

Article

Global Changes in Agricultural Water Demand Driven by Climate and Crop Area Change

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Abstract

Growing agricultural water demand, driven by climate change and land-use intensification, is accelerating global water scarcity and threatening food and environmental security. This study quantifies spatiotemporal changes in crop water requirements (CWR) and irrigation water requirement (IWR) from 1980 to 2017 for wheat, maize, and soybean. A corrected FAO crop coefficient method was used to estimate global CWR, while the logarithmic mean Divisia index (LMDI) was applied to decompose its drivers into climate and crop area changes. IWR was calculated to evaluate the increasing water stress in four representative river basins: the Haihe (HRB), Yellow (YRB), Mississippi (MRB), and Ganges (GRB) river basins. Multiple linear regression models were used to identify dominant drivers of water stress. Results show that from 1980 to 2017, CWR increased significantly for maize ($+210 \times 10^8 \text{ m}^3$) and soybean ($+523 \times 10^8 \text{ m}^3$) primarily due to crop area expansion, while wheat CWR declined ($-109 \times 10^8 \text{ m}^3$). Area growth contributed over $+850 \times 10^8 \text{ m}^3$ to global CWR increases. At the basin scale, IWR rose notably in HRB, YRB, and GRB, but declined in MRB. Regression analysis confirms that crop area change was the dominant driver of variations in IWR, particularly for soybean in HRB and maize in YRB, while precipitation exerted strong negative effects in some regions. This study provides a scalable framework for diagnosing agricultural water stress and its key drivers, supporting climate adaptation and irrigation planning under global change.



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1. Introduction

Freshwater scarcity is increasingly threatening the sustainable development of human societies due to rising global demand over recent decades [1]. Agriculture, as the largest consumer of water resources, accounts for approximately 86% of the global freshwater

use [2]. With growing populations and expanding food production, the tension between agricultural water supply and demand has intensified, particularly in arid regions where irrigation is essential for crop productivity [3–5]. Climate change, characterized by rising temperatures, uneven precipitation, and more frequent extreme weather events, further exacerbates water scarcity by altering crop water requirements (CWR) and irrigation water demands [6,7]. Concurrently, human activities, such as changes in crop cultivation patterns and land use, have significantly influenced global water demand for major crops [8–10]. Therefore, understanding the combined impacts of climate change and agricultural activities on CWR is critical for sustainable water use and global food security.

While many studies have investigated CWR at local or regional scales [11–15], few have examined their global dynamics or the combined impacts of climate and crop area changes. A broader perspective is essential to reveal large-scale water stress patterns, shared drivers, and support cross-regional water governance. For example, soybean expansion in South America, driven by Chinese demand, has induced telecoupled water stress in exporting regions [16], which regional studies alone cannot capture. Although the effects of climate change [10,17–19] and crop area changes [20,21] on CWR have been widely examined, they are often analyzed separately and within limited spatial contexts. Few studies have quantitatively compared their relative contributions to global agricultural water stress.

Irrigation water requirement (IWR) provides a practical metric for assessing agricultural water stress by quantifying the gap between crop water requirement per unit area (ET_c) and effective precipitation [22–24]. Deb et al. used the CROPWAT model to estimate IWR regionally [25], while Rosa et al. assessed global irrigation demand under climate scenarios [26]. IWR captures both biophysical and demand-side drivers [27,28]. Increasing trends in IWR have been observed in arid regions due to rising ET_c (e.g., Zhangye irrigation area and Iraq) [29,30]. However, its use for globally diagnosing spatial and temporal trends in irrigation needs, and linking those trends to climate and crop planting area drivers, remains limited.

To address these gaps, this study investigates the spatiotemporal dynamics of water requirements for three globally important, water-intensive crops, namely wheat, maize, and soybean, which are central to food security [31–33]. Reference evapotranspiration (ET_0) was estimated using the Penman-Monteith equation, and daily ET_c was calculated globally for 1980 to 2017 via crop coefficient corrections. Combining global crop distribution and area data, we analyzed spatial and temporal variations in total CWR across major agricultural regions.

To explore the drivers of changing water demand, the logarithmic mean Divisia index (LMDI) was applied to decompose CWR trends into climatic and crop area contributions. Concurrently, the IWR, defined as the product of the crop planting area and the net difference between ET_c and effective precipitation when the latter is insufficient, was used to assess supply-demand imbalances. Four river basins, including the Haihe River Basin (HRB), Yellow River Basin (YRB), Ganges River Basin (GRB), and Mississippi River Basin (MRB), were selected as case studies due to their hydroclimatic diversity, water stress, and agricultural relevance [34,35]. To systematically investigate the underlying drivers of changes in IWR across these contrasting regions, a multiple linear regression framework was applied. This approach enables the quantification of the contributions of individual driving factors while accounting for interannual variability and basin-specific dynamics, thereby facilitating a spatially explicit understanding of irrigation demand responses.

This study investigates the combined impacts of climate and crop area changes on agricultural water stress, both globally and at the basin scale. By linking these drivers to crop water deficit patterns, it offers a practical framework for assessment of crop water stress

risk and dominant stressor identification. The results inform targeted water management, climate adaptation, and transboundary cooperation. Supporting sustainable water use and agriculture, the study contributes to SDG 6 (clean water and sanitation) and SDG 12 (responsible consumption and production).

2. Methodology

2.1. Datasets

This study developed a multi-layered spatiotemporal integration framework to assess global CWR and IWR from 1980 to 2017. All datasets were processed and resampled to a uniform spatial resolution of $0.083^\circ \times 0.083^\circ$ and consistent daily or monthly temporal resolution.

Daily meteorological variables, including air temperature (mean, maximum, and minimum), wind speed, precipitation, relative humidity, and solar radiation, were obtained from the NCEP-DOE Reanalysis 2 dataset (2.5° resolution), statistically downscaled to 0.083° using bilinear interpolation combined with topographic correction, and subsequently used to estimate daily ET_0 based on the FAO-56 Penman-Monteith equation. These downscaled daily variables were also used to adjust crop coefficients (K_c) according to crop growth stages and local climatic conditions, following the guidelines provided in FAO-56. Crop growth periods were derived from FAO calendars and adjusted regionally using the Köppen–Geiger classification.

The MIRCA2000 dataset (0.083° resolution) provided the spatial distribution of crop planting areas, which served as a spatial mask. Annual crop areas for wheat, maize, and soybean from FAOSTAT were scaled each year to match the MIRCA2000 spatial pattern, ensuring temporal consistency in cultivated area.

ET_c was calculated based on ET_0 and K_c for each day, summed over the crop-specific growing season, and multiplied by annual crop area. The IWR was calculated as the product of crop planting area and the net difference between ET_c and effective precipitation, applied only when precipitation was insufficient. Detailed data information of the study is provided in Table S1 of the Supplementary Materials.

2.2. Calculation of ET_c

The crop coefficient method proposed by FAO was employed to calculate the CWR per unit area (ET_c) using the following equation [36]:

$$ET_c = ET_0 \times K_c \quad (1)$$

where ET_c denotes the daily CWR per unit area; ET_0 , the reference crop evapotranspiration (mm); and K_c , the crop coefficient.

2.2.1. Calculation of ET_0

The ET_0 was calculated using the FAO-56 Penman-Monteith equation [36]:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

where ET_0 denotes the reference crop evapotranspiration (mm/d); R_n , net radiation at the crop surface ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$); G , soil heat flux density ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$), which can be approximated to 0; T , mean daily air temperature at 2 m height ($^\circ\text{C}$); u_2 , wind speed at 2 m height ($\text{m} \cdot \text{s}^{-1}$); e_s , saturation vapor pressure (kPa); e_a , actual vapor pressure (kPa); Δ , slope of saturation vapor pressure curve at air temperature ($\text{kPa} \cdot ^\circ\text{C}^{-1}$); γ , psychrometric constant ($\text{kPa} \cdot ^\circ\text{C}^{-1}$).

