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

L. Zhuo[1], M. M. Mekonnen[1] and A. Y. Hoekstra[1]

[1]{ Twente Water Centre, University of Twente, Enschede, the Netherlands }

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

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 ton^{-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 arc minute 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}), parameters 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 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 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 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 that is propagated through the 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 795×10^3 km^2 (YRCC, 2011). The Yellow River is 5,464 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 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. The green and blue *WF* per unit mass of crop (m^3 ton^{-1}) were calculated by dividing the green and blue crop water use (CWU, m^3 ha^{-1}) by the crop yield (Y, ton 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 arc minute (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) at the end of the day (Mekonnen and Hoekstra, 2010):

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

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, $RO_{[t]}$ (mm) water runoff, $ET_{[t]}$ (mm) actual evapotranspiration and $DP_{[t]}$ (mm) deep percolation on day t.

CWU_{green} and 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):

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

$$CWU_{blue} = 10 \times \sum_{d=1}^{lgp} ET_{blue} \, , \qquad (3)$$

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:

$$ET = K_s[t] \times K_c[t] \times ET_0[t] \, , \qquad (4)$$

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 (Allen et al., 1998):

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

where $S_{max}[t]$ 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, the green water use was assumed to be equal to the *ET* 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, ton ha^{-1}) at the end of crop growing period for each grid cell was estimated using the equation proposed by Doorenbos and Kassam (1979):

$$Y = Y_m \times \left[1 - K_y \left(1 - \frac{\sum_{d=1}^{lgp} ET}{CWR}\right)\right] \tag{6}$$

where Y_m is the maximum yield (ton 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 $K_c \times ET_0$).

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, 2007; 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 ± 2SD (2× 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 with 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 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 three years within the study period: 1996 (wet year), 2000 (dry year), and 2005 (average year). For each MC simulation, 1,000 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 (2SD = 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 corresponding monthly ET_0 values in the CRU-TS dataset (Figure 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} (Figure 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% (2SD) at 95% confidence interval. The locations of CMA stations were different from the stations used for generating the CRU dataset (Harris et al., 2013) (see Figure 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% (2SD) 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% (2SD) 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.

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 arc minute 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 arc minute 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 arc minute 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 Figure 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* reduced 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) 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 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 Figure 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 Equation 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 GDD are plotted in Figure 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. 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 relatively larger decrease of green *CWU* for soybean. Apparently, the reduction in *CWU* of maize and wheat was due to 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 western Jilin Province of China by Qin et al. (2012) and North China (Jin et al., 2012; Sun et al., 2003) based on local field experiments. Late planting, particularly for maize, rice and wheat, could save water, particular blue water, while increasing *Y*. The response of wheat yield did not match with the field experiment results in North China by Sun et al. (2003). 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 longer growing period. Although growing periods for 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 the Figure 3, the *Y* and total *WF* both dropped (by 0.25% and 0.3% to 30 days earlier planting, 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: reduction of *Y* by 0.2% and total *WF* by 9.3% with 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 Figure 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* reduced while green *WF* increased with higher S_{max} for maize, soybean, and rice. For wheat we found 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* (Eq. 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 crop. 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 *WF*s. 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 *WF*s. 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* (Figure 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 (Figure 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 ton^{-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 three years are shown in Table 4. The uncertainties are expressed in terms of values for 2SD as a percentage of the mean value; the range of ± 2SD 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 ET_0. Uncertainties in *PR* hardly affect the assessment of total *WF* of crops in all three 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 ton^{-1}) given the uncertainties in the two climatic input variables and all four input variables combined.

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), 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 North China (Qin et al., 2012; Jin et al., 2012; Sun et al., 2003), such information should be confirmed further 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 part of all input variables and parameters; uncertainties in other parameters were not considered, like for instance 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. 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. Furthermore, the uncertainties in water footprint estimation are scale dependent and decline with 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.

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.

Acknowledgements

The authors would like to thank reviewer Tuomas J. Mattila, an anonymous reviewer and editor for valuable comments and suggestions. Zhuo is grateful for the scholarship she received from the China Scholarship Council (CSC), No.2011630181.

References

Ahn, H.: Sensitivity for correlated input variables and propagated errors in evapotranspiration estimates from a humid region, Water Resour. Res., 32, 2507-2516, 2007.

Aldaya, M. M. and Llamas, M. R.: Water footprint analysis for the Guadiana river basin, Value of Water research Report Series No 35, UNESCO-IHE, Delft, the Netherlands, 2008.

Allen, R. G., Pereira, L. S., Raes, D. and Smith, M.: Crop evapotranspiration: guidelines for computing crop water requirements, FAO Drainage and Irrigation Paper 56, Food and Agriculture Organization, Rome, Italy, 1998.

Batjes, N. H.: ISRIC-WISE global data set of derived soil properties on a 5 by 5 arc-minutes grid (version 1.2). Report 2012/01, ISRIC - World Soil Information, Wageningen, the Netherlands, available at: www.isric.org, 2012.

Bocchiola, D., Nana, E. and Soncini, A.: Impact of climate change scenarios on crop yield and water footprint of maize in the Po valley of Italy, Agr. Water Manage., 116, 50-61, 2013.

Bulsink, F., Hoekstra, A. Y. and Booij, M. J.: The water footprint of Indonesian provinces related to the consumption of crop products, Hydrol. Earth Syst. Sc., 14, 119−128, 2010.

Cai, X. M., Yang, Y-C. E., Ringler, C., Zhao, J. S. and You, L. Z.: Agricultural water productivity assessment for the Yellow River Basin, Agr. Water Manage., 98, 1297–1306, 2011.

Chapagain, A. K. and Hoekstra, A. Y.: Water footprints of nations, Value of Water Research Report Series No. 16, UNESCO-IHE, Delft, The Netherlands, 2004.

