

TWENTY-YEAR DYNAMICS OF MAIZE PRODUCTION WATER FOOTPRINT IN QIQIHAR CITY BASED ON CROPWAT MODEL AND ITS RESPONSE TO RAINFALL PATTERN

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Abstract

Evaluating staple crops like maize's water footprint (WF) is essential for improving agricultural water use efficiency, particularly in areas with limited water resources. The twenty-year dynamics of the maize production WF in Qiqihar City, a crucial maize-producing region in China's semi-arid black soil region, were examined in this study from 2005 to 2024. We applied the FAO CROPWAT 8.0 model to determine the green and blue water footprints and investigated their responses to different hydrological year types, namely wet, normal, and deficit (Fig. 1). The principal findings are: (1) GWF constituted the largest portion of the total WF, between 53.5% and 100.0% ($0.04\text{--}0.10\text{ m}^3\text{ kg}^{-1}$), emphasizing a primary dependence on rainfall. (2) BWF, ranging from 0.01 to $0.08\text{ m}^3\text{ kg}^{-1}$ and accounting for 2.13% to 46.45%, was present in only half of the years (10 years), showing a notable clustering effect during deficit and normal years. (3) The WF per unit yield showed a significant decreasing trend ($R^2 = 0.63$), indicating improved water use efficiency over the two decades, likely attributable to agricultural technological advancements. (4) Significant growth was observed in the cultivated area, peaking in 2015, and in the yield per unit area, peaking in 2012. The total WF showed a strong correlation with the planted area, described by a power function with an R^2 value of 0.79. This research highlights the importance of enhancing water resource management, especially by creating effective water-fertilizer strategies to lessen reliance on irrigation (BWF) during both dry and normal years, which is essential for ensuring high and stable maize yields and sustainable water use in Qiqihar. The findings from our research provide key data and a theoretical basis for establishing water-saving agricultural policies in this and similar semi-arid areas.

Key words: Green water footprint; Blue water footprint; CROPWAT model; Rainfall patterns; Water-use efficiency; Qiqihar

Introduction

Agriculture uses the greatest amount of global freshwater resources and the efficiency of agricultural water management is closely related to the food security and ecological sustainability (Ingrao *et al.*, 2023). Irrigation is important for maintaining food production, but about 52% of the irrigated areas in the world are situated in water-scarce regions, thus increasing the demand for limited water resources (Zhi *et al.*, 2024; Liu *et al.*, 2017).

The WF system divides green water footprint (GWF, water consumption stored in the soil by rainfall), blue water footprint (BWF, water consumption from surface and groundwater) and grey water footprint (GryWF, water needed to eliminate pollution) (Wang *et al.*, 2023; Liu *et al.*, 2020). It is estimated that the WF of agriculture was approximately $8362\text{ km}^3\text{ yr}^{-1}$ in 2011, which includes 80% green water, 11% blue water and 9% grey water (Li *et al.*, 2017), indicating the predominance of green water in crop production.

The semi-arid black soil area in the northeast of China, an important part of the "Golden Maize Belt" of the country, has great fluctuation in seasonal and inter-annual rainfall. Qiqihar City, situated in this region (47°N), is a major contributor to the grain production of China. However, the water shortage, caused by the uneven distribution of precipitation and the rising demand for evaporation, presents a serious challenge to the sustainability of maize production in this region (Liu *et al.*, 2020; Li *et al.*, 2017). The agricultural conditions are affected by a complicated interaction of natural factors such as sunshine duration, temperature, precipitation, wind speed and relative humidity (Feng *et al.*, 2018; Wu *et al.*, 2017; Hui *et al.*, 2021; Wang *et al.*, 2023). Therefore, a detailed understanding of its long-term changes is necessary for formulating effective water resource management strategies in the region (Chen *et al.*, 2023).

Research on agricultural virtual water has made great progress, mainly concentrating on the quantification

methods and driving force analyses. Hoekstra *et al.*, (2003) first introduced the concept of virtual water, defining it as the total volume of freshwater used directly and indirectly by a consumer or producer, which greatly promoted the theory of virtual water. Later studies have generalized and improved these concepts worldwide. For example, Mialyk *et al.*, (2022) calculated the global maize virtual water requirement using a grid-based crop model, and found the average value to be $728.0 \text{ m}^3 \text{ t}^{-1} \text{ yr}^{-1}$ for 2012–2016. Symeonidou *et al.* (2019) emphasized the significant differences in virtual water between rainfed and irrigated cropping systems in Rhodes. In China, virtual water studies have been carried out in different areas, such as the arid Northwest (Donoso *et al.*, 2016; Zhang *et al.*, 2023) and Northeast China (Zhang *et al.*, 2022; Miao *et al.*, 2020). The FAO's CROPWAT model (Liu *et al.*, 2002) is commonly used as a dependable tool for determining the crop water requirement and planning irrigation schedules, which has been applied in places like Sri Lanka (Zhang *et al.*, 2022), India (Huang *et al.*, 2019), and the Songnen Plain in China (Miao *et al.*, 2020).

