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

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Received: 3 December 2013 – Accepted: 16 December 2013 – Published: 7 January 2014

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Published by Copernicus Publications on behalf of the European Geosciences Union.
Abstract

Water Footprint Assessment is a quickly growing field of research, but as yet little attention has been paid to the uncertainties involved. This study investigates the sensitivity of water footprint estimates to changes in important input variables and quantifies the size of uncertainty in water footprint estimates. The study focuses on the green (from rainfall) and blue (from irrigation) water footprint of producing maize, soybean, rice, and wheat in 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 sensitivity and uncertainty analysis focused on the effects on water footprint estimates at basin level (in m$^3$·t$^{-1}$) of four key input variables: precipitation (PR), reference evapotranspiration ($\text{ET}_0$), crop coefficient ($K_c$), and crop calendar. The one-at-a-time method was carried out to analyse the sensitivity of the water footprint of crops to fractional changes of individual input variables. Uncertainties in crop water footprint estimates were quantified through Monte Carlo simulations.

The results show that the water footprint of crops is most sensitive to $\text{ET}_0$ and $K_c$, followed by crop calendar and PR. Blue water footprints were more sensitive to input variability than green water footprints. The smaller the annual blue water footprint, the higher its sensitivity to changes in PR, $\text{ET}_0$, and $K_c$. The uncertainties in the total water footprint of a crop due to combined uncertainties in climatic inputs (PR and $\text{ET}_0$) were about ±20 % (at 95 % confidence interval). The effect of uncertainties in $\text{ET}_0$ was dominant compared to that of precipitation. The uncertainties in the total water footprint of a crop as a result of combined key input uncertainties were on average ±26 % (at 95 % confidence level). The sensitivities and uncertainties differ across crop types, with highest sensitivities and uncertainties for soybean.
1 Introduction

More than two 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), and a country (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 globe (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 datasets 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). But 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 key input variables, and (2) to quantify the uncertainty in green, blue, and total water footprints of crops due to uncertainties in input variables at river basin level. 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 output uncertainty that accumulates due to the uncertainties in inputs that is propagated through the water footprint accounting process and is reflected in the resulting estimates (Walker et al., 2003).

2 Study area

The Yellow River Basin (YRB), drained by the Yellow River (Huanghe), is the second largest river basin in China with a drainage area of 795 km $\times$ $10^3$ km (YRCC, 2011). The Yellow River is 5464 km long, originates from the Bayanbula 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 at a total agriculture 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 suffering severe water scarcity. The blue water footprint in the basin is larger than the maximum sustainable blue water footprint (runoff minus environmental flow requirements) during eight months a year (Hoekstra et al., 2012).

3 Methods and data

3.1 Crop water footprint accounting

Annual green and blue water footprints (WF) of producing maize, soybean, rice, and wheat in the YRB for the study period were estimated using the grid-based dynamic water balance model developed by Mekonnen and Hoekstra (2010). 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 model is used to compute different components of crop water use (CWU) according to the daily soil water balance (Mekonnen and Hoekstra, 2010, 2011). 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) at the end of the day (Mekonnen and Hoekstra, 2010):

$$S_{[t]} = S_{[t-1]} + I_{[t]} + PR_{[t]} + CR_{[t]} - RO_{[t]} - ET_{a[t]} - DP_{[t]}, \quad (1)$$

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

The green water footprint (WF\textsubscript{green}, m\textsuperscript{3} t\textsuperscript{-1}) and blue water footprint (WF\textsubscript{blue}, m\textsuperscript{3} t\textsuperscript{-1}) per unit mass of crop were calculated by dividing the green (CWU\textsubscript{green}, m\textsuperscript{3} ha\textsuperscript{-1}) and blue (CWU\textsubscript{blue}, m\textsuperscript{3} ha\textsuperscript{-1}) CWU by the crop yield (\textit{Y}, tha\textsuperscript{-1}), respectively (Hoekstra et al., 2011). The total WF refers to the sum of green and blue WF:

\begin{align*}
WF\textsubscript{green} &= \frac{CWU\textsubscript{green}}{Y}, \\
WF\textsubscript{blue} &= \frac{CWU\textsubscript{blue}}{Y}, \\
WF\textsubscript{total} &= WF\textsubscript{green} + WF\textsubscript{blue}.
\end{align*}

