Agricultural Water Use Efficiency and Driving Force Assessment to Improve Regional Productivity and Effectiveness

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Abstract

Water use efficiency (WUE) improvements in agricultural production are of great significance to regional food security and ecological sustainability. Based on modified water footprint (WF) calculations for corn cultivation in China, WUE indices of water productivity (WP) and water efficiency (WE) for production capacity and the effective ratio of water resources were developed and quantified in the current study. Approaches to achieving national productive and effective improvements concurrently were sought by determining the spatial-temporal patterns and determinants of WP and WE during 1996–2015. The results show that the annual crop WF was estimated at 197.3 m³, including 14.1 % blue, 62.4 % green and 23.4 % gray components. WP and WE were calculated as 0.781 kg/m³ and 0.687, respectively, both of which increased over time in all subregions. Both WP and WE showed obvious spatial differences in the observed period. Low-value provinces were concentrated in the northwest and on the Huang-Huai-Hai Plain, and most high-value regions were distributed in the southeastern coastal zone. Agricultural production technology improvements contributed to WF reductions in specific areas, while meteorological elements and planting structure were the main factors affecting the spatial distribution of WP and WE. WF suppression in northwestern China and expansion of the production scale in southern China were conducive to increasing productive and effective agricultural water resource use in corn cultivation nationally. Agricultural production technology progress and crop spatial arrangement optimization are equally important to agricultural WUE enhancement in the WF framework.

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1 Introduction

Water shortages and food security are systemic issues currently being faced across the world. The agricultural system accounts for 70 % of the global water supply; this figure is as high as 90 % in some developing countries or regions (FAO 2016). In addition, green water (precipitation) consumption is twice that of irrigation water consumption in global crop cultivation (Lovarelli et al. 2016). With population growth and climate change, broader crop areas will require increased irrigation water withdrawals and extractions of water resources from natural vegetation (Cao et al. 2017; Sahoo et al. 2020). Agriculture is not only related to food production but also closely linked to regional water resources and water environmental sustainability. Evaluating and improving agricultural water use efficiency (WUE) are the basis for improving regional water resource management (Mehrazar et al. 2020).

Field evapotranspiration (ET) is an indispensable water resource for crop growth and the critical link among agricultural hydrological processes (Sedghamiz et al. 2018). Therefore, almost all existing agricultural WUE evaluations have been carried out with field ET as the core component. Crop water productivity (CWP) and irrigation efficiency (IE) are the indices most commonly used for WUE evaluation of agricultural production (Exposito and Berbel 2019; Cao et al. 2017). CWP, defined as the crop yield per unit of water consumption, can be used to measure productiveness. IE, the ratio of water consumption by crops in the form of ET to total irrigation water withdrawals, is used to describe the effectiveness of water resources (Wang et al. 2013; Berbel et al. 2018). The former depends on the amount of crop yield and water input, and the latter is mainly affected by the integrity of water conservation projects and the standard of field management. These traditional methods do not distinguish between blue and green water and cannot quantify the impact of agricultural production on water quality, whereas a water footprint (WF) contains blue, green, and gray components (Hoekstra et al. 2011; Shu et al. 2021). In agricultural systems, the blue and green WFs are irrigation (blue) water and effective precipitation (green water) consumption, respectively, in the form of field ET (Hoekstra 2019; Berger et al. 2021), and the gray WF is the amount of water that is required to assimilate the load of pollutants to meet given environmental standards (Shu et al. 2021). A regional WF reflects the total amount of water resources used during the crop growing season, and the WF per unit product measures WUE, i.e., crop production capacity of generalized water resources (Xu et al. 2019; Flach et al. 2020). The gray WF differentiates between blue and green water and measures the negative impact of agricultural production on the water environment (Wu et al. 2020). Thus, the concept of the WF framework involves generalized water resources and actual water consumption in the crop-water relationship. In addition, in comparison to the traditional CWP indices, the WF is more flexible in terms of objects and spatial-temporal scales (Sun et al. 2017; Fatemeh and Simunek 2018). Numerous estimations have demonstrated that agriculture accounts for a large proportion of the world's total WF (Marston et al. 2018). Given this large proportion, WF calculations, evaluations and regulations for crop production are the key to the efficient and sustainable use of regional and global water resources, and this topic is a popular research direction in the field of water resource management (Lovarelli et al. 2016; Zhang et al. 2017). Previous studies have used crop models to calculate and analyze WFs and the proportion of crops in these WFs at multiple spatial and temporal scales (Lovarelli et al. 2016). In addition, scholars have carried out many macro-level assessments and drawn conclusions on regional agricultural water resource utilization efficiency and management mechanisms (Atzori et al. 2019; Kayatz et al. 2019). Considering hydrological processes in agricultural systems, the regional water stress method

has also been used in sustainability assessments of crop water use and WFs from blue or generalized water resource perspectives (Multsch et al. 2020). The interesting studies quoted above have already illustrated the necessity and feasibility of agricultural evaluations and improvements based on the WF framework. In fact, it has long been recognized that a crop WF reduction indicates water management improvements on croplands. Common measures used to decrease water use in agriculture, such as ameliorating agronomic techniques, improving field management, and optimizing planting structures, are considered effective ways to reduce the WF of crops (Chouchane et al. 2019; Mekonnen et al. 2020). Existing studies have promoted the application of WFs in water management and have provided valuable information for agricultural water-saving strategy selection.