Although Northeast China is important for national food security and Qiqihar has particular water problems, there is a noticeable shortage of comprehensive and long-term research on the maize production WF and its special reaction to different hydrological years (wet, normal and dry) in this main semi-arid area (Cao *et al.*, 2019). Most of the current studies only give some brief analyses or do not focus on how the rainfall distribution affects the necessity of blue water irrigation.

To fill this gap this investigation uses the CROPWAT model to calculate the green and blue water footprints of maize production in Qiqihar during the last twenty years (2005–2024). The main purposes are: (1) To determine the annual fluctuations and structure of the maize production water footprint (GWF and BWF); (2) To study the different reactions of the water footprint components and maize yield to various hydrological years; (3) To examine the association between water footprint variations, changes in planting area and yield increase.

The findings of this study are expected to provide a scientific basis for developing targeted water-saving

management practices, optimizing water allocation during critical dry periods, and promoting the sustainable development of maize production in Qiqihar and analogous semi-arid regions

Materials and Methods

Study area: Qiqihar City is located in western Heilongjiang Province, in the central part of the Songnen Plain ($122^{\circ}24'–126^{\circ}41' \text{ E}$, $46^{\circ}13'–48^{\circ}56' \text{ N}$), with a total area of $42,500 \text{ km}^2$. The region experiences a mid-temperate continental monsoon climate, characterized by cold, dry winters and warm, humid summers. The mean annual temperature is 3.5°C , and the accumulated temperature above 10°C ranges from 2400 to 2600°C . The frost-free period lasts 120–135 days. Annual precipitation averages 415 mm, with more than 70% occurring between June and August. Evaporation exceeds 1500 mm per year, resulting in an aridity index of 1.2 to 1.5. Precipitation shows considerable interannual variability (coefficient of variation $>25\%$), leading to frequent spring droughts and summer waterlogging. The area is characterized by fertile soils such as chernozems, meadow soils, and black calcareous soils, which are deep, rich in organic matter, and highly productive. As a major commercial grain and livestock production base in China, Qiqihar's agricultural system is dominated by maize, soybeans, and rice. Maize, as the principal crop, is cultivated on more than 666,700 hectares annually, accounting for about 50% of the city's total grain sowing area.

Data sources and processing: Data required for the CROPWAT model, including reference evapotranspiration and rainfall, were obtained from the FAO CLIMWAT database. Crop parameters for maize were sourced from the FAO CROP database (both databases are publicly available at <http://www.fao.org/land-water/databases-and-software/cropwat/en/>). Meteorological data for Qiqihar City were provided by local weather stations, while data on maize cultivation area and yield from 2005 to 2024 were collected from the Qiqihar Statistical Yearbook. The key crop parameters used for maize are listed in Table 1.

Table 1. Crop parameters in CROPWAT model.

Parameter	Initial	Development	Mid	Late	Total
Growth stage (d)	30	50	60	40	180
Depletion coeff.	0.50	0.50	0.50	0.80	/
Root depth (m)	0.30	>>	>>	1.00	/
Crop coeff. (KC)	0.30	>>	1.20	0.50	/
Response factors	0.40	0.40	1.30	0.50	1.25

Methodology

Hydrological year classification: Based on effective rainfall (ER) data during the maize growing seasons from 2005 to 2024, years were classified into three hydrological year types using frequency analysis: Wet year: $\text{ER} = 478.8–574.3 \text{ mm}$; Normal year: $\text{ER} = 374.7–451.2 \text{ mm}$; Dry year: $\text{ER} = 206.7–312.9 \text{ mm}$.

Calculation of maize virtual water content and water footprint: Maize virtual water content (VWC) is defined

as the total volume of water consumed through crop transpiration during the growth cycle. In this study, the crop water requirement (CWR) for maize was simulated using the CROPWAT software, which is based on the FAO-standardized Penman-Monteith equation (Zhang *et al.*, 2023; Zhang *et al.*, 2022). The CWR is met by two sources: irrigation (blue water) and effective rainfall stored as soil moisture (green water). The irrigation requirement (IR) was calculated as the difference between CWR and effective rainfall (ER). Accordingly, the total VWC is the sum of green water VWC (the ratio of effective rainfall to

yield) and blue water VWC (the ratio of irrigation water to yield). As this study focuses on the relationship between rainfall utilization efficiency and yield, the grey water footprint, which pertains to water pollution, was excluded from the modeling and calculations. The specific equations (Eq. 1-4) used to calculate VWC are presented below.

$$IR = CWR - ER \quad (1)$$

$$ER \geq CWR, IR = 0 \quad (2)$$

where CWR is crop water requirement (mm); ER is Effective rainfall (mm) and IR is Irrigation requirement (mm).

$$VW_g = CWR/Y \quad (3)$$

$$ER < CWR, VW_b = IR/Y, VW_g = ER/Y, VW_{prod} = VW_g + VW_b \quad (4)$$

where VW_{prod} is virtual water content of maize ($m^3 t^{-1}$); VW_g is green virtual water content ($m^3 t^{-1}$); VW_b is blue virtual water content ($m^3 t^{-1}$); Y is crop yield ($t ha^{-1}$).