(CWU\textsubscript{green} and CWU\textsubscript{blue} over the crop growing period (in m\textsuperscript{3} ha\textsuperscript{-1}) were calculated from the accumulated corresponding actual crop evapotranspiration (ET, mm day\textsuperscript{-1}) (Hoekstra et al., 2011):

\begin{align*}
CWU\textsubscript{green} &= 10 \times \sum_{d=1}^{lgp} ET\textsubscript{green}, \\
CWU\textsubscript{blue} &= 10 \times \sum_{d=1}^{lgp} ET\textsubscript{blue}.
\end{align*}

The accumulation was done over the growing period from the day of planting (\textit{d} = 1) to the day of harvest (lgp, the length of growing period in days). The factor 10 converts water depths (in mm) into water volumes per unit land surface area in m\textsuperscript{3} ha\textsuperscript{-1}. The daily actual ET (mm day\textsuperscript{-1}) was computed according to Allen et al. (1998) as:

\begin{equation}
ET = K_s[t] \times K_c[t] \times ET_0[t],
\end{equation}
where $K_{c}[t]$ is the crop coefficient, $K_{s}[t]$ a dimensionless transpiration reduction factor dependent on available soil water and $ET_0[t]$ 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. $K_{s}[t]$ is assessed based on a daily function of the maximum and actual available soil moisture in the root zone (Mekonnen and Hoekstra, 2011):

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

(8)

where $S_{\text{max}}[t]$ is the maximum available soil water in the root zone (mm, when soil water content is at field capacity), and $p$ the fraction of $S_{\text{max}}$ that a crop can extract from the root zone without suffering water stress.

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 actual crop evapotranspiration over the length of the growing period. In the case of irrigated crop production, the green water use was assumed to be equal to the actual crop evapotranspiration for the case without irrigation. The blue water use was estimated as the CWU simulated in the case with sufficient irrigation water applied minus the green CWU in the same condition but without irrigation (Mekonnen and Hoekstra, 2010, 2011).

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

$$\left(1 - \frac{Y}{Y_m}\right) = K_y \left(1 - \frac{\sum_{d=1}^{lgp} ET}{CWR}\right),$$

(9)
where $Y_m$ is the maximum yield (t ha$^{-1}$), $K_y$ the yield response factor, and CWR the crop water requirement for the whole growing period (mm period$^{-1}$) (which is equal to $K_c \times ET_0$).

### 3.2 Sensitivity and uncertainty analysis

The estimation of WF of crop growing requires a number of input data, including: daily precipitation (PR), daily reference evapotranspiration ($ET_0$), crop coefficients in the different growing stages ($K_c$), and crop calendar (planting date and length of the growing period). The one-at-a-time method (see below) was applied to investigate the sensitivity of CWU, $Y$ and WF to changes in these input variables. The uncertainties in WF due to uncertainties in the four input variables were assessed through Monte Carlo simulations.

#### 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 the range of the mean value $\pm 2$ SD ($2 \times$ standard deviation), which represents the 95% confidence interval for the input variable. 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.
3.2.2 Uncertainty analysis

The advantage of uncertainty analysis with 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. We assumed that systematic errors in original climate observations at stations have been removed under a strict quality control and errors indicated as a proportion of input climatic variables are random, independent and close to a normal (Gaussian) distribution. The uncertainty analysis was carried out separately for three 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 μ ± 2SD. 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., 2013) 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$_0$ dataset 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$_0$ dataset. 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 monthly ET$_0$ values in the CRU-TS dataset (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. 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.

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 the crop growing period. Table 2 summarises the uncertainty scenarios considered in the study.

