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Quantitative study of the crop production water footprint using the SWAT model

Xiaobo Luan[a], Pute Wu[a,c,*], Shikun Sun[b,c,*], Yubao Wang[b,c], Xuerui Gao[c]

[a] Institute of Soil and Water Conservation, University of Chinese Academy of Sciences, Yangling 712100, Shaanxi, China
[b] Key Laboratory of Agricultural Soil and Water Engineering in Arid and Semiarid Areas, Ministry of Education, Northwest A&F University, Yangling 712100, Shaanxi, China
[c] Institute of Water Saving Agriculture in Arid regions of China, Northwest A&F University, Yangling 712100, Shaanxi, China

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ABSTRACT

Assessment of the water use efficiency is the key to effectively manage agricultural water resource. The water footprint is a new index for water use evaluation, and its quantification is a precondition for assessment of the agricultural water use efficiency. Due to the shortage of water footprint calculation methods and computational module defects, this study aims to establish a method for calculating the water footprint of crop production based on hydrological processes. In this study, the field-scale water footprints of wheat, corn and sunflower were calculated using the SWAT model in the Hetao irrigation district (HID), China. The results showed that the average total water footprints of wheat, corn and sunflower were 1.036 m^3/kg, 0.774 m^3/kg and 1.510 m^3/kg, respectively. Additionally, the proportions of green water footprints in wheat, corn and sunflower were 22.3%, 26.1% and 29.4%, respectively. Water footprint calculations based on the SWAT model can reflect the spatial differences of water footprints during the process of crop production. The overall distribution pattern of the green, blue and total water footprints for the three crops demonstrated that high values were in the east part of the HID, followed by the west and the central areas. The SWAT-based water footprint offers high spatial resolution and is effective in exploring the spatial heterogeneity of crop water footprints.

1. Introduction

Global consumption of freshwater resources has grown more than sixfold in the past century (Gleick, 2000). Local water consumption has accumulated as a global problem (Vörösmarty et al., 2015). With the growth of the population and people's changing lifestyles, future demand for freshwater resources will continue to increase (Rosegrant and Ringler, 2000; Liu et al., 2008). The need for effective evaluations of water use efficiency has become an important global problem as the demand for water resources increases (Perry, 2007; Vörösmarty et al., 2010). Agricultural production is a water-intensive and low-return industry; the agricultural sector accounts for 85% of global blue water (surface or groundwater) consumption (Shiklomanov, 2000). In China, more than 60% of annual water resources are used for agricultural production and irrigation is the most important way of agricultural fresh water consumption (NBSC, 2014). The rapid development of China's economy, industrial production and urban areas will cause enormous pressure on regional water resources (Yu et al., 2011; Wang et al., 2014; Sun et al., 2016). Industrial economic development will pressure limited water resources, which will have a significant negative impact on agricultural production. Therefore, it is crucial to develop quantitative assessments and improve the utilization efficiency of agricultural water use to reduce the adverse effects of reduced water availability. It is important to study these problems to safeguard food security in China.

The water footprint theory provides methods and ideas to solve such problems (Hoekstra, 2009; Aldaya et al., 2010; Hoekstra and Mekonnen, 2012; Galli et al., 2012; Jackson et al., 2015). The water footprint is an indicator of freshwater use and can be used to quantify water consumption throughout the entire production supply chain. It reflects the amount of water and types of resources that are consumed and identifies contamination and pollution in the system. The water footprint of crop production is the ratio of water consumed per unit area during the growth period and its yield (Hoekstra and Mekonnen, 2012). In the agricultural sector, the crop production water footprint shows whether water consumption in crop growth period water is from green water (rainfall) or blue water (surface or groundwater), along with their respective volumes and proportions (Hoekstra and Chapagain, 2008; Hoekstra et al., 2011). It can also evaluate whether the crop's water footprint is reasonable and whether it varies regionally.

* Corresponding authors at: Institute of Soil and Water Conservation, Chinese Academy of Sciences and Ministry of Water Resources, Yangling 712100, Shaanxi, China.
E-mail addresses: gjzwpt@vip.sina.com (P. Wu), sksun@nwafu.edu.cn (S. Sun).

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These results can help inform whether measures can be taken to reduce the crop production water footprint and limit the proportion of blue water consumption. Accurate and precise quantification of crop water footprints is beneficial in assessing crop water use, these would improve the agricultural water use efficiency and decrease the volume of agricultural water consumption (Hoekstra and Hung, 2002; Hoekstra, 2003).

Many scholars have quantified various levels of crop water footprints and there are two main methods for crop water footprint calculation. The first method is based on an empirical formula model, such as CROPWAT model (Mekonnen and Hoekstra, 2011; Sun et al., 2013a) and CropSyst model (Bocchiola, 2015). The second method is statistical method which is based on regional water balance (Zhao et al., 2009; Sun et al., 2013b). But these methods have following shortcomings: first, the evapotranspiration (ET) calculated by these two methods is a theoretical value (Allen et al., 1998). The ET was calculated under the optimal conditions (Mekonnen and Hoekstra, 2011; Sun et al., 2013a,c; Bocchiola, 2015), but the obtained results may not be in accord with facts. Therefore, the quantification method needs to be refined. Second, both of these methods do not consider the influence of actual soil moisture condition, terrain and farmland management practices on crop water consumption. Third, the low spatial resolution in these studies is not conducive to the actual operational management of agricultural water since it is at the regional or district level, such as in Europe (Vanham and Bidoglio, 2014), Spain (Duarte et al., 2014; Castellanos et al., 2016), the Yellow River basin (Zhao et al., 2010), the Haihe river basin (Zhuo et al., 2015) and the entire Hetao irrigation district (Sun et al., 2013b,c). Further, the accurate calculations of field scale water footprints are needed by the administration to effectively manage water resource, but few studies have focused on the spatial variation of crop production water footprints within an administrative region or river basin. Here, distributed hydrological models (SWAT model) can contribute to meeting these requirements.

Based on the water footprint computation framework, the aim of this study is to provide a new way for calculating the water footprint of crop production in the Hetao irrigation district based on a hydrological model.

2. Materials and methods

2.1. Study site

The Hetao irrigation district (HID) is located in the middle of the Yellow River basin in western Inner Mongolia (Fig. 1) and is one of the three largest irrigation districts in China. The area of HID is 1.12×10^4 km^2, and the average elevation is 1005–1060 m. The HID has a continental monsoon climate, with the lowest temperature in January (average −10 °C, the lowest −32 °C) and highest temperature in July (average 23 °C, the highest 35 °C). The annual precipitation is 145–216 mm and annual potential evaporation is 1987–2375 mm. The major crops are spring wheat, corn and sunflower. The growth period of wheat is between April and July, while the corn and sunflower is between May and October. Irrigation water is diverted from the Yellow River, and the primary irrigation technology used in HID is surface irrigation (Sun et al., 2013b). The irrigation and drainage system in HID are constituted by irrigation canals and drainage ditches. The irrigation system has a primary canal (228.9 km) and 12 supplementary canals (total 755 km). The drainage system has a primary main ditch (227 km) and 12 supplementary ditches (total 523 km) (AHID, 2015).

