

Article

Evolution and Driving Factors of Water Footprints for Major Grain Crops: Evidence from China's Main Grain-Producing Regions

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Abstract

The water footprint of grain crop production is a key indicator for assessing agricultural water stress and resource-use efficiency. This study analyzes the dynamic evolution, convergence characteristics, and driving forces of water footprints for major grain crops in China's primary producing regions from 2011 to 2022. The results show the following: (1) Total water footprints are mainly driven by blue and green water components, while grey water contributes relatively little, and the total footprint follows a fluctuating pattern of "decline–increase–decline–increase–decline." Rice exhibits the highest water footprint, with an average annual value of 59.8251 million m³, whereas beans and tubers show much lower levels, each with an average annual footprint below 20 million m³. Grey water footprints for all grain crops have declined significantly since 2018, with reductions exceeding 10% by 2022. (2) Significant absolute convergence is observed across provinces, with the absolute convergence rate ultimately approaching 0.1, indicating that inter-provincial differences in water footprints are narrowing and that high-footprint regions are improving more rapidly toward lower-footprint regions. (3) Conditional convergence is also confirmed, with the conditional convergence rate approaching 0.2, suggesting that provinces converge toward their own steady-state levels, though convergence speeds are influenced by heterogeneous factors such as economic development, technological progress, and population size. (4) Generalised Divisia Index Method (GDIM) decomposition reveals that per capita agricultural GDP and mechanization intensity are the core drivers of changes in water footprints, and their synergistic effects produce an amplification impact, with cumulative contributions exceeding 100%. The findings provide important policy implications for optimizing water resource management and promoting sustainable agricultural development in China's major grain-producing areas.

Keywords: grain crops; production water footprint; major grain-producing regions; driving factors



Academic Editor: Gui Jin

Received: 17 November 2025

Revised: 17 December 2025

Accepted: 18 December 2025

Published: 19 December 2025

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1. Introduction

The "three rural" issues (rural areas, agriculture, and farmers) constitute an essential foundation for national stability and security [1]. Grain-food security has always been a strategic issue that is closely connected to the national economy and people's livelihoods. The volume of grain production determines a country's survival and development. By 2023, the number of people globally facing food shortage is approximately 713 million to 757 million. This figure represents an increase of about 152 million compared with 2019, indicating that the global food-security situation is very severe [2].

Since the 1978 reform and opening-up, China's agricultural economy has achieved tremendous success. With approximately 9% of the world's arable land and about 6% of the world's freshwater resources, China has fed approximately 20% of the global population [3]. However, in the new era, grain-food security faces more challenges. These include the cumulative effects of natural disasters, climate change, and instability in international situations. Meanwhile, with population growth and shifts in consumption patterns, China's grain demand continues to rigidly increase. At the same time, according to the national land-use change survey results, from 2009 to 2023 the total arable land area in China declined from 135.38 million ha to 128.6 million ha, approaching the "120 million ha" arable-land red line. The combination of increasing rigid grain demand and the scarcity of arable land and freshwater resources has determined that China's grain-food issue remains in a long-term "tight equilibrium" state. This situation urgently requires alleviating the constraining relationships [4–6].

Water resources are a key factor in ensuring grain-food security. Meanwhile, the concept of the water-footprint provides a scientific basis for precisely measuring water-resource consumption in the grain-production process. It also allows clearer insight into the tight linkage between grain production and water [7]. The water footprint is defined as the total volume of fresh water consumed directly and indirectly by a specific population over a given period in the production and consumption of goods and services. It has been widely applied in the study of water use in crop production [8]. The concept of water footprint was first proposed by Arjen Y. Hoekstra in 2011, who regarded the agricultural-production water footprint as mainly referring to the amount of water resources needed to produce a given crop [9,10]. On this basis, in order to better evaluate sustainable water use, the water footprint can be divided into green, blue, and grey water footprints according to the types of water consumption and their impact on the water environment. The blue water footprint refers to irrigation water derived from surface or groundwater. The green water footprint derives from atmospheric precipitation and snow/ice melt; it is the effective precipitation absorbed during crop growth. The grey water footprint is the total volume of water required to dilute pollutants generated in agricultural production to the local water-quality standard [11]. By including blue, green and grey components in the assessment of agricultural water use, the water footprint can more comprehensively reflect the influence of agricultural production on water-resource utilization.

In recent years, scholars have applied the water-footprint theory to conduct extensive research on water use in grain-crop production. They have found significant differences in water footprints among different crops [12]. For example, Fu et al. [13] systematically assessed the production water-footprint of major crops (wheat, maize, cotton and peanut) in Shandong Province, and found that, except for maize, the production water footprint of the other three crops exhibited a downward trend. Wang et al. [14] proposed that in the North China Plain the double-cropping system of winter wheat–summer maize–spring maize under rain-fed conditions is the best alternative planting system to improve evapotranspiration utilization efficiency, enhance precipitation use efficiency, and reduce the water footprint of grain crops. In addition, the research on driving factors of water footprint has covered various perspectives [15–17]. For example, Yi Wuying et al. [18] used an extended Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to analyse the changes in the production water footprint of grain crops in Pingtang County, showing that dietary structure, precipitation, population, economy, technology and urbanization all exert certain driving effects. Meng Qinghao et al. [19] used the Logarithmic Mean Divisia Index (LMDI) model to analyse that the economic effect, technological effect, grain-planting area, and average daily sunshine hours have a large influence on crop production water footprints. From this review of existing research, it

can be seen that the water footprints of grain crops have been usefully explored; however, analyses focusing on water footprints in China's typical major grain-producing regions remain scarce. The comparative analysis of five specific major grain crops at the regional level is especially rarely addressed.

Therefore, this study calculates the production water footprints of five typical grain crops (wheat, maize, rice, soybean, tubers) in China's three major grain-producing regions during 2011–2022. We focus on the following three questions regarding the development of grain-crop production water footprints in China. First: What are the characteristics of production water footprints for grain crops in China's major grain-producing regions? What are the differences in blue, green and grey water footprints among different grain crops? Second: What are the evolution trends of production water footprints for grain crops in China? Third: Which factors drive the evolution of production water footprints for grain crops? To address these issues, we first explore the changes in production water footprints of grain crops in China from the perspective of typical crops. Next, through convergence analysis we reveal the dynamic evolution mechanism of production water footprints of grain crops in China's major grain-producing regions. On this basis, we adopt the GDIM decomposition to investigate the integrated effects of multiple factors on the production water footprints of grain crops.

The marginal contributions of this study are as follows: (1) It reveals the differentiated dynamic evolution mechanism of water footprints in China's major grain-producing regions. Due to substantial variations in water-resource endowments and crop types across these regions, the blue, green and grey water footprints of grain crops exhibit large disparities. Existing research provides limited insight into such heterogeneity within major grain-producing regions. This study expands the depth of research on the spatial differentiation of grain water footprints and offers data support for the efficient use of agricultural water. (2) It identifies the convergence patterns of water footprints in major grain-producing regions. By conducting absolute and conditional convergence tests for water footprints, we find that inter-regional disparities are narrowing, shifting the analytical perspective of grain-crop water footprints from static trend analysis toward dynamic stability analysis. (3) It extends the GDIM decomposition framework and accurately quantifies the absolute and relative contributions of multidimensional factors. By applying the GDIM and designing a decomposition system comprising three absolute factors and five relative factors, this study effectively distinguishes between the "absolute influencing factors" and "relative influencing factors" of grain-crop water footprints. Compared with previous factor-decomposition approaches, this framework not only identifies the key determinants but also precisely quantifies the specific direction and magnitude of each factor's contribution to changes in water footprints, thereby providing direct and reliable empirical evidence for targeted water-saving policies. The study examines the development trends and driving factors of production water footprints of grain crops in China's major grain-producing regions. It supplies recommendations for the sustainable development of China's grain-crop production water footprints, and provides reference value for other developing countries.

2. Materials and Methods

2.1. Overview of the Major Grain-Producing Regions

According to the current classification of grain production and marketing areas in China, 31 provinces, municipalities and autonomous regions (excluding the separate customs territories of Taiwan, Hong Kong and Macau) are divided into 13 major grain-producing regions. These include Heilongjiang Province, Jilin Province, Liaoning Province, Inner Mongolia Autonomous Region, Hebei Province, Shandong Province, Anhui Province,

Henan Province, Jiangxi Province, Hunan Province, Hubei Province, Jiangsu Province, and Sichuan Province [20]. The major grain-producing regions, while ensuring grain self-sufficiency, have consistently provided surplus grain to support other production areas [21]. Within these regions, synchronous rainfall and heat, widespread plains, and fertile soils provide the foundation supporting China's grain-food security.