2.2.2. Correction of K_c

The standard crop coefficient (K_c) values provided in FAO-56 represent generalized conditions and do not explicitly account for spatiotemporal variations in climatic factors across different climate zones. Therefore, following the procedures recommended in FAO-56, K_c values were adjusted for different crop growth stages to account for local variations in wind speed, minimum relative humidity, and crop height, resulting in more accurate, climate-specific crop coefficients. The detailed correction of K_c can be found in Supplementary Materials.

2.3. Estimating Crop Planting Area and Identification of the Main Crop-Producing Countries

To construct the spatiotemporal distribution of crop planting areas from 1980 to 2017, two datasets were integrated: MIRCA2000, which provides high-resolution crop-specific spatial distributions around the year 2000, and annual national statistics from FAOSTAT. A cross-country comparison of wheat, maize, and soybean areas in 2000 showed strong consistency between the two sources, with a correlation coefficient above 0.96 at the 95% confidence level (Figure S1 in the Supplementary Materials).

Based on this consistency, the spatial crop distribution for each year was derived by dynamically scaling the MIRCA2000 baseline using the ratio of annual FAOSTAT database planting area to that of the year 2000. Recent studies have utilized the CROPGRIDS dataset to generate temporally explicit crop distribution maps based on harmonized spatial inputs [37]. However, due to its limited temporal coverage and the need for consistency across decades, we employed a dynamic scaling approach using MIRCA2000 and FAOSTAT data to better support our long-term analysis from 1980 to 2017.

$$S_{crop(c,t)} = S_{MIRCA2000(c)} \times \frac{S_{FAOSTAT(c,t)}}{S_{FAOSTAT(c,2000)}} \quad (3)$$

$S_{crop(c,t)}$ represents the spatial crop planting area of country c in year t ; $S_{MIRCA2000(c)}$ represents the baseline spatial distribution from the MIRCA2000 dataset; $S_{FAOSTAT(c,t)}$ represents the crop planting area of country c in year t in FAOSTAT; $S_{FAOSTAT(c,2000)}$ represent crop planting area for the FAOSTAT baseline year.

In India, however, wheat planting area in MIRCA2000 deviated significantly from FAOSTAT records (difference > 30%). To address this, spatial correction was applied using national and regional agricultural reports [38], and a revised time series dataset for wheat planting areas in India was subsequently reconstructed.

Finally, the five countries with the largest planting areas for each crop were identified as primary producers. For wheat: China, the United States, India, France, and Russia (data for Russia cover 1992–2017); for maize: China, the United States, Brazil, India, and France; and for soybean: China, the United States, Brazil, Argentina, and India.

2.4. Calculation of Crop Water Requirement

The total CWR for wheat, maize and soybean was obtained by multiplying the CWR per unit area by the corresponding crop area:

$$CWR = ET_c \times S_{crop} \quad (4)$$

where S_{crop} denotes the crop planting area (m^2).

2.5. Calculation of the Irrigation Water Requirement

The IWR is defined as the portion of ET_c not met by effective precipitation, multiplied by the corresponding crop planting area [39]:

$$IWR = \max(ET_c - P_e, 0) \times S_{crop} \quad (5)$$

where IWR , the daily irrigation water requirement during the growth period; and P_e , the daily effective precipitation (mm).

The P_e was calculated using a piecewise function based on daily precipitation, as follows:

$$P_e = \begin{cases} P \times \frac{(4.17-0.2P)}{4.17}, & P < 8.3 \text{ mm} \\ 4.17 + 0.1P, & P \geq 8.3 \text{ mm} \end{cases} \quad (6)$$

where P is the daily precipitation (mm).

2.6. Decomposition Analysis

The logarithmic mean Divisia index (LMDI) method was used to quantify the contributions of climatic factors and crop area changes to variations in CWR. Derived from exponential decomposition analysis, LMDI is widely applied in energy, environmental, and agricultural water studies [40–42].

CWR was calculated as the product of ET_c and crop planting area. ET_c depends on ET_0 and the K_c , where ET_0 is derived from meteorological data. In this study, K_c values were assumed constant for each crop [36], meaning changes in ET_c primarily reflect climatic variations, independent of crop type or area.

Thus, CWR changes were driven by both ET_c (climatic influence) and crop planting area. While climate affects CWR through ET_c , planting area changes modify total water demand without altering individual crop requirements. Accordingly, we decomposed CWR changes into separate effects of climate and crop area using LMDI [11,27].

$$\Delta CWR = \Delta CWR_{ET_c} + \Delta CWR_{S_{crop}} \quad (7)$$

where ΔCWR denotes the change in CWR, and ΔCWR_{ET_c} and $\Delta CWR_{S_{crop}}$ denote the effects of climatic factors and crop area changes, respectively. The impact of each factor on the CWR changes was calculated as follows:

$$\Delta CWR_{ET_c} = \frac{CWR_T - CWR_{T-1}}{\ln CWR_T - \ln CWR_{T-1}} \ln \frac{CWR_{ET_c,T}}{CWR_{ET_c,T-1}} \quad (8)$$

$$\Delta CWR_{S_{crop}} = \frac{CWR_T - CWR_{T-1}}{\ln CWR_T - \ln CWR_{T-1}} \ln \frac{CWR_{S_{crop},T}}{CWR_{S_{crop},T-1}} \quad (9)$$

where CWR_T and CWR_{T-1} denote the CWR for years T and $T - 1$, respectively; $CWR_{ET_c,T}$ and $CWR_{ET_c,T-1}$ denote ET_c for years T and $T - 1$, respectively; and $CWR_{S_{crop},T}$ and $CWR_{S_{crop},T-1}$ denote the area of planted crops for years T and $T - 1$, respectively.

2.7. Trend Analysis

Trends in ET_c were assessed using the non-parametric Mann–Kendall test [43,44], complemented by linear regression to quantify trend magnitude [45], following standard procedures recommended by the World Meteorological Organization. Detailed formulations are provided in Supplementary Materials.

2.8. Multiple Linear Regression Models

To quantitatively assess the relative contributions of climatic factors and crop area changes to variations in irrigation water requirement (ΔIWR), multiple linear regression models were constructed for major crops (wheat, maize, soybean) across selected basins (HRB, YRB, MRB, GRB). Annual rates of change were used as model inputs to identify the influence of each driver.

2.8.1. Variable Construction

Annual relative change rates (i.e., percent changes) were computed for all relevant variables. For any variable X_t , the change rate was calculated as:

$$\Delta X_t = \frac{X_t - X_{t-1}}{X_{t-1}} \times 100\% \quad (10)$$

where X represents each variable, and t denotes time.

2.8.2. Regression Model Specification

For each basin-crop combination, the following multiple linear regression model was fitted [46]:

$$\Delta IWR = \beta_0 + \beta_1 \Delta A + \beta_2 \Delta P + \beta_3 \Delta W + \beta_4 \Delta T + \epsilon \quad (11)$$

where ΔIWR denotes the rate of change in irrigation water demand and serves as the dependent variable. ΔA , ΔP , ΔW , and ΔT represent the rates of change in planting area, precipitation, wind speed, and temperature, respectively. β_0 is the intercept term, while β_1 , β_2 , β_3 , and β_4 are the regression coefficients associated with each driving factor (ΔA , ΔP , ΔW , and ΔT), reflecting their respective influences on ΔIWR . The term ϵ denotes the random error, accounting for unexplained variability in the model.

Each model was estimated using ordinary least squares (OLS). The regression coefficients (β_i) were extracted to indicate the direction and magnitude of the influence of each factor on ΔIWR . Model performance was evaluated using the coefficient of determination (R^2), calculated as:

$$R^2 = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y})^2} \quad (12)$$

where y_t is the observed value, $\hat{y}_t$ is the predicted value, and $\bar{y}$ is the mean of the observed values.