2.2. Model description

The SWAT (soil and water assessment tool) model is at the scale of a small watershed to river basin and evaluates the physical hydrological distribution to simulate the quality and quantity of both surface and ground water as well as to predict the environmental impact of land use, land management practices, and climate change (Arnold et al., 1998; SWAT, http://swat.tamu.edu/). It also incorporates the effects of water, evapotranspiration, run off, topography, and agricultural management practices. The model partitions a watershed into subbasins by topography and then partitions the subbasins into hydrologic response units (HRU) based on soil type and land use to assess soil erosion, nonpoint pollution, and hydrologic processes (Haverkamp et al., 2002). HUR is the basic unit of model computation. Because each HRU hydrological simulation process is independent, the data obtained from the simulation results were different, causing the ET in output data to be different. The water balance equation governed by the hydrologic component of the SWAT model (Neitsch et al., 2011) is as follow:

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \tag{1}$$

where SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day i (mm H_2O), E_a is the amount of actual evapotranspiration on day i (mm H_2O), W_{seep} is the amount of percolation and bypass flow exiting the bottom of the soil profile on day i (mm H_2O), and Q_{gw} is the amount of return flow on day i (mm H_2O).

2.3. Data collection

The data required by the SWAT model includes topography, soil, land use, discharge and climate. The global digital elevation model (GDEM) (30 × 30 m resolution) was provided by the Geospatial Data Cloud site (CAS, 2009a). Soil data (1:1,000,000) were obtained from the China Soil Scientific Database (CAS, 2009b). Land use data (1:100,000) of 2010 were obtained from the Data Center for Resources and Environmental Sciences (CAS, 2010).

The discharge data (AHID, 2015) included monthly data from 2003 to 2012. Due to the gentle slope, low levels of precipitation and strong evaporation, the drainage network based on the DEM was not consistent with the actual water system. Therefore, to divide the subbasin, we defined the drainage ditch as the stream (AHID, 2015) and burn-in into the DEM, and the simulation results were verified by the discharge of the drainage ditch.

The climate data during 2003 and 2012 were obtained from the China meteorological data network (NMIC, 2015), which included daily data of precipitation, solar radiation, maximum and minimum temperature, wind speed and relative humidity for five weather stations in the HID (Fig. 1). The average precipitation (2006–2012) of five counties in the HID are shown in Fig. 2.

The crop yield (wheat, corn and sunflower) required for the calculation of the water footprint was obtained from the Statistical Yearbook of local agricultural administrations (AHID, 2015), the three crops yield and spatial distribution are shown in Fig. 3. The irrigation parameters (irrigation time, irrigation quota) of different crops (wheat, corn and sunflower) were obtained from the local farmers in the HID, and then these parameters are entered to the model for simulation.

2.4. Calibration, validation, and sensitivity analysis

The Sequential Uncertainty Fitting (SUFI-2) algorithm in SWAT-CUP was applied for calibration and validation (Abbaspour et al., 2007; Abbaspour, 2012) by comparing the simulated stream discharge from the model with the measured discharge data. The land use data from 2010 were used to represent the land use patterns of the 2010s (2003–2012). The calibration period was from 2006 to 2009, and the validation period was from 2010 to 2012. The global sensitivity analysis integrated within SUFI-2 was used to evaluate the hydrologic parameters for the discharge simulation.

For calibration and validation analyses, the monthly measured

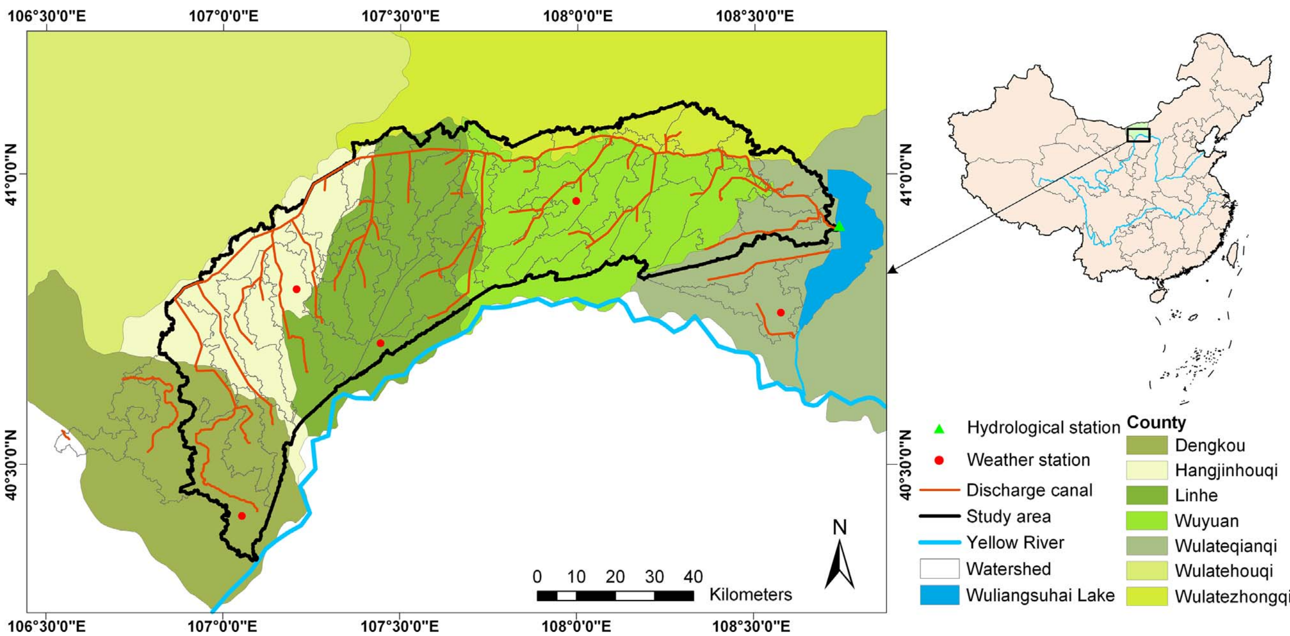

Fig. 1. Location of Hetao irrigation district (HID).