In this study, the production water footprint (WF_{prod}) of maize represents the total volume of water resources appropriated during crop growth, calculated as the sum of blue, green, and grey water footprints as expressed in Eq. 5.

$$WF_{prod} = WF_{prod,green} + WF_{prod,blue} + WF_{prod,grey} \quad (5)$$

where WF_{prod} is production water footprint of maize ($m^3 t^{-1}$); $WF_{prod,green}$ is green water footprint ($m^3 t^{-1}$); $WF_{prod,blue}$ is blue water footprint ($m^3 t^{-1}$); $WF_{prod,grey}$ is grey water footprint ($m^3 t^{-1}$). Grey water footprint was not considered in this study.

Data analysis

Statistical analyses, including one-way ANOVA (significance level: $p < 0.05$ with LSD post hoc testing) and correlation analysis, were performed using IBM SPSS Statistics 21.0. Data processing and graphical presentation were conducted using Origin 2018 (64-bit) and WPS Office respectively.

Analytical framework and econometric specification: To address the research objectives, a three-tiered analytical strategy was employed: (1) decomposition of driving factors via the Logarithmic Mean Divisia Index (LMDI), (2) regional typology construction through hierarchical Cluster Analysis, and (3) hypothesis testing of determinants using a Panel Data Model. All three methods were complementary and executed sequentially.

Logarithmic Mean Divisia Index (LMDI) decomposition: The LMDI method, in its additive form, was applied to quantify the contribution of distinct socioeconomic and technological factors to the aggregate change in the dependent variable (e.g., carbon emissions or energy consumption) over time. The identity function was constructed as follows:

Let V represent the total aggregate (e.g., total CO_2 emissions). This aggregate is decomposed into the product of n driving factors:

$$V = \sum_i v_i = \sum_i v_{1,i} \cdot v_{2,i} \cdot v_{3,i} \cdots v_{n,i}$$

Specifically, for this study, the total annual aggregate (V^t) was defined using the Kaya identity extension:

$$V^t = \sum_i \left(\frac{V_i^t}{E_i^t} \cdot \frac{E_i^t}{Y_i^t} \cdot \frac{Y_i^t}{P_i^t} \cdot P_i^t \right)$$

Where:

i denotes the sector or sub-category (e.g., industry, transport, residential)

E_i^t = Energy consumption of sector i at time t

Y_i^t = Economic output (GDP) of sector i at time t

P_i^t = Population (or activity level) in sector i at time t

V_i^t/E_i^t = Emission factor effect (technology)

E_i^t/Y_i^t = Energy intensity effect (efficiency)

Y_i^t/P_i^t = Economic activity effect (per capita output)

P_i^t = Scale effect (population/activity scale)

All computations for the LMDI were performed using a custom script written in MATLAB R2020a (MathWorks, Natick, MA, USA), which automated the iterative calculation across the entire study period (2000–2020).

Cluster analysis for regional classification: To identify heterogeneous subgroups within the study regions based on their developmental and emission characteristics, a hierarchical Cluster Analysis was conducted. The analysis employed the Ward's minimum variance method as the agglomeration rule, which minimizes the total within-cluster sum of squares. The squared Euclidean distance was selected as the proximity measure:

$$d_{ij} = \sum_{k=1}^m (x_{ik} - x_{jk})^2$$

where d_{ij} is the distance between region i and region j , m is the number of clustering variables, and x_{ik} is the standardized value of variable k for region i . Prior to clustering, all input variables were standardized to z-scores ($z = \frac{x - \mu}{\sigma}$) to eliminate scale effects. The optimal number of clusters was determined by examining the agglomeration schedule and the dendrogram; the elbow point, where the coefficient increase between successive fusion steps showed a marked jump, was used as the primary criterion. The input variables for the clustering procedure comprised per capita GDP, energy intensity, urbanization rate, and the cumulative LMDI factor contributions (derived in Section 2.3.1) over the final five-year period. This analysis was performed using the stats package in R 4.1.2 (R Core Team, Vienna, Austria).

Panel data model specification: Following the classification from Cluster Analysis, a panel data regression model was estimated to examine the quantitative effects of potential determinants on the dependent variable. The general linear panel model is specified as:

$$Y_{it}^i = \alpha + \beta x_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where:

Subscripts: $i=1,2,\dots,N$, $i=1,2,\dots,N$ denotes the cross-sectional units (provinces/regions); $t=1,2,\dots,T$, $t=1,2,\dots,T$ denotes the time period (years).

