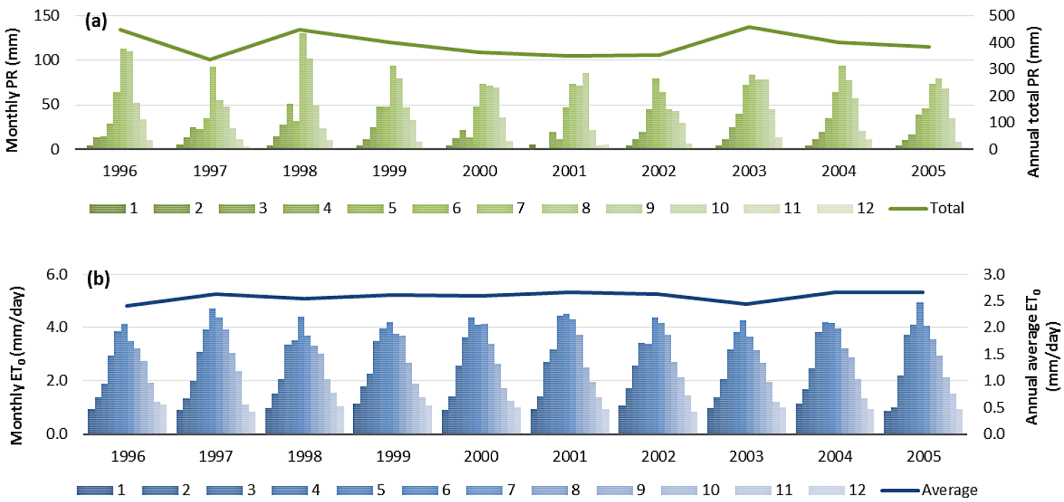

Figure 2. Monthly precipitation (PR) and monthly averages of daily reference evapotranspiration (ET_0) in the Yellow River basin from the CRU-TS database, for the period 1996–2005.

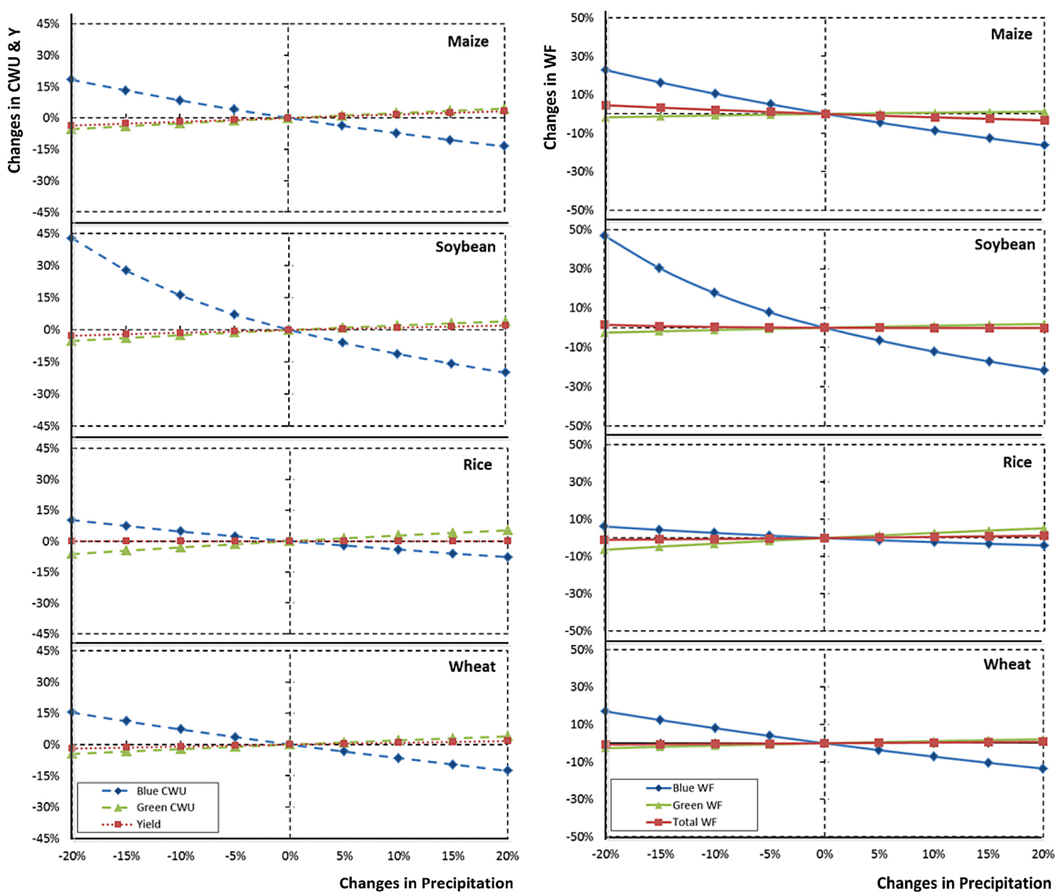

Figure 3. Sensitivity of CWU, Y and WF to changes in precipitation (PR), 1996–2005.