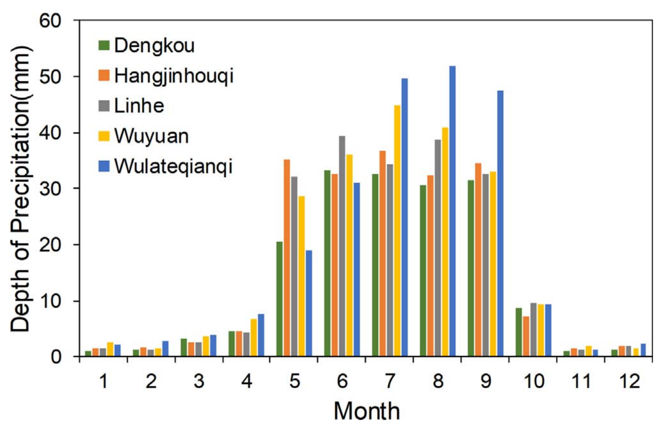

Fig. 2. Average precipitation (2006–2012) in the HID.

discharges were compared with the simulated discharge data and the model performance was evaluated using the coefficient of determination (R^2), Nash efficiency coefficient (NSE) (Nash and Sutcliffe, 1970; Moriasi et al., 2007) and percent deviation (PBIAS) (Gupta et al., 1999). The calculation formula is as follows:

$$R^2 = \frac{[\sum_{i=1}^{n}(Q_m-\overline{Q}_m)(Q_s-\overline{Q}_s)]^2}{\sum_{i=1}^{n}(Q_m-\overline{Q}_m)^2\sum_{i=1}^{n}(Q_s-\overline{Q}_s)^2} \tag{2}$$

$$NSE = 1-\frac{\sum_{i=1}^{n}(Q_m-Q_s)^2}{\sum_{i=1}^{n}(Q_m-\overline{Q}_m)^2} \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(Q_m-Q_s)}{\sum_{i=1}^{n}Q_{m,i}}\times 100 \tag{4}$$

where Q_m is the measured data, $\overline{Q}_m$ is the mean of measured data, Q_s is the model simulation data, and $\overline{Q}_s$ is the mean of model simulation data.

R^2 measures the simulated and measured values of goodness. The closer of the value to 1, the higher is the agreement between the simulated and the measured discharge. The NSE is widely applied in hydrologic models that range from negative infinity to 1, with 1 being the ideal value (Moriasi et al., 2007). The PBIAS assesses the average deviation of simulated values from observed values, with 0 as the ideal value, and a positive (negative) PBIAS value shows an underestimation (overestimation) bias of the simulated variable compared to the measured variable (Gupta et al., 1999). The model monthly data simulation results can be classified as satisfactory if $R^2 > 0.6$, NSE > 0.5 and PBIAS < ± 25 (Moriasi et al., 2007; Neupane and Kumar, 2015). These statistical measures were evaluated for monthly discharge simulation and then were used to assess land use change impacts on the irrigation district hydrologic process.

2.5. The crop production water footprint calculation method

The water footprint of crop production is the total volume of water that is used to produce the crops. Based on the water footprint theory framework provide by Montesinos et al. (2011) and Hoekstra et al. (2011), this study suggests a new way of quantifying the water footprint of a crop (Fig. 4). The ET_c was the total water consumed during the crop production process, so calculating the ET_c of the crop growth period is the key to calculate the water footprint of crop production. In this study, the hydrological model (SWAT model) was used to simulate the hydrological cycle process to obtain the ET_c data of the crop growth period. In this study, potential ET was calculated by Penman–Monteith method recommended by FAO (Allen et al., 1998). The SWAT model is a distributed hydrological model that divides the research area into different subbasins according to topography and stream, and then, the subbasins are divided into hydrological response units (HRU) based on the soil and land use types.

The green water footprint is the volume of precipitation consumed during the crop growth period. The blue water footprint is the volume of surface water or groundwater consumed during the crop growth period. In this study, HRU is the basic unit of water footprint calculation. After calculating the water footprint of each HRU, we further counted the average water footprint of all the HRU in each subbasin range to obtain each subbasin water footprint. Finally, we used the subbasin data to research the changing characteristics of the water footprint in space.

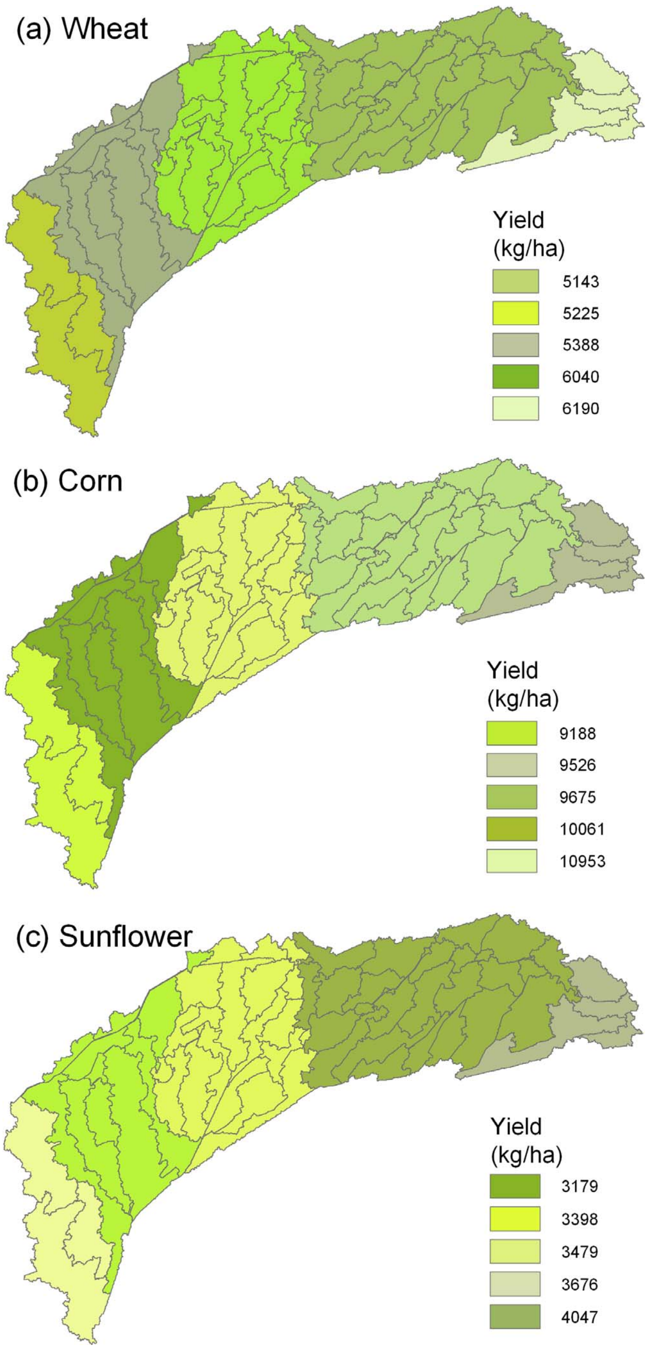

Fig. 3. The yield of crop, (a) wheat, (b) corn and (c) sunflower in the HID.