3. Results

3.1. Changes in Climatic Factors

Climatic factors, including temperature, precipitation, and wind speed, are key variables influencing ET_0 and ET_c . Significant geographic variations were observed in climatic trends from 1980 to 2017 (Figure 1). Globally, both maximum and minimum temperatures exhibited increasing trends, at a rate of approximately 0.04–0.1 °C per year across major crop-producing regions. Concurrently, precipitation decreased in northern China, western United States, Western Europe, most of South America, and northeastern India, particularly severe in southeastern Brazil (>7.5 mm/year decrease). Wind speeds notably declined in the Amazon Basin, northern Australia, the Indian northern mountains, and the Patagonia Plateau (decreased at a rate of 1–2 m/s). These climate changes have implications for ET_0 : temperature increases tend to enhance ET_0 , whereas reductions in wind speed and precipitation influence evaporative demand and water availability.

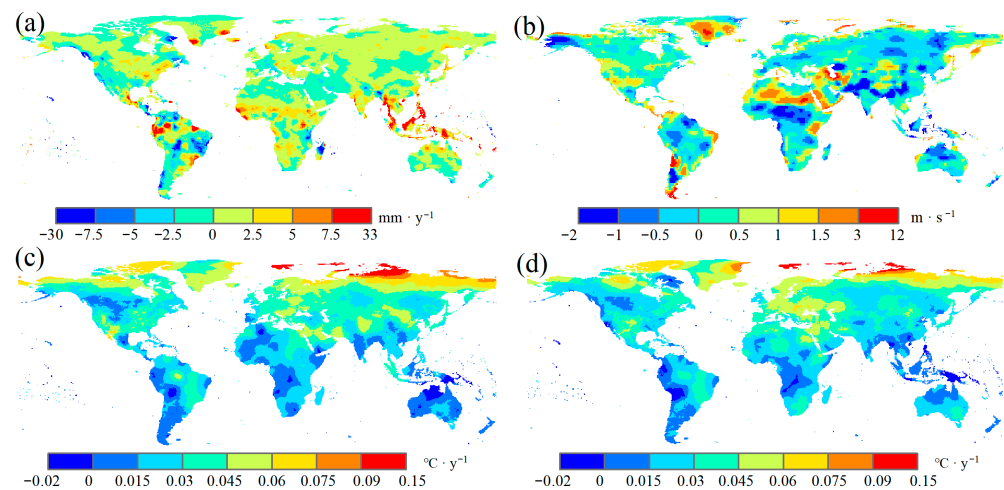


Figure 1. Global trends in the main climatic factors: (a) precipitation, (b) wind speed, (c) minimum temperature and (d) maximum temperature from 1980 to 2017.

3.2. Spatial and Temporal Variations in Global CWR

3.2.1. Changes in ET_c

The ET_c of wheat and soybean showed general declining trends globally from 1980 to 2017, while maize exhibited an increasing trend (Figure 2). Specifically, the ET_c of wheat decreased from 415 mm in 1980 to 397 mm in 1993, and then fluctuated around an average of 421 mm. Soybean ET_c declined by approximately 3.3% over the study period, with a total decrease of 15 mm. Maize ET_c increased by 5.5%, corresponding to a net increase of 25 mm. This reflects differing climatic sensitivities among crops.

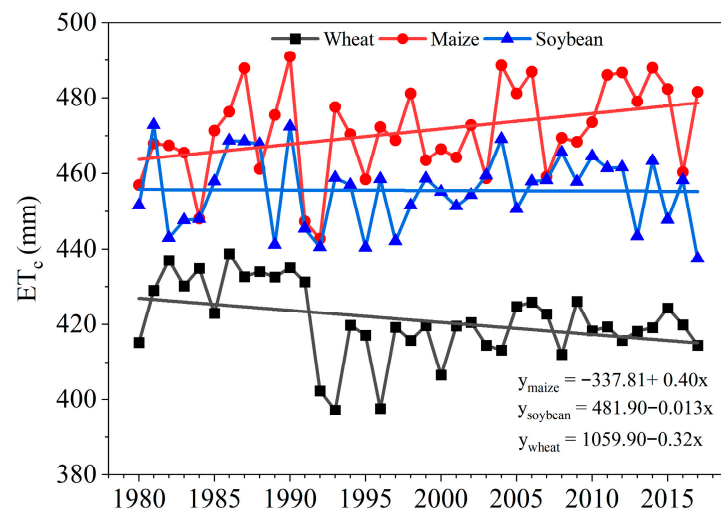
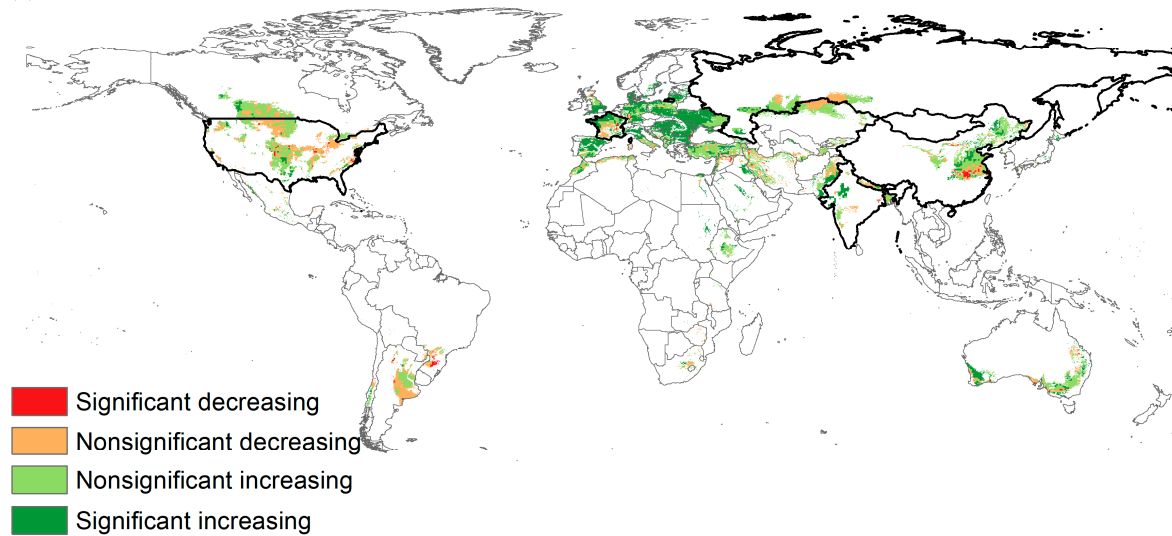


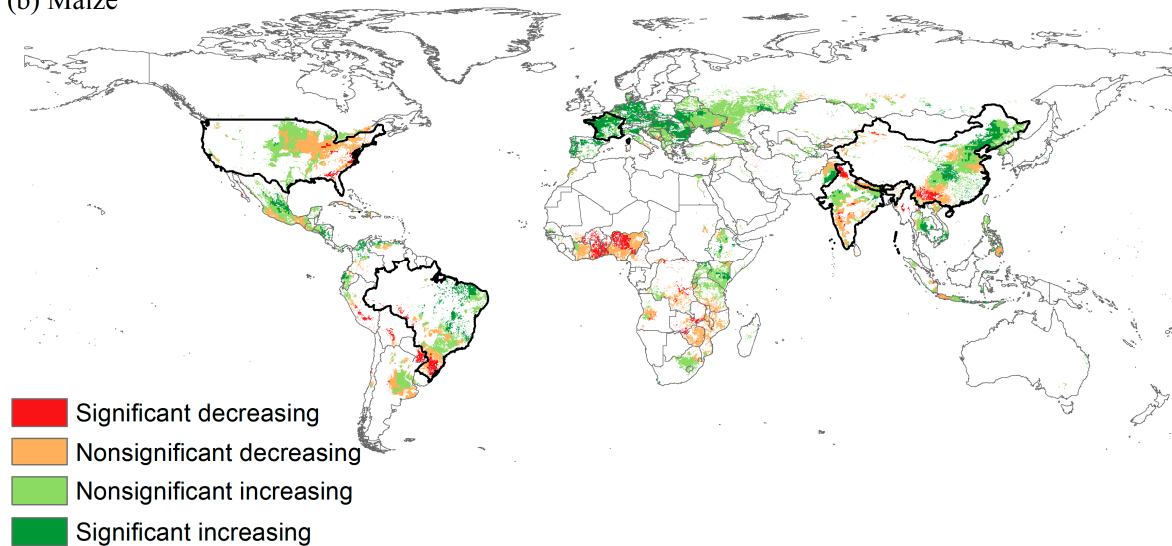
Figure 2. Temporal trends in global crop water requirements per unit area (ET_c) for wheat, maize, and soybean, 1980–2017.