WF regulation is significantly different from conventional water-saving irrigation, even though the two have the same goal of agricultural WUE promotion. The latter aims to reduce the water lost or wasted from water intake through the crop absorption process, while the former focuses on controlling ineffective field water consumption and negative environmental impacts. Therefore, some scholars have found that it is important to combine traditional paradigms and WF-related indices to evaluate crop-water relationships (Karandish and Simunek 2018; Novoa et al. 2019; Wang et al. 2020). Assessing and reducing the crop WF and providing more comprehensive information for regional agricultural water management due to advanced indicators are important. However, research on measures to achieve sustainable water use based on crop WFs and their reduction potential has rarely been reported. In the current paper, indices for water resource production capacity (water productivity, WP) and effective use ratio (water efficiency, WE) were established based on a modified crop WF calculation method. Taking corn production, one of the three major crops in China, as an example, the crop WUE indices for 31 provinces in China during 1996–2015 (based on the availability of data) calculated under a water footprint framework were analyzed. The driving factors of the spatial distribution of the WUE indices were identified by using the partial least squares regression (PLSR) model. Water management strategies to achieve productive and effective improvements in water resource use were discussed from regional and global perspectives.

2 Methods and Data

2.1 Calculation of Water Use Efficiency indices

This paper measured water use efficiency in crop production systems by combining the water productivity (WP) and effective utilization degree (WE) indices of the total water footprint (WF):

$$WP = Y/WF \tag{1}$$

$$WE = ET_c/WF \tag{2}$$

where ET_c represents the field crop ET, i.e., water effective consumption, and was estimated as:

$$ET_c = K_c \times ET_0 \tag{3}$$

where K_c is the crop coefficient for the whole growing period and is dimensionless. P and ET_0 are precipitation, in mm, and reference crop evapotranspiration, in mm, respectively, and the latter was simulated by the Penman-Monteith equation (Allen et al. 1998):

$$ET_0 = \frac{0.408(R_n - G) + \gamma \times \frac{900}{T+273} \times u_2 \times (e_s - e_a)}{+\gamma(1 + 0.34u_2)} \quad (4)$$

where Δ is the slope of the vapor pressure curve, kPa °C^{-1}; R_n is net radiation, MJ m^{-2} d^{-1}; G is the soil heat flux density, MJ m^{-2} d^{-1}; γ is the psychrometric constant, kPa °C^{-1}; T is average temperature, °C; u_2 is the wind speed measured at a height of 2 m, m s^{-1}; and e_s and e_a are the saturation and actual vapor pressure, respectively, kPa. The Penman-Monteith equation is the most recognized method for ET_0 estimation at the macroscale (Allen et al. 1998; Hoekstra et al. 2011; Cao et al. 2017, 2020). The process of obtaining the variables in Eq. (4) is explained in detail in the Supplementary Information.

WF is the modified water footprint, is calculated from a comprehensive perspective and is the total amount of water resources used and affected in the crop production process:

$$WF = WFA_{blue} + WF_{green} + WF_{grey} \quad (5)$$

where WFA_{blue} is the applied blue water footprint and includes field irrigation water evapotranspiration and indirect water losses (González et al. 2016). WFA_{blue} for a specific crop is related to the product of the irrigated cropland area (A_i) and the actual irrigation water applied:

$$WFA_{blue} = A_i \times RIS \times \frac{IWR}{IE} \quad (6)$$

where IE is the irrigation efficiency and dimensionless. RIS is the relative irrigation supply, which indicates how irrigation matches theoretical requirements. Regional RIS was estimated from the irrigation water withdrawal (IWW, mm) and irrigation water requirement (IWR) for all crops:

$$RIS = \frac{IE \times IWW}{\sum(ET_c - P_e)} \quad (7)$$

where P_e is the crop effective precipitation during the crop growth period, in mm, and was estimated according to the empirical formula (Cao et al. 2017, 2020):

$$P_e = \left\{ P \times \left(\frac{4.17 - 0.02 \times P}{4.17} \right), P \right. \quad (8)$$

WF_{green} is defined as the total precipitation consumed in the form of field evapotranspiration, regardless of irrigation facilities utilized in the cropland. In the current study, the amount of P_e exceeding the crop water requirement was not considered as part of the WF (Hoekstra et al. 2011):

$$WF_{green} = A \times Min(ET_c, P_e) \quad (9)$$

where A is the crop planting area in ha.

WF_{grey} was estimated based on the water footprint assessment manual:

$$WF_{grey} = \frac{\alpha \times AR}{c_{max} - c_{min}} \quad (10)$$

where α is the leaching-runoff fraction; AR is the rate of chemical application, kg/ha; c_{max} is the maximum acceptable concentration (10 mg/L for T-N); and c_{min} is the concentration in natural water (0 mg/L).