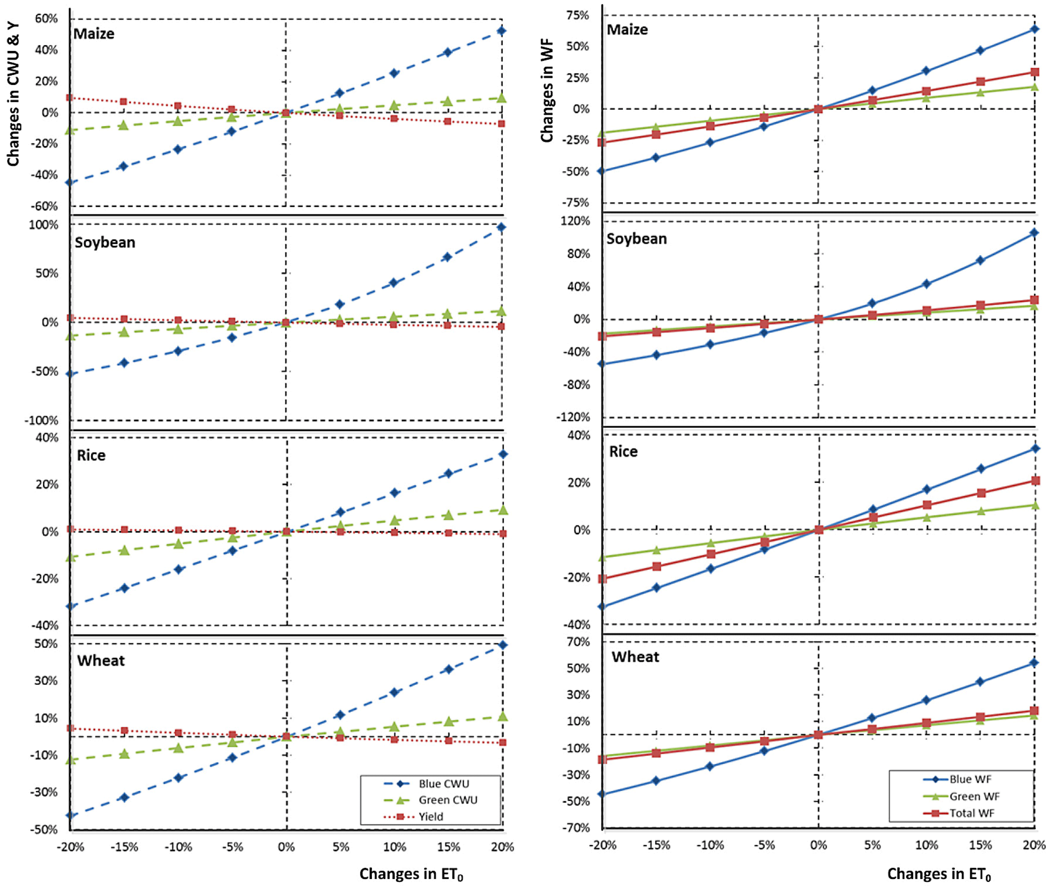

Figure 4. Sensitivity of CWU, Y and WF to changes in reference evapotranspiration (ET_0), 1996–2005.

to that of rice shows that the smaller the blue water footprint, the larger its sensitivity to a marginal change in precipitation.

4.1.2 Sensitivity to variability of ET_0 and K_c

Figure 4 shows the average sensitivity of CWU, Y, and WF to changes in ET_0 within a range of ±20 % from the mean for the period 1996–2005. The influences of changes in ET_0 on WF are greater than the effect of changes in precipitation. Both green and blue CWU increase with the rising ET_0. An increase in ET_0 will increase the crop water requirement. For rain-fed crops, the crop water requirement may not be fully met, leading to crop water stress and thus lower Y. For irrigated crops under full irrigation, the crop will not face any water stress, so that the yield will not be affected. The decline in yield at increasing ET_0 at basin level in Fig. 4 is therefore due to yield reductions in rain-fed agriculture only.

Due to the combined effect of increasing CWU and decreasing Y at increasing ET_0, an overestimation in ET_0 leads to a larger overestimation of WF. The strongest effect of ET_0 changes on blue WF was found for soybean, with a relative increase reaching up to 105 % with a 20 % increase in ET_0, while the lightest response was found for the case of rice, with a relative increase in blue WF of 34 %. The sensitivities of green WF were similar among the four crops. The changes in total WF were always smaller and close to ±30 % in the case of a ±20 % change in ET_0.

As shown in Eq. (4), K_c and ET_0 have the same effect on crop evapotranspiration. Therefore, the effects of changes in K_c on CWU, Y, and WF are exactly the same as the effects of ET_0 changes. The changes in total WF were less than ±25 % in the case of a ±15 % change in K_c values.