Spatially (Figure 3), wheat ET_c increased notably in the European Plains, the Huang Huai Hai Plain of China and the Indus Basin, but decreased slightly in the US wheat belt and southern West Siberia. Maize ET_c generally increased in northern and southwestern China, Brazil, the US Midwest, and parts of Europe, but decreased in southwestern China, parts of India, and the eastern-central US. For soybean, increases were evident in northeastern China and Brazil, while decreases were observed across much of the US. These patterns reflect the combined effects of regional climate changes and crop-specific physiological responses.

(a) Wheat



(b) Maize



(c) Soybean

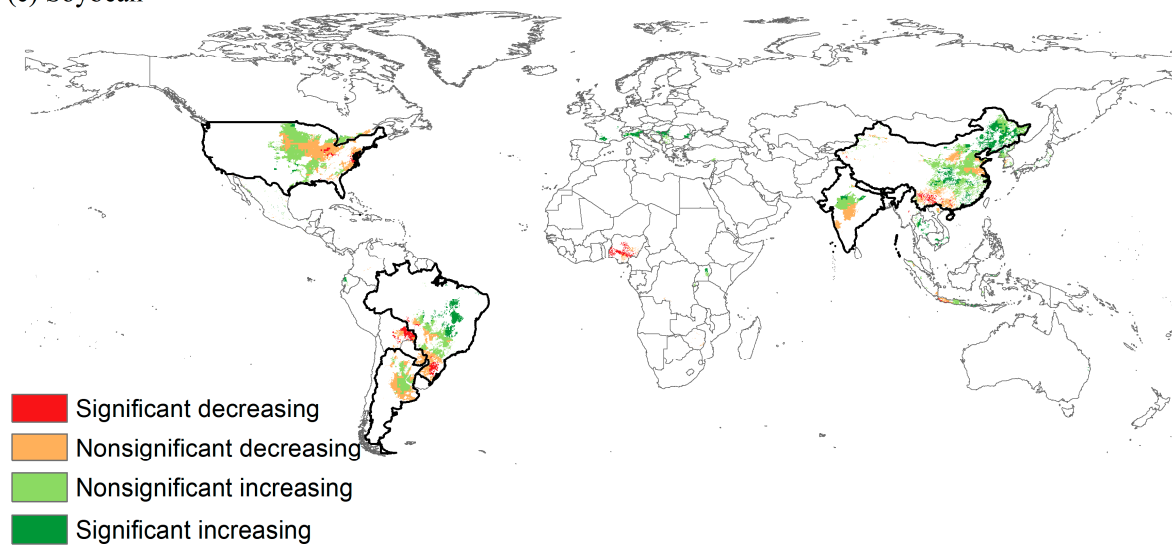


Figure 3. Spatial variation in the unit area crop water demand globally for total wheat, maize and soybean from 1980 to 2017.

3.2.2. Changes in CWR

The total global CWR of the three major crops displayed contrasting trends (Figure 4). From 1980 to 2017, wheat CWR decreased from $891 \times 10^8 \text{ m}^3$ to $782 \times 10^8 \text{ m}^3$ (decrease of $109 \times 10^8 \text{ m}^3$); maize CWR increased from $629 \times 10^8 \text{ m}^3$ to $839 \times 10^8 \text{ m}^3$ (increase of $210 \times 10^8 \text{ m}^3$); soybean CWR increased from $407 \times 10^8 \text{ m}^3$ to $930 \times 10^8 \text{ m}^3$ (increase of $523 \times 10^8 \text{ m}^3$).

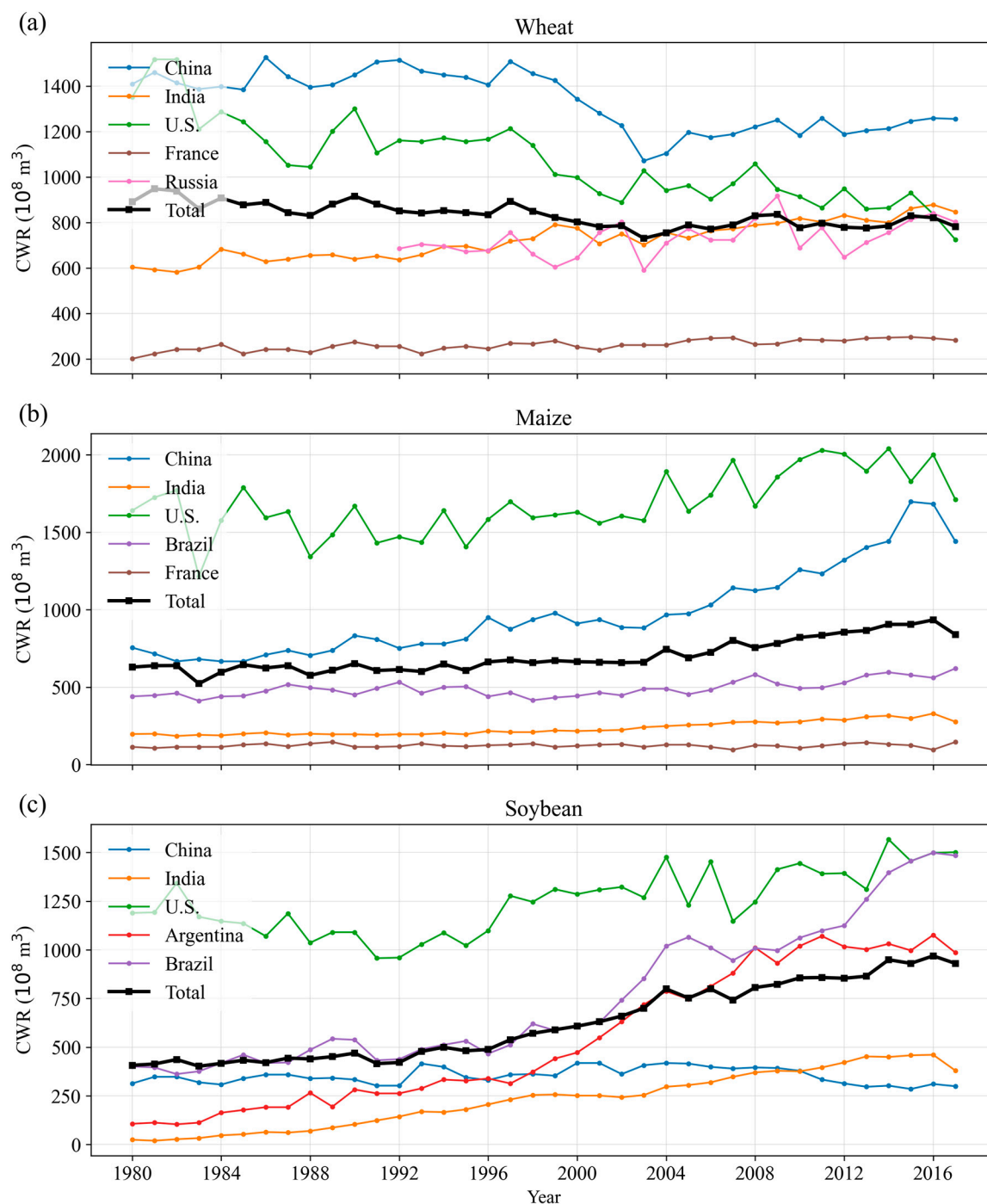


Figure 4. Spatial and temporal variation in total crop water requirements (CWR) for major crops worldwide, 1980–2017, Panels show (a) wheat, (b) maize, and (c) soybean.