These regions fall under temperate monsoon and subtropical monsoon climatic zones. Water-resource distribution is uneven. The provinces differ significantly in terms of rainfall. This reflects China's precipitation pattern of "more in the south, less in the north; more in the east, less in the west". From 2011 to 2022, the annual average precipitation in the southern provinces—e.g., Jiangxi (1749 mm), Hunan (1647 mm), Sichuan (1294 mm)—all exceeded 1200 mm, with Jiangxi the highest. By contrast, in the northern provinces—e.g., Inner Mongolia (346 mm), Hebei (569 mm), Shandong (682 mm), Heilongjiang (683 mm)—rainfall is below 700 mm. An exception is the Northeast: Heilongjiang (683 mm), Jilin (766 mm), Liaoning (717 mm) receive more precipitation than the North China Plain, approaching the level of the Huang-Huai region (for example, Henan at 756 mm). As of 2022, the total sown area of crops in the major grain-producing regions was 117,512.16 thousand hectares. Among them, Heilongjiang and Henan had the largest sown areas: respectively 15,209.412 thousand hectares (accounting for 12.94% of the major grain-producing regions) and 14,711.513 thousand hectares (12.52%). Based on data compiled from the National Bureau of Statistics of China, the agricultural water use in 2022 in these regions reached 216.41 billion m³, which is 57.23% of the national total of 378.12 billion m³. In the same year, grain production of the major grain-producing regions reached 53,718 ten-thousand tons, accounting for about 78.25% of the national total (68,652.6 ten-thousand tons).

Typical grain crops in these regions include wheat, maize, rice, soybean and tubers. In 2022, the planting area of these five typical crops in the 13 provinces ranged from 55.24% to 97.72% of the total sown area of all crops; the lowest share was in Hunan, the highest in Jilin. As shown in Figure 1, rice production is highly concentrated: Hunan (4050 thousand ha), Jiangxi (3377 thousand ha), Hubei (2206 thousand ha) form the rice belt of the middle-lower Yangtze River, accounting for 43.9% of the total area in the 13 provinces. Maize cultivation shows a northward shift: Heilongjiang (5644 thousand ha), Henan (3543 thousand ha), Inner Mongolia (3510 thousand ha) account for 42.2% of the maize area in the 13 provinces. Wheat is mainly grown around the Huang-Huai-Hai core region: Henan (5544 thousand ha), Shandong (3861 thousand ha), Hebei (2326 thousand ha) together account for 60.8% of the wheat area across the 13 provinces. Among legumes, Heilongjiang plays a dominant role: its soybean area (3573 thousand ha) is 3.5 times that of second-ranked Inner Mongolia. For tuber crops, the data-characteristics display a single-pole production in Sichuan and scattered provinces with minor plantings.

2.2. Research Methods

2.2.1. Water Footprint Calculation

The water footprint (WF) refers to the total volume of freshwater required for the production of a specific crop. According to the type of water consumption and its impact on the water environment, it can be divided into green, blue, and grey water footprints.

The green water footprint [22] represents the consumption of green water, which is the soil-stored moisture originating from effective rainfall used during the crop growth period. The blue water footprint denotes the volume of blue water—surface water and groundwater—consumed for irrigation during crop production. The grey water footprint [23] is a pollution-related indicator that quantifies the amount of water required to dilute pollutants, such as fertilizers and pesticides, to meet specific ambient water-quality standards.

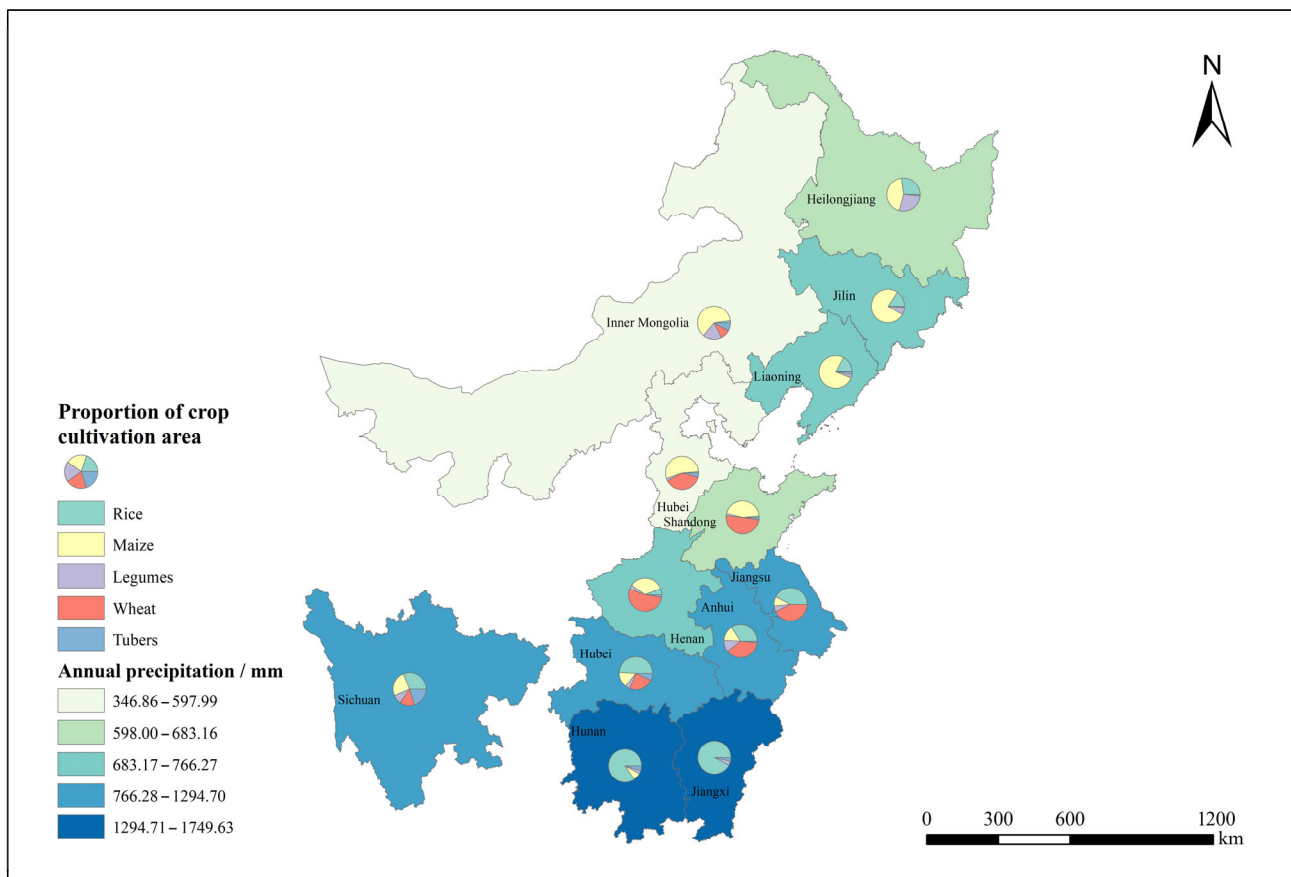


Figure 1. Average proportion of sown area for typical grain crops and multi-year mean precipitation in China's major grain-producing regions during 2011–2022.

The green, blue, and grey water footprints per unit sown area of a crop are calculated as follows:

$$\begin{aligned} CWU_{green} &= 10ET_{green} = 10 \min(ET_c, P_{eff}) \\ CWU_{blue} &= 10ET_{blue} = 10 \max(0, ET_c - P_{eff}) \\ CWU_{grey} &= 10ET_{grey} = \frac{\alpha AR}{C_{max} - C_{nat}} \end{aligned} \quad (1)$$

where CWU_{green} , CWU_{blue} , and CWU_{grey} are the unit-area green, blue, and grey water footprints ($\text{m}^3 \cdot \text{hm}^{-2}$); ET_{green} , ET_{blue} , and ET_{grey} are the corresponding evapotranspiration or evaporation losses (mm); 10 is a conversion factor for water depth; ET_c is the crop water requirement (mm); P_{eff} represents the effective precipitation during the crop-growing season (mm); α is the leaching rate (%); AR denotes the amount of pollutants in the leaching water ($\text{kg} \cdot \text{hm}^{-2}$); C_{max} and C_{nat} are the maximum allowable and natural background concentrations of pollutants ($\text{kg} \cdot \text{m}^{-3}$), respectively. C_{max} for nitrogen (N) is set at 20 mg/L, while C_{nat} is generally assumed to be zero [24].

The total green, blue, and grey water footprints for crop production in region i are expressed as:

$$GWF = CWU_{green} \times P_i / \eta \quad (2)$$

$$BWF = CWU_{blue} \times P_i / \eta \quad (3)$$

$$RWF = CWU_{grey} \times P_i / \eta \quad (4)$$

where GWF , BWF , RWF are the total green, blue, and grey water footprints (m^3) of crop production in region i ; P_i is the total crop yield (t); and η is the sown area (hm^2).

