

Article

Climate and Anthropogenic Drivers of Crop Water Productivity: A Double-Cropping Perspective from the North China Plain

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Abstract

Global water scarcity is intensifying, and agriculture remains the main consumer of fresh-water. Many studies have assessed agricultural water productivity (WP) in major farming regions. While previous studies have mainly assessed overall efficiency or single crops, crop-specific dynamics within double-cropping systems remain insufficiently understood. This study quantifies the spatial patterns and stage-wise changes in winter wheat and summer maize WP in the North China Plain based on five representative years (2000, 2005, 2010, 2015, and 2019) and examines their climatic and anthropogenic drivers. The Optimal Parameter-Based Geographical Detector (OPGD) model was used to assess the explanatory power of influencing factors, and the Multi-scale Geographically Weighted Regression (MGWR) model was applied to capture spatially heterogeneous relationships. Wheat WP ranged from 0.56 to 1.30 kg m⁻³ and showed a significant increasing trend, whereas maize WP ranged from 0.89 to 1.72 kg m⁻³. Both climatic and anthropogenic factors exhibited pronounced spatial heterogeneity. Beijing and Tianjin were classified as anthropogenic-dominated zones, while several cities in Henan displayed crop-specific dominant drivers. Fertilizer application was negatively associated with WP in multiple regions, indicating declining input efficiency under intensive management. These findings support irrigation zoning and differentiated water allocation strategies, contributing to sustainable intensification and progress toward water-related (SDG 6) and food security (SDG 2) goals in intensive double-cropping regions.

Keywords: grain crops; water productivity; water resources management; climate change; North China plain



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1. Introduction

The growing concern over global water scarcity has highlighted agriculture as the primary water-consuming sector, accounting for over 70% of global freshwater use [1,2]. This underscores the urgency of improving agricultural water use efficiency, particularly in the context of climate change and rising food demand driven by population growth [3–5]. Water scarcity reduces crop yields and exacerbates land degradation processes such as salinization and desertification [6–8], posing a serious threat to the long-term sustainability of global food systems. To evaluate and manage agricultural water use under such constraints, water productivity (WP) has become a key indicator.

WP is defined as the crop yield per unit of crop water consumption [9]. In this study, WP is quantified based on crop evapotranspiration (ETc), which reflects the actual water

requirements of crops under prevailing climatic conditions. While ET_c is largely controlled by climate through reference evapotranspiration and crop coefficients, WP is also indirectly influenced by agricultural management practices via their effects on crop growth and yield. In water-limited regions, the combined contributions of climate and management to WP are critical for securing stable crop production and promoting sustainable agricultural development [10–12]. Given the uneven distribution of global water resources and the multiple pressures facing food systems, investigating the spatiotemporal variation in WP and its driving mechanisms is important for understanding the resilience and sustainability of agricultural systems [13–15].

In recent years, research at various spatial scales has deepened our understanding of WP. At the national scale, studies have revealed the spatial variations and temporal dynamics of farmland WP, emphasizing its close relationship with the distribution of climatic resources [16]. At the basin scale, case studies in regions such as the Syr Darya Basin [17], the Mekong River Basin [18], and the North China Haihe River Basin [19] have highlighted significant regional variations and dynamic changes in agricultural water use efficiency. Researchers have also applied the WA+ framework to quantitatively describe the coupling between water resource use and agricultural output [20]. Meanwhile, crop models and scenario simulations have been widely used to predict changes in WP under future climate conditions [21–23]. At the crop level, research on key food crops such as wheat and maize has shown that WP can be improved through optimized irrigation and field management practices [24]. However, most research focuses either on individual crops or aggregates multiple crops at the regional scale, often overlooking crop-specific growth dynamics, management practices, and water requirements in double-cropping systems. Consequently, the distinct contributions of climate and human interventions to individual crop WP remain poorly understood, and the mechanisms driving WP variability within double-cropping systems are largely unexplored. Addressing this knowledge gap can support the development of targeted strategies to improve water use efficiency at both crop-specific and system-wide scales.

WP is influenced by multiple factors, including water availability, climate, irrigation infrastructure, crop type, soil properties, and management practices [25,26]. These drivers vary across regions and crops. For example, in southern Spain, the relative irrigation supply is a key determinant of WP [12], whereas in the arid regions of northwestern China, evapotranspiration plays a more critical role [16]. Human activities, including fertilizer application, mechanization, expansion of irrigated areas, and pesticide use, can also influence WP by affecting crop growth and yield. In water-limited agricultural systems, these anthropogenic interventions often function as regulatory mechanisms, partially mitigating climatic constraints and shaping crop-specific WP responses. Previous studies have explored the effects of climate and human activities on WP using model-based approaches or geographic detectors [27,28], but further work is needed to clarify their scale-dependent differences and spatial heterogeneity. In particular, climate and human activities affect different spatial scales differently, and their interactions within large-scale intercropping systems remain poorly understood.