At the national scale, the United States and China showed marked declines in wheat CWR, while India experienced a 40% increase. Maize CWR expanded significantly in China

(91% increase), while France and the US exhibited stability or slight decline. Soybean CWR rose sharply in Argentina, Brazil, and India, but declined in China by 32%.

3.3. Driving Factors of Changes in CWR

3.3.1. Changes in Crop Planting Area

The global maize planting area increased by 50.7%, rising from $1382 \times 10^8 \text{ m}^2$ in 1980 to $2082 \times 10^8 \text{ m}^2$ in 2017. This expansion was accompanied by a corresponding increase of $210 \times 10^8 \text{ m}^3$ (33.4%) in its total CWR. Similarly, the soybean planting area grew by 128.7%, from $922 \times 10^8 \text{ m}^2$ to $2109 \times 10^8 \text{ m}^2$, resulting in a substantial rise of $523 \times 10^8 \text{ m}^3$ (128%) in total CWR (Figure 5).

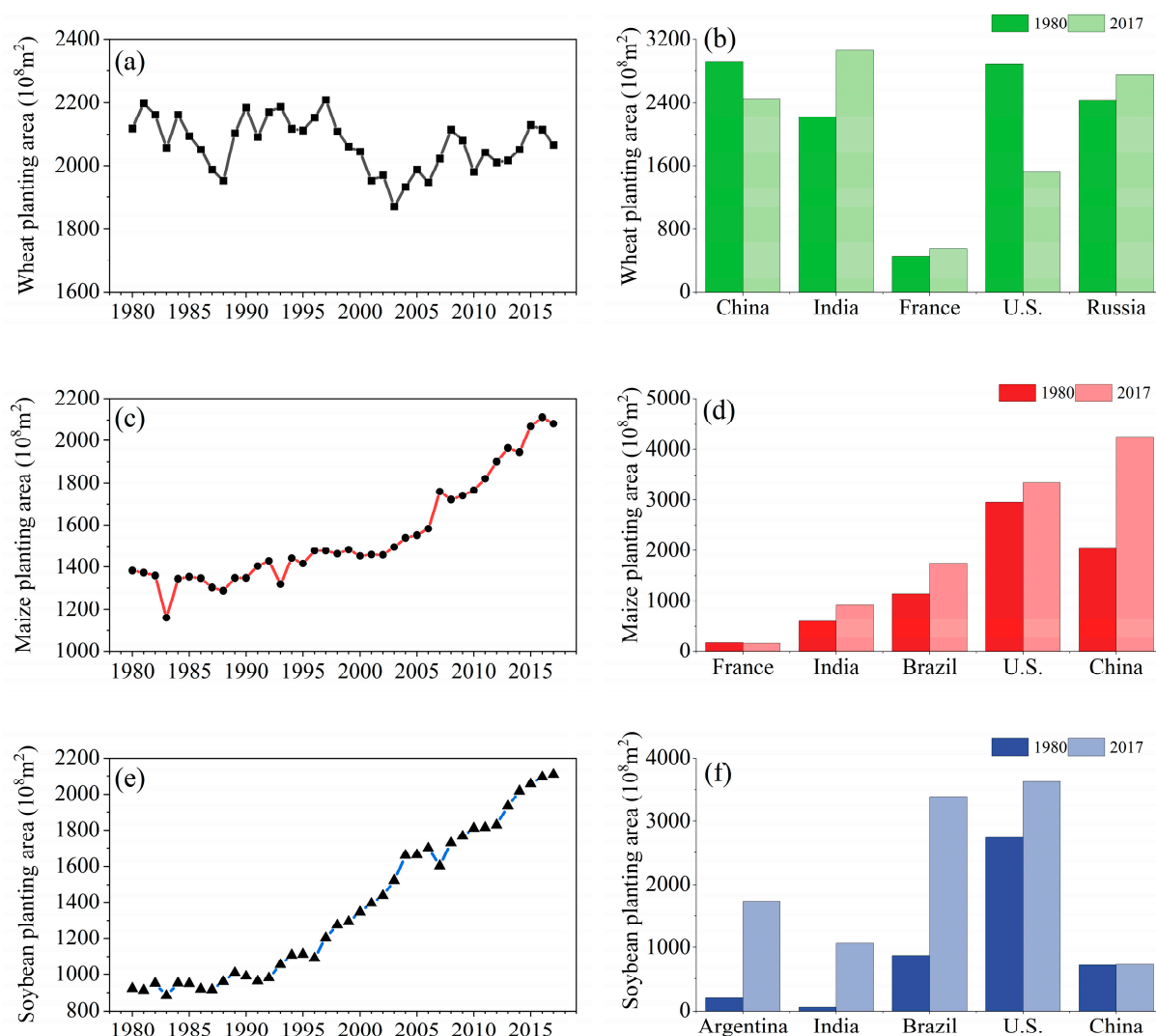


Figure 5. The trend of changes in the total planting area of major crops globally from 1980 to 2017 and the changes in the planting areas of various countries. (a) global wheat planting area, (b) wheat planting area by country, (c) global maize planting area, (d) maize planting area by country, (e) global soybean planting area, and (f) soybean planting area by country.

In contrast, the global wheat planting area declined by 2.5%, from $2118 \times 10^8 \text{ m}^2$ to $2066 \times 10^8 \text{ m}^2$ over the same period. This reduction partly offset the effects of climatic variations, leading to an overall decrease of $109 \times 10^8 \text{ m}^3$ in total wheat CWR. Notably, major reductions in wheat area were observed in the United States and China, with declines of $1357 \times 10^8 \text{ m}^2$ and $468 \times 10^8 \text{ m}^2$, respectively, contributing to corresponding decreases

in wheat CWR at the national level. These patterns suggest that changes in crop planting areas have played an important role in shaping CWR dynamics.

3.3.2. Contributions of Climatic Factors and Crop Area to the Changes in CWR

Using the LMDI method, we quantified the relative contributions of climatic and crop area changes to CWR dynamics (Figure 6). Wheat CWR decline was mainly due to reduced planting area ($-24.88 \times 10^8 \text{ m}^3$), offsetting minor positive climate impacts ($+1.86 \times 10^8 \text{ m}^3$). Maize CWR increase was primarily area-driven ($+314 \times 10^8 \text{ m}^3$), with climatic factors playing a secondary role ($+36 \times 10^8 \text{ m}^3$). Soybean CWR growth was dominated by area expansion ($+542 \times 10^8 \text{ m}^3$), partially offset by negative climate impacts ($-35 \times 10^8 \text{ m}^3$).

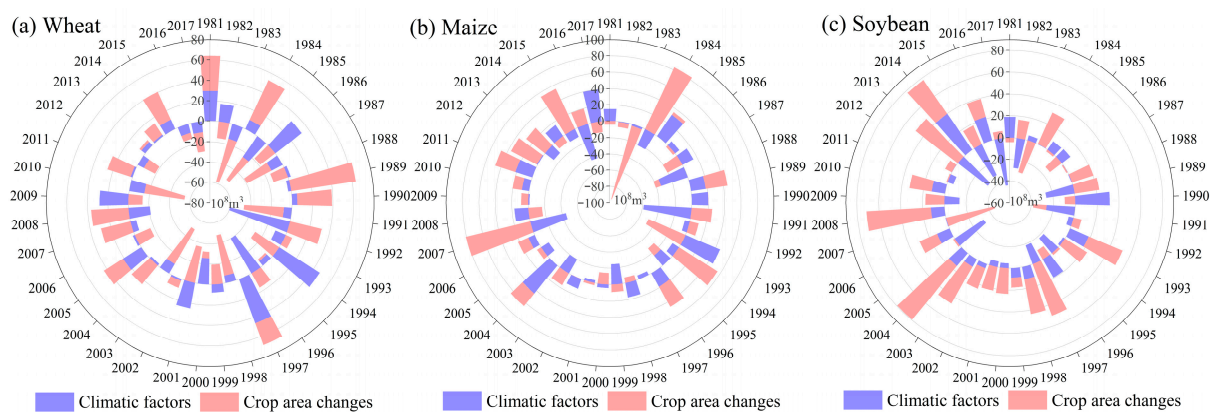


Figure 6. Contributions of climatic factors and crop area to changes in global CWR (wheat, maize and soybean) from 1980 to 2017.