The green, blue and total water footprint of crop production is calculated as:

$$\begin{cases} WF_{crop} = WF_{green} + WF_{blue} \\ WF_{green} = \frac{W_{green}}{Y} \\ WF_{blue} = \frac{W_{blue}}{Y} \\ W_{green} = 10\ \min(ET_c, P_e) \\ W_{blue} = 10\ \max(0, ET_c - P_e) \end{cases} \quad (5)$$

where WF_{corp} is the water footprint of crop production (m^3/kg), WF_{green} is the green footprint (m^3/kg), WF_{blue} is the blue water footprint (m^3/kg), W_{green} is the green water consumption during crop growth period, W_{blue} is the blue water consumption during crop growth period, Y is the crop yield per unit area (kg/ha), ET_c is the crop actual evapotranspiration during the crop growth period (mm), and P_e is the effective precipitation over the crop growth period (mm). Multiplication by 10 is intended to convert water depths (mm) into water volumes per land surface (m^3/ha).

ET_c was calculated by the SWAT model output data as follow:

$$ET_c = \sum_{i=1}^{t} E_a \quad (6)$$

where E_a is the amount of actual evapotranspiration on day i (mm H_2O), which is obtained by SWAT model output data, and t is the crop growth period (days).

P_e is calculated by the following equation (FAO, 2010):

$$\begin{cases} P_e = P(4.17 + 0.02P)/4.17 & P < 83\ \text{mm} \\ P_e = 41.7 + 0.1P & P \geq 83\ \text{mm} \end{cases} \quad (7)$$

where P represents 10 days of precipitation (CROPWAT uses calculation steps of 10 days and monthly climatic data) (mm).

3. Results

3.1. Calibration and validation of SWAT

The SWAT-CUP parameter sensitivity analysis procedure showed that the CN2, ESCO, GW_REVAP, SOL_AWC parameters were more sensitive to input changes than other parameters. These sensitive parameters were optimized using the auto-calibration extension of SWAT2012 to calibrate the model in this study (Abbaspour, 2012). The hydrographs obtained after model calibration substantially improved the fit of the modeled vs measured discharge values (Fig. 5). The final values of these parameters are shown in Table 1.

The results of the evaluation coefficients of the simulated discharge by various indices were as follows: the measured and simulated average annual discharges during the calibration were 4.83×10^8 m^3 and 4.36×10^8 m^3, respectively; the R^2, NSE, and PBIAS for the calibration period were 0.74, 0.66 and 18, respectively; and the R^2, NSE, and PBIAS for the validation period were 0.68, 0.63 and 23, respectively. Therefore, the results demonstrated that the SWAT model was applicable in HID for future hydrologic process assessments (Moriasi et al., 2007; Neupane and Kumar, 2015).

3.2. The green water footprint of crop production

The green water footprints of wheat, corn and sunflower per subbasin as well as their spatial variability in HID during the period 2006–2012 are shown in Fig. 6. It can be seen from the figure that the overall distribution of the green water footprint of the three crops was higher in the east than in the west. However, the distribution of green water footprints was somewhat different for each crop. Wheat had the largest green water footprint in Wuyuan (0.261 m^3/kg) and the lowest in Linhe (0.196 m^3/kg) (Fig. 1, Fig. 6a). Corn had a larger green water footprint in Wulateqianqi (0.235 m^3/kg) and the lowest in Hangjinhouqi (0.172 m^3/kg) (Fig. 1, Fig. 6b). Sunflower had the largest green water footprint in Wulateqianqi (0.601 m^3/kg) and the lowest in Linhe (0.376 m^3/kg) (Fig. 1, Fig. 6c). The green water footprint of crop production also varied across crops. The largest of the average green water footprint in HID was sunflower, followed by wheat and corn at 0.444 m^3/kg, 0.232 m^3/kg and 0.203 m^3/kg, respectively.

3.3. The blue water footprint of crop production

The blue water footprints of crop production (wheat, corn and sunflower) per subbasin and their spatial variability in the HID during 2006–2012 are shown in Fig. 7. It can be seen from the figure that the overall distribution of the blue water footprint of the three crops was higher in the east than in the west, followed by the central region.

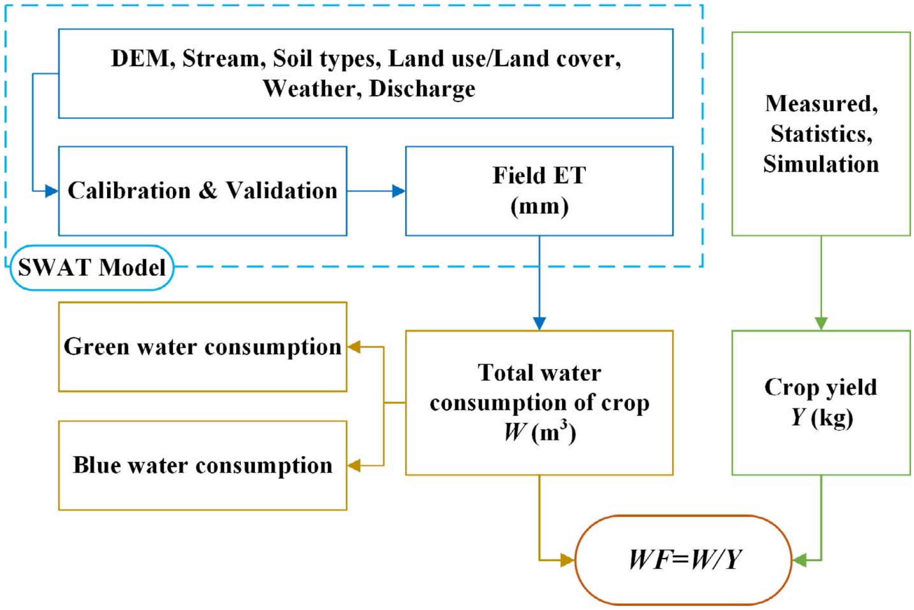

Fig. 4. The flowchart for calculating the water footprint of crop production based on the SWAT model.