Chen, Y., Guo, G., Wang, G., Kang, S., Luo, H. and Zhang, D.: Main crop water requirement and irrigation of China, Hydraulic and Electric Press, Beijing, China, 1995.

CMA: SURF_CLI_CHN_MUL_MON_CES v3.0, China Meteorological Data Sharing Service System, Chinese Meteorological Administration, available at: http://cdc.cma.gov.cn, 2008.

CMWR: China Water Resources Bulletin 2009, China Ministry of Water Resources, available at: www.mwr.gov.cn, last access: October 2010 (in Chinese), 2010.

Doorenbos, J. and Kassam, A. H.: Yield response to water, FAO Drainage and Irrigation Paper 33, FAO, Rome, Italy, 1979.

Droogers, P. and Allen, R. G.: Estimating reference evapotranspiration under inaccurate data conditions, IRRIG DRAIN 16, 33-45, 2002.

Estévez, J., Gavilán, P. and Berengena, J.: Sensitivity analysis of a Penman-Monteith type equation to estimate reference evapotranspiration in southern Spain, Hydrol. Process., 23, 3342-3353, 2009.

Falkenmark, M. and Widstrand, C.: Population and water resources: a delicate balance. Population Bulletin, Population Reference Bureau, Washington, D.C., USA, 1992.

Fekete, B. M., Vörösmarty, C. J., Roads, J. O. and Willmott, C. J.: Uncertainties in precipitation and their impacts on runoff estimates, J. Climate, 17, 294-304, 2004.

Feng, K. S., Siu, Y. L., Guan, D. and Hubacek, K.: Assessing regional virtual water flows and water footprints in the Yellow River Basin, China: A consumption based approach, Appl. Geogr., 32, 691-701, 2012.

Galli, A., Wiedmann, T., Ercin, E., Knoblauch, D., Ewing, B. and Giljum, S.: Integrating ecological, carbon and water footprint into a “footprint family” of indicators: Definition and role in tracking human pressure on the planet, Ecol. Indic., 16, 100-112, 2012.

Ge, L., Xie, G., Zhang, C., Li, S., Qi, Y., Cao, S. and He, T.: An evaluation of China’s water footprint, Water Resour. Manag., 25, 2633–2647, 2011.

Goyal, R. K.: Sensitivity of evapotranspiration to global warming: a case study of arid zone of Rajasthan (India), Agr. Water Manage., 69, 1-11, 2004.

Guieysse, B., Béchet, Q. and Shilton, A.: Variability and uncertainty in water demand and water footprint assessments of fresh algae cultivation based on case studies from five climatic regions, Bioresource Technol. 128, 317-323, 2013.

Hamby, D. M.: A review of techniques for parameter sensitivity analysis of environmental models, Environ. Monit. Assess., 32, 135-154, 1994.

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H.: Updated high-resolution grids of monthly climatic observations, Int. J. Climatol., doi:10.1002/joc.3711, 2013.

Hoekstra, A. Y. (Ed.): Virtual water trade: Proceedings of the International Expert Meeting on Virtual Water Trade, IHE Delft, the Netherlands, 12-13 December 2002, Value of Water Research Report Series No.12, UNESCO-IHE, Delft, the Netherlands, 2003.

Hoekstra, A. Y. and Chapagain, A. K.: Water footprints of nations: water use by people as a function of their consumption pattern, Water Resour. Manag., 21, 35-48, 2007a.

Hoekstra, A. Y. and Chapagain, A. K.: The water footprints of Morocco and the Netherlands: Global water use as a result of domestic consumption of agricultural commodities, Ecol. Econ., 64, 143-151, 2007b.

Hoekstra, A. Y., Chapagain, A. K., Aldaya, M. M. and Mekonnen, M. M.: The water footprint assessment manual: Setting the global standard, Earthscan, London, UK, 2011.

Hoekstra, A. Y., Mekonnen, M. M., Chapagain, A. K., Mathews, R. E. and Richter, B. D.: Global monthly water scarcity: Blue water footprints versus blue water availability, PLoS ONE, 7, e32688, 2012.

Hoekstra, A. Y. and Mekonnen, M. M.: The water footprint of humanity, P. Natl. Acad. Sci. USA, 109, 3232–3237, 2012.

Jagtap, S. S. and Jones, J. W.: Stability of crop coefficients under different climate and irrigation management practices, Irrigation Sci., 10, 231-244, 1989.

Jensen, M. E., Burman, R. D. and Allen, R. G. (Eds.): Evaporation and irrigation water requirements, ASCE Manuals and Reports on Engineering Practices No.70, American Society of Civil Engineers, New York, USA, 1990.

Kampman, D. A., Hoekstra, A. Y. and Krol, M. S.: The water footprint of India, Value of Water Research Report Series No.32, UNESCO-IHE, Delft, the Netherlands, 2008.

Lehner, B., Verdin, K. and Jarvis, A.: New global hydrography derived from space borne elevation data, Eos, 89, 93-94, 2008.

Liu, J. and Yang, H.: Spatially explicit assessment of global consumptive water uses in cropland: green and blue water, J. Hydrol., 384, 187–197, 2010.

Liu, J. and Savenije, H. H. G.: Food consumption patterns and their effect on water requirement in China, Hydrol. Earth Syst. Sci., 12, 887–898, 2008.

Liu, Q., Yang, Z., Cui, B. and Sun, S.: The temporal trends of reference evapotranspiration and its sensitivity to key meteorological variables in the Yellow River Basin, China, Hydrol. Process., 24, 2171-2181, 2010.