2.2 Partial Least Squares Regression (PLSR)

PLSR is an alternative method to ordinary regression for processing highly correlated noise-corrupted data sets by explicitly assuming dependency among the variables and estimating the underlying structures (Huang et al. 2016). A total of 11 factors were extracted for each province in the statistical analysis that were considered to be driving factors of WP and WE (Table 1). Considering covarying driving factors (Figure S1), the PLSR models were constructed to identify how the WP and WE of the 31 provinces were related to the 11 selected variables. We used SIMCA-P + 14.0 (Huang et al. 2016) to perform the PLSR. To address overfitting, cross-validation was used to determine an appropriate number of components. An optimal balance between the explained variation (R^2) and the model's predictive ability (goodness of prediction: Q^2) needed to be achieved; when Q^2 is greater than 0.5, the PLSR model can be considered a good model (Huang et al. 2016). In PLSR modeling, the variable importance in the projection (VIP) value is calculated to indicate the importance of a predictor. Large VIP values, especially greater than 1, are the most important variables for explaining the response variable. The regression coefficients (RC) can indicate the direction and strength of the impact of each variable in the PLSR model. Prior to using the PLSR, a preliminary analysis showed that many of the factors were colinear (Figure S1).

2.3 Data Resource

The region of the current study contained the 31 provinces (Figure S2) in China, and the study occurred in 1996–2015. Provincial total water use, agricultural water use and irritation efficiency (IE) were obtained from the China Water Resources Bulletins 1996–2015. Provincial arable land, sown area, chemical application to the field and corn production in the observed years were collected from the China Statistical Yearbook 1997–2016. Finally, the meteorological data from 443 weather stations (Figure S2) in China that were used for the

Table 1 Abbreviations and descriptions of the selected variables

Variables	Abbreviation	Unit	Description
Relative humidity	RH	%	Average annual relative humidity
Temperature	T		Average annual temperature
Precipitation	P	mm	Average annual precipitation
Sunshine duration	SSD	hr	Yearly sunshine time
Fertilizer application amount	FAA	kg/ha	Fertilizer application per unit cropland
Pesticide application amount	PAA	kg/ha	Pesticide application per unit cropland
Agricultural machinery power	AM	W/ha	Agricultural machinery power per unit cropland
Irrigation rate	IR	%	Ratio of irrigated cropland to total cropland
Irrigation efficiency	IE	/	Proportion of irrigation water consumption in total withdrawal
Grain crops ratio	GCR	/	Ratio of grain crop area to total cultivated area
Gross Domestic Product	GDP	10^4 CNY	Per capita GDP

Penman-Monteith equation and the PLSR were downloaded from the Climatic Data Center, China Meteorological Administration.

3 Results

3.1 Water Use and Efficiency in Corn Production

The annual corn production and water resource exploitation in China was 154.19 Mt and 197.3 Gm³ during 1996 to 2015, respectively. The proportions of the blue, green, and gray components in the WF were calculated at 14.1 %, 62.4 and 23.4 %, respectively. Provincial corn production and the water footprint components during 1996–2015 are listed in Table 2.

Corn production, WF_{green}, WF_{grey} and total WF displayed similar spatial distribution patterns, showing that high-value provinces were concentrated on the Huang-Huai-Hai Plain (HHH) and Northeast China (NE), while low-value provinces were mainly located in the subregions in South China (SC), the middle and lower Reaches of the Yangtze River (MLY)

Table 2 Provincial corn production and water footprint in during 1996–2015

Subregion	PAMs	Corn production (Mt)	WFA_{blue} (Gm³)	WF_{green} (Gm³)	WF_{grey} (Gm³)	WF (Gm³)
North China (NC)	Beijing	0.75	0.21	0.59	0.23	1.03
	Tianjin	0.80	0.20	0.65	0.24	1.09
	Shanxi	6.19	1.12	4.95	1.89	7.96
Huang-Huai-Hai Plain (HHH)	Hebei	13.21	4.28	10.57	3.94	18.79
	Anhui	3.13	0.06	2.79	0.91	3.77
	Shandong	17.04	2.08	14.76	4.99	21.84
	Henan	13.68	1.53	11.07	3.98	16.59
Northeast (NE)	Liaoning	10.81	0.40	9.18	3.21	12.79
	Jilin	19.32	0.70	16.23	5.83	22.76
	Heilongjiang	17.47	0.99	13.87	5.21	20.07
Northwest (NW)	Neimenggu	12.27	7.04	8.97	3.84	19.85
	Shaanxi	4.66	0.19	3.36	1.38	4.92
	Gansu	3.17	1.31	1.89	0.99	4.20
	Qinghai	0.06	0.01	0.04	0.02	0.07
	Ningxia	1.39	1.16	0.80	0.43	2.39
	Xinjiang	4.12	6.28	1.88	1.51	9.67
South China (SC)	Guangdong	0.66	<0.01	0.58	0.19	0.77
	Guangxi	2.03	<0.01	1.76	0.59	2.36
	Hainan	0.06	<0.01	0.04	0.02	0.06
Middle and Lower Reaches of the Yangtze River (MLY)	Jiangsu	2.30	0.05	2.12	0.67	2.84
	Jiangxi	0.08	0.01	0.07	0.02	0.11
	Hubei	2.23	0.02	1.77	0.65	2.45
	Hunan	1.37	<0.01	1.07	0.40	1.48
Southeast (SE)	Shanghai	0.03	<0.01	0.03	0.01	0.04
	Zhejiang	0.20	0.02	0.1	0.06	0.26
	Fujian	0.14	<0.01	0.12	0.04	0.16
Southwest (SW)	Chongqing	2.25	0.02	1.85	0.66	2.53
	Sichuan	6.24	0.07	4.70	1.82	6.59
	Guizhou	3.30	<0.01	2.83	0.96	3.80
	Yunnan	5.23	0.08	4.45	1.56	6.09
	Xizang	0.02	<0.01	0.02	0.01	0.02
China		154.19	27.87	123.20	46.27	197.33