Since multiple pollutants can be diluted in the same water body, the grey water footprint is determined by the pollutant that requires the largest dilution volume. Provincial statistical data indicate that the amount of nitrogen fertilizer applied is significantly higher than that of phosphorus and potassium fertilizers. Therefore, nitrogen is selected as the dominant pollutant for estimating the grey water footprint in crop production. It is assumed that a fixed proportion of applied nitrogen fertilizer leaches into the water body (the nitrogen leaching rate) [25]. Following common practice, the nitrogen leaching rate is taken as 7% [26]. To verify the sensitivity of the core conclusions to this key assumption (the nitrogen leaching rate), we conducted a scenario analysis. The results indicate that the overall trend of grey water footprints and the relative differences among crops remain highly robust. Complete results are provided in the sensitivity analysis section of the Supplementary Materials.

The total water footprint of crop production can thus be expressed as:

$$TWF = GWF + BWF + RWF \quad (5)$$

2.2.2. Time Series Trend Analysis Method

To investigate whether there were significant changes in the water footprint of grain crop production during the study period, the Mann–Kendall (M–K) test, a non-parametric statistical method, was employed to analyze the temporal variation trends of water footprint for grain crop production [27].

The M–K test procedure is as follows:

The null hypothesis H_0 : the time series data $(x_1, x_2, \dots, x_n)$ are n independent and identically distributed random variables. The alternative hypothesis H_1 : for all $i, j \leq n$, the distributions of x_i and x_j are not identical. The test statistic S is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (6)$$

$$\text{sgn} = \begin{cases} 1, x_j - x_i > 0 \\ 0, x_j - x_i = 0 \\ -1, x_j - x_i < 0 \end{cases} \quad (7)$$

where x_j and x_i represent the values of the j -th and i -th years in the time series, respectively; n is the number of samples (years); When $n > 10$, the standardized normal variable Z can be calculated as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, S < 0 \end{cases} \quad (8)$$

where $\text{Var}(S)$ is the variance of S , and Z is the standardized test statistic representing the trend of the time series. When $Z > 0$, it indicates an increasing trend; when $Z < 0$, it indicates a decreasing trend. If $|Z|$ exceeds 1.65, 1.96, or 2.58, the trend passes the significance test at the 90%, 95%, and 99% confidence levels, respectively.

2.2.3. Convergence Model for Examining the Evolution of the Water Footprint of Grain Production

To investigate the evolution trend and convergence speed of the water footprint of grain-crop production across major grain-producing regions, this study constructs a convergence model. The initial model is expressed as:

$$\frac{1}{T-t} \cdot \ln\left(\frac{TWF_{iT}}{TWF_{it}}\right) = O - \left[\frac{1 - e^{-\beta(T-t)}}{T-t}\right] \cdot \ln(TWF_{it}) + \gamma_i + \mu_{it} \quad (9)$$

where i denotes region, t represents the starting period, and T denotes the ending period. TWF_{it} represents the water footprint of grain-crop production in region i at time t , and TWF_{iT} denotes the water footprint at period T . O is a constant term, γ_i is the individual fixed effect, β represents the convergence (or divergence) rate, and μ_{it} is the error term.

Solving Equation (9) yields:

$$h_{iT} = \alpha_0 - \alpha_1 \ln(TWF_{it}) + \gamma_i + \varepsilon_{it} \quad (10)$$

In Equation (10), h_{iT} represents the logarithmic growth rate of the water footprint during period (t, T) , and α_0 is a constant term.

$$\alpha_1 = \frac{1 - e^{-\beta(T-t)}}{T-t} \quad (11)$$

If $\alpha_1 > 0$, regions with a higher initial water footprint experience faster growth during period (t, T) , indicating a divergence pattern, and thus $\beta < 0$.

If $\alpha_1 < 0$, regions with a higher initial water footprint experience slower growth during period (t, T) , indicating a convergence pattern, and thus $\beta > 0$.

Taking the natural logarithm on both sides of Equation (11) and multiplying by $(T - t)$, we obtain:

$$\ln(TWF_{iT}) = (T - t)O + B \cdot \ln(TWF_{it}) + (T - t)\gamma_i + (T - t)\mu_{it} \quad (12)$$

where $(T - t)O$ is a constant term, $(T - t)\gamma_i$ is the regional fixed effect, and $(T - t)\mu_{it}$ represents the error term. Based on this, the following conclusions can be drawn: when $\beta > 0$ and $B < 1$, grain-crop production water footprint demonstrates a convergence trend. When $\beta < 0$ and $B > 1$, the water footprint exhibits a divergence trend. When $\beta = 0$ and $B = 1$, the water footprint remains in steady state without convergence or divergence.

The convergence (or divergence) rate is defined as:

$$\beta = -\frac{\ln(B)}{T-t} \quad (13)$$

According to Equation (12), when $T - t = 1$, the annual dynamic evolution of the water footprint of grain-crop production can be expressed as follows:

$$\ln(TWF_{i,i+1}) = B \cdot \ln(TWF_{it}) + O + \gamma_i + \mu_{it} \quad (14)$$

The convergence rate is therefore expressed as:

$$\beta = -\ln(B) \quad (15)$$

Equation (15) represents the dynamic panel model. To eliminate unobserved interference terms, the first-order difference is taken, as shown in Equation (16):

$$\Delta \ln(TWF_{i,i+1}) = B \cdot \Delta \ln(TWF_{it}) + \Delta \mu_{it} \quad (16)$$

If the water footprint of grain-crop production exhibits a divergence trend, then regions with a higher initial water footprint continue to show higher growth rates, and the growth gap widens over time. If this growth gap persists, regions with initially high water footprints will continue to diverge from regions with lower footprints. Conversely, if the water footprint exhibits a convergence trend, regions with higher initial footprints will show lower growth rates, narrowing the gap over time, indicating efficiency improvement and resource optimization in high-footprint regions.

Equation (16) only considers absolute convergence of the water footprint. To incorporate additional influencing factors x_i and reflect conditional convergence, the model is modified as follows:

$$\Delta \ln(TWF_{i,t+1}) = B \cdot \Delta \ln(TWF_{it}) + \rho \Delta x_{i,t} + \Delta \mu_{it} \quad (17)$$

2.2.4. GDIM for Driving-Factor Analysis

To further explore the comprehensive effects of multiple factors on the convergence of the water footprint of grain-crop production, and to achieve rational resource allocation and sustainable grain production, this study applies the GDIM [28] to decompose the water footprint of grain-crop production in China's major grain-producing regions during 2011–2022. The model is expressed as follows:

$$\begin{aligned} TWF_t &= (TWF_t / AGDP_t) \cdot AGDP_t = (TWF_t / AMP_t) \cdot AMP_t = (TWF_t / RP_t) \cdot RP_t \\ &= AGDP_t \cdot AWFPI_t = AMP_t \cdot AWFMP_t = RP_t \cdot RPWFI_t \end{aligned} \quad (18)$$

In Equation (18), TWF_t represents the water footprint of grain-crop production; $AGDP_t$ denotes agricultural GDP; AMP_t denotes total agricultural machinery power; and RP_t represents rural population. These variables are absolute factors.

$AWFPI_t$ represents water footprint intensity, reflecting the water footprint per unit of agricultural GDP, and measuring the strength of agricultural water consumption relative to economic output.

$AWFMP_t$ represents mechanization efficiency, indicating water resources conserved through agricultural mechanization. $RPWFI_t$ represents the per capita water footprint of grain-crop production.

Next, this study considers the relationships among $AGDP$, RP , and AMP . Equations (19) and (20) show the specific relationships:

$$RAGDP_t = AGDP_t / RP_t = (TWF_t / RP_t) / (TWF_t / AGDP_t) = RPWFI_t / AWFPI_t \quad (19)$$

$$AMPI_t = AMP_t / AGDP_t = (TWF_t / AGDP_t) / (TWF_t / AMP_t) = AWFPI_t / AWFMP_t \quad (20)$$

Here, $RAGDP_t$ represents per capita agricultural GDP, and $AMPI_t$ represents agricultural mechanization intensity. Thus, Equations (21) and (22) can be derived as:

$$TWF_t = AGDP_t \cdot AWFPI_t \quad (21)$$

$$\begin{cases} AGDP_t \cdot AWFPI_t - AMP_t \cdot AWFMP_t = 0 \\ AGDP_t \cdot AWFPI_t - RP_t \cdot RPWFI_t = 0 \\ AGDP_t - RP_t \cdot RAGDP_t = 0 \\ AMP_t - AGDP_t \cdot AMPI_t = 0 \end{cases} \quad (22)$$

Vaninsky [29] emphasized that time variations in the model do not affect the final decomposition results. Therefore, by extending the decomposition to multiple dimensions, we can analyze changes in the water footprint of grain-crop production and identify the contribution of each factor. The decomposition equation is shown in Equation (23).