4.1.3 Sensitivity to changing crop planting date (D)

The responses of CWU, Y, and WF to the change of the crop planting date with constant GDD are plotted in Fig. 5. There is no linear relationship between the cropping calendar and WF. Therefore, no generic information can be summarized for the sensitivity of WF of crops to a changing cropping calendar. But some interesting regularity can still be found. With the late sowing dates, the crop-growing periods in days became longer for rice and soybean, while shorter for maize and wheat. WF was smaller with late planting date for all four crops, which is mainly due to the decrease in the blue and green CWU for maize, rice and wheat, as well as a relatively

Table 2. Input uncertainties for crop water footprint accounting in the Yellow River basin.

Input variable	Unit	95 % confidence interval of input uncertainties	Distribution of input uncertainties
Precipitation (PR)	mm day^{-1}	±20 % (2 SD*)	Normal
Reference evapotranspiration (ET_0)	mm day^{-1}	±20 % (2 SD)	Normal
Crop coefficient (K_c)	–	±15 % (2 SD)	Normal
Planting date (D)	days	±30	Uniform (discrete)

* 2 SD: 2 × standard deviation of input uncertainties.

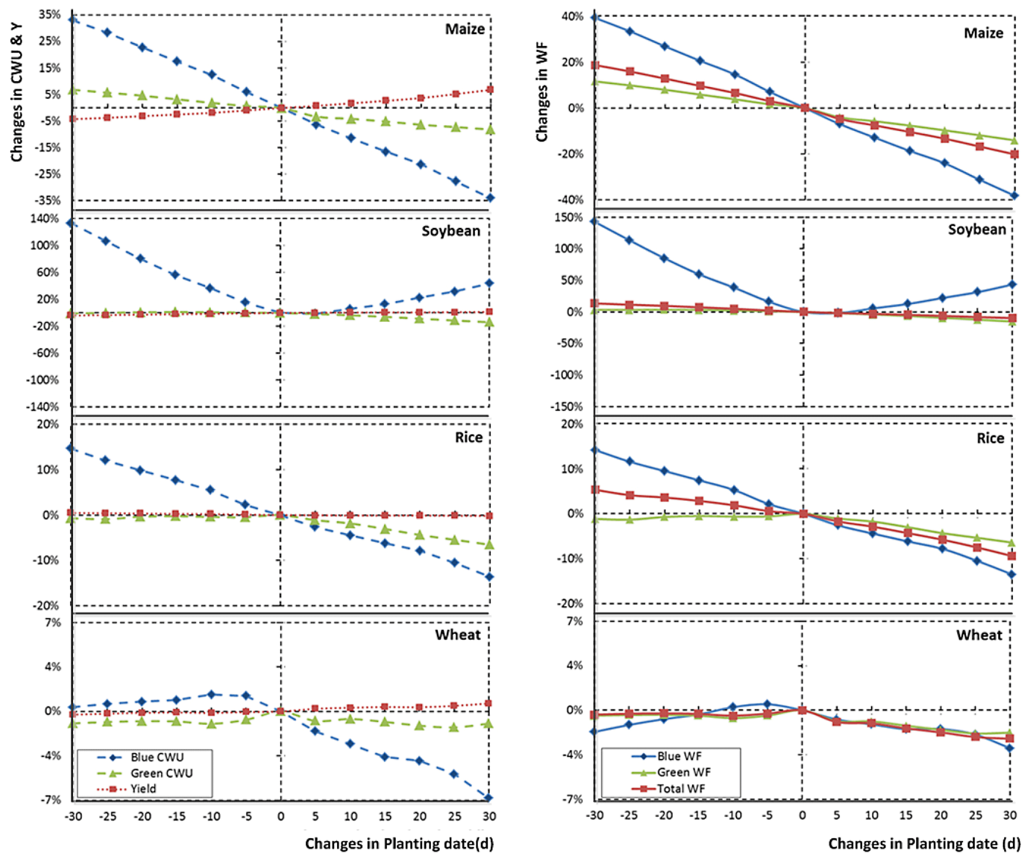

Figure 5. Sensitivity of CWU, Y and WF to changes in crop planting date (D), 1996–2005.

larger decrease of green CWU for soybean. Apparently, the reduction in CWU of maize and wheat was due to a shortening of the growing period. Meanwhile, we found a reduced ET_0 over the growing period with delayed planting of the rice and soybean, which led to a decrease in the crop water requirement. This is consistent with the result observed for maize in the western Jilin Province of China by Qin et al. (2012) and northern China (Jin et al., 2012; Sun et al., 2007) based on local field experiments. Late planting, particularly for maize, rice and wheat, could save water, particularly blue water, while increasing Y. The response of wheat yield did not match with the field experiment results in northern China by Sun et al. (2007). The difference was because they set a constant growing period when changing the sowing date of wheat, not taking the GDD into consideration. With late planting of soybean, the reduction of PR was larger than the reduction of crop water requirement of soybean, resulting in a larger blue WF. Since blue WF is more sensitive to ET_0 and PR than green WF, the relative change in blue WF was always more than green WF. When planted earlier, both green and blue WF of maize increased because of increased CWU with a longer growing period. Although growing periods for