and Southeast China (SE). The greatest corn production and water use occurred in Jilin, followed by in Heilongjiang and Shandong. These three provinces jointly accounted for approximately one-third of China's corn production (34.9 %) and WF (32.8 %). In contrast, there were 4 provinces, Qinghai, Hainan, Shanghai and Xizang, with corn production that had a WF less than 0.10 Gm³. The WFA_{blue} in Neimenggu exceeded 7.00 Gm³, ranking as the largest in the country. This component in most of the remaining provinces was less than 1.00 Gm³ and no more than 0.01 Gm³ in 8 provinces. The annual WP and WE in corn cultivation were estimated as 0.781 kg/m³ and 0.687, respectively, for the country. Agricultural water use efficiency has substantial potential to improve, e.g., reducing the inappropriate water uses that account for 40 % of the WF, when connecting the paradigms water use and water footprint. The yearly crop output, WF, WP and WE for the country in the studied period are shown in Figs. 1 and 2.

Fig. 1 Location and regional delimitation of the 31 provinces in China
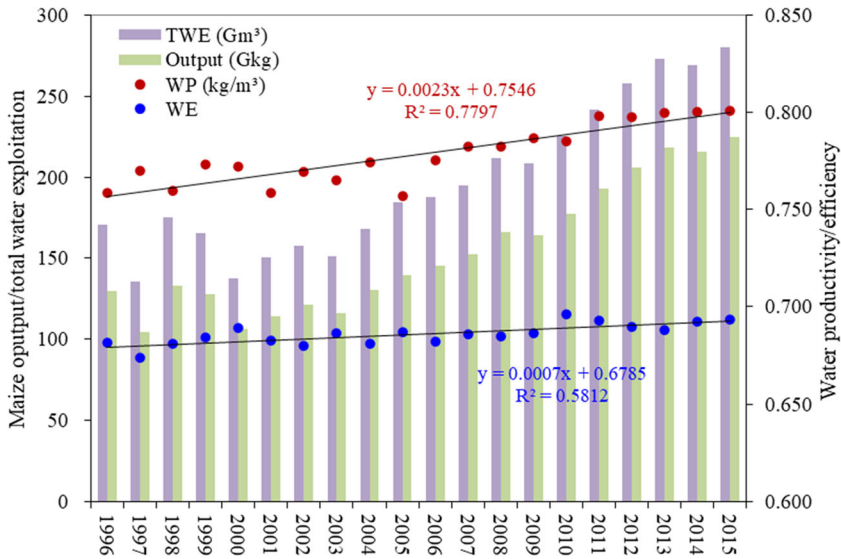
Fig. 2 National corn output, water footprint (WF), water productivity (WP) and water efficiency (WE) from 1996 to 2015

As illustrated in Fig. 2, before 2000, neither the corn output nor the WF showed noticeable changes over time. However, both increased obviously after 2000, and the crop output changed from 106.0 Gkg in 2000 to 224.6 Gkg in 2015; similarly, the WF changed from 137.3 to 280.4 Gm³ during the same period. The change in crop planting scale was the main reason for the change in crop production and water use. The initial sowing area of corn was 24.5 Mha, which dropped to its lowest value of 23.1 Mha in 2000, and then, it increased with time. The crop area was as large as 38.1 Mha in 2015, ranking as the largest size in the observed period. With an increase of more than three quarters, the national corn output increased from 127.5 Mt in 1996 to 224.6 Mt in 2015. The increase in crop output may have helped improve the water use efficiency. Figure 2 shows that WP showed a trend of growth over time, while the WE did not show a clear increase during the research period. The WP increased from 0.759 kg/m³ in 2000 to 0.801 kg/m³ at the end of the period. The increase in this indicator was mainly reflected from 2005 to 2011. WP increased and decreased but was not greater than 0.765 kg/m³ before 2004 and remained at 0.800 kg/m³ in the last five years. The maximum and minimum values of WE appeared in 1997 (0.674) and 2010 (0.696), respectively. WP was jointly affected by water resource demand and crop yield. The WF per unit area changed little, and the crop yield increased with time, which was the direct reason why WP increased with time. WE is the characterization of the water consumption structure and field management level. Because of the abundant precipitation during the corn growing season in China, green water accounted for the largest proportion (> 90 %) of crop field crop evapotranspiration (ET) in all years; at the same time, the gray water footprint in the current paper was estimated using the standard method of Tier 1 (Hoekstra et al. 2011), which also led to the minimal time variation in the results. These factors lead to a stable pattern of water resource utilization effectiveness over time.

3.2 Distribution of Water Use Efficiency Indices

Provincial water use efficiency indicators during the observed period are mapped in Fig. 3. The results show that both WP and WE exert obvious spatial variability in China. PAMs with high WP was found in the subregions SW, SC and MLY, and high WE PAMs were located in the HHH, SW and SC. The arid provinces in northern China, e.g., Ningxia, Xinjiang and Neimenggu, had both low WP and WE.