$$\begin{cases} TWF_t = (TWF_1 / TWF_0)^t \\ AGDP_t = (AGDP_1 / AGDP_0)^t \\ AMP_t = (AMP_1 / AMP_0)^t \\ RP_t = (RP_1 / RP_0)^t \\ AWFPI_t = (AWFPI_1 / AWFPI_0)^t \\ AWFMP_t = (AWFMP_1 / AWFMP_0)^t \\ RPWFI_t = (RPWFI_1 / RPWFI_0)^t \\ RAGDP_t = (RAGDP_1 / RAGDP_0)^t \\ (AMPI)_t = (AMPI_1 / AMPI_0)^t \end{cases} \quad (23)$$

where $Q(TWF_t, AGDP_t, \dots)$ represents the current value, and $Q_0(TWF_0, AGDP_0, \dots)$ represents the base-period value. According to the decomposition principle of the GDIM method, the variation in the water footprint of grain-crop production can be decomposed into absolute and relative factors, as shown in Equation (24):

$$\Delta TWF[X|\Phi] = \int_L \nabla TWF^T (I - \Phi_X \Phi_X^+) dX \quad (24)$$

where ∇TWF is the gradient vector of the function with respect to TWF , defined as:

$$\nabla TWF = (AWFPI_t, AGDP_t, 0, 0, 0, 0, 0, 0)^T \quad (25)$$

denotes the Jacobi matrix shown in Equation (26):

$$\Phi_X = \begin{pmatrix} AWFPI & AGDP & -AWFMP & -AMP & 0 & 0 & 0 & 0 \\ AWFPI & AGDP & 0 & 0 & -RPWFI & -RP & 0 & 0 \\ 1 & 0 & 0 & 0 & -RAGDP & 0 & -RP & 0 \\ -AMPI & 0 & 1 & 0 & 0 & 0 & 0 & -AGDP \end{pmatrix} \quad (26)$$

Here, I is the identity matrix and $+$ denotes the generalized inverse matrix. If the column vectors of the Jacobi matrix Φ_X are linearly independent, then $\Phi_X^+ = (\Phi_X^T \Phi_X)^{-1} \Phi_X^T dX$. dX is a diagonal matrix, as shown in (27):

$$dX = \text{diag}(AGDP_t, AMP_t, RP_t, AWFPI_t, AWFMP_t, RPWFI_t, RAGDP_t, AMPI_t) dt \quad (27)$$

From Equation (26), it follows that the water footprint of grain-crop production can be decomposed into three absolute factors and five relative factors, forming eight components. The absolute factors reflect the impact of economic development, technological progress, and population on the water footprint of grain production. The relative factors represent unit agricultural GDP water footprint intensity, water-use efficiency, per capita water footprint, per capita agricultural GDP, and mechanization intensity. The specific indicators are shown in Table 1.

Table 1. Variables and definitions used in the model.

Variable	Formula/Definition	Description
TWF	—	Water footprint of grain-crop production
$AGDP$	—	Agricultural gross domestic product (economic level), deflated by the price index to 2015 constant prices
$AWFPI$	$AWFPI = TWF / AGDP$	Water footprint per unit agricultural GDP, measuring agricultural water-use intensity and resource consumption pressure
AMP	—	Total agricultural machinery power (technology level)
$AWFMP$	$AWFMP = TWF / AMP$	Water footprint per unit of agricultural machinery power, indicating mechanization water-use efficiency
RP	—	Rural population (population scale)
$RPWFI$	$RPWFI = TWF / RP$	Water footprint per rural capita, reflecting per capita agricultural water use
$RAGDP$	$RAGDP = AGDP / RP$ (Rural AGDP per Capita)	Per capita agricultural GDP
$AMPI$	$AMPI = AMP / AGDP$	Agricultural mechanization intensity, reflecting mechanization level relative to economic scale

2.3. Data Sources

In this study, meteorological variables—including precipitation, evaporation, air pressure, air temperature, ground temperature, relative humidity, wind speed and direction, and sunshine duration—were obtained from the China Meteorological Data Service Center (<http://data.cma.cn>) (accessed on 15 May 2025) and derived from the China Surface

Climate Daily Dataset (V3.0). Data on sown area, crop yield, precipitation, and nitrogen fertilizer application were collected from the China Statistical Yearbook, National Bureau of Statistics of China, Provincial Statistical Yearbooks, and Agricultural Statistical Yearbooks. Crop coefficients and irrigation water use coefficients were obtained from published literature and empirical studies. The benchmark parameters for crop water footprint estimation were derived from indicators recommended by the Food and Agriculture Organization of the United Nations (FAO) and from Gao et al. [30]. For the calculation of the grey water footprint, this study adopted the natural background concentration and maximum allowable concentration values of pollutants based on the Environmental Quality Standards for Surface Water (GB 3838–2002) [31], Class III water standard. Socioeconomic data—including population, GDP, and total agricultural machinery power—were obtained from the China Statistical Yearbook and corresponding Provincial Statistical Yearbooks. To eliminate the influence of price fluctuations, all value-related variables (such as agricultural gross domestic product, AGDP) were converted into constant prices using 2015 as the base year and deflated with the corresponding price indices. Moreover, to avoid inconsistencies caused by changes in land accounting methods during the Third National Land Survey (2018–2020), this study uniformly adopts the continuous and survey-independent sown area as the basis for calculating water footprints and related indicators. This ensures data comparability and the robustness of conclusions across the entire study period (2011–2022).

3. Results

3.1. Blue and Green Water Footprint of Grain Crop Production in Major Grain-Producing Regions

According to Figure 2, the blue and green water footprints of five typical grain crops exhibited distinct temporal variations from 2011 to 2022. Rice had the highest combined blue–green water footprint throughout the study period, generally fluctuating between 550 and 650 billion m³. This indicates that rice production demands a large volume of water resources. The high water footprint of rice is closely related to its growing environment—it is cultivated primarily in paddy fields, which require continuous water saturation. Consequently, its blue water footprint accounts for a large share of the total. The water footprint of maize showed an overall increasing trend, ranging mostly between 450 and 550 billion m³. This reflects the rising importance of maize in national grain production and the continuous expansion of its planting area. However, it also suggests that the water-use efficiency of maize cultivation could be further improved. Compared with rice, wheat exhibited a relatively lower blue–green water footprint, mostly within 200–400 billion m³. A sharp decline was observed in 2012, followed by a slight rebound in 2013, after which the overall trend continued to fluctuate downward. This reduction can be attributed to the adoption of more efficient irrigation technologies and improved cropping structures, leading to reduced blue water consumption and enhanced water-use efficiency. Legumes and tubers showed relatively stable patterns with the lowest water footprint values among the five crops. This indicates that their overall water demand remained modest and stable. Nonetheless, minor fluctuations were observed, likely influenced by crop-specific growth characteristics, planting structures, and irrigation practices.

As shown in Figure 2, the blue–green water footprint of grain production in China's major grain-producing regions exhibits a clear fluctuating pattern over the study period, with distinct troughs and peaks occurring in 2012 and 2020, respectively. This fluctuation reflects the inherently complex, multi-factor dynamics that shape agricultural water use.

The decline observed in 2012 temporally aligns with the introduction of China's "most stringent water resources management system," under which the Three Red Lines established stricter constraints on water use and strengthened water-saving awareness. These institutional measures may have contributed to improvements in water-use efficiency [31].

However, extensive empirical evidence also indicates a strong negative correlation between precipitation levels and irrigation (blue water) demand. In 2012, major grain-producing regions such as North China experienced above-average precipitation, which likely reduced reliance on irrigation water. Therefore, the decline in 2012 is more plausibly the combined result of both “strong policy intervention” and “favorable climatic conditions,” and attributing the change solely to policy effects may overstate its direct impact.

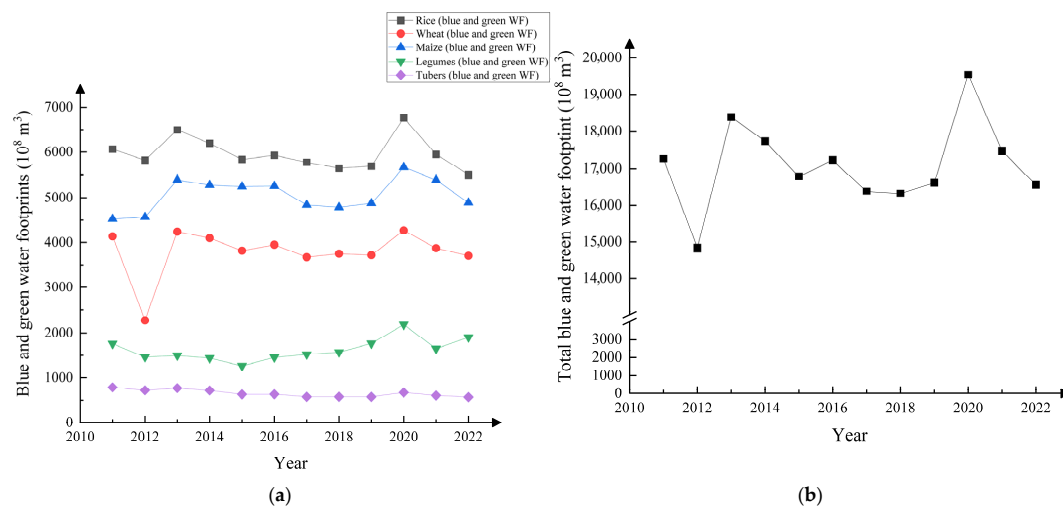


Figure 2. (a) Blue and green water footprints of five major grain crops in China’s main grain-producing regions; (b) total blue and green water footprints.