At the country level, over 80% of nations exhibited positive CWR trends linked to crop planting area expansion, notably India, Brazil, and Argentina. Strategic wheat area reductions in China and the US led to localized CWR declines (Figure S2 in the Supplementary Materials).

3.4. Spatiotemporal Variations in IWR Across Different Basins

While the LMDI decomposition highlights the dominant role of planting area changes in driving CWR at global and national scales, such aggregated analyses may obscure spatial heterogeneity in irrigation demand. Given that water management is typically implemented at the basin level, an assessment of IWR at basin-scale is essential to capture localized patterns and their underlying biophysical drivers. To this end, four representative river basins were selected due to their agricultural importance, diverse climatic conditions, and contrasting water resource challenges.

3.4.1. Temporal and Spatial Patterns of the IWR Across Basins

IWR displayed distinct temporal and spatial patterns across the four river basins (Figure 7). In the HRB, IWR increased across 93.6% of the basin area, with 71.2% of these increases being statistically significant. The mean annual total IWR over 1980–2017 was $164.87 \times 10^8 \text{ m}^3$, with an increasing trend of $1.38 \times 10^4 \text{ m}^3/\text{year}$. IWR in the northern and eastern regions increased more significantly compared to other areas, even though the southern region had the highest absolute IWR values.

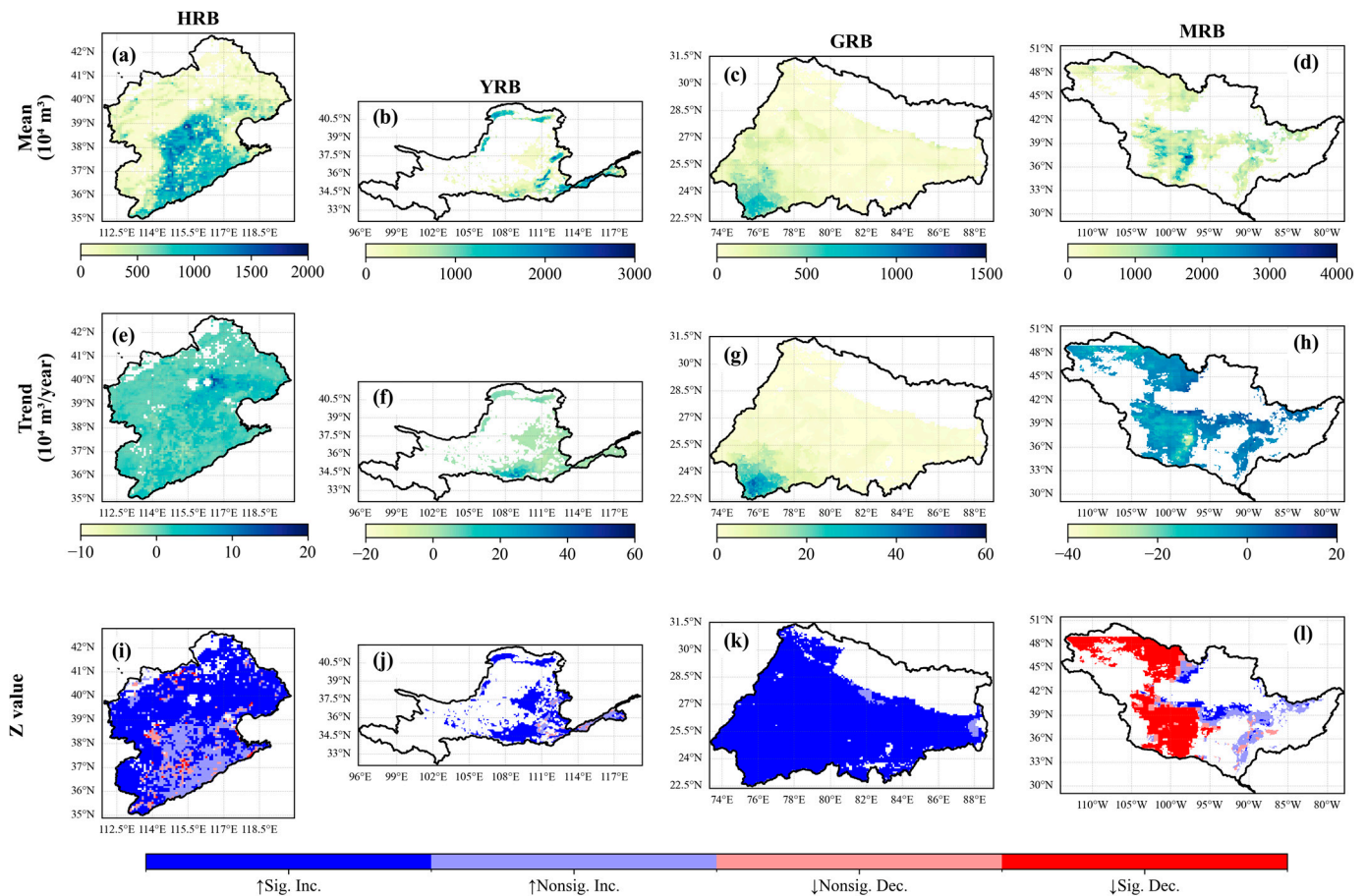


Figure 7. Spatiotemporal patterns of total IWR for three major crops across four river basins during 1980–2017. (Panels (a–d) show the average annual IWR, (e–h) present the linear trends, and (i–l) depict the significance classification of trends based on the Mann–Kendall test. Each column corresponds to a specific river basin: HRB, YRB, GRB, and MRB. IWR values represent the sum of wheat, maize, and soybean).

In the YRB, IWR increased in 94.2% of the area, with 80.9% showing significant trends. The mean annual total IWR was $202.92 \times 10^8 \text{ m}^3$, increasing at a rate of $2.53 \times 10^4 \text{ m}^3/\text{year}$. IWR in the southern and eastern parts of the basin exhibited stronger increasing trends than in other regions.

The GRB exhibited the most extensive and uniform increase in IWR, with increases observed consistently across the entire basin. Although the mean annual total IWR in GRB was relatively low ($78.53 \times 10^8 \text{ m}^3$), it showed the highest rate of increase among the four basins, reaching $2.81 \times 10^4 \text{ m}^3/\text{year}$. IWR in the southern and western parts of the basin increased most rapidly.

In contrast, the MRB exhibited an overall decline in IWR. Decreasing trends were observed in 69.3% of the area, and 57.8% of them were statistically significant. The mean annual total IWR was $1176.88 \times 10^8 \text{ m}^3$, with a decreasing trend of $-2.55 \times 10^4 \text{ m}^3/\text{year}$. IWR in the southern and western regions declined more sharply, with average rates of $-3.49 \times 10^4 \text{ m}^3/\text{year}$ and $-4.15 \times 10^4 \text{ m}^3/\text{year}$, respectively. A slight increase was observed in IWR in the eastern region.