However, the distribution of blue water footprints was somewhat different based on the crop type. Wheat had the largest blue water footprint in Wuyuan and Wulateqianqi (0.970 m^3/kg) and the lowest in Linhe (0.676 m^3/kg) (Fig. 1, Fig. 7a). Corn had a larger blue water footprint in Wuyuan (0.652 m^3/kg) and the lowest in Hangjinhouqi (0.497 m^3/kg) (Fig. 1, Fig. 7b). Sunflower had the largest blue water footprint in Wulateqianqi (1.239 m^3/kg) and the lowest in Linhe (0.935 m^3/kg) (Fig. 1, Fig. 7c). The blue water footprint of crop production also varied across crops. The largest of the average blue water footprint in the HID was sunflower, followed by wheat and corn at 1.066 m^3/kg, 0.805 m^3/kg and 0.572 m^3/kg, respectively.

3.4. Total water footprint of crop production

The total water footprint of crop production consists of both blue and green water footprints during the crop growth period. Fig. 8 shows the total water footprint of crop production and spatial variability of wheat, corn, and sunflower in the HID during the period 2006–2012. The overall distribution of the total water footprint of the three crops was higher in the east than in the west, followed by the central region. However, the distribution of the total water footprint was somewhat different for each crop. Wheat had the largest total water footprint in

Table 1
Final values of sensitive parameters.

Parameter	Description	Range	Last value
r_CN2	SCS curve number	(−0.3) to 0.5	−0.35
v_ESCO	Soil evaporation compensation factor	0.2–0.9	0.50
r_SOL_AWC	Available water capacity	(−0.3) to 0.4	-0.20
v_GW_REVAP	Groundwater “revap” coefficient	0.01–0.2	0.05

Note: r_ indicates that the existing parameter value is multiplied by (1 + a given value), v_ indicates that the existing parameter value is to be replaced by the given value.

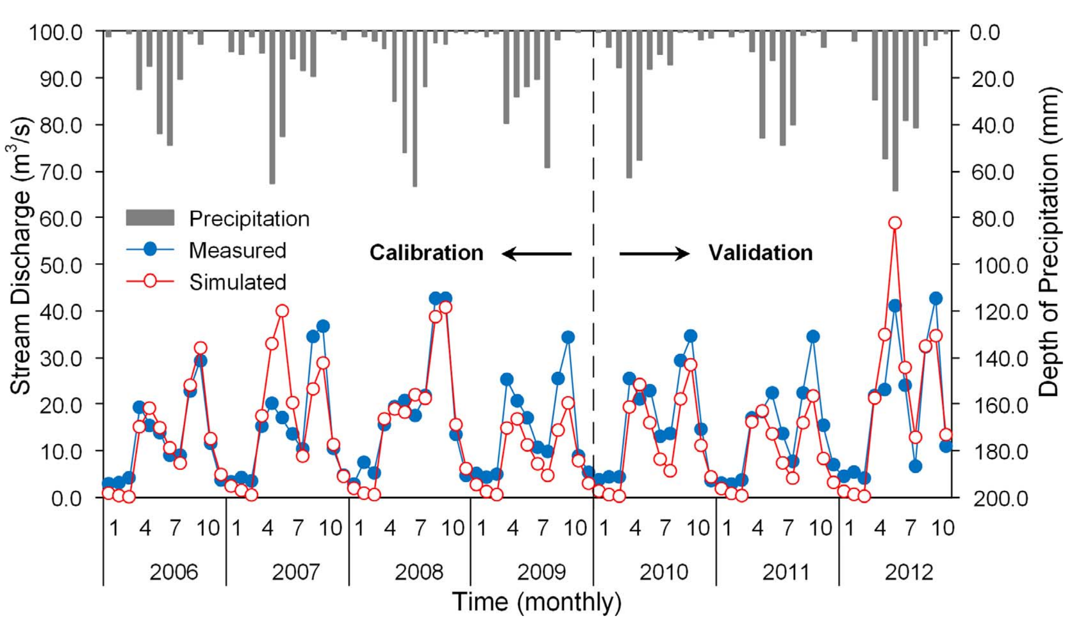

Fig. 5. The HID monthly observed and simulated discharge in the period 2006–2012.

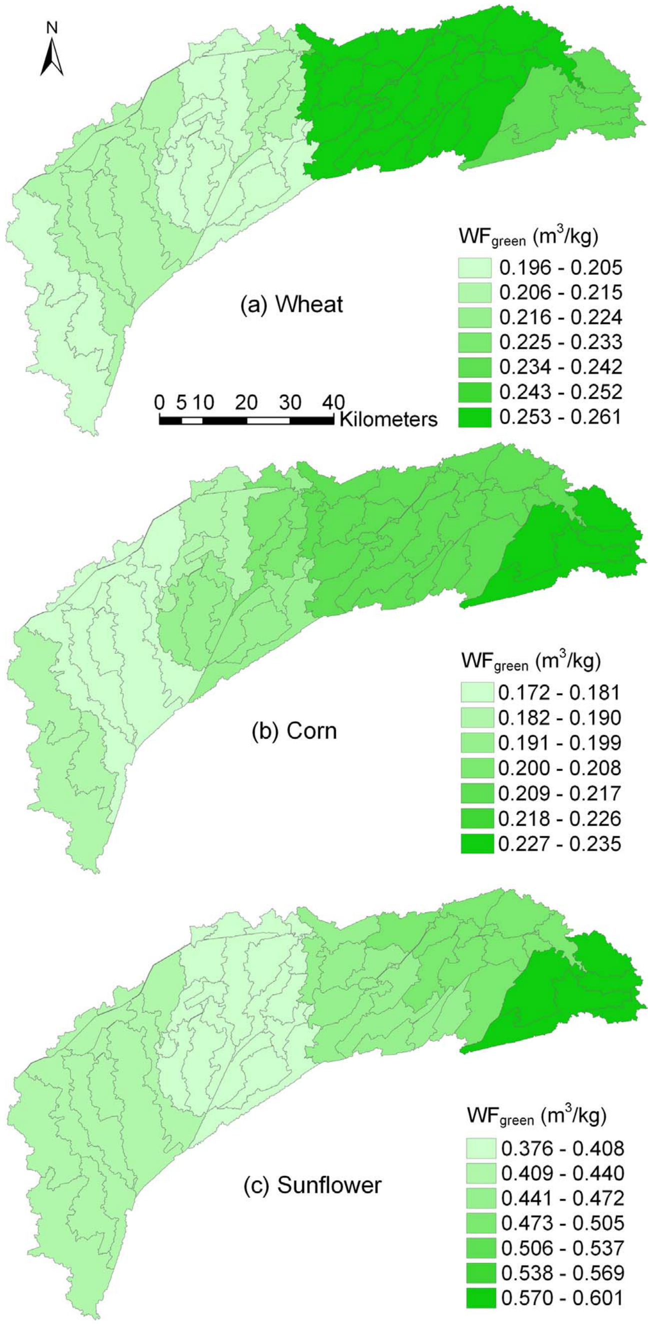

Fig. 6. The green water footprint of crop production in the HID for (a) wheat, (b) corn and (c) sunflower.