Ma, J., Hoekstra, A.Y., Wang, H., Chapagain, A.K., and Wang, D.: Virtual versus real water transfers within China. Philos. T. R. Soc. B, 361, 835–842, 2006.

MAPRC: Sixty years agricultural statistics of New China, Ministry of Agriculture of the People's Republic of China, China Agriculture Press, Beijing, China, 2009.

Mattila, T., Leskinen, P., Soimakallio, S. and Sironen, S.: Uncertainty in environmentally conscious decision making: beer or wine? Int. J. Life Cycle Ass., 17, 696-705, 2012.

McMaster, G. S. and Wilhelm, W. W.: Growing degree days: one equation, two interpretations, AGR FOREST METEOROL, 87, 297-300, 1997.

Mekonnen, M. M. and Hoekstra, A. Y.: A global and high-resolution assessment of the green, blue and grey water footprint of wheat, Hydrol. Earth Syst. Sci., 14, 1259–1276, 2010.

Mekonnen, M. M. and Hoekstra, A. Y.: The green, blue and grey water footprint of crops and derived crop products, Hydrol. Earth Syst. Sci., 15, 1577-1600, 2011.

Meyer, S. J., Hubbard, K. G. and Wilhite, D. A.: Estimating potential evapotranspiration: the effect of random and systematic errors. Agric. For. Meteorol., 46, 285-296, 1989.

Meyer, V. R.: Measurement uncertainty, J. Chromatogr. A, 1158, 15-24, 2007.

NBSC: China agricultural statistical yearbook assembly 1949-2004, National Bureau of Statistics of China, China Statistics Press, Beijing, China, 2006.

NBSC: China Rural statistical yearbook 2006, National Bureau of Statistics of China, China Statistics Press, Beijing, China, 2007.

Oki, T. and Kanae, S.: Global hydrological cycles and world water resources, Science, 313, 1068-1072, 2006.

Parker, R. W. R. and Tyedmers, P. H.: Uncertainty and natural variability in the ecological footprint of fisheries: A case study of reduction fisheries for meal and oil, Ecol. Indic., 16, 76-83, 2012.

Phillips, D. L. and Marks, D. G.: Spatial uncertainty analysis: propagation of interpolation errors in spatially distributed models, Ecol. Model., 91, 213-229, 1996.

Portmann, F. T., Siebert, S. and Döll, P.: MIRCA2000 – Global monthly irrigated and rain-fed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling, Global Biogeochem. Cy., 24, GB 1011, 2010.

Qin, L. J., Jin, Y. H. and Duan, P. L.: Impact of different planting dates on green water footprint of maize in western Jilin Province, Acta Ecologica Sinica, 32(23): 7375-7382, 2012.

Raes, D., Steduto, P., Hisiao, T. C. and Fereres, E.: Reference Manual, Annex I – AquaCrop, Version 4.0, Italy, 2012.

Reynolds, C. A., Yitayew, M., Slack, D. C., Hutchinson, C. F., Huete, A., and Petersen, M. S.: Estimating crop yields and production by integrating the FAO Crop Specific Water Balance model with real-time satellite data and ground-based ancillary data, Int. J. Remote Sens., 21(18), 3487–3508, 2000.

Ringler, C., Cai, X. M., Wang, J. X., Ahmed, A., Xue, Y. P., Xu, Z. X., Yang, E. T., Zhao, J. S., Zhu, T. J., Cheng, L., Fu, Y. F., Fu, X. F., Gu, X. W. and You, L. Z.: Yellow River basin: living with scarcity, Water Int., 35, 681-701, 2010.

Röös, E., Sundberg, C. and Hansson, P. A.: Uncertainties in the carbon footprint of food products: a case study on table potatoes, Int. J. Life Cycle Ass., 15, 478–488, 2010.

Röös, E., Sundberg, C. and Hansson, P. A.: Uncertainties in the carbon footprint of refined wheat products: a case study on Swedish pasta, Int. J. Life Cycle Ass., 16, 338–350, 2011.

Schuol, J. and Abbaspour, K. C.: Using monthly weather statistics to generate daily data in a SWAT model application to West Africa, Ecol. Model., 201, 301-311, 2007.

Siebert, S. and Döll, P.: Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation, J. Hydrol., 384, 198-217, 2010.

Singh, V. P. and Xu, C. Y.: Sensitivity of mass transfer-based evaporation equations to errors in daily and monthly input data, Hydrol. Process., 11, 1465-1473, 1997.

Sun, S. K., Wu, P. T., Wang, Y. B. and Zhao, X. N.: Temporal variability of water footprint for maize production: The case of Beijing from 1978 to 2008, Water Resour. Manag., 27, 2447-2463, 2013.

Sun, X. Y., Newham, L. T. H., Croke, B. F. W. and Norton, J. P.: Three complementary methods for sensitivity analysis of a water quality model, Environ. Model. Softw., 37, 19-29, 2012.

Thomas, A.: Development and properties of 0.25-degree gridded evapotranspiration data fields of China for hydrological studies, J. Hydrol., 358, 145-158, 2008.

Troutman, B. M.: Errors and Parameter Estimation in Precipitation-Runoff Modeling: 1. Theory. Water Resour. Res., 21, 1195-1213, 1985.

Vörösmarty, C. J., Green, P., Salisbury, J. and Lammers, R. B.: Global water resources: Vulnerability from climate change and population growth, Science, 289, 284-288, 2000.

Walker, W. E., Harremoës, P., Rotmans, J., Van der Sluis, J. P., Van Asselt, M. B. A., Janssen, P. and Krayer von Krauss, M. P.: Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integrat. Ass., 4(1): 5-17, 2003.

Xu, C. Y., Tunemar, L., Chen, Y. Q. D. and Singh, V. P.: Evaluation of seasonal and spatial variations of lumped water balance model sensitivity to precipitation data errors, J. Hydrol., 324, 80-93, 2006a.