The North China Plain (NCP) is one of the world's major grain-producing regions. Its typical double-cropping system of winter wheat and summer maize contributes about 45% of China's wheat and 30% of its maize production [29]. In this system, winter wheat is generally sown in October, overwinters in the field, and is harvested in June, while summer maize is planted immediately after wheat harvest and harvested in September or October. As a result, the two crops differ markedly in their growing seasons, water requirements, and management regimes, including irrigation scheduling, fertilization intensity, and field

operations during their respective growth stages, yet they depend on the same limited water resources.

The NCP has long faced severe water scarcity and pronounced conflicts between agricultural water demand and limited freshwater availability [30–32]. In this context, chronic water stress combined with a relatively fixed double-cropping system limits adjustments to cropping calendars and irrigation intensity [33]. WP in the NCP is influenced by both climatic variability and continuous human management. Practices such as irrigation scheduling, fertilization, and other field interventions play a key role in maintaining crop yields under limited water conditions, while showing substantial spatial differences across sub-regions. This intensive, water-limited, multiple-cropping system is increasingly common in major food-producing regions worldwide. The NCP, therefore, provides a representative case for examining crop-specific WP dynamics under combined climatic and anthropogenic constraints.

Previous studies on agricultural WP in the NCP have mainly focused on single crops or aggregated regional indicators [34–36]. Systematic comparisons of crop-specific WP within a double-cropping system are still limited. The differential responses of winter wheat and summer maize to climatic variability and human interventions remain unclear. This study establishes a unified analytical framework to directly compare winter wheat and summer maize under shared water and management constraints in the double-cropping system. By incorporating scale-dependent interaction analysis, we reveal how climatic and human drivers affect the two crops differently and vary across sub-regions. This mechanism-focused comparison goes beyond descriptive single-crop assessments, providing a system-level understanding of WP regulation under long-term water stress.

The objectives of this study are to (1) quantify the spatiotemporal patterns of crop-specific WP for winter wheat and summer maize in the NCP; (2) identify and quantify the scale-dependent and interactive effects of climatic and anthropogenic drivers on crop-specific WP; and (3) delineate dominant driving zones and propose crop-oriented water management strategies adapted to regional conditions.

2. Materials and Methods

2.1. Study Area Overview

The NCP, located between 112.5–119.5° E and 34.8–40.4° N, forms a major part of the Eastern Great Plains in East Asia (Figure 1). The region has a temperate to subtropical monsoon climate with high evaporation potential. Cumulative temperatures above 0 °C range from 4100 °C to 5400 °C, and above 10 °C from 3700 °C to 4700 °C, supporting a long growing season suitable for intensive agriculture. The NCP is vital for national food production, containing about one-sixth of the country's arable land and contributing roughly one-seventh of total grain output. Its dominant cropping pattern is a double-cropping system of winter wheat followed by summer maize, enabling efficient use of thermal and land resources across seasons.

2.2. Data Sources

This study compiled a comprehensive dataset for five time points: 2000, 2005, 2010, 2015, and 2019. The data fall into three main categories: meteorological observations, agricultural production indicators, and spatial crop distribution (Table 1). These data were obtained from the China Rural Statistical Yearbook, Shandong Rural Statistical Yearbook, and China Regional Economic Statistical Yearbook. These variables include yield per unit area of wheat and maize, fertilizer application, agricultural machinery power, effective irrigated area, and pesticide use. Spatial distribution data for wheat and maize, covering the five study years, were obtained from the National Ecological Science Data Center [37].

All agricultural and anthropogenic variables were derived from official statistical yearbooks and compiled at the prefecture-level city scale.