Y_t^i = Dependent variable (e.g., total carbon emissions or per capita emissions) for unit i at time t .

x_{it} = Vector of independent explanatory variables.

β = Vector of slope coefficients to be estimated.

μ_i = Individual-specific fixed or random effects (capturing unobserved time-invariant heterogeneity).

λ_t = Time-specific effects (capturing common shocks, e.g., national policies, business cycles).

ε_{it} = Idiosyncratic error term, assumed to be independently and identically distributed (i.i.d.) with zero mean and constant variance.

Supplementary statistical analyses

One-way analysis of variance (ANOVA): To test for statistically significant differences in continuous variables (e.g., energy intensity, emissions per capita) among the distinct clusters identified in Section 2.3.2, a one-way ANOVA was performed. The significance threshold was set at $\alpha=0.05$. In cases where the ANOVA result was significant, Fisher's Least Significant Difference (LSD) post hoc test was employed for pairwise multiple comparisons between clusters. This test was chosen for its sensitivity in detecting differences when the overall F-test is significant, without excessive correction for Type II errors. This analysis was executed using IBM SPSS Statistics 21.0.

Bivariate correlation analysis: To provide a preliminary assessment of linear associations between key variables prior to multivariate modeling, Pearson's correlation coefficient (rr) was calculated for normally distributed continuous variables; otherwise, Spearman's rank-order correlation (pp) was used. The correlation matrix was computed in SPSS 21.0, and significance was evaluated at the $p<0.05$ and $p<0.01$ levels (two-tailed). The resulting correlation coefficients were visualized as a correlogram using the `corrplot` package in R 4.1.2.

Results and Discussion

Composition characteristics of maize water footprint in Qiqihar (2001–2020)

Dynamics of water requirement and supply during maize growing seasons: As summarized in Table 2, the effective rainfall (ER) during the maize growing season in Qiqihar (2005–2024) averaged 426.98 mm, with considerable interannual fluctuations (range: 249.7–574.6 mm; CV: 24.5%). The average crop water requirement (CWR) was slightly lower at 391.1 mm (range: 289.7–497.6 mm). Notably, the irrigation requirement (IR) was positive in 10 out of the 20 years (50%), indicating that CWR exceeded ER and irrigation was necessary. Conversely, during the next 10 years, IR was zero or negative ($ER \geq CWR$), indicating that the rainfall met the complete crop water requirement. Years requiring irrigation were concentrated in 2007, 2008, 2010, 2011, 2014, 2016, 2017, 2023 and 2024, with the highest IR of 252 mm recorded in 2001.

Analysis of water consumption and water footprint in maize production: From Table 3, the annual water demand (green + blue) for maize planting varies greatly, ranging from 10.10×10^8 to 80.61×10^8 m³ yr⁻¹. The green water demand, calculated by effective rainfall, has an important difference (206.7–574.3 mm). But the blue water

demand, which appears only in 11 years, has a smaller variation (9.4–252 mm).

During this period, there were considerable changes in agriculture. The total production of maize rose greatly, reaching 1020.4×10^4 t in 2012 from only 327.0×10^4 t in 2005. This was mainly due to the large increase in the area under cultivation, which grew to 14.99×10^5 ha in 2015, together with an increase of 193.3% in the yield per unit area, up to 7.89 t ha⁻¹ in 2012.

The protein water footprint (WF_{prot}) has kept a relatively constant level, ranging from 0.04 and 0.09 m³ kg⁻¹. The green water footprint (GWF) is the main part, accounting for 53.5% to 100.0% of the total WF_{prot} . The blue water footprint (BWF) existed only in the 11 years with irrigation requirement, contributing 2.13% to 46.51% of the WF_{prot} . In fact, even in the years when irrigation was needed, the GWF still played the major role (51% to 98%), indicating the stable significance of rainfall in the maize production system of the region.

Table 2. Water usage and maize consumption in Qiqihar from 2001–2020 (mm).

Year	CWR	ER	IR
2005	356.4	432.4	9.4
2006	321.0	447.8	-6
2007	320.3	312.9	143.8
2008	337.7	288.8	158.9
2009	298.6	451.2	0
2010	345.8	420.1	31.7
2011	291.1	388.8	53.4
2012	289.7	478.8	-41.1
2013	339.2	551.0	-124.3
2014	423.7	374.7	49.0
2015	346.1	446.9	-23.1
2016	449.0	255.1	193.9
2017	466.3	249.7	216.6
2018	467.4	530.0	-62.6
2019	460.9	522.1	-61.2
2020	497.6	549.0	-51.4
2021	497.6	549.0	-51.4
2022	422.4	574.6	-151.8
2023	452.8	430.6	22.7
2024	438.9	286.0	153.3