Specifically, the highest WP was 0.973 kg/m³ and calculated in Hainan, followed by 0.947 kg/m³ in Sichuan and 0.945 kg/m³ in Shaanxi. In contrast, the WP in 10 provinces was lower than the national value of 0.781 kg/m³, and almost all these provinces were located in the SW and NC subregions. The corn product per unit water resource exploitation in Xinjiang was only 0.426 kg, which was the lowest in China, and Xinjiang was the only province with a WP of no more than 0.500 kg/m³. High WE values were found in Shanghai, Jiangsu and Guangdong, all of which exceeded 0.750. The WE in another 18 provinces was above 0.700, including all the provinces located in the SW, SC, SE and NE. The WP (0.782 kg/m³) and WE (0.693) values in Jiangxi were both equivalent to the national values and lower than those of other southern provinces. The WEs in Neimenggu, Ningxia and Xinjiang were below 0.600, accounting for a low amount within the country. These were the provinces with the lowest WUEs in corn production observed from the water footprint framework. The spatial performance of WP and WE is largely determined by the regional climate and agricultural system characteristics. The southern subregions are rich in green water resources, and only minimal irrigation is needed to meet the growth of corn; thus, the WF per unit area was lower, while the WP and WE were higher than the PAMs in the northern part of the country. NE China is an irrigated agricultural region with a lack of precipitation, and most of the crop water consumption is from irrigation water, which also causes a large amount of WFA_{blue} during water transmission and distribution processes, making WP and WE lower in NE China than in other regions. The precipitation in North China and the Huang-Huai-Hai
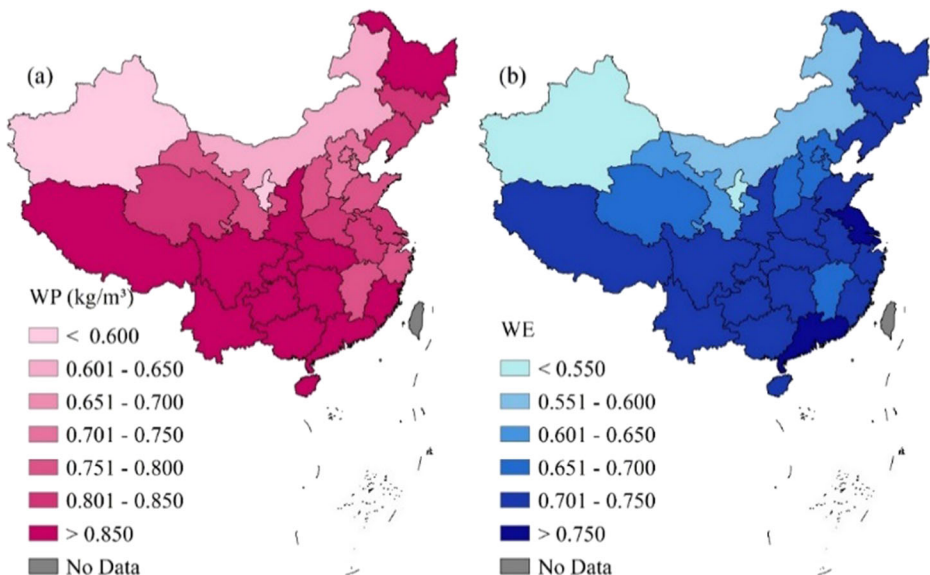

Fig. 3 Spatial distribution of annual (a) WP and (b) WE in China in 1996–2015

region suitable for wheat-maize rotations was slightly higher than that in the NE, which resulted in a low WF per unit area and high WUE indices.

Since the corn output and water utilization parameter showed the characteristics of spatial aggregation (Table 2), the spatial-temporal patterns of corn production and WUE were analyzed taking the subregion as a geographical unit. The proportions of corn yield and WF from eight subregions during different periods are shown in Fig. 4.