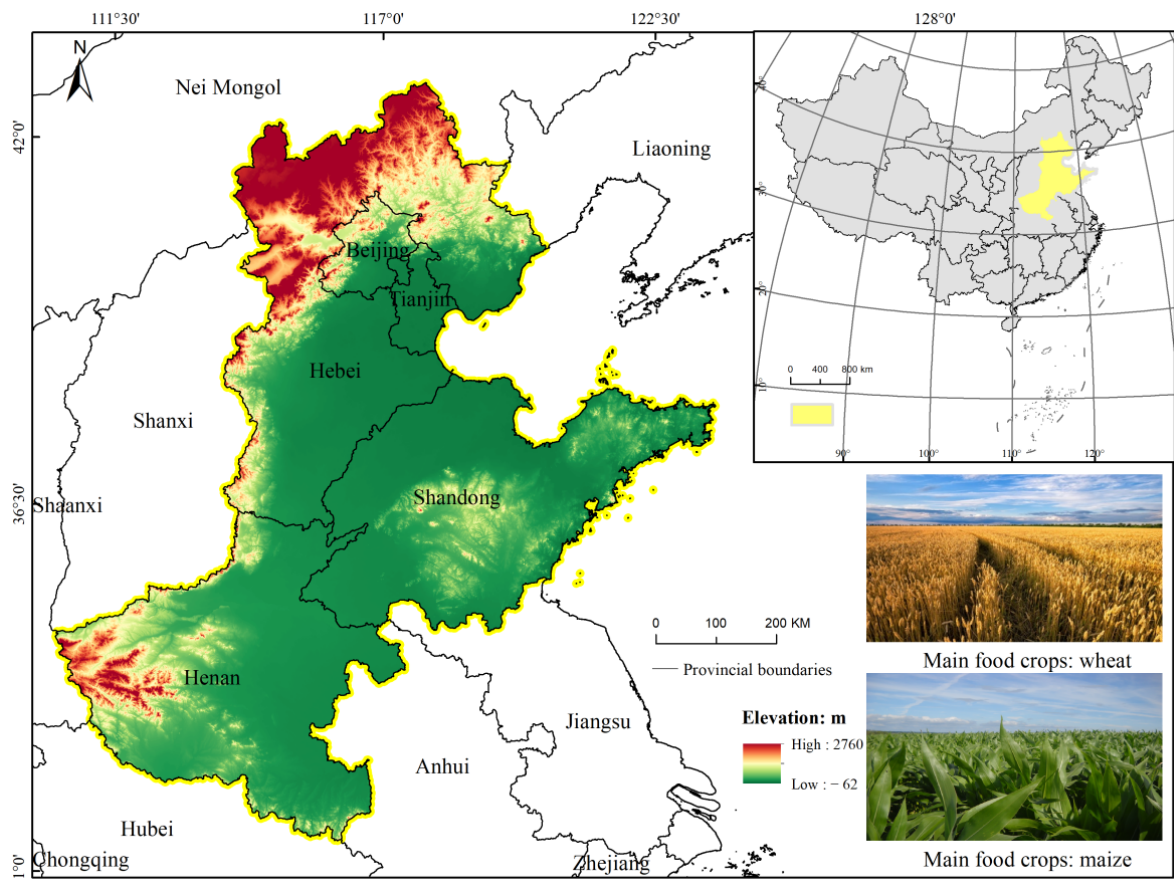


Figure 1. Location of the NCP.

Table 1. Description of Data Sources.

Data Type	Variables	Years	Source
Meteorological	Temperature, Relative humidity, Sunshine hours, etc.	2000–2019	NCEI (https://www.ncei.noaa.gov) (accessed on 23 August 2025); TPDC (https://data.tpdc.ac.cn/home) (accessed on 23 August 2025)
Agricultural statistics	Yield, Fertilizer application, Total power of agricultural machinery, etc.	2000–2019	National Yearbooks
Crop maps	Maize, Wheat area	2000, 2005, 2010, 2015, 2019	NESDC (http://www.nesdc.org.cn/) (accessed on 3 September 2025)

Note: NCEI, National Centers for Environmental Information; TPDC, National Tibetan Plateau Data Center; NESDC, National Earth System Science Data Center.

2.3. Research Methodology

This study focused on the typical winter wheat–summer maize double-cropping system in the NCP and developed a technical framework consisting of five sequential steps (Figure 2): (1) estimation of WP, (2) analysis of spatiotemporal patterns, (3) identification of

driving factors, (4) exploration of spatial differentiation mechanisms, and (5) regional zoning. Reference evapotranspiration (ET_0) for each prefecture-level city was first calculated using the FAO Penman–Monteith method implemented in CROPWAT 8.0. ET_c was then obtained by multiplying ET_0 by province-specific crop coefficients (K_c). WP was calculated as the ratio of crop yield to ET_c . These calculations were performed for five representative years (2000, 2005, 2010, 2015, and 2019) to examine spatial patterns and medium-term temporal variations in WP for winter wheat and summer maize.