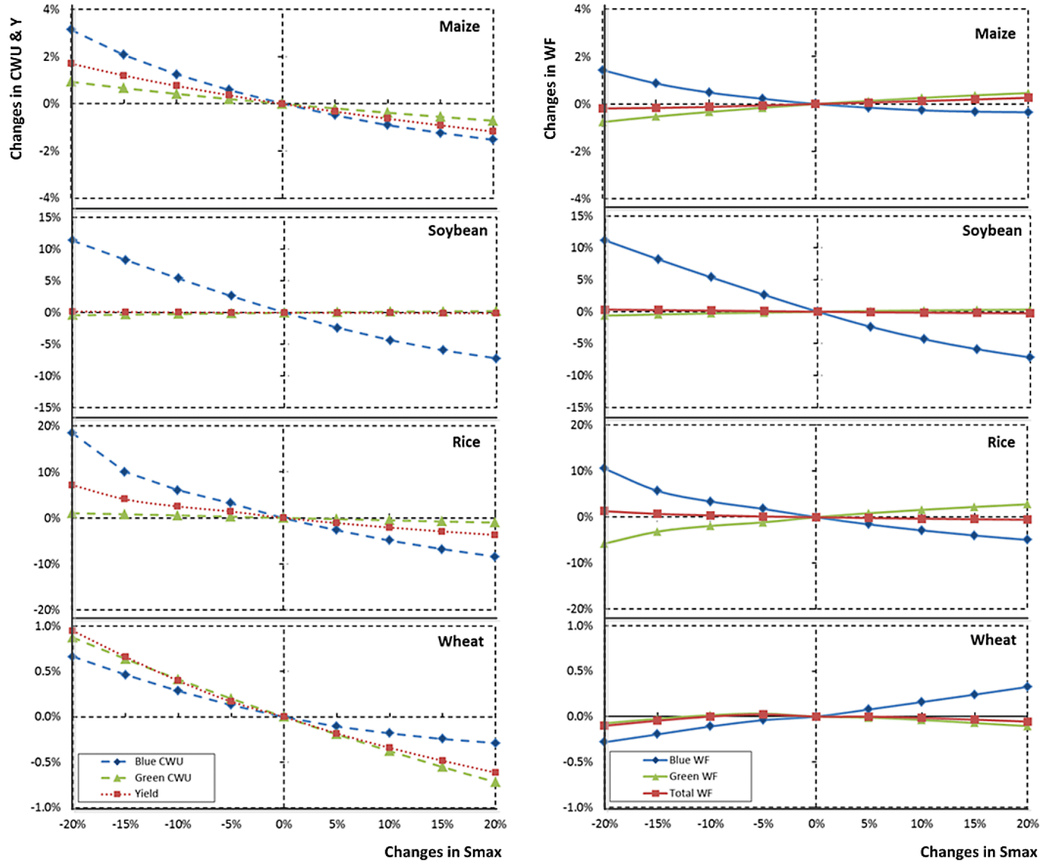

Figure 6. Sensitivity of CWU, Y and WF to changes in the field capacity of the soil water (S_{max}), 1996–2005.

rice and soybean were shorter with earlier sowing, the increased rainwater deficit resulted in more blue CWU and less green CWU for irrigated fields and a slight increase in total WF with little change in Y. Meanwhile, a different response curve was observed for wheat with earlier planting. The explanation for the unique sensitivity curve for wheat is that the crop is planted in October after the rainy season (June to September) and the growing period lasts around 335 days (Table 1), which leads to a low sensitivity to the precise planting date. However, as interesting as the phenomenon found in Fig. 3, the Y and total WF both dropped (by 0.25 and 0.3 % to 30 days earlier planting, respectively) when the planting date was shifted by more than 15 days earlier than the reference sowing date of wheat. A similar instance also arose for rice with a delayed sowing date: reduction of Y by 0.2 % and total WF by 9.3 % when delaying the planting day by 30 days.

Therefore from perspective of the agricultural practice, the response of both crop production and crop water consumption with change in the planting date should be considered in agricultural water-saving projects. In general, the results show that the crop calendar is one of the factors affecting the magnitude of crop water consumption. A proper planning of the crop-growing period is, therefore, vital from the perspective of water resources use, especially in arid and semi-arid areas like the YRB. However, our estimate, which was based on a sensitivity analysis by keeping all other input parameters such as the initial soil water content constant, could be different from the actual cropping practice. There are techniques to maintain or increase the initial soil moisture, for instance by storing off-season rainfall (through organic matter) in the cropping field.

4.1.4 Sensitivity to changes of soil water content at field capacity (S_{max})

The sensitivity curves of CWU, Y and WF to the changes of the S_{max} within ± 20 % are shown in Fig. 6. The total WF varied no more than 1.3 % to changes in the S_{max}. The maximum sensitivity was found for rice. But the responses of blue and green WF were different per crop type. Blue WF decreased, while green WF increased with higher S_{max} for maize, soybean, and rice. For wheat we found the opposite. Figure 6 shows that CWU and Y become smaller with higher S_{max}. In the model, higher S_{max} with no change in the soil moisture defines a higher water stress in crop growth, resulting in smaller K_{s}, ET (Eqs. 4 and 5), and thus lower Y (Eq. 6).