Xu, C. Y., Gong, L. B., Jiang, T., Chen, D. L. and Singh, V. P.: Analysis of spatial distribution and temporal trend of reference evapotranspiration and pan evaporation in Changjiang (Yangtze River) catchment, J. Hydrol., 327, 81-93, 2006b.

YRCC: Yellow River water resource bulletin 2010, Yellow River Conservancy Commission, Zhengzhou, China, available at: www.yellowriver.gov.cn (in Chinese), 2011.

Zeng, Z., Liu, J., Koeneman, P. H., Zarate, E., and Hoekstra, A. Y.: Assessing water footprint at river basin level: a case study for the Heihe River Basin in northwest China, Hydrol. Earth Syst. Sci., 16, 2771-2781, 2012.

Zhao, T. B. and Fu, C. B.: Comparison of products from ERA-40, NCEP-2, and CRU with station data for summer precipitation over China, Adv. Atmos. Sci., 23, 593–604, 2006.

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

	Crop coefficients			Planting date	Growing period (days)	Relative crop growing stages			
	K_c_ini	K_c_mid	K_c_end			*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-October	335	0.48	0.22	0.22	0.07

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.

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

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

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 (m^3/t)	Changes in the *WF* to variability of input variables (%)											
		PR		ET_0		*Kc*		*D*		S_{max}		K_y	
		-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

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

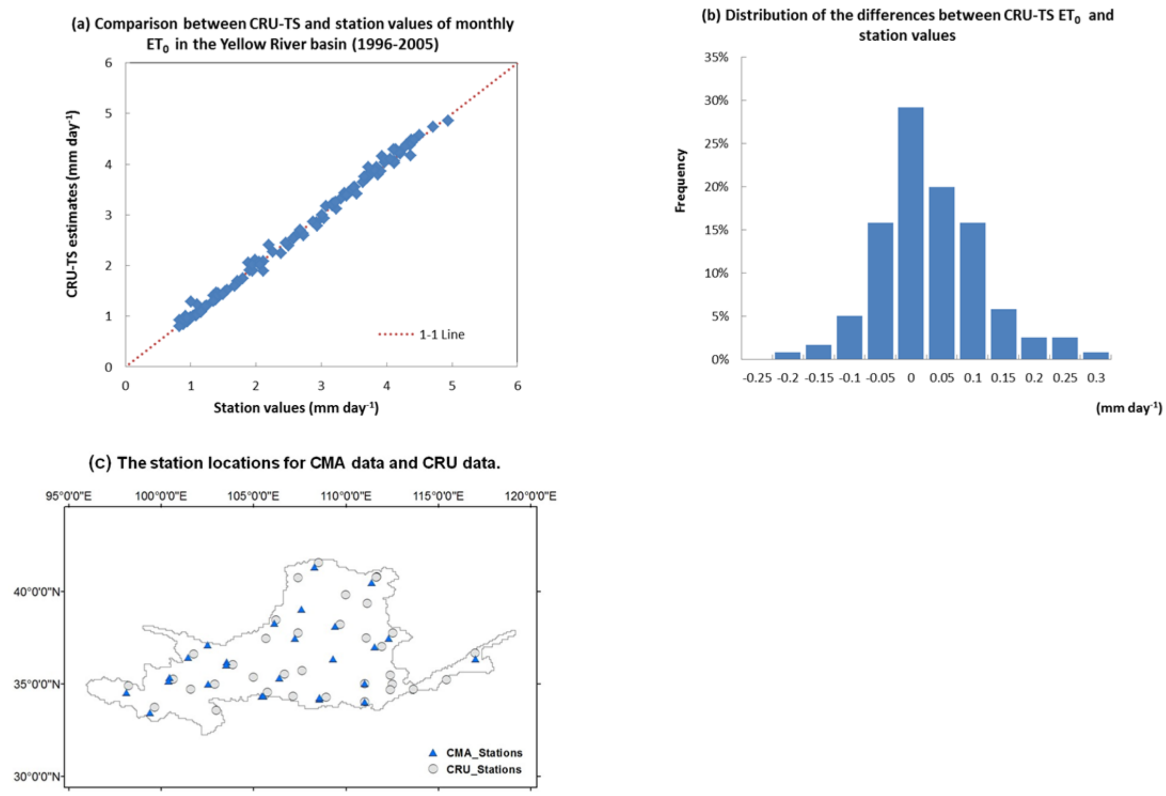

Figure 1. Differences between monthly averages of daily ET_0 data from CRU-TS and station-based values for the Yellow River Basin, 1996-2005.