The surge in 2020 occurred against the broader backdrop of safeguarding national food security and responding to climatic risks. On one hand, national agricultural incentive policies strengthened farmers’ motivation to increase grain production, thereby raising water demand [32]. On the other hand, meteorological drought events recorded in several major producing areas around this period likely reduced the availability of green water and increased the need for supplemental irrigation (blue water), driving up the blue water footprint. In addition, after years of decline, the marginal effectiveness of water-saving technologies may have approached a plateau, constituting another potential contributing factor. Thus, the 2020 peak can be interpreted as the outcome of interacting forces, including “policy incentives, climatic stress, and the technological progress cycle.”

3.2. Grey Water Footprint of Grain Crop Production in Major Grain-Producing Regions

As shown in Figure 3, the grey water footprint of the five typical grain crops displayed distinct inter-annual variations from 2011 to 2022, with clear differences in magnitude among crops. Overall, maize exhibited relatively higher WFgrey values in most years, whereas tubers showed the lowest levels.

For maize, the grey water footprint increased before 2016 and reached its peak in that year. This peak may be associated with an expansion of planting area and increased application of fertilizers and pesticides during that period. After 2016, the WFgrey of maize began to decline, indicating that environmental and agricultural pollution-control measures may have started to take effect, leading to reductions in nutrient runoff and pollutant discharge into water bodies.

The grey water footprint of wheat fluctuated between 2010 and 2014 and reached a relatively high level in 2014. Afterward, it declined and remained relatively stable at a lower level. This suggests that the pollution discharge associated with wheat cultivation—or its impact on water quality—was effectively controlled after 2014, likely due to improved fertilization management and sustainable farming practices.

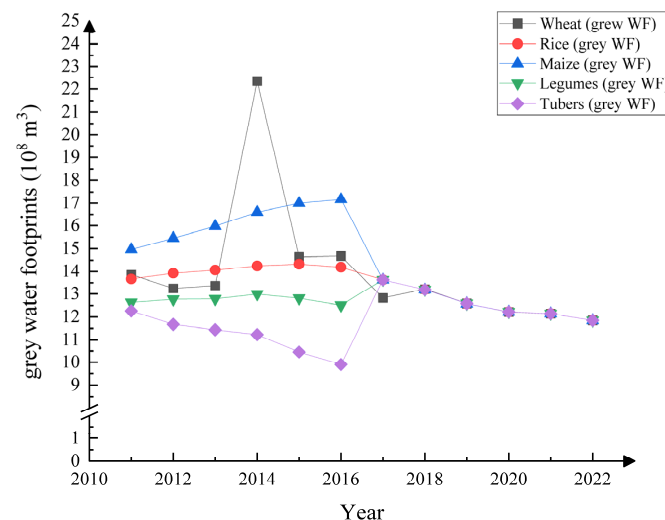


Figure 3. Grey water footprints of five major grain crops in China's main grain-producing regions.

Rice showed mild fluctuations in WF_{grey} between 2010 and 2018, with no substantial overall change. However, a gradual downward trend appeared after 2018, indicating a progressive reduction in water pollution pressure from rice production. This improvement may be attributed to the adoption of green farming technologies, optimized fertilizer and irrigation strategies, and enhanced nutrient-management practices in paddy fields.

For legumes and tubers, the grey water footprints remained relatively stable and consistently low across the study period. These patterns likely reflect lower reliance on chemical fertilizers and pesticides and relatively cleaner production processes, resulting in limited pollutant emissions and smaller impacts on water environments compared with other crops.

The analysis indicates that the grey water footprint of grain crop production in China's major grain-producing regions shows an overall downward trend over time. In particular, a notable decline occurred after 2016 across all five typical grain crops. Starting in 2016, China implemented the Environmental Protection Tax Law and the Key River Basin Water Pollution Prevention and Control Plan (2016–2020). Meanwhile, the State Council emphasized in the Government Work Report that “overall ecological and environmental quality should continue to improve.” These policies gradually tightened pollutant discharge standards and environmental governance requirements, encouraging increased environmental investment in the major grain-producing regions. As a result, the excessive application of chemical inputs in agricultural production was reduced, leading to a decrease in the grey water footprint [33].

Looking ahead, China is expected to continue promoting green agricultural technologies and optimizing cropping structures. These measures will contribute to further reducing agricultural pollution loads and mitigating the adverse impacts of grain production on water environments. After 2018, the absolute values of grey water footprints among different crops became increasingly close, and the differences were small relative to the full scale of the vertical axis ($0\text{--}25 \times 10^8 \text{ m}^3$). As a result, the lines for different crops appear visually overlapped in the figure. The specific values for each crop are provided in Table S1 of the Supplementary Materials.

3.3. Total Water Footprint of Grain Crop Production in Major Grain-Producing Regions

As shown in Figure 4, the total water footprint of the five typical grain crops displayed patterns consistent with their blue–green water footprint levels. Rice had the highest total water footprint, which aligns with its paddy-field cultivation system that relies on

continuous flooding and high irrigation demand. Wheat and maize also exhibited relatively high WF_{total} values, indicating considerable water consumption and pollution intensity during their production processes. By contrast, legumes and tubers consistently showed the lowest WF_{total} values with very limited fluctuation. This is attributed to the relatively stable and modest water requirements of legume crops, as well as the strong drought tolerance of tuber crops, which typically require less irrigation. In addition, both crop categories maintained relatively stable planting areas, resulting in minimal variation in their total water footprints over the study period.

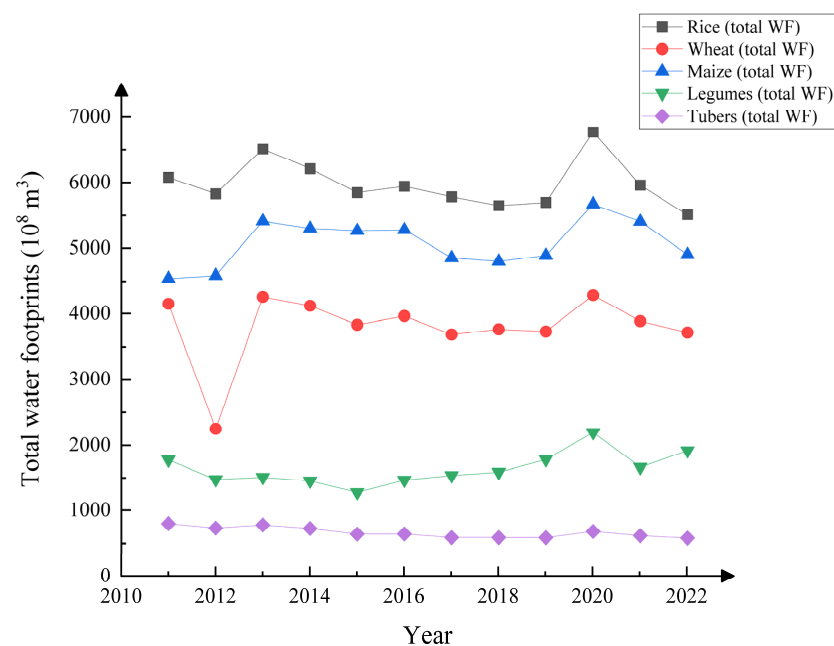


Figure 4. Total water footprints of five major grain crops in China's main grain-producing regions.

Overall, the total water footprint in China's major grain-producing regions followed a fluctuation pattern similar to that of the combined blue–green water footprint, characterized by phases of decline followed by increases, specifically: decline → rise → decline → rise → decline. This pattern suggests that the blue–green components play a dominant role in shaping the WF_{total} , while the grey water footprint exerts a comparatively smaller influence. The peaks (minimum and maximum values) were observed in 2012 and 2020, respectively. After the peak around 2020, the total water footprint declined, reflecting the combined effect of reductions in both blue–green and grey water footprint components.