3.4.2. Driving Factors of Changes in IWR

To quantify the relative contributions of planting area and climatic drivers to inter-annual changes in irrigation water requirement (ΔIWR), standardized multiple linear regression models were applied across basin–crop combinations (Figure 8). The models

explain 18–76% of the variance in ΔIWR . Positive regression coefficients indicate drivers associated with an acceleration of ΔIWR growth, whereas negative coefficients indicate drivers associated with a suppression of ΔIWR growth.

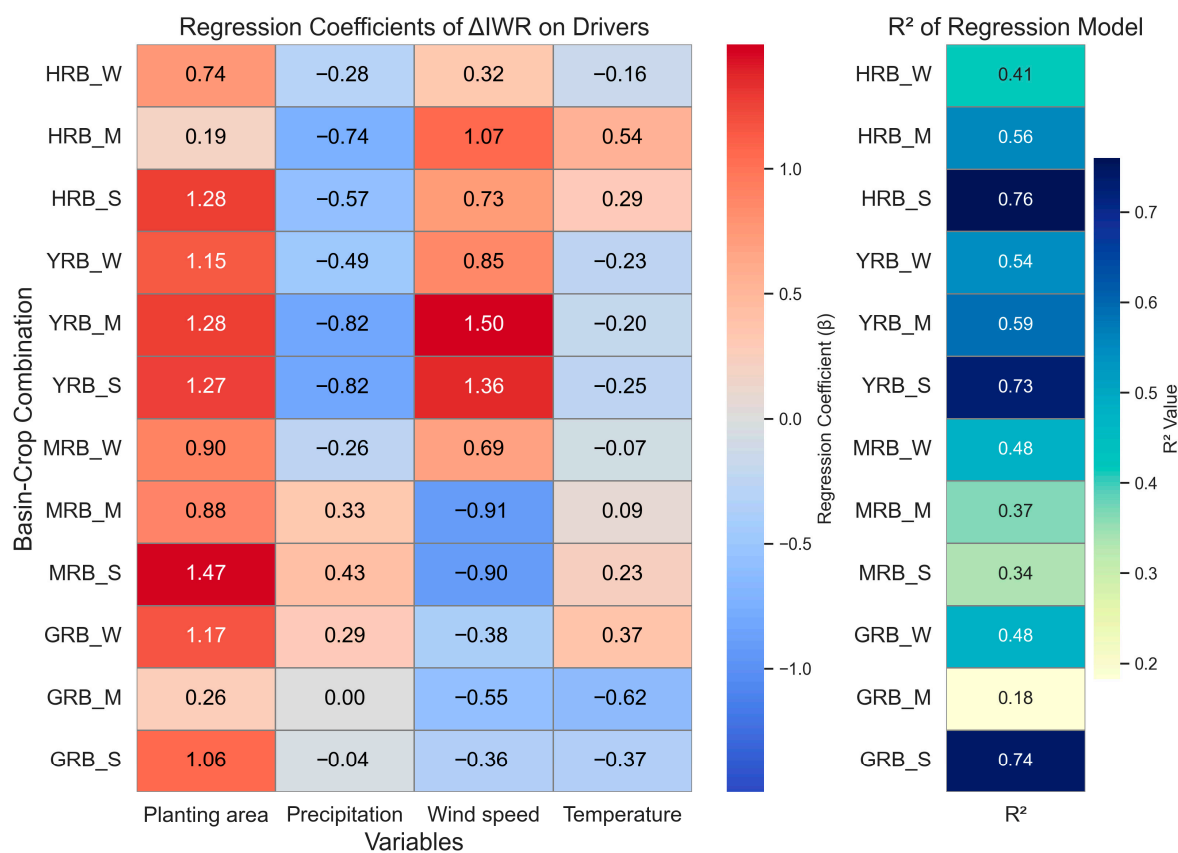


Figure 8. Regression coefficients (β) and R^2 values for changes in ΔIWR explained by planting area and climatic factors across basin–crop combinations. Positive (negative) coefficients indicate that increases in the corresponding driver are associated with higher (lower) rates of change in irrigation water requirement (ΔIWR), while larger absolute coefficient values indicate stronger associations. W represents wheat, M represents maize, and S represents soybean.

For wheat in the HRB, ΔIWR growth was positively associated with changes in planting area ($\beta = 0.74$) and wind speed ($\beta = 0.32$), while precipitation ($\beta = -0.28$) and temperature ($\beta = -0.16$) were associated with suppressing effects. Maize exhibited positive associations with planting area ($\beta = 0.19$), wind speed ($\beta = 1.07$), and temperature ($\beta = 0.54$), contrasted by a strong negative association with precipitation ($\beta = -0.74$). For soybean, planting area ($\beta = 1.28$) and wind speed ($\beta = 0.73$) were the dominant positive drivers, whereas precipitation exerted a negative influence ($\beta = -0.57$) and temperature showed a weak positive association ($\beta = 0.29$).

In the YRB, wheat, maize, and soybean exhibited a consistent response pattern to the main driving factors. Across all three crops, planting area and wind speed were positively associated with ΔIWR growth (planting area: $\beta = 1.15$, 1.28 , and 1.27 ; wind speed: $\beta = 0.85$, 1.50 , and 1.36 for wheat, maize, and soybean, respectively). In contrast, precipitation and temperature were negatively associated with ΔIWR growth.

In the GRB, wheat exhibited positive associations between ΔIWR growth and planting area ($\beta = 1.17$), precipitation ($\beta = 0.29$), and temperature ($\beta = 0.37$), while wind speed showed a negative association ($\beta = -0.38$). For maize, planting area was positively associated with ΔIWR growth ($\beta = 0.26$), whereas wind speed ($\beta = -0.55$) and temperature ($\beta = -0.62$) exhibited negative associations and precipitation played a negligible role. Soy-

bean showed a strong positive association with planting area ($\beta = 1.06$), while wind speed ($\beta = -0.36$) and temperature ($\beta = -0.37$) were negatively associated with ΔIWR growth.

In the MRB, wheat showed positive associations between ΔIWR growth and planting area ($\beta = 0.90$) as well as wind speed ($\beta = 0.69$), while precipitation ($\beta = -0.26$) and temperature ($\beta = -0.07$) were weakly negative. Maize exhibited positive associations with planting area ($\beta = 0.88$) and precipitation ($\beta = 0.33$), but a strong negative association with wind speed ($\beta = -0.91$) and a weak positive association with temperature ($\beta = 0.09$). For soybean, planting area ($\beta = 1.47$) and precipitation ($\beta = 0.43$) were positively associated with ΔIWR growth, whereas wind speed exerted a strong negative influence ($\beta = -0.90$) and temperature showed a modest positive association ($\beta = 0.23$).

4. Discussion

4.1. Divergent Responses of ET_c to Climatic Factors

This study reveals that ET_c has responded heterogeneously to long-term climate changes. While global warming has generally intensified thermal demand, ET_c for wheat and soybean declined in many regions, likely due to decreased wind speeds and solar radiation, which offset the temperature-driven increases in evaporative demand [47–49]. In contrast, maize ET_c increased steadily, driven by rising temperatures and geographical expansion into hotter regions such as northern China and Brazil. These findings underscore the importance of considering a comprehensive set of climatic drivers, rather than temperature alone, when assessing crop water use in a changing climate [50–52]. Future modeling efforts should incorporate solar radiation and humidity to better capture these multi-factor responses.

Although air temperature increased widely during the study period (1980–2017), temperature did not emerge as the dominant driver of changes in ET_c or IWR in many regions. This seemingly counterintuitive result can be explained by the multi-variable structure of the FAO Penman–Monteith framework, in which temperature interacts nonlinearly with wind speed, vapor pressure deficit, net radiation, and humidity. In several major agricultural regions, declining wind speed and changes in atmospheric moisture effectively counterbalanced the temperature-driven increase in evaporative demand, resulting in weak or even negative net trends in ET_c .