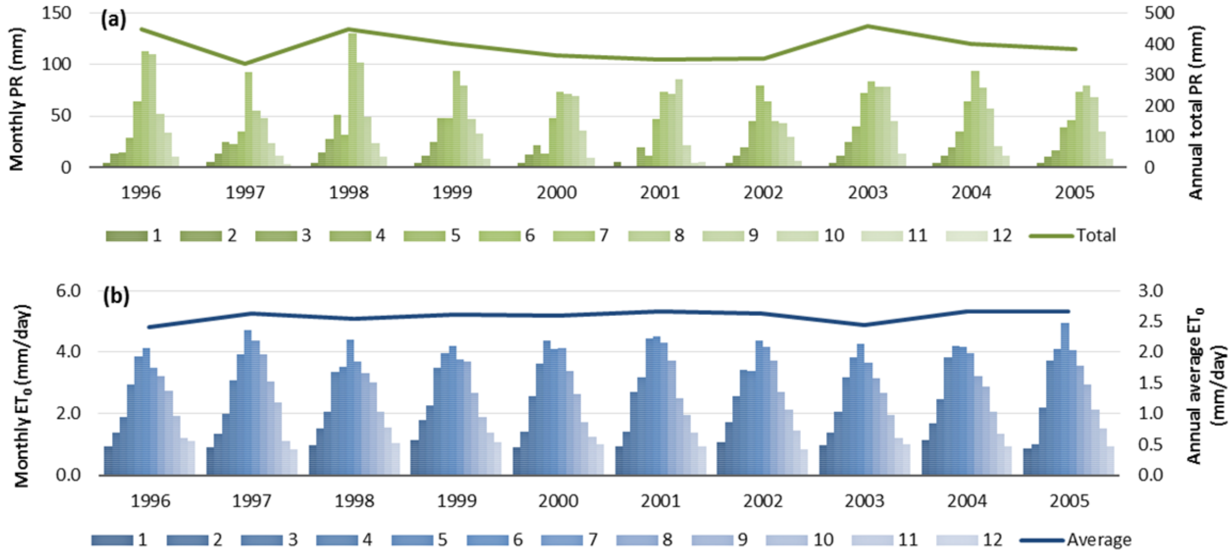

Figure 2. Monthly precipitation (*PR*) and monthly averages of daily reference evapotranspiration (ET_0) in the Yellow River Basin from the CRU-TS database, for the period 1996-2005.

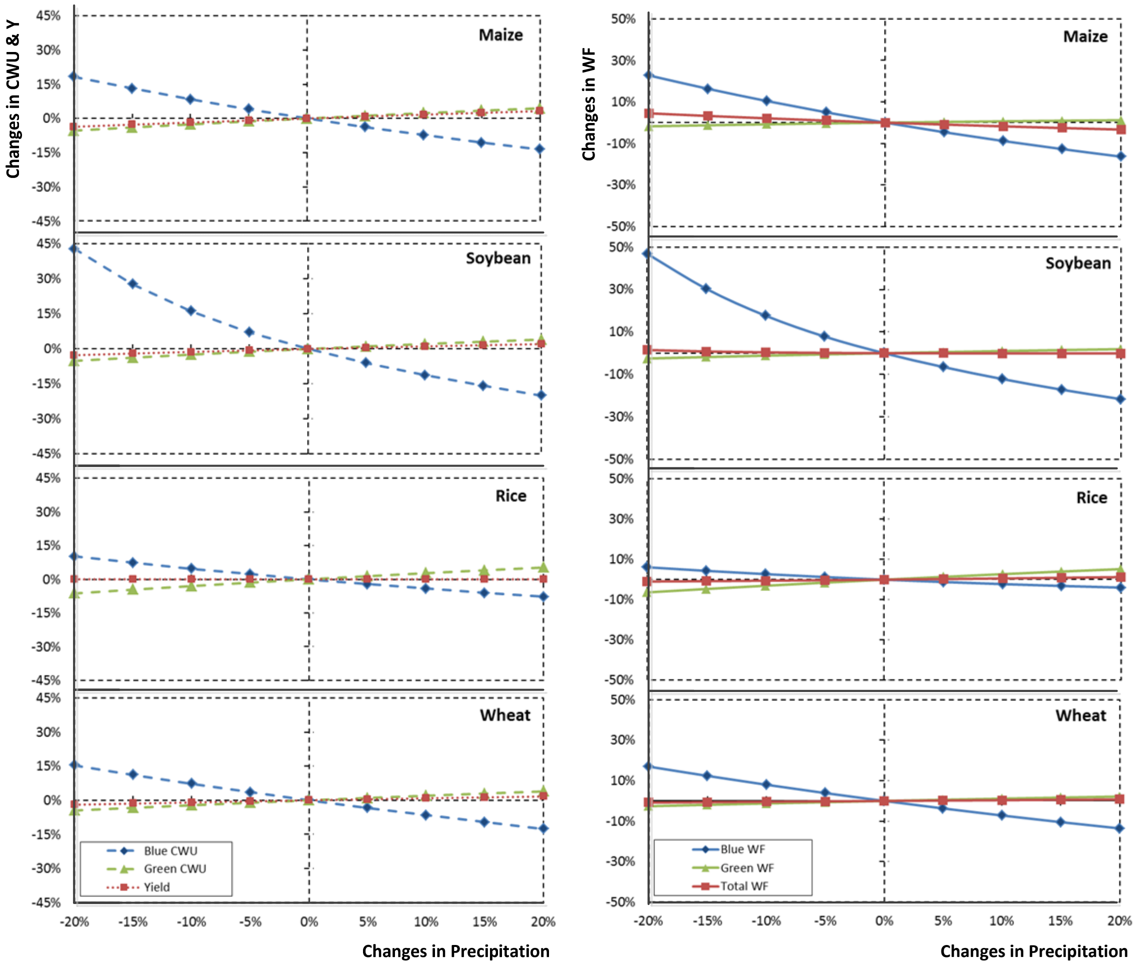

Figure 3. Sensitivity of *CWU, Y* and *WF* to changes in precipitation (*PR*), 1996-2005.