Assessment of maize water footprint

Relationship between hydrological year types and maize yield: According to the virtual water theory, the total water requirement for maize cultivation in Qiqihar varies from 20.40×10^8 to 80.60×10^8 m³·year⁻¹. Blue water was used in 10 out of the 20 years and showed the periods with positive irrigation needs, while it was not applied in the other years. The green water values were from 249.7 to 574.6 mm, and the blue water values ranged from 9.4 to 216.6 mm (Fig. 3). During this time, the maize production changed from 0.955×10^6 to 10.204×10^6 tons, together with a considerable increase in the cultivated land—from 5.70×10^5 hectares in 2005 to 15.0×10^5 hectares in 2015, which represents an increase of 163% (Fig. 3). The yield per unit area also increased obviously from 3.27 t·ha⁻¹ to 10.20 t·ha⁻¹, indicating an increase of 212%. There is a positive relationship between the yield and the rainfall. The water footprint of maize has kept relatively stable during the study period, with an average of about 0.08 m³·kg⁻¹.

Table 3. Water consumption and virtual water content of maize production in Qiqihar City from 2005-2024.

Year	Water consumption ($\times 10^8$ m ³ /year)			Annual output of maize ($\times 10^4$ t)	maize planting area ($\times 10^5$ ha)	Unit yield of maize (t ha ⁻¹)	Virtual water consumption (m ³ /kg)		
	BWF ($\times 10^8$ m ³)	GWF ($\times 10^8$ m ³)	Total consumption ($\times 10^8$ m ³)				BWF (m ³ /kg)	GWF (m ³ /kg)	total consumption (m ³ /kg)
2024	17.91	33.4	51.31	762.6	11.18	6.82	0.02	0.04	0.07
2023	2.65	50.29	52.95	727.6	10.65	6.83	0.00	0.07	0.07
2022	0	67.11	67.11	690.0	10.30	6.70	0	0.10	0.10
2021	0	64.12	64.12	799.6	12.47	6.41	0	0.08	0.08
2020	0.0	58.9	58.9	709.8	10.7	6.6	0.00	0.08	0.08
2019	0.0	61.5	61.5	771.5	11.8	6.6	0.00	0.08	0.08
2018	0.0	66.1	66.1	803.7	12.5	6.4	0.00	0.08	0.08
2017	25.3	29.2	54.6	730.4	11.7	6.2	0.03	0.04	0.07
2016	25.1	33.0	58.0	736.0	12.9	5.7	0.03	0.04	0.07
2015	0.0	67.0	67.0	892.3	15.0	6.0	0.00	0.08	0.08
2014	6.6	50.3	56.9	886.8	13.4	6.6	0.01	0.06	0.07
2013	0.0	80.6	80.6	870.7	14.6	6.0	0.00	0.09	0.09
2012	0.0	61.9	61.9	1020.4	12.9	7.9	0.00	0.06	0.06
2011	5.3	44.2	33.1	750.3	11.4	6.6	0.01	0.06	0.07
2010	3.2	42.3	34.8	654.4	10.1	6.5	0.00	0.06	0.06
2009	0.0	44.0	44.0	540.3	9.8	5.5	0.00	0.08	0.08
2008	4.0	23.4	27.3	483.1	8.1	6.0	0.03	0.05	0.08
2007	0.6	23.3	23.9	335.2	7.5	4.5	0.03	0.07	0.10
2006	0.0	29.6	29.6	382.0	6.6	5.8	0.00	0.08	0.08
2005	0.9	24.7	20.4	327.0	5.7	5.7	0.00	0.08	0.08

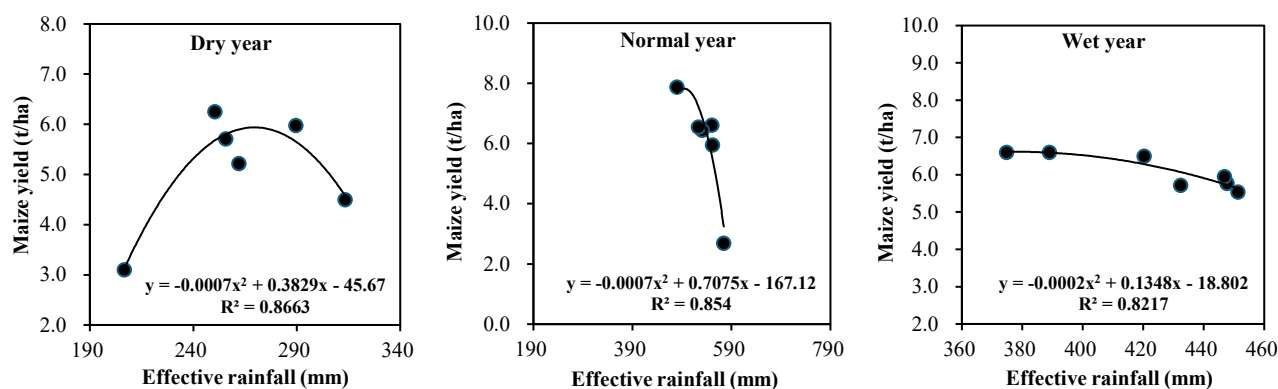


Fig. 1. Linear regression of effective rainfall vs. maize yield by hydrological year type.