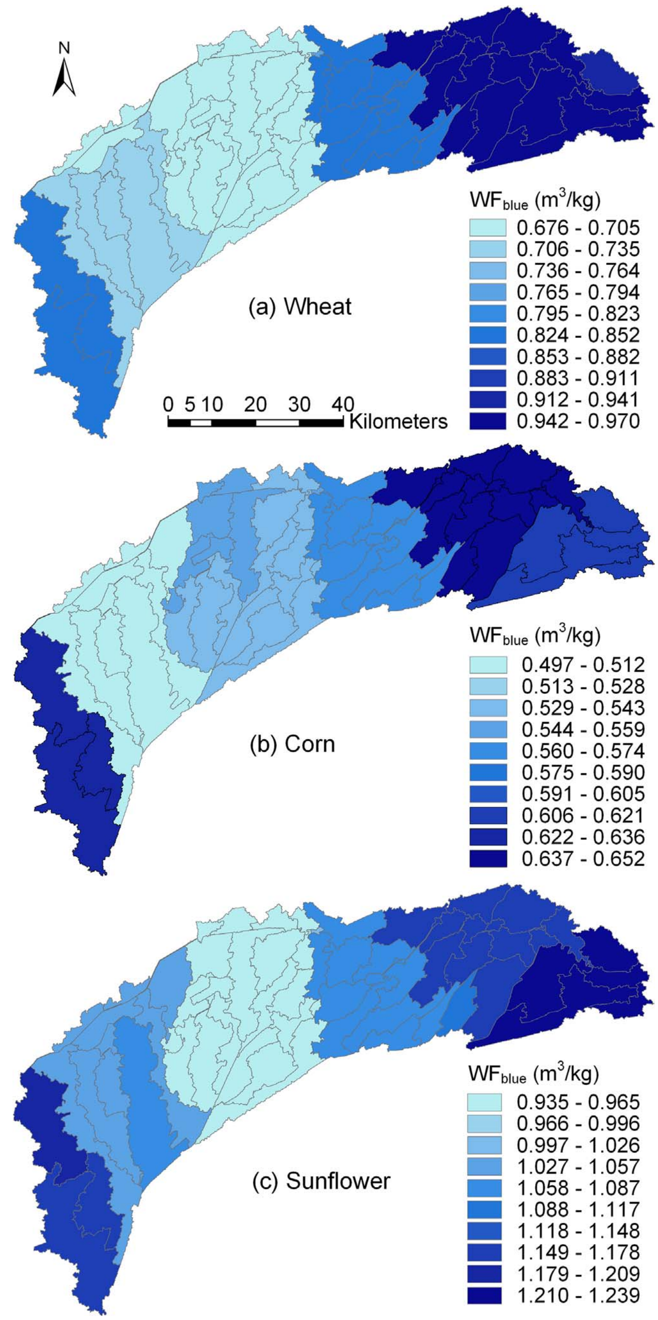

Fig. 7. The blue water footprint of crop production in the HID for (a) wheat, (b) corn and (c) sunflower.

eastern Wuyuan (1.231 m^3/kg), and the lowest in Linhe and Hangjinhouqi (0.888 m^3/kg) (Fig. 1, Fig. 8a). Corn had a larger total water footprint Wuyuan (0.867 m^3/kg) and the lowest in Hangjinhouqi (0.669 m^3/kg) (Fig. 1, Fig. 8b). Sunflower had the largest total water footprint in Wulateqianqi (1.823 m^3/kg) and the lowest value was in Linhe (1.330 m^3/kg) (Fig. 1, Fig. 8c). The total water footprint of crop production also varied across crops. The largest of the average total water footprint in the HID was sunflower, followed by wheat and corn at 1.510 m^3/kg, 1.036 m^3/kg and 0.774 m^3/kg, respectively.

4. Discussion

4.1. Comparison of crop production water footprint calculation methods

The SWAT model can be used to calculate the water footprint of crop production. The SWAT model is a hydrological model that is based physical mechanisms and is used to quantify the water consumption during crop growth from the perspective of the hydrological cycle. Besides, the SWAT model can consider more factors than the two methods (statistical methods and empirical models) in water consumption, such as soil type, soil distribution, soil depth and terrain, farmland management operations etc. (Table 2). We can obtain actual evapotranspiration data of crops during their growth period from the output data of the model simulation results and then use the obtained crop production data to calculate the crop production water footprint. Therefore, this is a new way to calculate the crop water footprint comparing to previous statistical methods based on the principle of water balance (Qin et al., 2003; Sun et al., 2013b) as well as the method of empirical model simulation, such as the CROPWAT (Mekonnen and Hoekstra, 2011) and CropSyst models (Bocchiola et al., 2013). In the

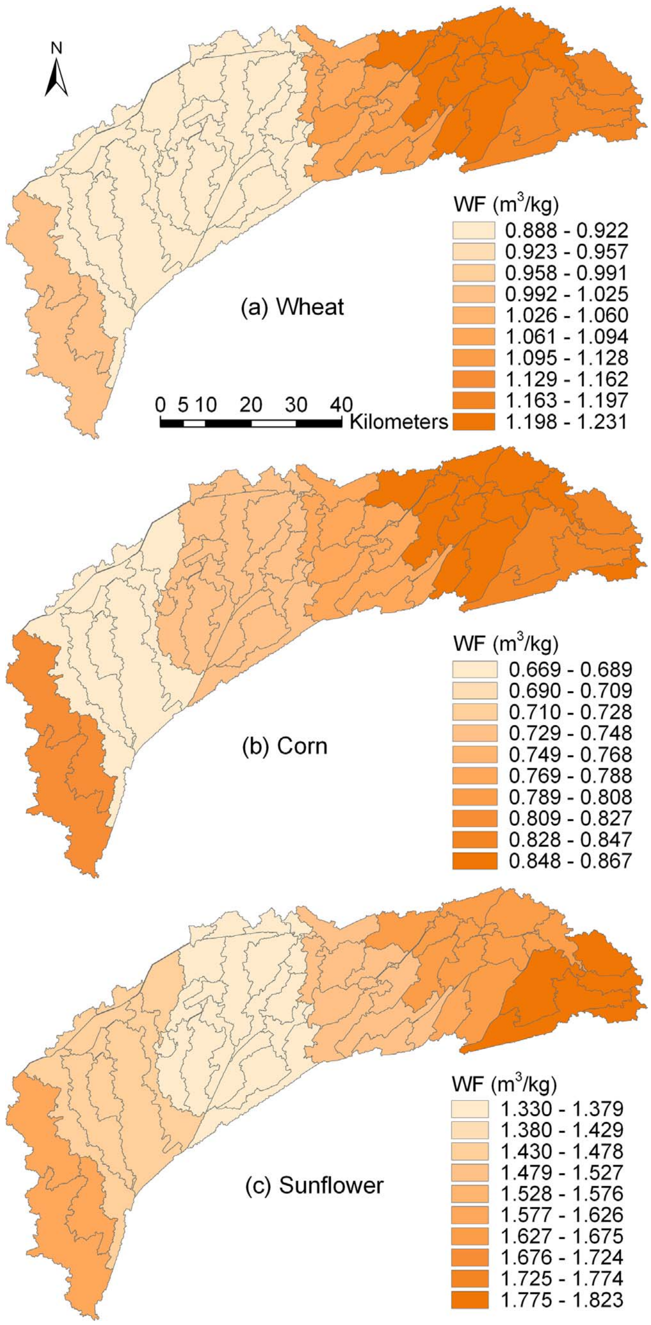

Fig. 8. The total water footprint of crop production in the HID for (a) wheat, (b) corn and (c) sunflower.