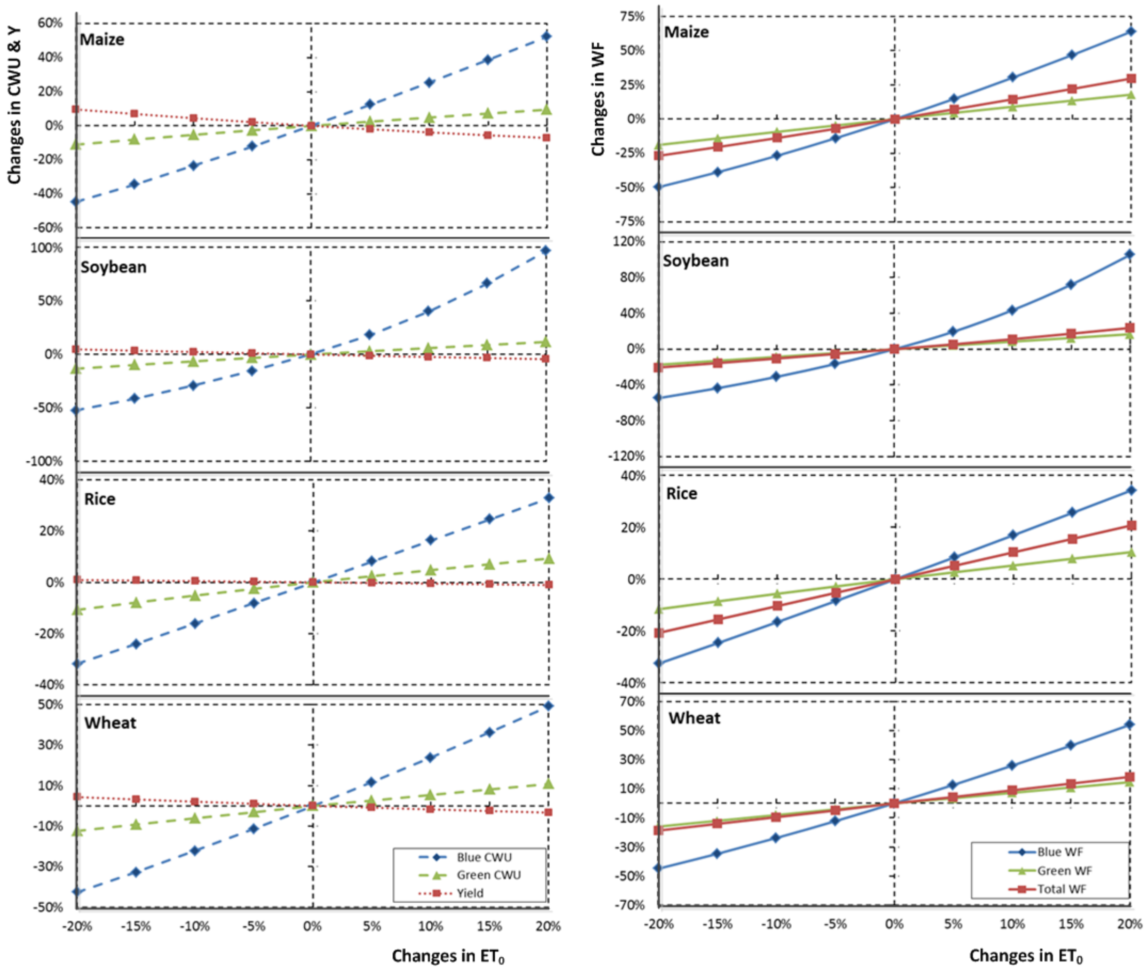

Figure 4. Sensitivity of *CWU*, *Y* and *WF* to changes in reference evapotranspiration (ET_0), 1996-2005.