Importantly, the relative importance of climatic versus planting drivers varied across spatial scales. At the national scale, changes in crop planting area exerted a stronger influence on CWR variability than climatic factors in most countries during the 1980–2017 period, with over 80% of analyzed nations exhibiting a positive association between crop-land expansion and increasing CWR. However, climatic factors remained the dominant driver in several individual cases. For example, in France, climate-related variables positively influenced CWR for both wheat and maize, indicating climate-driven intensification of water demand despite relatively stable planting areas (Figure S2).

In addition, the temporal coverage of this study ends in 2017, prior to the recent acceleration of global warming observed over the past decade. While the selected period captures long-term climatic variability, it may underestimate the influence of recent warming extremes on irrigation demand. Therefore, the limited contribution of temperature identified here should not be interpreted as a negligible role of global warming, but rather as evidence that, over multi-decadal timescales, interactions among multiple climatic variables and planting factors—particularly crop distribution and area expansion—can outweigh temperature effects in shaping total agricultural water demand.

4.2. Crop Area Expansion as the Primary Driver of CWR Increase

The LMDI decomposition clearly shows that crop area expansion, particularly of maize and soybean, has been the primary contributor to rising global CWR. Wheat, on the other hand, experienced declining CWR due to area contraction in key producing countries such as the United States and China. These shifts reflect underlying changes in dietary demand, bioenergy policies, and global trade dynamics [53,54]. Of particular concern is the expansion of water-intensive crops into water-scarce regions, where unregulated agricultural intensification may aggravate groundwater depletion and long-term environmental degradation [55]. These trends highlight the urgent need for integrated land and water planning in regions where hydrological limits are already stressed.

4.3. Basin-Specific IWR Drivers and Adaptive Management Priorities

Drivers of IWR change differed markedly across basins and crop types. In the HRB and YRB, increases in IWR were mainly attributed to the expansion of maize and soybean cultivation, while increased precipitation partially offset irrigation demand. In the GRB, wheat showed substantial increases driven by planting area, whereas wind and temperature exerted negative or variable effects on other crops. The MRB displayed weaker trends overall, with limited impact from planting area and some negative influences from wind. Across basins, changes in crop area consistently played a leading role in driving IWR increases, while climate impacts varied by region and crop [55–59]. Accordingly, basin-scale water management should be adapted to the dominant biophysical drivers and environmental conditions of each basin.

In the HRB, IWR increased across most areas, with the strongest trends in the north despite higher baseline values in the south. This pattern reflects irrigation expansion into drier zones driven by intensified cultivation. Regression results confirmed that crop area expansion, particularly for soybean, was the main driver. These changes call for improved irrigation efficiency and land-use regulation in water-scarce northern regions [60].

The YRB also showed widespread IWR increases, especially in southern and eastern areas. Despite similar average IWR across subregions, localized hotspots of irrigation intensification have emerged. Maize and soybean area expansion played a dominant role, while the strong negative effect of precipitation highlights the basin's sensitivity to climate variability [61]. This underscores the need for crop planning, climate-informed irrigation, and water-saving technologies [56].

The GRB had the steepest and most uniform increase in IWR, despite having a lower mean value than other basins. Soybean area expansion was a key driver ($\beta = 1.06$), while wind and temperature had negative effects on maize, indicating increasing climatic stress. Management should focus on land-use control, wind protection, and drought-tolerant cultivars [62,63].

In contrast, the MRB exhibited a distinct pattern, characterized by a widespread decline in IWR across most areas during the study period [64]. Unlike the other basins, this decrease cannot be attributed primarily to crop area contraction alone, as overall planting area changes in the MRB were relatively modest.

Instead, the observed reduction in IWR reflects the combined influence of climatic changes and structural adjustments in cropping systems. A long-term decline in wind speed across much of the basin has reduced atmospheric evaporative demand, thereby lowering crop water deficits and irrigation requirements, as reflected by the consistently negative regression coefficients for wind speed (Figure 8) and the observed wind speed trends (Figure 1).

In parallel, changes in crop composition have played a critical role. In particular, reductions in wheat cultivation and the northward relocation of wheat production toward

cooler and more humid regions have contributed to a decrease in basin-scale irrigation demand. These structural shifts reduced the share of high water-demand cropping systems within the MRB, reinforcing the suppressing effect of declining wind speed on IWR.

Although wind speed decline alone cannot fully explain the magnitude of the observed reduction in IWR, its interaction with crop structural adjustment provides a coherent explanation for the contrasting trend observed in the MRB. Together, these factors distinguish the MRB from the other basins and highlight the importance of considering both climatic drivers and crop composition changes when interpreting long-term irrigation dynamics in large, intensively cultivated river basins.

4.4. Limitations and Uncertainties

Despite the comprehensive framework, this study has limitations. The NCEP–DOE Reanalysis 2 (NCEP-2) dataset offers a globally consistent source of meteorological data for ET_0 estimation, especially in data-scarce regions. Key variables have proven useful for ET_0 modeling. For example, combining NCEP-2 radiation with GFS humidity and temperature improved ET_0 forecasts in the southeastern U.S. [65], while Zhao et al. [66] confirmed the reliability of its temperature data in central and eastern China, particularly in autumn. Downscaling studies further show that NCEP-2 can produce high-resolution inputs aligned with observations [67]. Although the NCEP-2 dataset exhibits relatively coarse spatial resolution and contains errors in regions such as high-altitude areas and Antarctica [68], it proves sufficiently valid for this study's broad-scale research with a primary focus on agricultural regions. Additionally, uncertainties may arise from assumptions in crop coefficient corrections and the use of MIRCA2000 as a static spatial mask. These factors may influence the accuracy of CWR and IWR estimations, particularly at local scales.

5. Conclusions

This study integrates three complementary methods: (i) physically based estimation of ET_c using the FAO Penman–Monteith approach combined with climate-adjusted K_c , (ii) LMDI decomposition to separate the contributions of climatic factors and crop area changes to total CWR, and (iii) basin-scale multiple linear regression analysis to quantify the dominant drivers of IWR across major river basins. Together, these methods form a coherent framework for diagnosing the drivers of agricultural water demand under global change, enabling a comprehensive, crop-specific assessment of long-term changes in agricultural water demand and irrigation stress from 1980 to 2017 for wheat, maize, and soybean at both global and basin scales. Based on this integrated framework, several key conclusions can be drawn.

First, analysis of ET_c revealed pronounced crop-specific differences in response to long-term climatic variability. Wheat and soybean generally exhibited stable or declining ET_c trends, whereas maize ET_c increased over time, reflecting differences in crop physiological characteristics and their interactions with multi-factor climatic conditions.

Second, decomposition of total CWR using the LMDI method showed that expansion of crop planting area was the dominant driver of increasing global agricultural water demand during the study period. This effect was particularly strong for maize and soybean and exceeded the contribution of climatic change at the global scale.

Third, basin-scale regression analysis of IWR highlighted strong spatial heterogeneity in irrigation dynamics. The HRB, YRB, and GRB experienced increasing IWR, driven mainly by crop area expansion and climate-related increases in evaporative demand, whereas the MRB exhibited a contrasting decline in IWR, associated with reduced atmospheric evaporative demand and crop structural adjustments.

Overall, these findings underscore the critical role of land-use and cropping structure decisions in shaping long-term agricultural water demand and demonstrate that climate impacts on irrigation are highly basin- and crop-specific. The integrated methodological framework developed in this study is scalable and transferable, providing a robust basis for basin-specific irrigation planning, climate adaptation strategies, and sustainable water resource management under increasing agricultural water stress.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w18020267/s1>, Table S1: Data information in this research; Table S2: Approximate values of K_{cini} for moderately wet processes (10–40 mm) and moderately textured soils; Figure S1: Correlation analysis between FAOSTAT and MIRCA2000 planting areas of three major crop producing countries; Figure S2: Contribution of climatic factors and crop area changes to changes in the total global CWR in major producing countries from 1980 to 2017. Reference [69] is cited in Supplementary Materials.

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