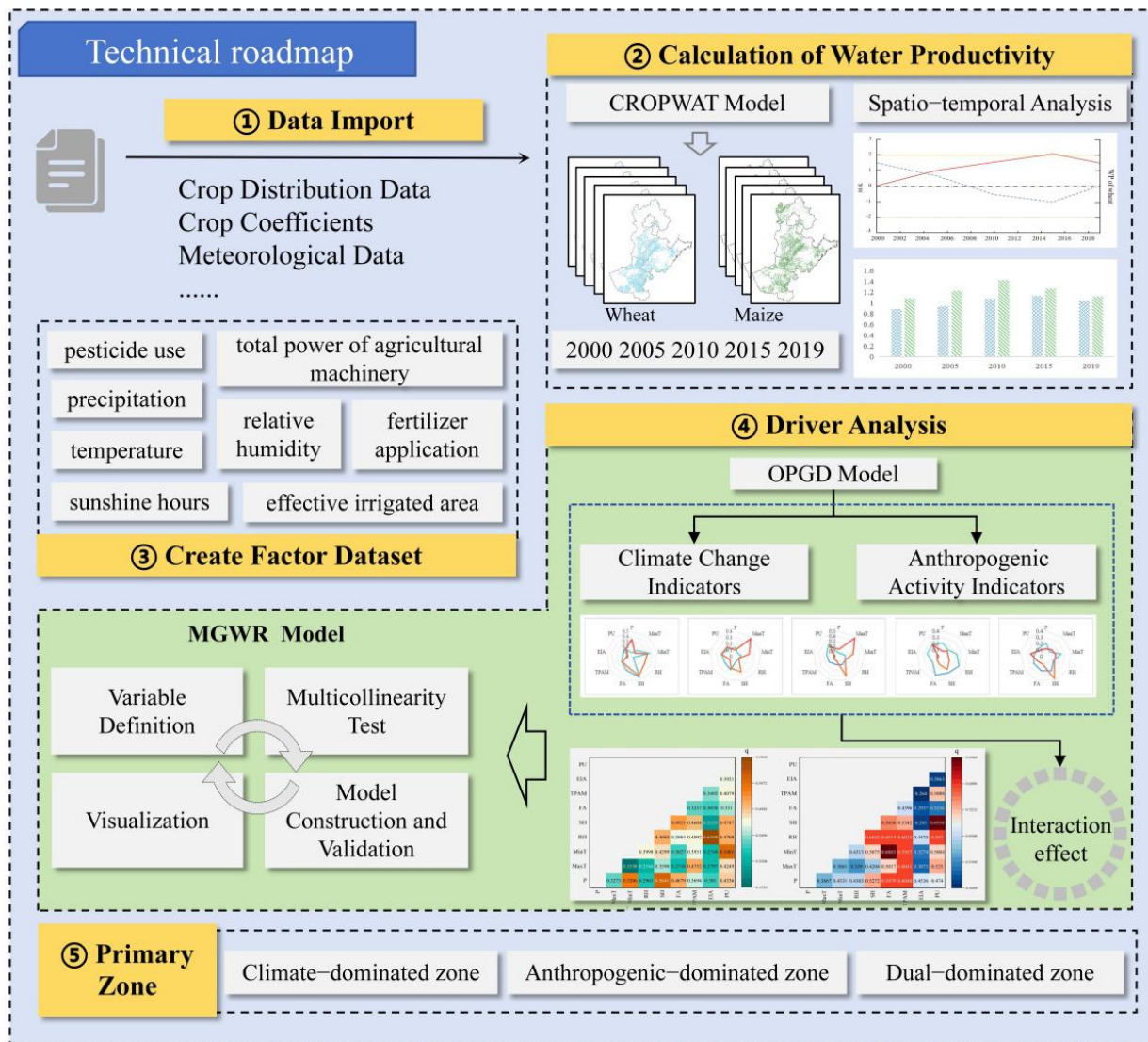


Figure 2. Technical roadmap.

To assess the contributions of climate and human activities, the Optimal Parameter-Based Geographical Detector (OPGD) model was applied to quantify the relative importance of each driver and their interaction effects. Building on this, the Multi-scale Geographically Weighted Regression (MGWR) model was used to explore spatial non-stationarity and multi-scale heterogeneity of influencing factors, addressing the limitations of single-scale regression approaches. Finally, dominant factor types were classified across the double-cropping system in the NCP, providing a scientific basis for differentiated regional water management strategies in water-scarce areas.