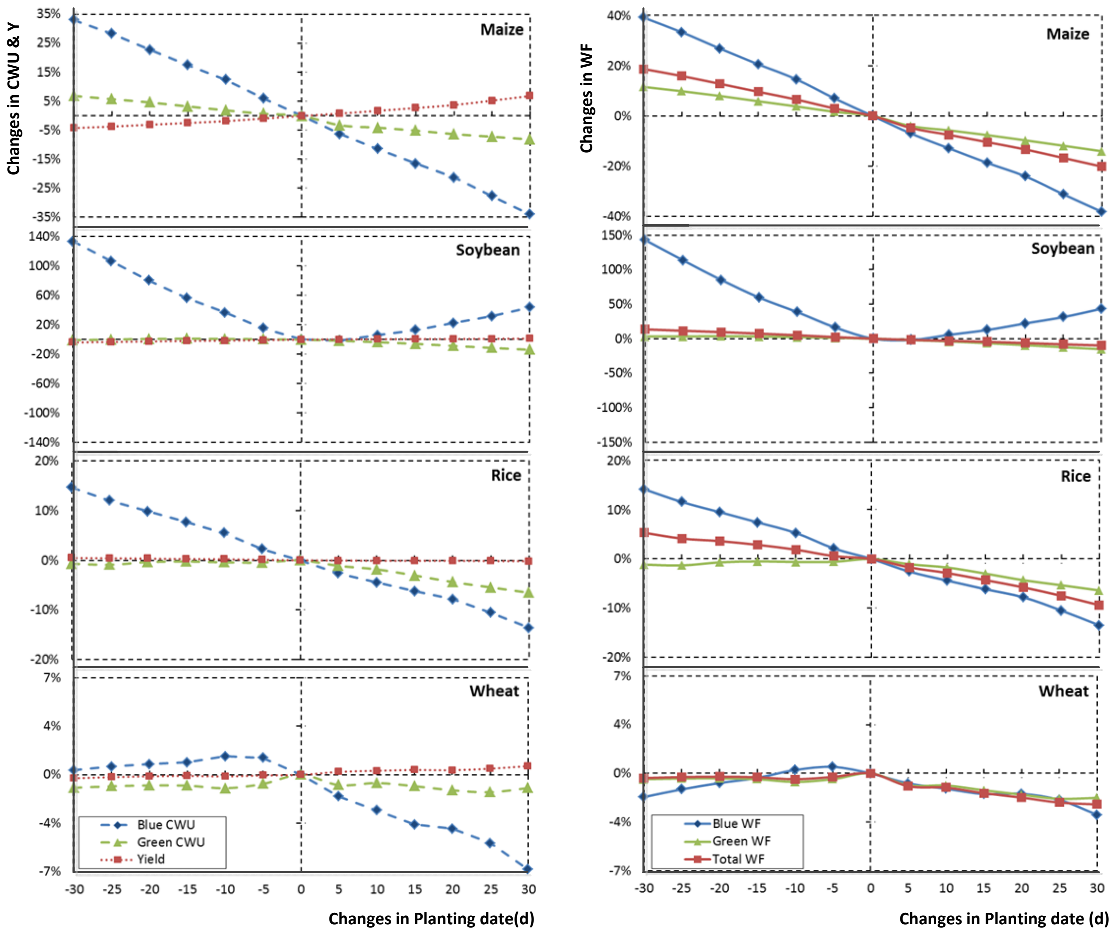

Figure 5. Sensitivity of *CWU*, *Y* and *WF* to changes in crop planting date (*D*), 1996-2005.

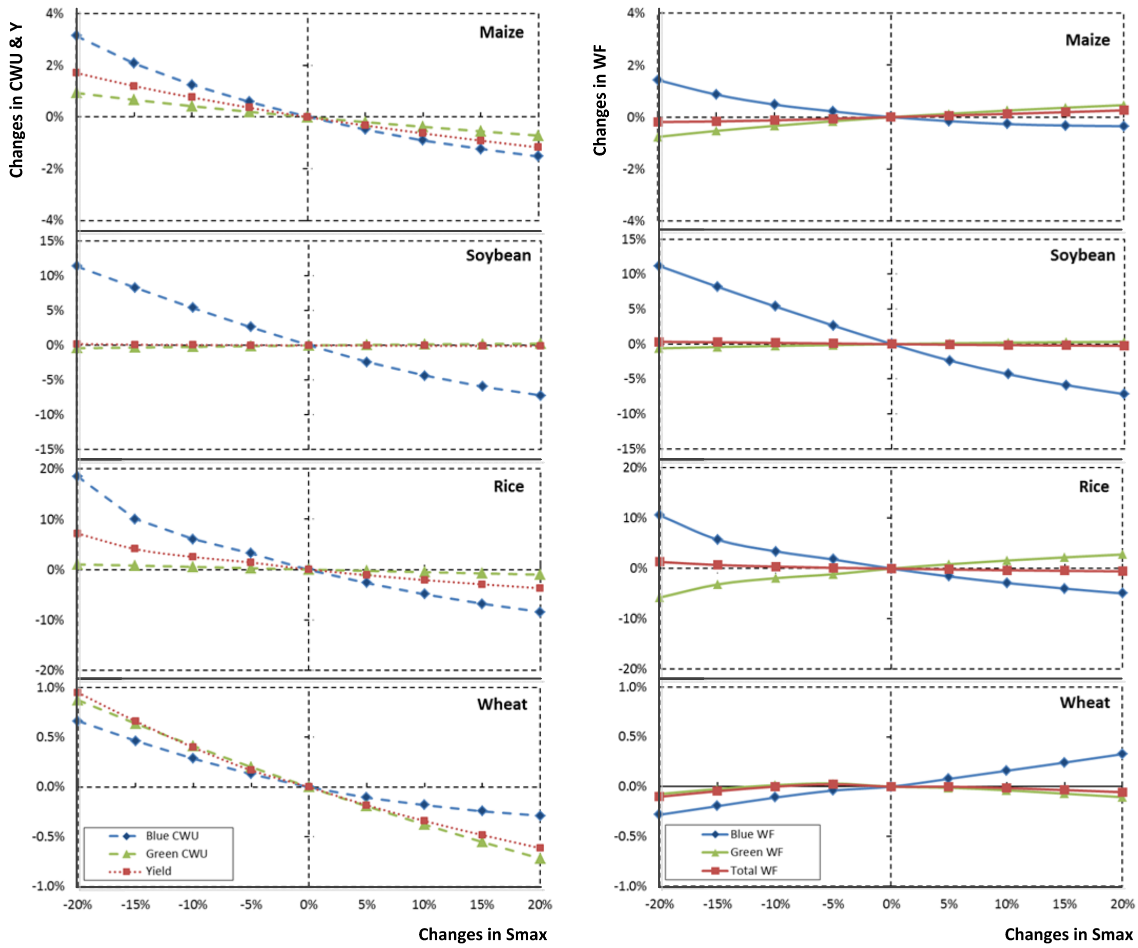

Figure 6. Sensitivity of *CWU*, *Y* and *WF* to changes in the field capacity of the soil water (S_{max}), 1996-2005.

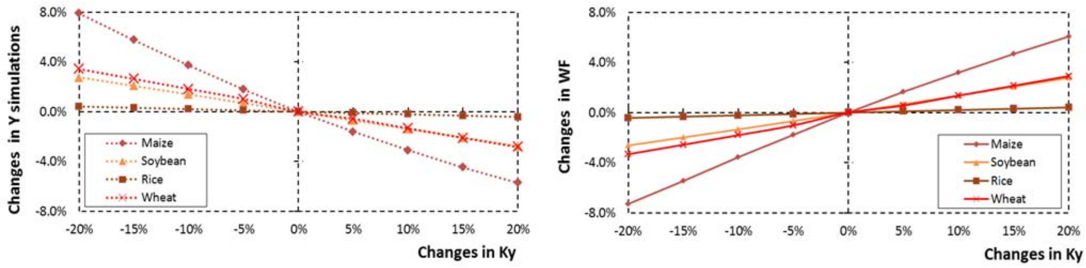

Figure 7. Sensitivity of *Y* and *WF* to changes in yield response factor (K_y), 1996-2005.