Crop outputs and WFs had similar spatial distribution patterns in all periods. Figure 4 shows that of the regions, the HHH, NE and NW accounted for most of the corn production and required the most water in China. Both corn production and the WFs in the HHH and SW declined over the study periods, while they increased obviously in the NE and NW over time. Neither of these parameters changed significantly over time for the other areas. Specifically, the corn production and WF proportion of the national total in the SE was approximately 0.2 % in each period, which was the lowest proportion in China. Both crop output and water exploitation in NC, SC and MLY accounted for less than 5.0 % of the national amount. The SW area produced 10.8 % of the corn and used 9.4 % of the water resources during the observed period. The corn production in the NE and arid NW accounted for 24.3 and 11.9 %
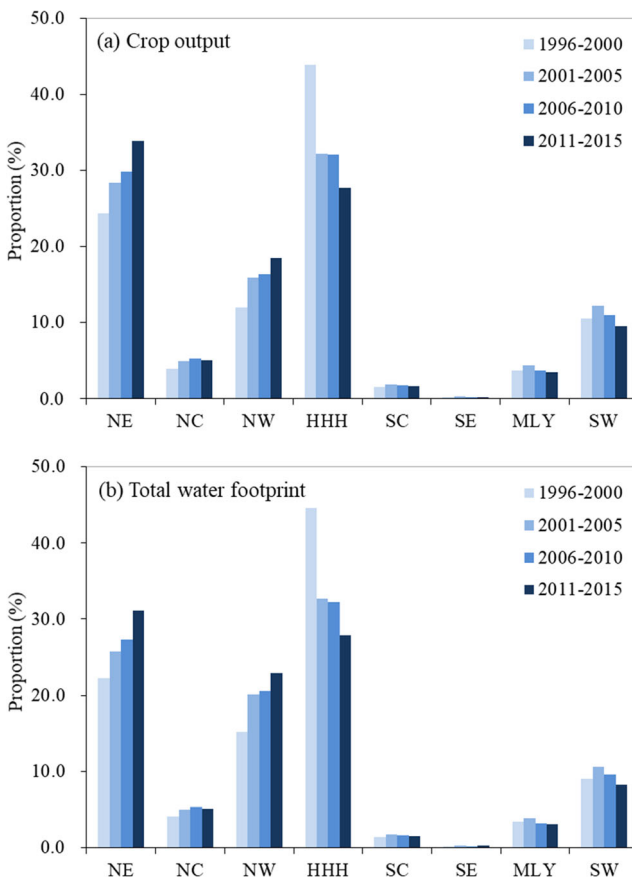
Fig. 4 Proportions of (a) corn output and (b) total water footprint in eight subregions during different periods

of the total production in 1996–2000 and increased to 33.9 and 18.5 %, respectively, in the last five years of the study. The share of water resources jointly used by these two regions increased from 37.4 % in 1996–2000 to 54.0 % in 2011–2015. The HHH accounted for 43.8 % of the corn production and 44.6 % of the WF of the country in the first five years. Subsequently, both amounts have fallen to approximately 28 % in the last 5 years. The dominance of the HHH in corn production and water use in China has been replaced by that of the NE. Agricultural the WUE evaluation indices WP and WE in each subregion over the study years were calculated by using provincial crop yield and water exploitation data, as shown in Fig. 5.

The eight subregions were divided into three categories according to the WP and WE values: high (including the NE, the MLY, the SW and SC), middle (including the HHH, NC and the SE) and low (including NW). The highest WP and WE were found in the SW (0.895 kg/m³) and SC (0.749), respectively. The WP and WE in the high-value subregions were above 0.800 kg/m³ and 0.700, respectively, and did not show a perceptible trend over time. The average WP and WE of the low-value region (NW) in 1996–2015 were only 0.574 kg/m³ and 0.618, respectively, both of which were much lower than those of the other
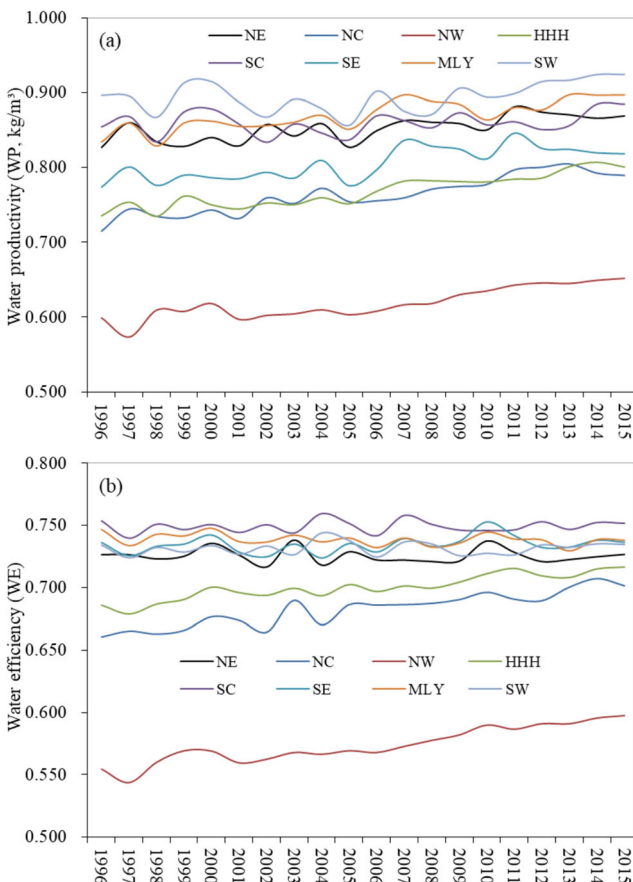