### 3.3 Data

The GIS polygon data for the YRB were extracted from the HydroSHEDS dataset (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., 2013). 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 dataset (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 dataset (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 significant 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 variabil-
ity 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 agricul-
ture. 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 reduced
with less precipitation. Purposes of modern agriculture are mainly keeping or improv-
ing 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) reduced.
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 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 wa-
ter 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. (7), $K_c$ 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 crop planting date with constant growing period are plotted in Fig. 5. There is no linear relationship between the cropping calendar and WF. Therefore, no generic information can be summarised for the sensitivity of WF of crops to a changing cropping calendar. But some interesting regularity can still be found for maize, soybean and rice: WF was smaller at later planting date, mainly because of the decreased blue CWU and increased $Y$. We found a reduced $ET_0$ over the growing period with delayed planting of the three crops, which leads to a decrease in the crop water requirement, while precipitation over this later period was higher for maize and slightly lower for soybean and rice. Since blue WF is more sensitive to $ET_0$ than to PR, the decreased crop water requirement was the dominant factor, resulting in a decreased blue CWU and increased $Y$. This is consistent with the result observed for maize in western Jilin Province of China by Qin et al. (2012).
Late planting, particularly for maize and rice, could save blue water, while increasing \( Y \) (for maize). Meanwhile, a different response curve was observed for wheat. Green WF increased when the planting date was delayed and blue WF decreased, but changes are small in both cases. 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 335 days (Table 1), which leads to a low sensitivity to the precise planting date. However, as interesting as the phenomenon found in the Fig. 3, the \( Y \) and total WF both dropped (by 0.5 and 3.3\% to 30 days earlier, respectively) when changing more than 15 days earlier than the reference sowing date of wheat. A similar instance also arose for rice with delaying the sowing date: 0.1\% less \( Y \) and 12.8\% less total WF to 30 later days of planting. From perspective of the agricultural practice, it at least reminds that the response of both crop production and crop water consumption 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.

### 4.1.4 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 key input variables for each specific year in the period 1996–2005. As can be seen from the table, the sensitivity of green WF to the four key input variables was relatively stable around the mean annual level. But there was substantial inter-annual fluctuation of sensitivity of blue WF, observed for all four crops. For each year and each crop, the slope \((S)\) of the sensitivity curve of change in blue WF vs. change in PR, \( \text{ET}_0 \), and \( K_c \) was computed, measuring the slope at mean values for PR, \( \text{ET}_0 \), and \( K_c \). The slopes (representing the percentage change in blue WF per percentage change in input variable) were plotted against the corresponding blue WF (Fig. 6). The results show – most clearly for maize and rice – that the smaller the annual blue WF, the higher the sensitivity to changes in PR, \( \text{ET}_0 \), or
As shown by the straight curves through the data for maize (Fig. 6), 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.

### 4.2 Uncertainties in WF per unit of crop due to input uncertainties

In order to assess the uncertainty in WF (in m³ 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 ET₀ alone, (3) uncertainties in the two climatic input variables (PR and ET₀), and (4) combined uncertainties in all four key input variables considered in this study (PR + ET₀ + Kc + D). The resultant uncertainties in blue, green and total WF of the four crops for the four scenarios and three 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.

In general, for all uncertainty scenarios, blue WF shows higher uncertainties than green WF. Uncertainties in green WF are similar for the three 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 ET₀. Uncertainties in PR hardly affect the assessment of total WF of crops in all three different hydrologic years. Among the four crops, soybean had the highest uncertainty in green and blue WF. The uncertainty in total WF for all crops was 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 ±24 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 \( \text{ET}_0 \). Figure 7 shows, for maize as an example, the probability distribution of the total WF (in m\(^3\)t\(^{-1}\)) given the uncertainties in either the two climatic input variables or all four input variables.

5 Conclusions

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 level of the Yellow River Basin: (1) WF is most sensitive to errors in \( \text{ET}_0 \) and \( K_c \) followed by the crop planting date and precipitation; (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 \( \text{ET}_0 \); (4) uncertainties in total WF as a result of all uncertainties considered are on average ±26% (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, \( \text{ET}_0 \), 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), particularly relevant for the blue WF. Therefore, optimizing the planting period for such crops could save irrigation water in agriculture.