4.1.5 Sensitivity to parameters for yield simulation

The yield response factor (K_y) and maximum yield (Y_m) are important parameters defining the Y simulation (Eq. 6). They are always set with a constant default value for different crops. It is clear from the equation that crop WF is negatively correlated to Y_m: a 20 % increase in Y_m results in a 20 % increase in Y and a 20 % decrease in the WFs. Figure 7 shows the sensitivity of Y and WF of each crop to changes in the values of K_y within ±20 % of the default value. The figure shows that an increase in K_y leads to a decrease in simulated Y and an increase in the WFs. Due to the difference in the sensitivity of crops to water stress, different crops have different default K_y values, leading to different levels of sensitivity in Y and WF estimates to changes in K_y with crop types. Among the four crops, maize had the highest, while wheat had the lowest sensitivity in Y and WF to the variation of K_y.

4.2 Annual variation of sensitivities in crop water footprints

As an example of the annual variation of sensitivities, Table 3 presents the sensitivity of blue, green and total WF of maize to changes in PR, ET_0, K_c, D, S_{max}, and K_y for each specific year in the period 1996–2005. As can be seen from the table, the sensitivity of green WF to the PR, ET_0, K_c, D, and S_{max} was relatively stable around the mean annual level. But there was substantial inter-annual fluctuation of sensitivity of blue WF for all four crops. For each year and each crop, the slope (S) of the sensitivity curve of change in blue WF versus change in PR, ET_0, and K_c was computed, measuring the slope at mean values for PR, ET_0, and K_c. The slopes (representing the percentage change in blue WF over percentage change in input variable) are plotted against the corresponding blue WF (Fig. 8). The results show that – most clearly for maize and rice – the smaller the annual blue WF, the higher the sensitivity to changes in PR, ET_0, or K_c. As shown by the straight curves through the data for maize (Fig. 8), we can roughly predict the sensitivity of blue WF to changes in input variables based on the size of blue WF itself. The blue WF of a specific crop in a specific field will be more sensitive (in relative terms) to the three inputs in wet years than in dry years, simply because the blue WF will be smaller in a wet year.

4.3 Uncertainties in WF per unit of crop due to input uncertainties

In order to assess the uncertainty in WF (in $m^3 t^{-1}$) due to input uncertainties, Monte Carlo (MC) simulations were performed at the basin level for 1996 (wet year), 2000 (dry year), and 2005 (average year). For each crop, we carried out a MC simulation for four input uncertainty scenarios, considering the effect of: (1) uncertainties in PR alone, (2) uncertainties in ET_0 alone, (3) combined uncertainties in the two climatic input variables ($PR + ET_0$), and (4) combined uncertainties in all four key input variables considered in this study ($PR + ET_0 + K_c + D$). The uncertainty results in blue, green and total WF of the four crops for the four scenarios and 3 years are shown in Table 4. The uncertainties are expressed in terms of values for 2 SD as a percentage of the mean value; the range of ±2 SD around the mean value gives the 95 % confidence intervals.

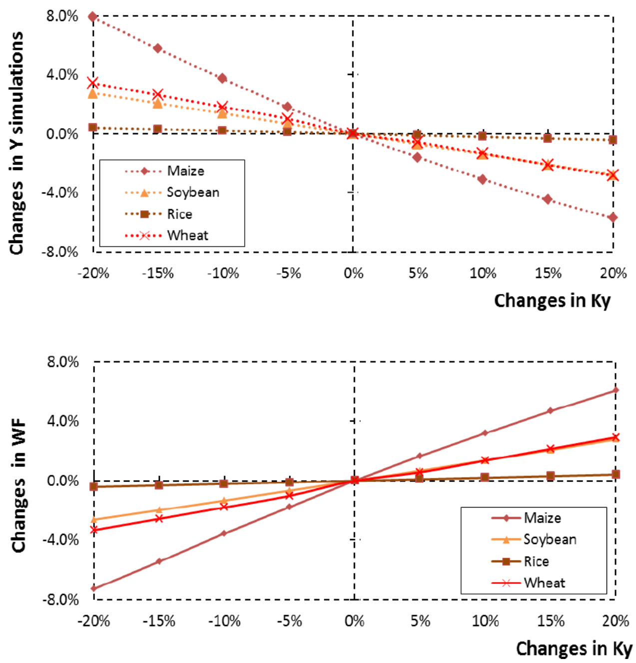

Figure 7. Sensitivity of Y and WF to changes in yield response factor (K_y), 1996–2005.