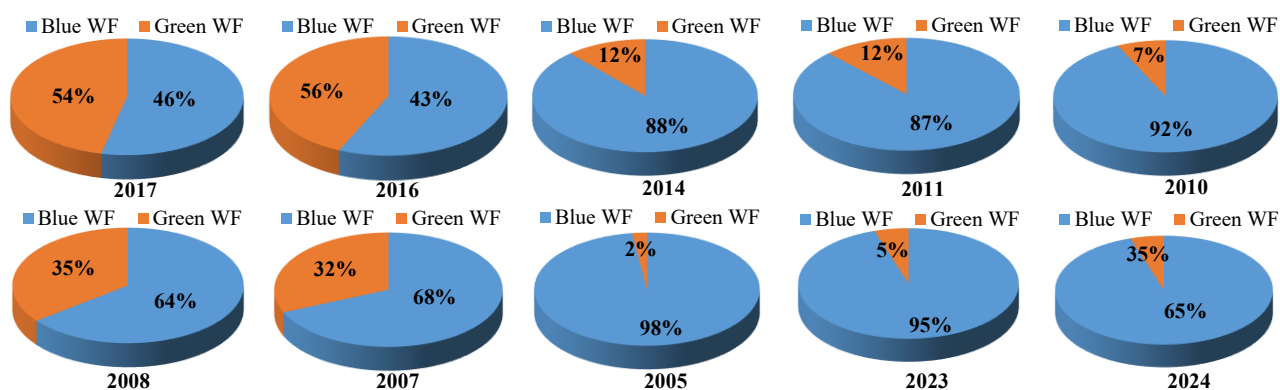


Fig. 2. Composition of maize production water footprint (Green WF vs. Blue WF) in a typical dry year in Qiqihar.

Relationship between water footprint dynamics and production scale: The dynamics of the maize water footprint reflect the intricate relations among water resource usage, agricultural extension and technological advancement (Siebert *et al.*, 2010; Chen *et al.*, 2019). A power function is applied to express the relationship between the total water footprint (WF_{total}) and the cultivated land (Fig. 4). The optimal fitting equation demonstrates a super-linear growth in WF_{total} with an increasing planted area (exponent > 1), indicating that the expansion of production causes stress on water resources -

this situation is particularly obvious in dry years. From 2005 to 2015, the maize planting area in Qiqihar increased remarkably, reaching its highest point of 15.0×10^5 ha in 2015, after which it began to decline (Fig. 3). As there was no need for irrigation in the normal year 2015 (BWF=0), the dry years from 2016–2017, along with the maintenance of a large cultivating area, resulted in a substantial increase in the blue water footprint (BWF values ranging from 0.03–0.04 m³/kg). This phenomenon shows the susceptibility of large-scale maize production systems under high hydrological variability.

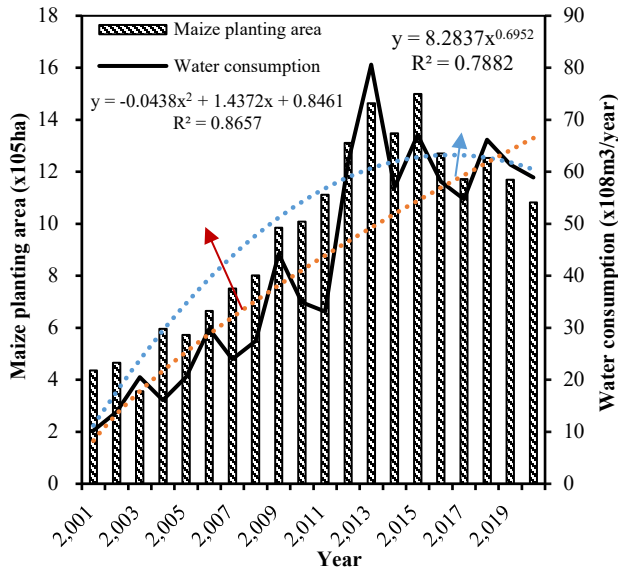


Fig. 3. Power function regression of total water footprint vs. maize planting area (2005–2024).