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. 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 four key input variables; uncertainties in other input variables were not considered, like for instance uncertainties around volumes and timing of irrigation. 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). Furthermore, the quantification of uncertainties in the four input variables considered is an area full of uncertainties and assumptions itself. 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 processes, to other regions and at different spatial and temporal scales.

Acknowledgements. L. Zhuo is grateful for the scholarship she received from the China Scholarship Council (CSC), No. 2011630181.
References


Sensitivity and uncertainty in crop water footprint accounting

L. Zhuo et al.
Sensitivity and uncertainty in crop water footprint accounting

L. Zhuo et al.


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

<table>
<thead>
<tr>
<th></th>
<th>$K_{c\text{-ini}}$</th>
<th>$K_{c\text{-mid}}$</th>
<th>$K_{c\text{-end}}$</th>
<th>Planting date</th>
<th>Length of growing period (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maize</td>
<td>0.70</td>
<td>1.20</td>
<td>0.25</td>
<td>1 Apr</td>
<td>150</td>
</tr>
<tr>
<td>Soybean</td>
<td>0.40</td>
<td>1.15</td>
<td>0.50</td>
<td>1 Jun</td>
<td>150</td>
</tr>
<tr>
<td>Rice</td>
<td>1.05</td>
<td>1.20</td>
<td>0.90</td>
<td>1 May</td>
<td>180</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.70</td>
<td>1.15</td>
<td>0.30</td>
<td>1 Oct</td>
<td>335</td>
</tr>
</tbody>
</table>

Sources: Allen et al. (1998); Chen et al. (1995); Chapagain and Hoekstra (2004).
Table 2. Input uncertainties for crop water footprint accounting in the Yellow River Basin.

<table>
<thead>
<tr>
<th>Input variable</th>
<th>Unit</th>
<th>95% confidence interval</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation (PR)</td>
<td>mm day$^{-1}$</td>
<td>±20% (2 SD)</td>
<td>Normal</td>
</tr>
<tr>
<td>Reference evapotranspiration (ET$_0$)</td>
<td>mm day$^{-1}$</td>
<td>±20% (2 SD)</td>
<td>Normal</td>
</tr>
<tr>
<td>Crop coefficient ($K_c$)</td>
<td>–</td>
<td>±15% (2 SD)</td>
<td>Normal</td>
</tr>
<tr>
<td>Planting date ($D$)</td>
<td>days</td>
<td>±30</td>
<td>Uniform (discrete)</td>
</tr>
</tbody>
</table>
Table 3. Sensitivity of annual water footprint of maize to input variability at the level of the Yellow River Basin, for the period 1996–2005.