In general, for all uncertainty scenarios, blue WF shows higher uncertainties than green WF. Uncertainties in green WF are similar for the 3 different hydrologic years. Uncertainties in blue WF are largest (in relative sense) in the wet year, conform our earlier finding that blue WF is more sensitive to changes in input variables in wet years. The uncertainties in WF due to uncertainties in PR are much smaller than the uncertainties due to uncertainties in ET_0. Uncertainties in PR hardly affect the assessment of total WF of crops in all 3 different hydrologic years. Among the four crops, soybean has the highest uncertainty in green and blue WF. The uncertainty in total WF for all crops is within the range of ±18 to 20 % (at 95 % confidence interval) when looking at the effect of uncertainties in the two climate input variables only, and within the range of ±28 to 32 % (again at 95 % confidence interval) when looking at the effect of uncertainties in all four input variables considered. In all cases, the most important uncertainty source is the value of ET_0. Figure 9 shows, for maize as an example, the probability distribution of the total WF (in $m^3 t^{-1}$) given the uncertainties in the two climatic input variables and all four input variables combined.

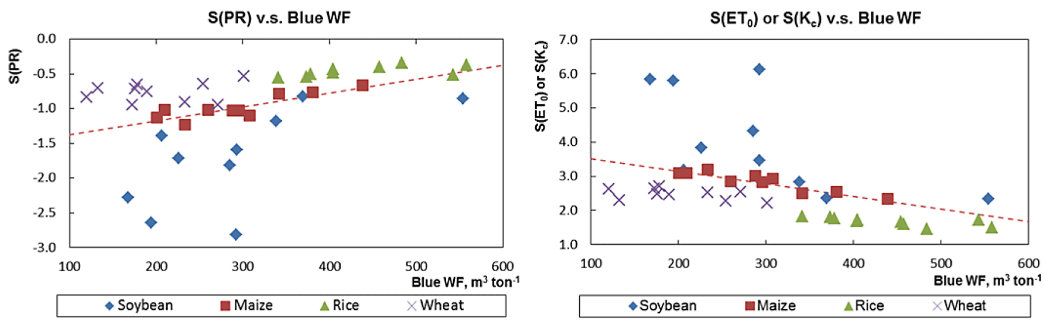

Figure 8. The slope (S) of the sensitivity curve for the blue WF for each crop for each year in the period 1996–2005 (vertical axis) plotted against the blue WF of the crop in the respective year (x axis). The graph on the left shows the relative sensitivity of blue WF to PR; the graph on the right shows the relative sensitivity of blue WF to $\mathrm{ET_0}$ or K_c. The sensitivities to $\mathrm{ET_0}$ and K_c were the same. The trend lines in both graphs refer to the data for maize.

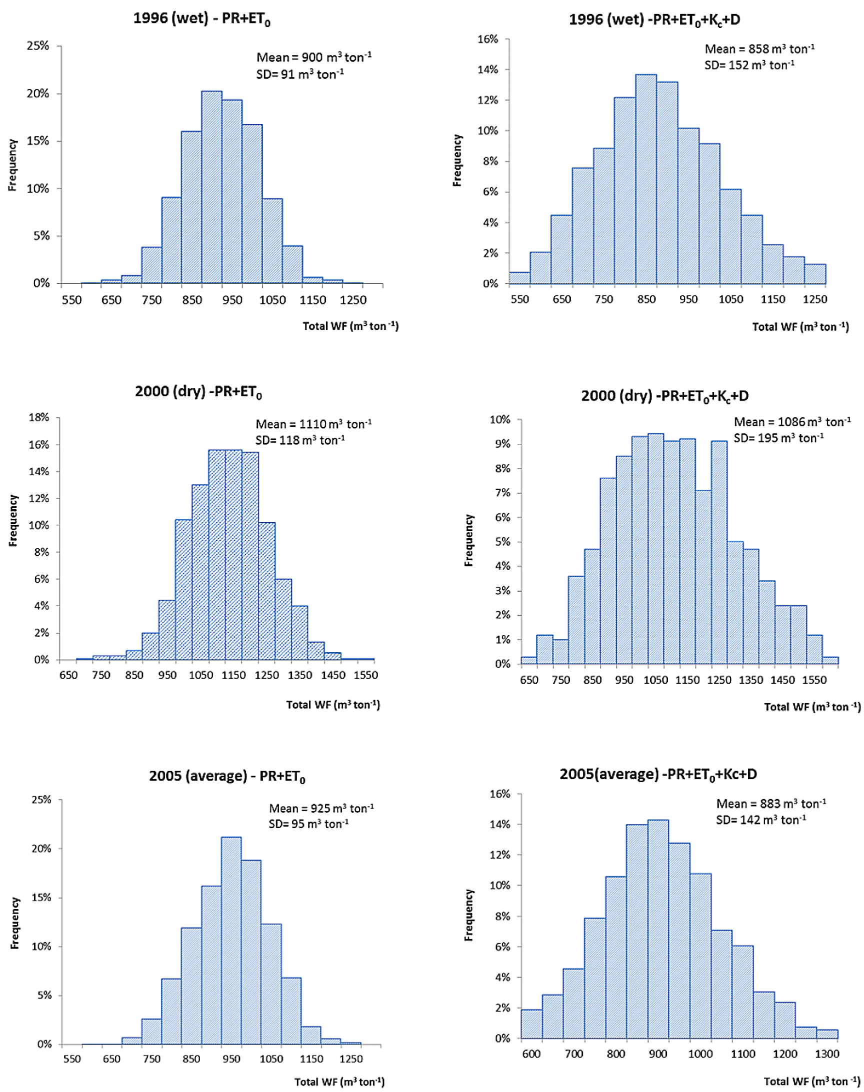

Figure 9. Probability distribution of the total WF of maize given the combined uncertainties in PR and $\mathrm{ET_0}$ (graphs at the left) and given the combined uncertainties in PR, $\mathrm{ET_0}$, K_c and D (graphs at the right), for the years 1996, 2000 and 2005.