2.3.1. WP Calculation

WP is defined as the ratio of crop yield to water consumption [28]. This is example 1 of an equation

$$WP = \frac{Y}{10ET_c} \quad (1)$$

where WP is water productivity (kg m^{-3}); Y is crop yield (kg ha^{-1}); ET_c is the crop water requirement (mm).

ET_c represents crop evapotranspiration under standard, non-stressed conditions following the FAO-56 framework. ET_c was calculated as follows [38]. This is example 2 of an equation:

$$ET_c = K_c \times ET_0 \quad (2)$$

K_c is the crop coefficient; ET_0 is the reference crop evapotranspiration (mm).

1. ET_0 Calculation

ET_0 was calculated using CROPWAT 8.0 developed by the FAO [39]. CROPWAT integrates crop phenology and regional climate data to simulate seasonal water demands for winter wheat and summer maize. The model applies the FAO Penman–Monteith equation to estimate ET_0 based on standard meteorological variables [40]. This is example 3 of the equation:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (3)$$

ET_0 is the reference crop evapotranspiration (mm day^{-1}); Δ is the slope of the saturated water vapor pressure curve ($\text{kPa } ^\circ\text{C}^{-1}$); R_n is the net radiation at the surface ($\text{MJ m}^{-2} \text{ day}^{-1}$); G is the heat flux density; γ is the dry and wet table constant ($\text{Pa } ^\circ\text{C}^{-1}$); T is the average daily air temperature ($^\circ\text{C}$); u_2 is the wind speed at a height of 2 m from the ground (m s^{-1}); e_s and e_a are saturation and actual vapor pressure (kPa).

A prefecture-level city panel dataset was constructed for the NCP. Monthly minimum and maximum temperature, relative humidity, and related meteorological variables were used to calculate monthly ET_0 for each city. Based on crop-specific growing seasons (winter wheat: October to June of the following year; summer maize: June to September/October), monthly ET_0 values were accumulated to obtain growing-season ET_0 for wheat and maize.

The summer maize growing season is confined to a single calendar year, whereas winter wheat spans two consecutive years. To ensure consistency in temporal attribution, evapotranspiration for winter wheat was uniformly assigned to the harvest year. To capture medium-term temporal variation while maintaining spatial comparability, ET_0 and subsequent WP calculations were conducted for five representative years: 2000, 2005, 2010, 2015, and 2019. These years were selected at five-year intervals to reflect decadal-scale changes rather than continuous annual fluctuations.

2. K_c Determination

In the FAO-56 framework, K_c are generally defined for four growth stages: initial, development, mid-season, and late-season. Stage lengths vary across climatic regions. Because this study focuses on regional-scale statistical analysis using prefecture-level aggregated yield data, seasonal average crop coefficients were adopted to capture the integrated water demand over the entire growing period under standard agronomic conditions.

Based on a comprehensive assessment of FAO crop coefficients, irrigation quotas for major crops in northern China, and related studies [41,42], K_c values for summer maize and winter wheat were set as follows: Beijing, 0.74 and 0.70; Tianjin, 0.73 and 0.60; Henan, 0.86 and 0.79; Hebei, 0.77 and 0.68; and Shandong, 0.79 and 0.80. Using seasonal average

Kc values ensures methodological consistency and spatial comparability across cities and years, which is crucial for regional spatiotemporal assessment of WP.

2.3.2. Mann–Kendall Trend Test

The Mann–Kendall test is a commonly used non-parametric method for detecting monotonic trends in hydrological and climatic time series. It does not assume a normal distribution and is robust to outliers and missing values, making it particularly suitable for long-term datasets [43]. These are examples 4 and 5 of the equation:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{\text{var}(S)}}, & S < 0 \end{cases} \quad (4)$$

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^n \text{sgn}(x_k - x_i) \quad (5)$$

x_k and x_i are the sample data values; n is the sample size; Z is the standardized statistic; S is the Mann–Kendall statistic; $|Z| > 1.96$ indicates a significant trend at $\alpha = 0.05$, with $Z > 0$ indicating an upward trend and $Z < 0$ a downward trend.

2.3.3. OPGD Model

The Geographical Detector is a spatial statistical tool used to identify the drivers of spatial heterogeneity. In this study, the OPGD model was applied to evaluate the explanatory power of climate and human activity variables on WP [35,44]. Quantifying the relative influence of each driving factor on WP changes for wheat and maize in the NCP is necessary to improve understanding of their regulation mechanisms.