Fig. 5 Yearly (a) WP and (b) WE in eight subregions during 1996–2015

7 subregions. The WUE indices showed an obvious increasing trend with time in this region. The annual WE in the SE was estimated to be 0.735, just below the values in SC and the MLY. However, the WP of this area was significantly lower than that of the other high-value subregions. The WUE also improved over time in the HHH and NC during the study period. The WP and WE in HHH were 0.736 kg/m³ and 0.686 in the beginning and increased to 0.801 kg/m³ and 0.716, respectively, in 2015. The amelioration of the crop-water relationship in the HHH and NW was the main reason for the improvement in agricultural water use efficiency in corn production in China (Fig. 2). Improvements in irrigation systems and the adoption of water-saving technologies contributed to the increase in WP and WE. As the main corn production area in China, the total irrigated area of the HHH increased, and the irrigation system improved significantly. The water-saving irrigated area expanded from less than 5.0 Mha to 8.2 Mha during the study period. NC is the most economically developed region in northern China. Although the change in irrigation scale was not obvious here, the IE improved from 0.432 to 0.624 due to the adoption of advanced water-saving technology. These factors resulted in a higher growth rate of the WUE indices in the HHH and NC than in the other subregions.
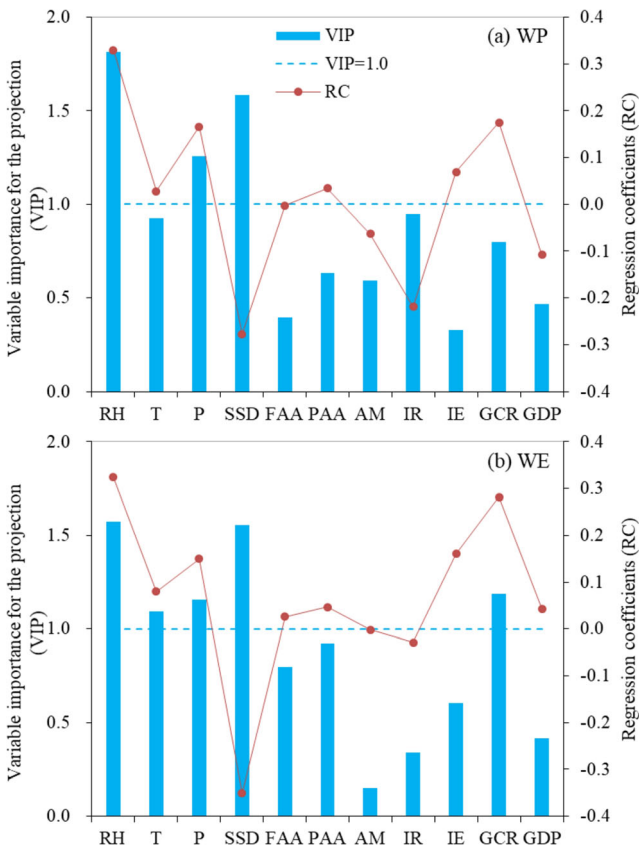
3.3 Driving Factors of Water Use Efficiency

A summary of the two PLSR models constructed for WP and WE is provided in Table 3. The optimal model for WP and WE extracts two components to reach the Q^2 maximum. A further increase in the number of components in the PLSR models could improve the explanation but decrease the predictive ability. The optimal PLSR models explained 81 % of the variation for WP and explained 82 % of the variation for WE (Table 3).

Figure 6 illustrates the VIP values for WP and WE with the RCs plotted against the predictors. The VIP value and the RC are convenient and comprehensive expressions of the relative importance of the selected variables. For WP, climate factors, including RH, SSD and P, were key variables; RH and P were positively correlated with the WP, while SSD was negatively correlated with the WP. For the WE model, all climate-related variables (SSD, RH, P and T) were important driving factors, and the higher RH, P and T were correlated with the higher WE. In addition, for WE, GCR also played a vital role in the WE. It should be noted that all selected variables were to some extent related to both WP and WE but that variables with VIP < 1 were considered of minor importance (Huang et al. 2016). The VIP of all agricultural production technology- and management-level-related elements, FAA, PAA, AM, IR and IE, was lower than 1.0. In comparison to natural elements, anthropic factors were not the main driving force of the WUE indices when combined with water quantity and quality.

Table 3 Summary of the PLSR models for WP and WE

Response variable Y	R^2	Q^2	Component	Explained variability in Y (%)	Cumulative explained variability in Y (%)	Q^2_{cum}
WP	0.81	0.51	1	0.707	0.707	0.563
			2	0.107	0.814	0.665
WE	0.82	0.68	1	0.660	0.660	0.564
			2	0.163	0.823	0.688

Fig. 6 Variable importance for the projection (bars) and regression coefficients (lines) of the 11 selected variables. (a) the WP; (b) the WE. The important predictors with VIP > 1 are consecutively numbered to show their relative importance. The straight dashed line indicates a threshold above which the predictors are considered to be important for predictive purposes. The abbreviations for the selected variables are listed in Table 1

Relative humidity (RH) and precipitation (P) are the main positive factors of the WUE indices. RH is directly affected by rainfall, and its spatial distribution patterns are similar. P is an important source for crop water consumption. Where P is high, there are sufficient green water resources for crops to absorb and use, which makes irrigation water demand low. Low field irrigation water demand directly reduces the amount of irrigation water loss, thus reducing the total WF. The lower the water resource input item is, the higher the WP. WE increased with a high effective field ET proportion in the WF in the areas with a small amount of irrigation water loss. However, SSD had a negative impact on the two WUE evaluation indices. Rain reduces the sunshine duration, which is the main reason that SSD became the dominant factor (VIP > 1.0 and RC < 0) of the WUE indices. In contrast, the VIPs of the fertilizer application amount (FAA), pesticide application amount (PAA) and agricultural machinery power (AM) were significantly lower than 1.0. In addition, the RC values of these elements were close to 0. This result may have mainly been determined by the small spatial differences in these inputs in China. This result also showed that the spatial distribution of the WUE indices for corn production was almost unaffected by agricultural resource inputs. IR

and IE, the representative elements of irrigation development, did not show a noticeable importance in terms of WUE, which may have been related to the low irrigation water demand in the corn growth period. In addition, agricultural planting structure had a certain impact on WP and WE. A high GCR can promote both indices, especially WE. The regions with high GCR values are the main grain producing areas and commodity grain supply bases in China and carry out the main grain production tasks for the whole country. These areas are required to attach importance to agricultural production. The populations in these areas have shown enthusiasm for introducing new crop varieties and adopting advanced agronomic measures. Therefore, it is justifiable that high water footprint efficiency occurred in these areas with a high planting proportion of grain crops.