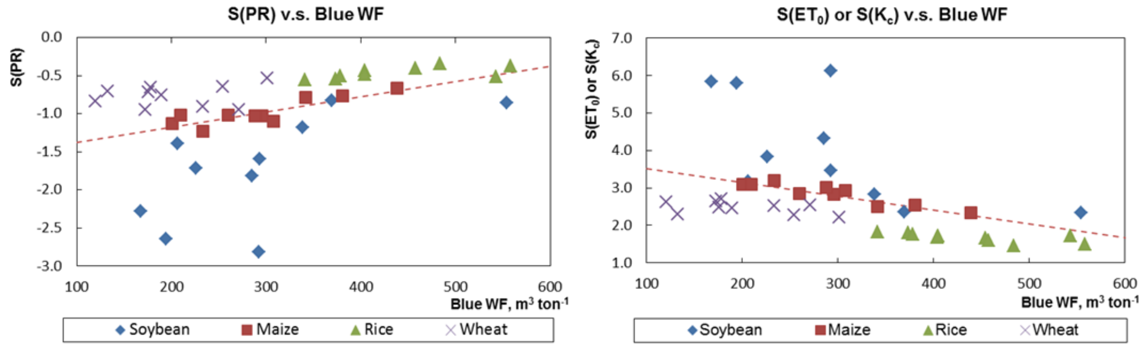

Figure 8. The slope (S) of the sensitivity curve for the blue *WF* for each crop for each year in the period 1996-2005 (vertical axis) plotted against the blue *WF* of the crop in the respective year (x-axis). The graph on the left shows the relative sensitivity of blue *WF* to *PR*; the graph on the right shows the relative sensitivity of blue *WF* to 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.

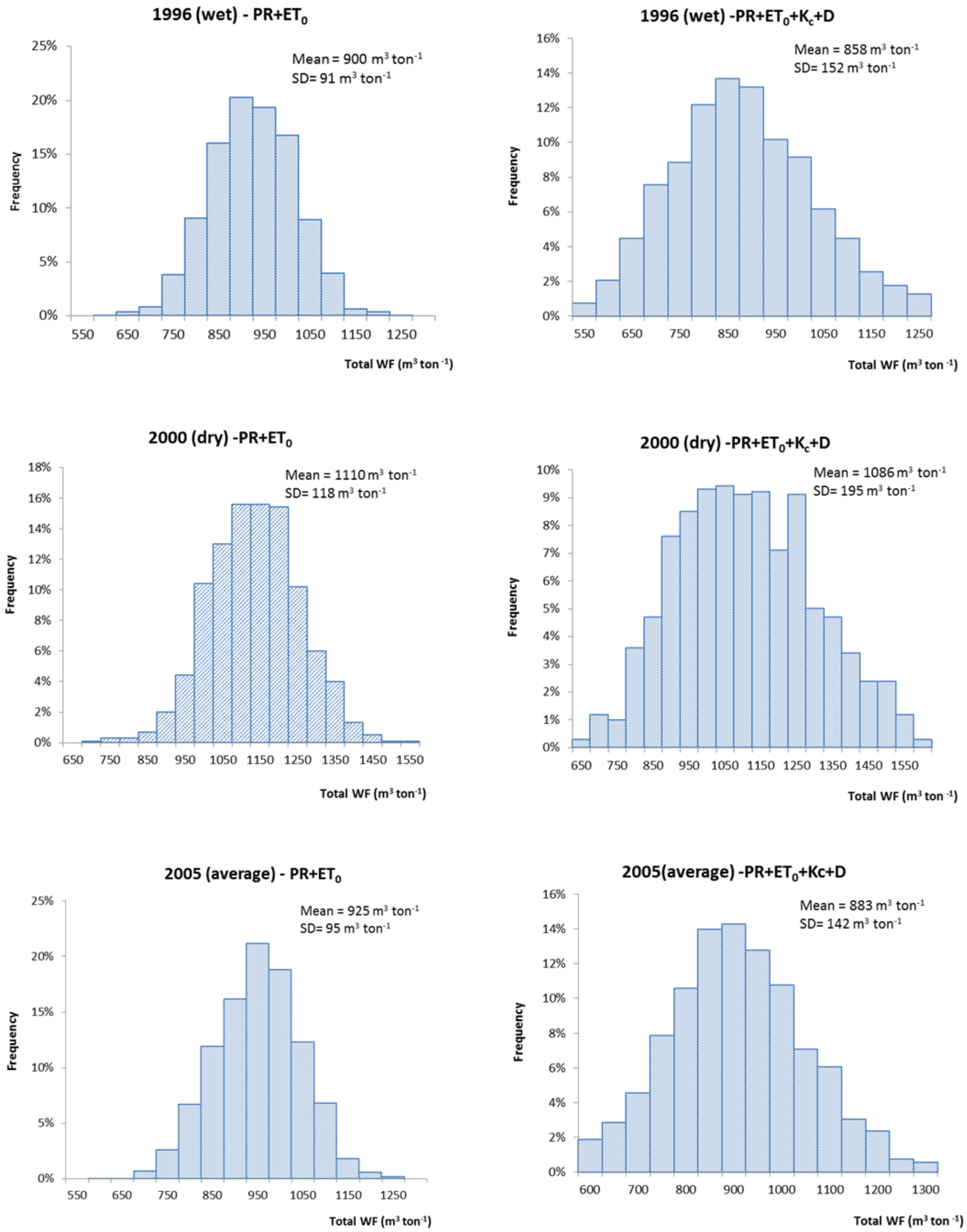

Figure 9. Probability distribution of the total *WF* of maize given the combined uncertainties in *PR* and ET_0 (graphs at the left) and given the combined uncertainties in *PR*, ET_0, K_c and *D* (graphs at the right), for the years 1996, 2000 and 2005.