Table 3. Sensitivity of annual water footprint (WF) of maize to input variability at the level of the Yellow River basin, for the period 1996–2005.

	WF	Changes in the WF to variability of input variables (%)											
		PR		ET_0		K_c		D		S_{max}		K_y	
	($m^3\,t^{-1}$)	−20 %	20 %	−20 %	20 %	−15 %	15 %	−30d	30d	−20 %	20 %	−20 %	20 %
Blue WF													
1996	201	27	−18	−52	72	−41	52	51	−51	−3.2	1.4	−4.1	4.1
1997	381	17	−14	−47	55	−36	41	19	−25	0.9	0.9	−9.4	8.0
1998	209	25	−16	−53	70	−42	51	31	−42	4.1	−1.6	−5.6	4.8
1999	308	26	−18	−50	67	−39	49	44	−42	1.9	−1.3	−7.5	6.2
2000	342	18	−14	−46	54	−35	40	48	−45	0.6	0.3	−8.6	6.8
2001	439	15	−12	−44	50	−34	37	38	−33	0.4	0.8	−9.8	7.4
2002	296	23	−18	−51	62	−39	46	23	−24	6.7	−3.1	−5.8	5.1
2003	233	29	−21	−56	72	−44	53	45	−41	0.8	0.3	−4.9	5.0
2004	260	24	−17	−49	65	−39	47	51	−43	1.0	−0.1	−7.2	6.4
2005	288	25	−17	−50	71	−39	51	39	−37	1.2	−1.0	−9.9	6.9
Mean	295	23	−16	−50	64	−39	47	39	−38	1.4	−0.3	−7.3	6.1
Green WF													
1996	754	−1.4	0.9	−18	18	−14	14	12	−17	−0.5	0.2	−4.1	4.1
1997	820	−2.0	1.3	−19	18	−14	13	10	−14	−1.0	0.6	−9.4	8.0
1998	792	−1.3	0.7	−19	18	−14	14	12	−11	−0.8	0.4	−5.6	4.8
1999	864	−2.1	1.3	−19	18	−14	13	12	−13	−0.8	0.6	−7.5	6.2
2000	831	−2.0	1.3	−19	18	−14	13	12	−15	−0.8	0.5	−8.6	6.8
2001	819	−2.3	1.7	−19	17	−14	13	11	−15	−0.8	0.5	−9.8	7.4
2002	865	−1.7	1.2	−18	18	−14	13	12	−15	−0.7	0.3	−5.8	5.1
2003	882	−1.4	1.0	−19	18	−14	14	12	−16	−0.6	0.4	−4.9	5.0
2004	838	−1.5	0.9	−19	18	−14	14	13	−13	−0.8	0.6	−7.2	6.4
2005	733	−2.1	1.6	−19	17	−14	13	10	−11	−0.7	0.5	−9.9	6.9
Mean	820	−1.8	1.2	−19	18	−14	13	12	−14	−0.8	0.5	−7.3	6.1
Total WF													
1996	955	4.7	−3.1	−26	29	−20	22	20	−24	−1.1	0.5	−4.1	4.1
1997	1200	3.9	−3.6	−28	30	−21	22	13	−18	−0.4	0.7	−9.4	8.0
1998	1001	4.2	−2.8	−26	29	−20	22	16	−17	0.2	0.0	−5.6	4.8
1999	1172	5.3	−3.7	−27	31	−21	23	20	−21	−0.1	0.1	−7.5	6.2
2000	1172	3.7	−3.1	−27	28	−20	21	23	−24	−0.4	0.5	−8.6	6.8
2001	1257	3.6	−3.1	−27	28	−21	21	20	−21	−0.4	0.6	−9.8	7.4
2002	1160	4.7	−3.7	−27	29	−20	22	15	−17	1.2	−0.5	−5.8	5.1
2003	1116	4.9	−3.5	−26	30	−20	22	19	−21	−0.4	0.3	−4.9	5.0
2004	1098	4.4	−3.3	−26	29	−20	22	22	−20	−0.4	0.4	−7.2	6.4
2005	1021	5.4	−3.6	−28	32	−21	24	18	−19	−0.2	0.1	−9.9	6.9
Mean	1115	4.5	−3.3	−27	30	−20	22	19	−20	−0.2	0.3	−7.3	6.1

5 Conclusions and discussion

This paper provides the first detailed study of the sensitivities and uncertainties in the estimation of green and blue water footprints of crop growing related to input variability and uncertainties at river-basin level. The result shows that at the scale of the Yellow River basin (1) WF is most sensitive to errors in ET_0 and K_c, followed by the crop planting date and PR, and less sensitive to changes of S_{max}, K_y, and Y_m; (2) blue WF is more sensitive and has more uncertainty than green WF; (3) uncertainties in total (green + blue) WF as a result of climatic uncertainties are around ±20 % (at 95 % confidence level) and dominated by effects from uncertainties in ET_0; (4) uncertainties in total WF as a result of all uncertainties considered are on average ±30 % (at 95 % confidence level); (5) the sensitivities and uncertainties in WF estimation, particularly in blue WF estimation, differ across crop types and vary from year to year.