3.4. M–K Test Results

The Mann–Kendall test provides a more scientific and rigorous assessment of the significance of temporal trends in the water footprint of grain crop production, addressing the limitations of relying solely on visual trend interpretation [34]. The M–K results for the five typical grain crops are presented in Table 2. From a crop-level perspective, the green, blue, and grey water footprints exhibit heterogeneous temporal trends. Most crops show a significant decreasing trend in the grey water footprint, indicating effective pollution control progress in agricultural production. For the green water footprint, certain crops in specific regions present significant upward trends, potentially linked to climate change effects and advancements in water-saving agronomic practices. The blue water footprint shows mostly insignificant trends, implying relatively stable surface and groundwater extraction across regions [35]. The M–K test results and detailed analysis for the five typical grain crops are provided in Table S7 of the Supplementary Materials.

Table 2. Estimation results of absolute convergence in major grain-producing regions.

Variables	2011–2012 (1)	2011–2013 (2)	2011–2014 (3)	2011–2015 (4)	2011–2016 (5)	2011–2017 (6)	2011–2018 (7)	2011–2019 (8)	2011–2020 (9)	2011–2021 (10)	2011–2022 (11)
L1_ln_TWF	0.7584 *** (0.1959)	0.5827 *** (0.1568)	0.7029 *** (0.1079)	0.7630 *** (0.0837)	0.8077 *** (0.0685)	0.8360 *** (0.0584)	0.8588 *** (0.0504)	0.8754 *** (0.0443)	0.8868 *** (0.0415)	0.8869 *** (0.0380)	0.8968 *** (0.0350)
Wald chi2	34,720.9032 ***	62,242.3688 ***	130,630.2077 ***	228,082.9148 ***	348,737.7832 ***	497,348.3236 ***	668,994.8531 ***	860,607.5964 ***	981,328.3194 ***	1,174,655.3648 ***	1,410,158.5713 ***
Arellano-Bond test											
AR(1)	−1.6585	−1.7546	−1.8997	−2.1493 *	−2.9840 ***	−3.0049 ***	−3.6253 ***	−4.1163 ***	−4.8785 ***	−3.9341 ***	−4.2160 ***
AR(2)	0.8374	−0.3332	−0.3435	−0.1532	0.4855	−0.3269	0.4497	0.3666	1.207	−1.4734	−0.0415
AR(3)	−1.1022	−1.1901	−0.1695	−0.327	0.2834	1.1029	0.2357	1.1579	0.5609	1.9272	−0.9516
AR(4)	−0.0008	1.6528	−0.2765	0.0048	−0.6853	−0.6944	0.0301	−1.0678	−0.332	0.11	1.3207
Sargan test	299.529	723.1601	786.3115	820.7776	845.8948	866.2359	878.1627	889.1597	980.2449	1023.388	1038.5376
Observations	12	25	38	51	64	77	90	103	116	129	142

Note: Values in parentheses represent standard errors. *** denotes $p < 0.01$; * denotes $p < 0.1$. AR(1) indicates the first-order serial correlation test statistic of the residuals; AR(2) indicates the second-order serial correlation test statistic; AR(3) indicates the third-order serial correlation test statistic; AR(4) indicates the fourth-order serial correlation test statistic. L1.TWF denotes the one-period lag of lnTWF, used as a GMM-type instrumental variable. Same below.

4. Discussion

4.1. Absolute Convergence Results

To ensure the stationarity of time-series data and the existence of long-run equilibrium relationships, we first performed unit-root tests and cointegration tests before regression analysis [36]. These diagnostics provide a reliable basis for subsequent modelling and help us identify the linkage between grain production and water-resource use with greater precision, thereby informing agricultural water-resource management and decision-making [37]. The unit-root results indicate that some variables are non-stationary in levels but become stationary after first differencing; the null of a unit root is rejected for the first differences. The Johansen tests show that the trace or maximum-eigenvalue statistics exceed the critical values, implying significant cointegration among the variables. Detailed unit-root and cointegration test results are reported in Tables S5 and S6 of the Supplementary Materials.

Spatial evolution trends of the water footprint for grain-crop production during 2011–2022 can be inferred from Equations (21) and (22). However, for dynamic panels, fixed-effects estimators suffer from small-sample bias and tend to be upward biased; hence Generalized Method of Moments (GMM) estimators are preferred [38]. We therefore estimate the models using GMM. The results are reported in Table 2. To ensure the robustness of the convergence results and to avoid reliance on a single time interval, we adopt an expanding-window analysis. Specifically, we fix the starting year at 2011 and then systematically extend the ending year from 2012 to 2022, thereby constructing eleven windows of increasing length (e.g., 2011–2012, 2011–2013, ..., 2011–2022). Models (1)–(11) present GMM estimates of absolute convergence for the water footprint from 2011–2012 through 2011–2022. Model adequacy was evaluated using standard specification tests. Wald chi-square statistics confirm overall model significance (large-sample chi-square inference; econometric standard). Arellano–Bond tests assess serial correlation in the first-differenced residuals under the null of no autocorrelation; results show significant AR(1) but insignificant AR(2), AR(3), and AR(4), indicating no higher-order serial correlation. The Sargan test of over-identifying restrictions supports the validity of the instrumental set. Taken together, these diagnostics indicate that the GMM estimates of the spatio-temporal convergence of crop-production water footprints for 2011–2012 and 2011–2022 are statistically credible.

From a spatio-temporal perspective, absolute convergence characterizes the evolution of the water footprint across China's major grain-producing regions. All eleven models in Table 2 yield coefficient values $B < 1$, indicating absolute convergence of grain-crop production water footprints. In other words, regional water footprints are converging toward a typical steady-state level over time. Regions with higher initial water-footprint levels exhibit slower growth (or faster reduction), while regions with lower initial levels catch up more rapidly. Hence, high-footprint regions improve faster and gradually approach the low-footprint regions.

The core mechanism behind the narrowing differences is consistent with the law of diminishing marginal returns in efficiency gains: regions with high initial footprints often have greater scope for improvement and thus reap higher marginal benefits from technology adoption, policy support, and spillovers; conversely, regions already near the frontier face natural-resource constraints and technology ceilings, so their improvement slows. The coordinated effects of economic investment, population pressure, and technological innovation promote diffusion and policy alignment across regions, ultimately steering the major grain-producing areas toward a more balanced and efficient water-use regime.

4.2. Conditional Convergence Results

Table 3 presents the conditional convergence results based on the dynamic panel estimations. Models (12)–(22) report the GMM estimation outcomes. All models pass

the Wald chi-square test, the Arellano–Bond serial correlation test, and the Sargan test, confirming the validity of the GMM estimation procedure. The results indicate that the water footprint of grain-crop production in China's major grain-producing regions exhibits a conditional convergence trend ($B < 1$). The conditional convergence rate is relatively low and generally shows a fluctuating downward pattern, stabilizing around 0.2 during the period from 2011–2019 to 2011–2021.

The essence of conditional convergence is that each region converges toward its own steady-state level of water-use efficiency, but the convergence speed varies due to regional heterogeneity in factors such as economic development level, technological capacity, and population scale. Our results show that the impact of economic development on water-footprint convergence shifts from negative to positive. This turning pattern is broadly consistent with the development trajectory described by the Environmental Kuznets Curve (EKC). The GDIM decomposition provides a key piece of supporting evidence: in the later years of the study period, the contribution share of the “intensity effect,” which reflects technological efficiency, increases markedly and becomes the dominant driver, supporting the interpretation that economic growth fosters water-saving technological progress. At the same time, we cannot rule out another channel—that economic development may also be accompanied by adjustments in cropping patterns toward lower-water-footprint crops (the “structure effect”). Although the decomposition results initially point to the primacy of technological effects, a complete separation of these two channels would require more granular data. Taken together, the observed shift is more plausibly the outcome of technology-led efficiency improvements, acting in combination with possible optimisation of cropping structures. Looking ahead, policy should focus on promoting water-saving technologies and guiding agricultural restructuring in a more sustainable direction.

Under the influence of technological progress, represented by total agricultural machinery power, technology exerts a positive effect on reducing the water footprint of grain-crop production. This reflects the convergence effect of technology diffusion, whereby high-water-footprint regions achieve rapid reduction in unit water footprint by adopting efficient technologies such as smart drip irrigation and drought-resistant varieties, while technology-leading regions (such as those in the middle-lower Yangtze River) diffuse experience and management practices through cross-regional agricultural demonstration programs. However, the contribution of technological progress is declining due to diminishing marginal returns. As regions approach their steady-state development level, the marginal efficiency gains from water-saving technology investments decrease.