statistical method based on the principle of watershed water balance, the amount of water lost by the basin evaporation was calculated by the difference in the amount of water flowing into and out of the basin. Then, the total crop production water footprint in a region was calculated using crop yield data and the water lost. The empirical model was used as an irrigation schedule option in the CROPWAT model. Here, the simulation of crop actual evapotranspiration during the growth period was based on the daily soil moisture balance under optimal or non-optimal conditions, thus inferring crop water consumption and calculating the water footprint of crop production (Hoekstra et al., 2011). These three methods were based on the theory of water footprint computation, but the water consumption in the crop growth process was calculated in different ways.

Water footprint calculations have different scales, such as field and regional scales (Fig. 9). In the SWAT and CROPWAT models, the calculation of the crop production water footprint was based on a field scale calculation method, whereas the statistic method calculates the crop production water footprint at a regional scale. This is because the SWAT model and CROPWAT model obtain and utilize field actual evapotranspiration data. This excludes 1) the evaporation of water from artificial surface water reservoirs built for storing irrigation water as well as evaporation of water from transport canals that bring the irrigation water from the place of abstraction to the field and 2) the return flow that was not available for reuse within the same catchment within the same period of withdrawal. Therefore, the water footprint that excludes these two areas of loss was at the field-scale. In the statistical method, the loss of water was considered over the entire region, which includes the evaporation in the field, drainage system and basin drainage. Therefore, the statistical method calculated the water footprint at a regional scale. The annual average water footprint of integrated-crop production in Hetao irrigation district calculated by Sun et al. (2013b) using this method was 3.91 m^3/kg. This result was larger than we calculated, possibly because the method calculated many kinds of water consumption and we only calculated the crop evapotranspiration.

The water footprint of crop production calculated by the SWAT model reflects the spatial variability in the study area. At the same time, the variation of crop yields across different regions also contributes to different crop production water footprints.

The results demonstrated that the crop production water footprints differed spatially in the different subbasins of the HID. Since the subbasin area was smaller than the overall administrative region, the crop production water footprint was also different in the HID when comparing the results from the statistic and empirical model methods (Table 2). Using empirical method, Sun et al. (2013a) calculated the HID total water footprint of wheat and corn were 1.071 m^3/kg and 0.83 m^3/kg, Mekonnen and Hoekstra (2011) calculated the global total water footprint of wheat and corn were 1.619 m^3/kg and 1.028 m^3/kg, while we using SWAT model calculated the HID average total water footprint of wheat and corn are 1.036 m^3/kg and 0.774 m^3/kg, both of wheat and corn water footprint we calculated was smaller than the result calculated by empirical method. The empirical method only calculated an average water footprint of a large region or the world, which is detrimental to compare the difference of the water footprint

Table 2
Comparison of three methods.

Method		SWAT model	Empirical model	Statistical method
Crop water consumption	Scale	Field	Field	Area
	Calculation rationale	Hydrological cycle process	Crop growth process	Water balance equation
	Is it based on hydrological processes	Yes	No	No
	Whether the soil factors are considered	Yes (Detailed)	Yes (Simple)	No
	Whether the terrain factor is considered	Yes	No	No
	Whether the farmland management operations factor is considered	Yes	No	No
	Calculated unit	HRU	County or Grid	Study area
Crop yield	Data obtained	Statistical data		

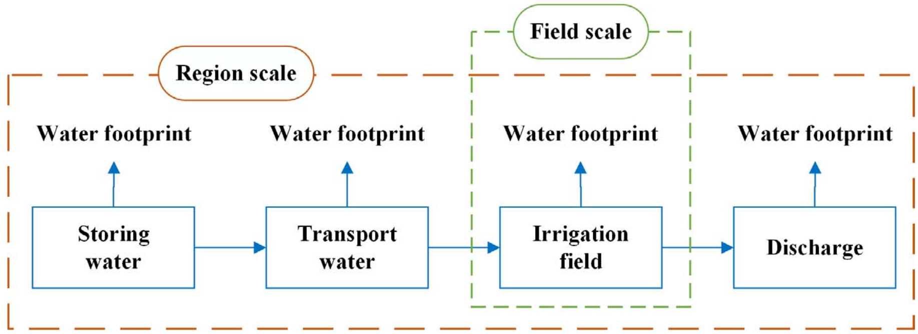

Fig. 9. Different crop production water footprint scales.

between smaller regions. Further, since the method used in this study was applicable to calculating the water footprint of crop production at the scale of the borough or watershed, it can show the difference between the water footprints in smaller plots within an administrative region or watershed, as well as different types of water footprints. This can help water resource management identify different regional water resource utilization and more precisely manage the deployment of the region's water resources. For example, if green water resources in a region are high, we can reduce the use of blue water resources, conversely increasing the amount of available blue water.

4.2. Analyses of the different crop production water footprints in the HID

In this study, the average green, blue and total water footprints of wheat in the HID were 0.232 m^3/kg, 0.805 m^3/kg, and 1.036 m^3/kg; corn water footprints were 0.203 m^3/kg, 0.572 m^3/kg, and 0.774 m^3/kg; and sunflower water footprints were 0.444 m^3/kg, 1.066 m^3/kg, and 1.510 m^3/kg. These results differ from the data from Mekonnen and Hoekstra (2011) and Sun et al., (2013b). Mekonnen and Hoekstra (2011) calculated the global average water footprint, where the green and blue water footprints of wheat were 1.277 m^3/kg and 0.342 m^3/kg, respectively; corn footprints were 0.947 m^3/kg and 0.081 m^3/kg, respectively; and sunflower were 3.017 m^3/kg and 0.148 m^3/kg, respectively. The average green footprint of the world was higher than the blue water footprint. This was different from our research results, which may be due to precipitation in some countries that can satisfy most of the water needs of crop growth or the fact that some countries that lack irrigation conditions only rely on precipitation. Our results showed that the precipitation of the Hetao irrigation area cannot satisfy crop growth needs. Therefore, the HID mainly relies on irrigation for water maintenance, so its blue water footprint is higher than its green footprint. This result is consistent with Mekonnen and Hoekstra (2011), as demonstrated in Figs. 6 and 7. Sun et al. (2013b) calculated green and blue water footprints of wheat of 0.930 m^3/kg and 1.580 m^3/kg, which were higher than the results of this study. This may be because Sun et al. (2013b) calculated the regional scale of the water footprint, including irrigation water losses.