<table>
<thead>
<tr>
<th></th>
<th>WF (m³ t⁻¹)</th>
<th>PR -20%</th>
<th>PR 20%</th>
<th>ET₀ -20%</th>
<th>ET₀ 20%</th>
<th>Kc -15%</th>
<th>Kc 15%</th>
<th>D -30d</th>
<th>D 30d</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>-18.1</td>
<td>-21.9</td>
<td>-33.8</td>
<td>-30.0</td>
<td>-30.0</td>
<td>-29.0</td>
<td>-30.0</td>
<td>-29.0</td>
</tr>
<tr>
<td>Blue WF</td>
<td>1996 201</td>
<td>27.3</td>
<td>-18.1</td>
<td>-52.2</td>
<td>71.9</td>
<td>-41.1</td>
<td>52.3</td>
<td>58.3</td>
<td>-40.7</td>
</tr>
<tr>
<td></td>
<td>1997 381</td>
<td>16.7</td>
<td>-14.0</td>
<td>-46.9</td>
<td>55.0</td>
<td>-36.1</td>
<td>40.7</td>
<td>-1.9</td>
<td>-11.3</td>
</tr>
<tr>
<td></td>
<td>1998 209</td>
<td>24.8</td>
<td>-15.8</td>
<td>-53.0</td>
<td>70.4</td>
<td>-41.6</td>
<td>51.4</td>
<td>25.7</td>
<td>-34.4</td>
</tr>
<tr>
<td></td>
<td>1999 308</td>
<td>26.1</td>
<td>-17.7</td>
<td>-50.1</td>
<td>67.4</td>
<td>-39.3</td>
<td>49.1</td>
<td>32.3</td>
<td>-32.1</td>
</tr>
<tr>
<td></td>
<td>2000 342</td>
<td>17.6</td>
<td>-13.9</td>
<td>-45.6</td>
<td>54.4</td>
<td>-35.3</td>
<td>40.2</td>
<td>35.7</td>
<td>-42.7</td>
</tr>
<tr>
<td></td>
<td>2001 439</td>
<td>14.6</td>
<td>-12.2</td>
<td>-43.7</td>
<td>49.9</td>
<td>-33.6</td>
<td>37.0</td>
<td>22.8</td>
<td>-27.1</td>
</tr>
<tr>
<td></td>
<td>2002 296</td>
<td>23.2</td>
<td>-17.9</td>
<td>-50.5</td>
<td>62.4</td>
<td>-39.3</td>
<td>45.9</td>
<td>-13.0</td>
<td>-6.2</td>
</tr>
<tr>
<td></td>
<td>2003 233</td>
<td>28.7</td>
<td>-20.5</td>
<td>-55.5</td>
<td>72.0</td>
<td>-43.5</td>
<td>52.7</td>
<td>35.7</td>
<td>-37.2</td>
</tr>
<tr>
<td></td>
<td>2004 260</td>
<td>23.6</td>
<td>-16.9</td>
<td>-49.2</td>
<td>64.6</td>
<td>-38.5</td>
<td>47.1</td>
<td>46.5</td>
<td>-37.7</td>
</tr>
<tr>
<td></td>
<td>2005 288</td>
<td>24.6</td>
<td>-16.7</td>
<td>-49.8</td>
<td>71.0</td>
<td>-39.3</td>
<td>51.3</td>
<td>19.8</td>
<td>-31.7</td>
</tr>
<tr>
<td>Mean</td>
<td>295</td>
<td>22.7</td>
<td>-16.4</td>
<td>-49.6</td>
<td>63.9</td>
<td>-38.8</td>
<td>46.8</td>
<td>26.2</td>
<td>-30.1</td>
</tr>
</tbody>
</table>

| Green WF | 1996 754    | -1.4   | 0.9    | -18.4   | 18.2    | -13.8   | 13.7    | -7.3    | -2.1   |
|          | 1997 820    | -2.0   | 1.3    | -19.1   | 17.8    | -14.2   | 13.5    | -10.7   | -1.1   |
|          | 1998 792    | -1.3   | 0.7    | -19.0   | 18.3    | -14.2   | 13.8    | -7.0    | -2.1   |
|          | 1999 864    | -2.1   | 1.3    | -19.0   | 17.7    | -14.1   | 13.4    | -8.2    | -3.4   |
|          | 2000 831    | -2.0   | 1.3    | -18.9   | 17.8    | -14.1   | 13.5    | -6.9    | -3.8   |
|          | 2001 819    | -2.3   | 1.7    | -18.6   | 16.9    | -13.9   | 12.9    | -8.5    | -2.6   |
|          | 2002 865    | -1.7   | 1.2    | -18.4   | 17.6    | -13.8   | 13.3    | -6.3    | -3.7   |
|          | 2003 882    | -1.4   | 1.0    | -18.8   | 18.4    | -14.1   | 13.9    | -6.0    | -3.5   |
|          | 2004 838    | -1.5   | 0.9    | -19.2   | 18.5    | -14.4   | 14.0    | -5.2    | -5.3   |
|          | 2005 733    | -2.1   | 1.6    | -19.1   | 17.2    | -14.2   | 13.1    | -9.0    | -1.8   |
| Mean    | 820         | -1.8   | 1.2    | -18.9   | 17.9    | -14.1   | 13.5    | -7.5    | -2.9   |