With regard to population scale, population growth exerts a negative impact on the water footprint of grain-crop production due to demand-driven agricultural expansion. Higher population increases grain demand, forcing high-water-footprint regions to expand irrigated area or increase cropping intensity to maintain production. However, this negative effect is weakening over time. Under increasing population pressure, high-water-footprint regions are compelled to break path dependence and accelerate technological upgrading. Additionally, densely populated regions in the middle-lower Yangtze River rely on virtual-water trade and “north-to-south grain transfer” to ease local production pressure, indirectly mitigating excessive exploitation in high-water-footprint areas by reducing rice planting reliance and increasing supply from Northeast China.

Table 3. Estimation results of conditional convergence in major grain-producing regions.

Variables	2011–2012 (12)	2011–2013 (13)	2011–2014 (14)	2011–2015 (15)	2011–2016 (16)	2011–2017 (17)	2011–2018 (18)	2011–2019 (19)	2011–2020 (20)	2011–2021 (21)	2011–2022 (22)
L1.lnTWF	0.9718 *** (0.2382)	0.5036 *** (0.1423)	0.6038 *** (0.1161)	0.6686 *** (0.1028)	0.7057 *** (0.0898)	0.7353 *** (0.0831)	0.7611 *** (0.0754)	0.7819 *** (0.0684)	0.7778 *** (0.0597)	0.7897 *** (0.0597)	0.8158 *** (0.0574)
lnAGDP	−0.4573 (0.3810)	0.1333 (0.3002)	0.1176 (0.2260)	0.0893 (0.1774)	0.0877 (0.1404)	0.0685 (0.1146)	0.0596 (0.0976)	0.0536 (0.0842)	0.0964 (0.0744)	0.0488 (0.0665)	0.0188 (0.0583)
lnAMP	0.1464 (0.2735)	0.2463 (0.1956)	0.1813 (0.1426)	0.1471 (0.1090)	0.1441 (0.0917)	0.1405 * (0.0796)	0.1340 * (0.0720)	0.1289 * (0.0659)	0.1281 ** (0.0620)	0.1230 ** (0.0591)	0.1129 ** (0.0568)
lnRP	−0.0352 (0.2915)	−0.2341 (0.1615)	−0.1581 (0.1092)	−0.1129 (0.0874)	−0.1124 (0.0735)	−0.1 (0.0653)	−0.0915 (0.0583)	−0.0887 * (0.0528)	−0.1224 *** (0.0454)	−0.0761 * (0.0436)	−0.0491 (0.0386)
Wald chi2	120,038.5903 ***	84,742.7270 ***	183,118.6060 ***	319,555.3540 ***	536,380.4850 ***	792,165.4036 ***	1,152,756.3151 ***	1,610,388.5772 ***	1,956,544.6781 ***	1,793,395.8367 ***	2,140,275.3310 ***
Arellano-Bond test											
AR(1)	−1.9830 *	−1.4087	−1.6583	−1.7374	−2.5567**	−2.5122 **	−2.9269 ***	−3.3475 ***	−3.8563 ***	−3.2329 ***	−3.3706 ***
AR(2)	1.4354	−0.3969	−0.1074	−0.3094	0.6457	−0.2056	0.4243	0.4879	1.4266	−1.2179	−0.1058
AR(3)	−1.6706	−1.8763	−0.3192	−0.1246	0.1424	1.3266	0.4071	1.1917	0.9323	2.2444 **	−0.6073
AR(4)	0.3571	1.7504	−0.935	−0.1089	−0.5821	−0.913	0.1721	−0.9697	−0.3356	0.3858	1.55
Sargan test	407.1888	1124.1284	1245.3321	1329.2688	1365.7696	1410.0262	1435.1308	1455.8189	1544.987	1673.7087	1732.6989
Observations	12	25	38	51	64	77	90	103	116	129	142

Note: Values in parentheses represent standard errors. *** denotes $p < 0.01$; ** denotes $p < 0.05$; * denotes $p < 0.1$.

4.3. Decomposition Analysis of Water Footprint in Grain Production

GDIM is constructed by transforming the Kaya identity and building a decomposition model that includes multiple absolute and relative factors, thereby revealing the driving forces behind changes in the target variable. In contrast, LMDI is limited by consistency requirements in continuous multiplicative decomposition and can only evaluate the impact of a single absolute factor on energy consumption. However, relative factors often explain socio-economic phenomena more effectively [39]. Therefore, this study applies GDIM, as its decomposition results offer stronger policy relevance.

Following the GDIM approach, we selected data for the total water footprint of grain-crop production in the major grain-producing regions from 2011 to 2022 and decomposed the influencing factors. We used the R programming language to conduct the calculations, and the cumulative contribution values of eight key factors—such as economic level and population size—were obtained. The results are presented in Figure 5.

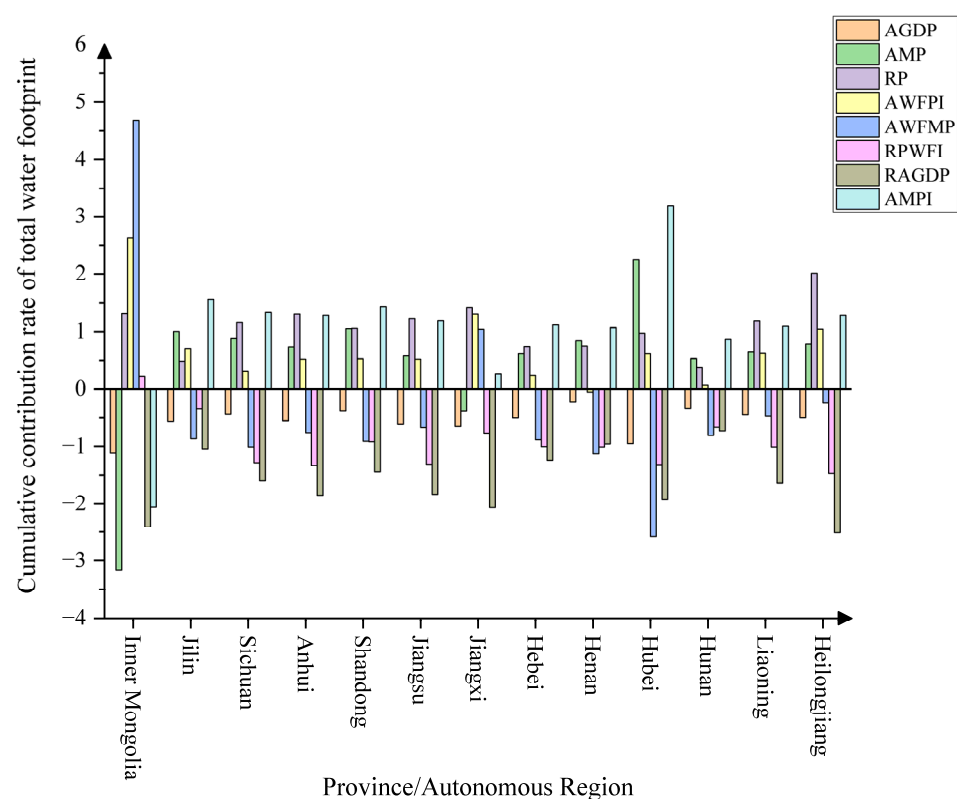


Figure 5. Cumulative contribution rates of total water footprint across provinces in China’s major grain-producing regions.

Based on historical data for the water footprint of grain-crop production in major grain-producing regions from 2011 to 2022, the GDIM was applied to decompose the influencing factors and quantify the contribution of eight drivers. The results are summarized as follows:

Agricultural output value, total agricultural machinery power, rural population, water footprint per unit of agricultural GDP, water-use efficiency, per capita water footprint of grain-crop production, per capita agricultural GDP, and agricultural mechanization intensity all influence the water footprint of grain-crop production to varying degrees. Ranking the eight factors by cumulative contribution from largest to smallest and from positive to negative shows the following order: per capita agricultural GDP > agricultural mechanization intensity > water-use efficiency > rural population > total agricultural ma-

chinery power > per capita grain-crop water footprint > water footprint per unit agricultural GDP > agricultural output value.

Total agricultural machinery power, rural population, water footprint per unit agricultural GDP, and agricultural mechanization intensity exhibit positive contributions, meaning they promote increases in the water footprint. A larger cumulative contribution indicates a stronger promoting effect (i.e., higher water consumption). In contrast, agricultural output value, per capita agricultural GDP, water-use efficiency, and per capita grain-crop water footprint show negative contributions, meaning they restrain the water footprint. A larger absolute cumulative contribution reflects a stronger inhibitory effect (i.e., reduced water consumption).

Per capita agricultural GDP and agricultural mechanization intensity (AMPI) are the primary contributors affecting the water footprint of grain-crop production. GDIM accounts for inter-factor interactions; when synergy exists among factors, their contribution may be amplified. During the study period, the average cumulative contributions of these two factors were 163.29% and 136.30%, respectively. Higher per capita agricultural GDP indicates greater financial capacity for investing in agricultural technology development and dissemination, such as water-saving irrigation and precision agriculture, which improve water-use efficiency and reduce the water footprint. Likewise, higher agricultural mechanization intensity implies greater mechanization in production. Mechanization increases production efficiency, enhances irrigation performance and fertilizer-use precision, and thereby reduces both the blue and grey water footprint in grain production.