The water footprint of crop production was closely related to the crop yield and precipitation during the crop growth period. Fig. 10 showed the correlation between yield and total water footprint, precipitation and green water footprint. The water footprint of the three crops was negatively correlated with the crop yield (Fig. 10, a1, a2, a3). When the regional crop yields were high, the total water footprints were low, and vice versa (Fig. 8, Fig. 10). The yields of wheat were higher in Hangjinhouqi and Linhe (6040 kg/ha and 6190 kg/ha, respectively), and the total water footprint in these regions was the lowest (0.888 m^3/kg). The corn yield in Hangjinhouqi was the highest (10,953 kg/ha), and its water footprint was the lowest in this area, at 0.669 m^3/kg. The sunflower yield in Linhe was the highest (4047 kg/ha), and its total water footprint was the lowest in this area (1.330 m^3/kg).

The precipitation was positively correlated with the green water footprint (Fig. 10, b1, b2, b3). Rainfall was unevenly distributed in the HID. Precipitation gradually decreased from the east to the west. The distribution of the green water footprints of the three crops were consistent with the distribution of precipitation; in the regions where precipitation was high, the green water footprint was higher. The average contribution rates of the green water footprints of wheat, corn and sunflower were 22.3%, 26.1% and 29.4%, respectively. The contribution rates of blue water footprints were larger because the HID is an arid and semi-arid region where water scarcity is high. The growth of crops required a large amount of irrigation water, which imposes stress on poor local water resources. Therefore, measures need to be taken to reduce the local blue water footprint.

5. Conclusions

In this study, the SWAT model was used to calculate field-level crop production water footprints. The following conclusions were drawn:

A quantitative method for measuring crop production water footprints based on the Hydrological model (SWAT) was established, and the results demonstrated that the SWAT could be an alternative in calculating water footprint of crop production. This was a field-scale crop production water footprint calculation method, and the calculation results were less than the empirical method (field scale) and the statistical method (region scale).

The water footprints have spatial variability in the subbasins and the overall distribution of the green, blue, and total water footprints for the three crops were higher in the east part of the HID and gradually reduced to the west. By using the SWAT model to calculate water footprints at the unit of the subbasin rather than the administrative area (e.g. county), the results can be used to assess the water consumption volumes by water source and type. This is advantageous for the agricultural water management sector to accurately manage and allocate water resources in the region.

The total water footprint of crop production was negatively correlated with crop yield, but the green water footprint was positively correlated with the precipitation. In arid and semi-arid areas of the HID, the contribution rate of blue water footprint to total water footprint was larger than green water footprint, and the average contribution rates of green water footprints in wheat, corn and sunflower were 22.3%, 26.1% and 29.4%, respectively. In three crops, the sunflower water footprint was the largest, followed by wheat and corn. The average total water footprint of crop production for sunflower in the period of 2006–2012 in the HID was 1.510 m^3/kg, whereas it was 1.036 m^3/kg and 0.774 m^3/kg for wheat and corn.

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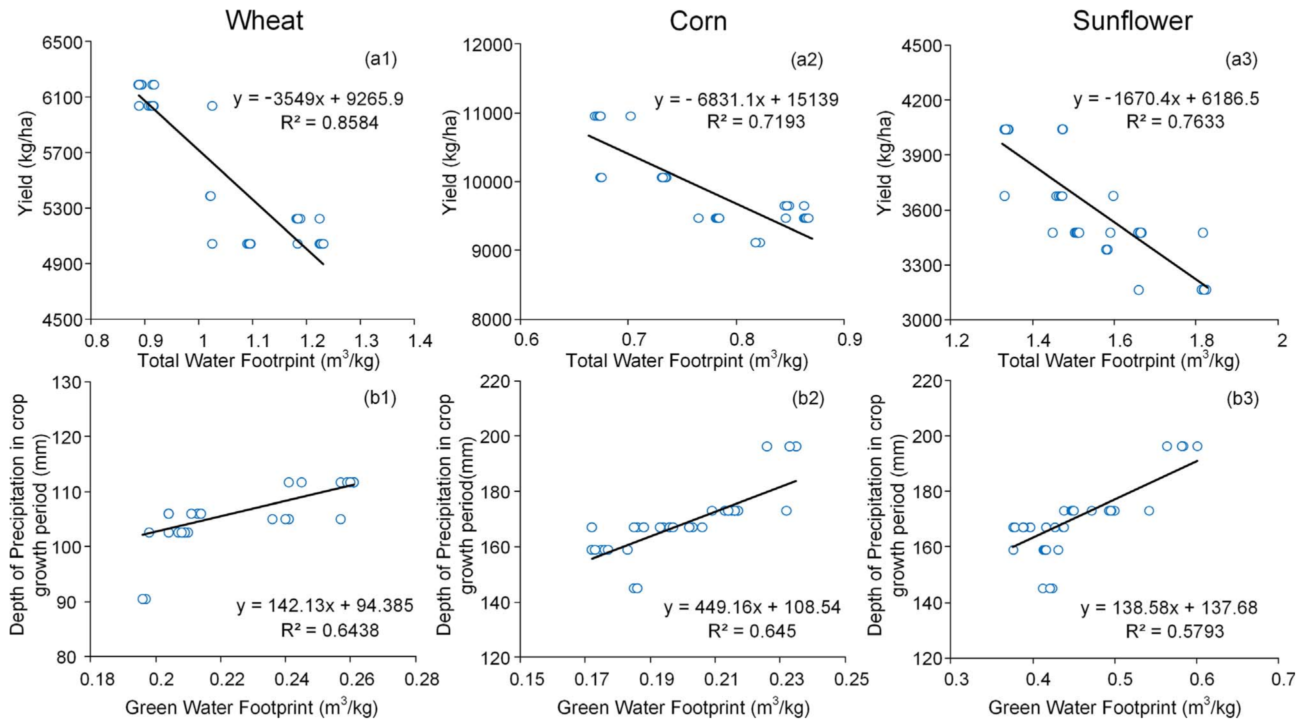

Fig. 10. The correlation between yield and total water footprint (a), precipitation and green water footprint (b) of three crops in the HID.

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