4 Discussion

WUE evaluation and promotion in agricultural production is a systematic issue at a large scale. Crop-water relationship measurements should not only consider field evapotranspiration but also include the real impact of agricultural production on water resources from the perspective of water quantity and quality. National (global) agricultural WUE improvements should not be limited to reducing diversion irrigation supply (water-saving irrigation) and increasing fields but should be based on assessing regional production capacity and efficient utilization of water resources simultaneously (González et al. 2016). The comprehensiveness of the water footprint makes it a reliable tool to describe the relationship between agricultural production and water resource utilization. At the same time, the modified crop WF helps to evaluate agricultural WUE from the above perspective because the water loss in the irrigation process is critical to agricultural water management (Berbel et al. 2018). Based on the overall process of agricultural production observations, the current study combined WP and WE to conduct a regional agricultural WUE investigation. This study represents progress compared with the previous single indicator because no indicator could provide comprehensive information for agricultural water management decision-making from local and global perspectives. WP is an intuitive revelation of agricultural WUE. Reducing a crop WF and improving WP are the pursuit of agricultural producers and water resource allocation departments. However, it is difficult to determine the potential for water footprint reduction and propose countermeasures focusing on WP alone (Cao et al. 2017, 2020). The index WE is a supplement to this. Moreover, the spatial differences in WE can provide visual evidence for a water-saving layout. Therefore, it provides a foothold for regional water resource management based on the water footprint when analyzing the two simultaneously.

In China, the WF per unit of corn exceeded 1.25 m³/kg, of which the gray water footprint and applied irrigation water loss jointly accounted for 31.8 %, indicating that there was great potential for WUE improvement. For specific districts, measures that previously involved improving agricultural WUE and reducing nonpoint source pollution, such as crop variety amelioration, irrigation technique exploitation, fertilization practice improvement, irrigation facility renovation, and planting structure optimization, remained effective within the water footprint framework in the current study. The spatial distribution pattern of WP and WE has not changed over time, and each region may be unique in terms of its urgency for crop WF reduction and WUE improvement. Although increases have occurred with time, the NW has always had a decreased WUE in corn production. Productive and effective improvement are urgently needed in the northwestern compared with other regions. In addition, the HHH and

some southern provinces, such as Jiangxi and Fujian, also need to strengthen agricultural water management and improve their WUE. Corn outputs and WFs varied greatly among regions in China. At the same time, the spatial patterns of these two parameters changed during the study period. For example, the NE replaced the HHH as the region with the largest WF in recent years. Therefore, it is of great policy significance to determine the driving mechanism of two WUE indices from a spatial perspective. Our study found that climatic conditions, especially precipitation, were the main driving factors of water footprint efficiency. Their impacts on WP and WE were more significant than those of agricultural technology and socioeconomic conditions. In terms of space, deciding products according to water resources is more important than technological progress. In other words, optimizing crop layout is an effective way to improve national agricultural WP and WE. Obviously, the corn cultivation pattern in China during the observed period was not an optimal allocation. Northwestern China should limit the further increase of its crop WF as much as possible, while southwestern and southern China could expand crop cultivation to jointly promote the sustainability of water use in corn production. Corn was selected as the object of this paper, and the WUE of other food crops, such as wheat and rice, may be affected by different factors. In addition, the WP and WE calculations and driving mechanism exploration were carried out at the provincial scale, and the spatial variability in the WUE indices, driving factors and efficiency improvement measures within the province were ignored in the current study. Therefore, a comparative analysis of the water use efficiency of various crops and scales could provide more comprehensive information for local and national agricultural water management decision.

5 Conclusions

Temporal-spatial patterns and influencing factors of the WUE index evaluation provide decision-making information for local and global water management improvement. The blue, green and gray water footprint method is a new opportunity in the development of agricultural water management theory. The modified water footprint calculation is helpful to bridge the gap between the new method (WF) and the traditional agricultural water use assessment paradigms. Corn cultivation in China needs 197.3 Gm³ water resources per year, most of which were effective precipitation soaked into the soil. More than one-third of the corn WF does not serve field evapotranspiration even without heavy reliance on irrigation. WUE can be comprehensively measured by WP and WE based on the crop WF of the whole agricultural production process. Irrigation technology, fertilizer utilization, water supply facilities, and main factors driving the spatial distribution of WUE indices have a positive effect on local crop WF reduction. The role of plants in terms of water resource use cannot be ignored in water management decision-making under the framework of the water footprint. In addition to improving agronomic techniques and water allocation, optimizing the spatial distribution of crops is a reliable way to achieve global productive and effective improvements simultaneously.

Data Availability The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Code Availability Not applicable.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publish Not applicable.

Competing Interests The authors declare that they have no competing interests.

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