An interesting finding was that the smaller the annual blue WF (consumptive use of irrigation water), the higher the sensitivity of the blue WF to variability in the input variables PR, ET_0, and K_c. Furthermore, delaying the crop planting date was found to potentially contribute to a decrease of the WF of spring or summer planted crops (maize, soybean, rice),

Table 4. Values of 2 × standard deviation for the probability distribution of the blue, green and total WF of maize, soybean, rice and wheat, expressed as % of the mean value, from the Monte Carlo simulations.

Crop	Perturbed inputs	1996 (wet year)			2000 (dry year)			2005 (average year)		
		Blue WF	Green WF	Total WF	Blue WF	Green WF	Total WF	Blue WF	Green WF	Total WF
Maize	P	14	4	0.2	10	4	0.2	8	4	0
	ET_0	48	12	20	38	12	20	36	12	18
	$P+ET_0$	48	12	20	42	12	20	38	14	20
	$P+ET_0+K_c+D$	88	21	34	78	20	36	66	19	32
Soybean	P	22	1.2	0.2	18	2	2	14	2	0.8
	ET_0	56	16	18	50	14	16	40	14	16
	$P+ET_0$	62	16	18	56	14	18	44	14	18
	$P+ET_0+K_c+D$	87	26	29	92	25	31	66	25	28
Rice	P	10	6	0	8	6	0	7	6	0
	ET_0	34	12	20	30	12	20	30	12	20
	$P+ET_0$	34	12	20	32	12	20	32	13	20
	$P+ET_0+K_c+D$	70	18	31	66	21	32	61	19	29
Wheat	P	14	2	0.4	14	2	0.4	16	2	0
	ET_0	48	16	20	46	16	18	52	16	18
	$P+ET_0$	52	16	20	48	16	18	54	16	18
	$P+ET_0+K_c+D$	85	24	26	83	24	31	88	22	30

Optimizing the planting period for such crops could save irrigation water in agriculture, particularly for maize and rice. Although the conclusion closely matches the result from several experiments for maize carried out in some regions in northern China (Qin et al., 2012; Jin et al., 2012; Sun et al., 2007), such information should be confirmed by future field agronomic experiments.

The study confirmed that it is not enough to give a single figure of WF without providing an uncertainty range. A serious implication of the apparent uncertainties in Water Footprint Assessment is that it is difficult to establish trends in WF reduction over time, since the effects of reduction have to be measured against the background of natural variations and uncertainties.

The current study shows possible ways to assess the sensitivity and uncertainty in the water footprint of crops in relation to variability and errors in input variables and parameters. Not only can the outcomes of this study be used as a reference in future sensitivity and uncertainty studies on WF, but the results also provide a first rough insight in the possible consequences of changes in climatic variables like precipitation and reference evapotranspiration on the water footprint of crops. However, the study does not provide the complete picture of sensitivities and uncertainties in Water Footprint Assessment. Firstly, the study is limited to the assessment of the effects from only a part of all input variables and parameters; uncertainties in other parameters were not considered, such as the uncertainties around volumes and timing of irrigation, parameters affecting runoff and deep percolation. Secondly, there are several models available for estimating the WF of crops. Our result is only valid for the model used, which is based on a simple soil water balance (Allen et al., 1998; Mekonnen and Hoekstra, 2010) and which considers water as the main factor in the yield estimation (Eq. 6). Thirdly, the quantification of uncertainties in the input variables considered is an area full of uncertainties and assumptions itself. Furthermore, the uncertainties in water footprint estimation are scale dependent and decline with a growing extent of the considered study region. Our study is carried out for the aggregated crop water footprint estimation for the whole basin scale. The result should be interpreted with caution at a higher resolution. Besides, the uncertainty range of an input variable, especially for climatic inputs, is location specific. Thus the level of input uncertainties will be different in different places, resulting in a different level of uncertainties in crop water footprints. Therefore, the current result is highly valuable for the region of the YRB and should be referenced with caution at other regions.

Therefore, in order to build up a more detailed and complete picture of sensitivities and uncertainties in Water Footprint Assessment, a variety of efforts needs to be made in the future. In particular, we will need to improve the estimation of input uncertainties, include uncertainties from other input variables and parameters, and assess the impact of using different models on WF outcomes. Finally, uncertainty studies will need to be extended towards other crops and other water using sectors, to other regions and at different spatial and temporal scales.

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