| Total WF | 1996 955    | 4.7    | -3.1   | -25.5   | 29.5    | -19.6   | 21.8    | 6.5     | -10.2  |
|          | 1997 1200   | 3.9    | -3.6   | -27.9   | 29.6    | -21.2   | 22.1    | -7.9    | -4.3   |
|          | 1998 1001   | 4.2    | -2.8   | -26.1   | 29.2    | -19.9   | 21.7    | -0.2    | -8.9   |
|          | 1999 1172   | 5.3    | -3.7   | -27.1   | 30.8    | -20.7   | 22.7    | 2.4     | -10.9  |
|          | 2000 1172   | 3.7    | -3.1   | -26.7   | 28.5    | -20.3   | 21.3    | 5.5     | -15.1  |
|          | 2001 1257   | 3.6    | -3.1   | -27.4   | 28.4    | -20.8   | 21.3    | 2.4     | -11.2  |
|          | 2002 1160   | 4.7    | -3.7   | -26.6   | 29.0    | -20.3   | 21.6    | -8.0    | -4.3   |
|          | 2003 1116   | 4.9    | -3.5   | -26.5   | 29.6    | -20.2   | 22.0    | 2.7     | -10.5  |
|          | 2004 1098   | 4.4    | -3.3   | -26.3   | 29.4    | -20.1   | 21.8    | 7.0     | -13.0  |
|          | 2005 1021   | 5.4    | -3.6   | -27.7   | 32.4    | -21.3   | 23.9    | -0.9    | -10.2  |
| Mean    | 1115        | 4.5    | -3.3   | -26.8   | 29.6    | -20.4   | 22.0    | 1.0     | -9.9   |
Table 4. 2 SD for the probability distribution of the blue, green and total WF of maize, soybean, rice and wheat, expressed as % of the mean value.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Perturbed inputs</th>
<th>1996 (wet year)</th>
<th>2000 (dry year)</th>
<th>2005 (average year)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Blue WF</td>
<td>Green WF</td>
<td>Total WF</td>
<td>Blue WF</td>
</tr>
<tr>
<td>Maize</td>
<td>PR</td>
<td>14</td>
<td>4</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>ET₀</td>
<td>48</td>
<td>12</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀</td>
<td>48</td>
<td>12</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀ + K₀ + D</td>
<td>76</td>
<td>18</td>
<td>24</td>
</tr>
<tr>
<td>Soybean</td>
<td>PR</td>
<td>22</td>
<td>1.2</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>ET₀</td>
<td>56</td>
<td>16</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀</td>
<td>62</td>
<td>16</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀ + K₀ + D</td>
<td>98</td>
<td>26</td>
<td>30</td>
</tr>
<tr>
<td>Rice</td>
<td>PR</td>
<td>10</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>ET₀</td>
<td>34</td>
<td>12</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀</td>
<td>34</td>
<td>12</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀ + K₀ + D</td>
<td>62</td>
<td>16</td>
<td>28</td>
</tr>
<tr>
<td>Wheat</td>
<td>PR</td>
<td>14</td>
<td>2</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>ET₀</td>
<td>48</td>
<td>16</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀</td>
<td>52</td>
<td>16</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>PR + ET₀ + K₀ + D</td>
<td>68</td>
<td>20</td>
<td>24</td>
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</tbody>
</table>
Fig. 1. Differences between monthly averages of daily ET₀ data from CRU-TS and station-based values for the Yellow River Basin, 1996–2005.
**Fig. 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.
Fig. 3. Sensitivity of CWU, Y and WF to changes in precipitation (PR), 1996–2005.
Fig. 4. Sensitivity of CWU, Y and WF to changes in reference evapotranspiration ($ET_0$), 1996–2005.
**Fig. 5.** Sensitivity of CWU, Y and WF to changes in crop planting date, 1996–2005.
Fig. 6. 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 $ET_0$ or $K_c$. The sensitivities to $ET_0$ and $K_c$ were the same. The trend lines in both graphs refer to the data for maize.
Fig. 7. Probability distribution of the total WF of maize given the combined uncertainties in PR and $ET_0$ (graphs at the left) and given the combined uncertainties in PR, $ET_0$, $K_c$ and $D$ (graphs at the right), for the years 1996, 2000 and 2005.