The total water footprint (WF_{total}) was mainly affected by the cultivated area, showing a significant positive correlation which was well-explained by a power function model ($R^2 = 0.87$; Fig. 3). At the same time, the maize yield per unit area presented an overall increasing tendency, reaching its maximum value of $7.90 \text{ t} \cdot \text{ha}^{-1}$ in 2012. Conversely, the production water footprint (WF_{prod}) per unit yield declined remarkably, following a quadratic relationship ($R^2 = 0.63$; Fig. 4). This enhancement in water utilization efficiency is also indicated by the decrease in the green water footprint (GWF)—the consumptive green water usage per unit yield, from $0.10 \text{ m}^3 \cdot \text{kg}^{-1}$ in 2007 to a stable range of $0.04\text{--}0.08 \text{ m}^3 \cdot \text{kg}^{-1}$ in recent years, with an average of about $0.07 \text{ m}^3 \cdot \text{kg}^{-1}$ from 2005 to 2015.

The blue water contribution to the total footprint differed greatly in the years when irrigation was necessary, especially in dry and normal years (as shown in Fig. 2 for a typical dry year). During the last twenty years, a blue water footprint (BWF) has been found in five dry years (2007, 2008, 2016, 2017, 2024) and five normal years (2005, 2010, 2011, 2014, 2023). In the other years, the BWF is zero, indicating that the total water footprint is made up of only GWF. Generally, GWF accounts for more than 45% of WF_{prod} , which suggests that green water resources are the main source for maize growth in this rainfed agricultural system. The existence of BWF in drought years, nevertheless, implies the requirement for supplementary irrigation to maintain the production (Sun *et al.*, 2013).

By analyzing the reasons for the decrease of 30% in WF_{prod} (from $0.10 \text{ m}^3/\text{kg}$ in 2007 to $0.06\text{--}0.08 \text{ m}^3/\text{kg}$ recently) with the help of Logarithmic Mean Divisia Index (LMDI) method, it is found that the decline is mainly due to three aspects: technological progress (68.2% share), scale effect (22.5%) and climatic change (9.3%). The significant negative correlation between WF_{prod} and the area yield ($R^2 = 0.63$) indicates the influence of yield increase on enhancing water productivity. The sharp reduction in GWF demonstrates an increasing efficiency in using rainfall. Although BWF occurred in only half of the

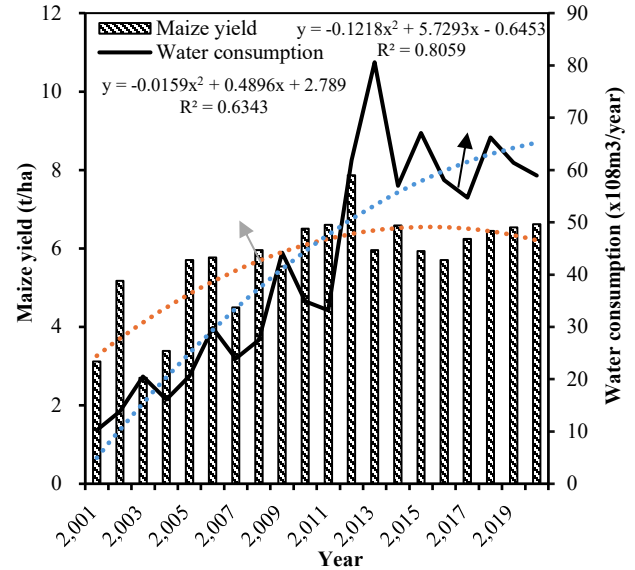


Fig. 4. Trends of production water footprint (WF_{prod}) and yield per unit area (2005–2024).

years, it showed large variability ($CV = 85.7\%$) and could account for up to 46.5% of WF_{total} in drought and normal years, which shows the significance of irrigation management during water shortage.

Cluster analysis classified the 20 years into three categories: high, medium and low WF_{prod} . The low WF_{prod} group (2005–2011) had the smallest footprint ($0.07 \pm 0.01 \text{ m}^3/\text{kg}$) and exhibited a higher yield stability ($CV = 2.2\%$) than the high WF_{prod} group (2021–2024, $CV = 10.49\%$). This indicates that it is important to improve water use efficiency for the stability and sustainability of the production system. Furthermore, a panel data model demonstrated that WF_{prod} was significantly and negatively associated with the degree of agricultural mechanization and the proportion of effectively irrigated area ($p < 0.05$), confirming the significant effect of technological progress on efficiency improvement.

This study applied the CROPWAT model to examine the twenty-year variation of the maize production water footprint in Qiqihar. The findings show that green water has a significant influence and the green water footprint (GWF) occupies 53.5% to 100% of the total footprint, which is consistent with the local rainfed agricultural circumstances (Hoekstra *et al.*, 2003; Symeonidou *et al.*, 2019). Nevertheless, the irrigation demand ($BWF > 0$) appeared in half of the years (50%), especially in the dry and normal years (Fig. 2, Table 3), indicating a clear "blue water clustering effect". Such a phenomenon has also been observed in other semi-arid rainfed systems like Harbin (Huang *et al.*, 2019). The higher frequency of irrigation years in Qiqihar (55%) compared to the data in Huang *et al.*, (2019) implies a more severe water shortage problem in this important semi-arid region. According to meteorological, soil and crop factors (Miao *et al.*, 2020; Zhang *et al.*, 2022), the CROPWAT model has precisely computed the crop water requirement (CWR), effective rainfall (ER) and irrigation amount (IR), thus serving as a reliable basis for assessing the occurrence and seriousness of blue water usage.