4.4. Model Scale and Future Directions

The macro-level framework adopted in this study for assessing the water footprint and grey water footprint is designed to reveal long-term national-scale trends and their dominant driving mechanisms. To achieve this, the model incorporates several necessary simplifications. Temporally, daily meteorological data were aggregated over the full crop growing period to smooth short-term weather fluctuations and highlight interannual variations as well as the influence of slow-moving factors such as policy. In pollution accounting, nitrogen fertilizer was selected as a representative indicator, and uniform parameters were applied. While this framework effectively captures macro-patterns, it inevitably presents three limitations. First, it cannot resolve the nonlinear impacts of extreme weather events—such as droughts or heavy rainfall—occurring during critical phenological stages. Second, by excluding other pollutants such as phosphorus and pesticides, it may underestimate the total pollution load. Third, the omission of spatial heterogeneity in soil and climate conditions restricts its ability to support fine-grained regional management. Future research should focus on developing higher-resolution dynamic models that couple high-frequency meteorological data with crop growth processes, incorporate multi-pollutant accounting, and differentiate parameters based on soil attributes and hydrological zoning. Such advancements would enable a transition from describing macro-level trends to diagnosing underlying process mechanisms and supporting refined risk management.

5. Conclusions

The water footprint of grain production is a crucial indicator for measuring the total amount of water consumed in agricultural production and the efficiency of water use. It helps assess the pressure exerted by agricultural production on water resources and supports sustainable agricultural development. This study examined the dynamic evolution of the water footprint in China's major grain-producing regions and quantified the contributions of influencing factors. The main conclusions are as follows.

The total water footprint and total blue–green water footprint of grain production in the three major grain-producing regions show similar fluctuation patterns, characterized by a sequence of decline, rise, decline, rise, and decline. This pattern indicates that blue and green water dominate the total water footprint, while the grey water footprint has a relatively smaller impact. Among the five typical grain crops, the magnitude of total water footprint is consistent with blue–green water consumption. Rice has the highest total water footprint due to its dependence on paddy irrigation. Wheat and maize also show high water footprints, indicating intensive water consumption and associated pollution. In contrast, legumes and tubers exhibit consistently low water footprints with minimal variation over time.

The water footprint of grain production in China’s major grain-producing regions exhibits absolute convergence. This indicates that differences in water use among the 13 provinces are narrowing. Regions with higher initial water footprints show slower growth or faster reduction, while regions with lower initial levels show faster improvement, meaning high-water-footprint regions are catching up with low-water-footprint regions. In recent years, the absolute convergence rate has remained above zero and gradually decreased, stabilizing around 0.1 during 2011–2019 to 2011–2021.

The water footprint of grain production also exhibits conditional convergence. The conditional convergence rate shows a declining trend. Conditional convergence reflects that each region converges toward its own steady-state level of water-use efficiency, but the convergence speeds differ due to heterogeneity in economic development, technological capacity, and population scale. The effect of economic development shifts from negative to positive and gradually strengthens, indicating improved efficiency with economic upgrading. Technological progress (measured by total agricultural machinery power) has a positive effect on reducing the water footprint, though its marginal benefit is weakening due to diminishing returns. Population growth exerts a negative effect due to demand-driven agricultural expansion.

According to the factor decomposition results, relative factors such as per capita agricultural GDP and AMPI are the primary drivers, with average cumulative contribution rates of 163.29% and 136.30%, respectively. Higher per capita agricultural GDP implies more investment in technology R&D and diffusion, thereby reducing the water footprint. Higher agricultural mechanization intensity enhances production efficiency, irrigation efficiency, and fertilizer utilization, leading to reductions in both blue and grey water footprints.

6. Policy Implications

To alleviate water-resource pressures in major grain-producing regions and enhance grain-security capacity, this study—based on the 2011–2022 trends and driving mechanisms of the water footprint—proposes the following policy recommendations aimed at improving water-use efficiency and ensuring the sustainability of agricultural water use. All recommendations are directly grounded in the quantitative findings of this research.

6.1. Implement Region–Crop Differentiated Targeted Regulation Based on Convergence and Structural Patterns

The findings reveal that (i) regional water footprints exhibit conditional convergence, but steady-state levels differ significantly across regions; and (ii) maize consistently shows the highest water footprint, particularly in terms of grey water.

Policy implications: (1) Provide technological safeguards for “lagging regions.” For regions with high water-footprint levels and slow convergence (e.g., certain provinces in the Huang–Huai–Hai Plain), policy resources—including funding and technology—should be preferentially allocated. A county-level “full-coverage water-saving technology deploy-

ment” program should be implemented to push these regions toward advanced steady-state levels. (2) Conduct full-process governance for “critical crops.” Maize should be designated as a flagship crop for tackling agricultural non-point-source pollution and advancing water-saving efforts. In major maize-producing regions, a “Maize Green Production Negative List” should be introduced to strictly cap irrigation quotas and nitrogen application limits, with compliance directly tied to producer subsidies.

6.2. Consolidate the Dominant Driving Force and Translate “Intensity-Effect” Gains into Institutional Outcomes

The results show that technological progress is the most robust contributor to reductions in the water footprint.

Policy implications: (1) Link technological subsidies to the contribution rate of the intensity effect. Current agricultural technology subsidies should be reformed by establishing a “Water Efficiency Improvement Fund,” with priority given to technologies that directly and measurably enhance water productivity (e.g., fertigation systems, conservation tillage). Regions with lower intensity-effect contributions should receive stronger support. (2) Build smart water-management platforms to institutionalize technological gains. In digitally advanced regions such as the middle-lower Yangtze River basin, governments should take the lead in establishing an “Agricultural Water-Footprint Monitoring and Resource-Optimization Platform.” By integrating IoT monitoring, quota management, water trading, and subsidy verification, technological gains can be locked in through digital governance mechanisms.

6.3. Use the “Growth-Transition Window” to Guide Spatial Layout and Subsidy Reforms Through Binding Constraints

The results show that the impact of economic development on the water footprint has shifted from negative to positive, suggesting that some major grain-producing regions have entered a new stage where economic growth promotes water-use efficiency.

Policy implications: (1) Apply binding “water-led spatial planning.” In developed regions where economic growth exerts a positive effect, the water footprint per unit of GDP and crop-specific water-footprint intensity should be incorporated as mandatory indicators in agricultural land-use planning. Regions exceeding water-resource carrying capacity should reduce the planting area of high-water-footprint crops and promote low-footprint alternatives. (2) Reform subsidy mechanisms to incentivize “green growth.” Agricultural water-use efficiency indicators should be fully integrated into eco-compensation schemes and agricultural-support subsidy assessments. A pilot “Water-Saving Yield Enhancement Award” should be introduced to reward producers who simultaneously achieve higher yields and lower water footprints, thereby making decoupling of water use from economic growth more profitable at the micro level.

Ensuring water security in major grain-producing regions requires a shift from generalized, large-scale interventions to data-driven precision policies. Concretely, this means: (1) Targeting “lagging regions” and “critical crops” identified through quantitative diagnostics; (2) Investing in and institutionalizing proven intensity-effect drivers; (3) Leveraging the growth-transition window through binding constraints and market incentives, so that water-resource carrying capacity becomes a decisive force shaping agricultural layout and subsidy reform. Through this integrated strategy, China can safeguard grain security while achieving a fundamental transformation of agricultural water-use patterns.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w18010009/s1>, Table S1: Grey Water Footprints of the Five Major Grain Crops in China’s Main Grain-Producing Regions; Sensitivity Analysis: Table S2: Sensitivity

Analysis; Table S3: Statistical Properties of the Parameter; Table S4: Crop-Specific Sensitivity Analysis; Table S5: Unit Root Test Results; Table S6: Cointegration Test Results; Table S7: Mann–Kendall test results for water footprints of five major grain crops in China’s main grain-producing regions.

Author Contributions: Conceptualization, H.M.; Methodology, H.Y.; Formal analysis, Y.G.; Data curation, Y.G.; Writing—original draft preparation, H.Y.; Writing—review and editing, H.M.; Funding acquisition, H.M.; Supervision, H.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Foundation of China, project title “Institutional Nesting Dilemmas and Adjustment Strategies for the Synergistic Allocation of Water, Soil, and Energy under Food Security” (grant number 25BGL243). The APC was funded by the authors.

Data Availability Statement: Data available on request due to restrictions (privacy: because part of the data is obtained from statistical yearbooks and meteorological data platforms that are subject to access restrictions).

Conflicts of Interest: The authors declare no conflicts of interest.

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