A significant increase in the blue water footprint from 2016 to 2017 (Table 3) was mainly due to extremely low

effective rainfall, which was 36.15% and 37.51% below the 20-year average, respectively, occurring at the same time as the historical high planting areas (Fig. 3). This is consistent with the reported trends of increased potential evaporation and rainfall variability under climate warming (Elbeltagi *et al.*, 2020), as well as the water use pressure caused by agricultural expansion.

An important result is the substantial decrease in the water footprint per unit production (WF_{prod}), especially the green water part (GWF), during the research period (Fig. 4). This decrease is accompanied by a noticeable rise in the maize yield per unit area (Fig. 4), showing an improvement in the water productivity for green water. These advantages mainly result from the progress in agricultural mechanization and field management techniques, such as using improved varieties, appropriate planting density and precise fertilization (Zhang *et al.*, 2018), which together increase the water use efficiency (WUE). These findings are consistent with the studies by Hui *et al.*, (2021) and Wu *et al.*, (2017) on the effect of technology on reducing the crop water footprint.

The main problem in maize cultivation in Qiqihar is that the natural rainfall is not enough to satisfy the crop water requirement (ER less than CWR) in about 45% of the years, which leads to an irrigation demand of up to 252 mm and causes serious concern in areas with over-exploited groundwater (Sun *et al.*, 2013; Elbeltagi *et al.*, 2020). Therefore, it is important to reduce the dependence on blue water and improve the efficiency of green water usage for the sustainable management of agricultural water (Cao *et al.*, 2022; Mekonnen *et al.*, 2020). We suggest: (1) using conservation tillage methods such as straw mulching and no-till, together with organic-inorganic fertilization (Geng *et al.*, 2019; Onyena *et al.*, 2025), to enhance the soil structure and water retention, thus making full use of the effective rainfall (Qin *et al.*, 2024); (2) promoting integrated drip irrigation and fertigation systems under mulch (Li *et al.*, 2020) for precise supply of blue water during the critical growth stages in dry years (Liu *et al.*, 2021); (3) optimizing the irrigation schedule according to the real-time soil moisture monitoring (Hu *et al.*, 2021); and (4) investigating the rainwater harvesting and reasonable use of surface runoff at the watershed scale to increase the irrigation supplies (Li *et al.*, 2020). Different water management strategies and contingency plans should be established according to the local hydrogeological conditions and seasonal rainfall forecasts (Chukalla *et al.*, 2015; Man *et al.*, 2016). Future studies could incorporate GryWF for a more comprehensive assessment.

Conclusions

This research used the CROPWAT model to investigate the long-term changes (from 2005 to 2024) of the maize production water footprint in Qiqihar City, Heilongjiang Province, and its connection with various hydrological years. The results show that the green water footprint (GWF) accounts for the main part (53.5% to 100%) of the total water footprint. The blue water footprint (BWF) is found in only 50% of the years and exhibits distinct clustering during dry and normal years, a phenomenon called the 'blue water clustering effect', indicating the importance of irrigation management during this time. The water footprint per unit yield (mainly GWF) has shown a noticeable decrease

throughout the whole study period, indicating an improvement in water use efficiency due to the development of agricultural techniques.

Quadratic relationships between effective rainfall and maize yield were found in all hydrological year types, and the highest correlation was observed in the dry years ($R^2 = 0.8663$), providing a dependable foundation for precipitation-guided production planning. The cultivated area (reaching its maximum in 2015) and the yield per unit area (reaching its maximum in 2012) also increased significantly. The total water footprint had a strong positive correlation with the planted area, whereas the water footprint per unit yield decreased with an increase in yield.

To promote high-yield maize growth and conserve water resources in semi-arid black soil areas, it is suggested to take the following actions: (1) improve the soil's water holding capacity by using conservation tillage and organic additions; (2) apply precise water-saving techniques, like drip fertigation under plastic mulch, to efficiently utilize green water and decrease the dependence on blue water during dry and normal years; and (3) establish regional water management systems and emergency plans suited to various hydrological years.

These results offer important data and a scientific foundation for improving water resource management in maize farming systems in Qiqihar and other semi-arid areas, especially for increasing water productivity and facilitating sustainable development under the condition of enhanced precipitation variability due to climate change.

Appendix A. Supplementary data: Not applicable

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administration. Huibo Shen: Funding acquisition, Resources. Yuxian Wang: Supervision, Writing – review & editing. Xu Shang: Conceptualization, Supervision, Funding acquisition, Writing – review & editing. Nicholas John Clarke: Writing – review & editing, Validation.

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