1. Factor Detection

Based on regional production characteristics, data availability, and previous agronomic studies on agriculture, water, and climate [28,45–47], eight indicators were selected as candidate driving factors for crop WP. Four climate factors are represented: precipitation (P), maximum and minimum temperature (MaxT, MinT), relative humidity (RH), and sunshine hours (SH). The other four represent human activity factors: fertilizer application (FA), total power of agricultural machinery (TPAM), effective irrigated area (EIA), and pesticide use (PU).

All indicators were processed for each study year, as they exert certain effects on crop performance and water variability [16,28]. They were therefore used as explanatory variables in the OPGD model to quantify both individual and interactive effects on WP. The explanatory power of each variable was evaluated using the q-statistic (Equation (6)) [48]. Variables identified as important by the OPGD were then included in the MGWR models after multicollinearity screening to assess spatially varying relationships.

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2 \quad (6)$$

where q is the explanatory power ($0 \leq q \leq 1$); L is the number of strata; N_h is the number of samples in stratum h ; N is the total number of samples; σ^2 and σ_h^2 are the within-stratum and total variance, respectively; A higher q value indicates stronger explanatory power and more pronounced spatial differentiation.

2. Interaction Detection

To assess whether variables jointly strengthen or weaken their explanatory power, the OPGD model performs interaction detection (Table 2). By examining the spatial coupling

of two variables, it is possible to identify potential causal relationships and determine the combined influence of the two drivers on WP within the study area.

Table 2. Classification of interaction effects among driving factors.

Basis of Judgment	Interaction
$q(X_1 \cap X_2) < \min[q(X_1), q(X_2)]$	Nonlinear weakening
$\min[q(X_1), q(X_2)] < q(X_1 \cap X_2) < \max[q(X_1), q(X_2)]$	Single-factor non-linear weakening
$q(X_1 \cap X_2) > \max[q(X_1), q(X_2)]$	Two-factor enhancement
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Independent
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Nonlinear enhancement

2.3.4. MGWR Model

The MGWR model is an advanced spatial econometric model designed to capture spatial non-stationarity in relationships between dependent and explanatory variables. Unlike traditional regression models, which assume global stationarity, MGWR allows coefficients to vary across locations. This makes it particularly suitable for analyzing the spatially heterogeneous effects of climate and human activity factors on WP in wheat and maize.

1. Multicollinearity Diagnosis and Predictor Selection

Multicollinearity occurs when explanatory variables are highly correlated, which can produce biased or unstable coefficient estimates. To ensure the robustness of MGWR results, a Variance Inflation Factor (VIF) analysis was performed before model fitting. This is example 7 of the equation:

$$VIF_j = 1 / (1 - R_j^2) \quad (7)$$

VIF_j is the variance inflation factor for variable j ; R_j^2 is the coefficient of determination from regressing variable j on all other predictors; $VIF > 10$ is generally considered evidence of severe multicollinearity.

Based on this criterion, MinT exceeded the threshold ($VIF = 12.21$) in 2000 and was therefore excluded. To ensure interannual comparability, MinT was also removed in 2019 so that identical sets of predictors could be applied to both years. The remaining variables were retained (Table A1). Following OPGD screening and VIF-based multicollinearity diagnosis, P, MaxT, RH, SH, FA, TPAM, EIA, and PU were finally selected as predictors for the MGWR models in both wheat and maize.

2. MGWR Model Specification and Spatial Heterogeneity Analysis

MGWR model calibration was performed using MGWR version 2.2.1 with a Gaussian model family. Spatial relationships were represented through a fixed Gaussian kernel. Optimal bandwidths for individual predictors were determined using a golden-section search procedure based on the corrected Akaike Information Criterion (AICc). All variables were standardized prior to model fitting, and model convergence was achieved using the SOC-f algorithm with a tolerance threshold of 1×10^{-5} . Detailed model configurations and diagnostics are provided in Table A2.

The MGWR model extends traditional Geographically Weighted Regression by allowing each explanatory variable to have its own spatial bandwidth, which differentiates the scale of influence among variables. This improves the model's ability to detect localized patterns and spatial sensitivities in WP dynamics [49]. The general MGWR formulation is as follows [50]. This is example 8 of an equation:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^q \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \quad (8)$$

y_i is the dependent variable at location i ; $\beta_0(u_i, v_i)$ is the local intercept; $\beta_k(u_i, v_i)$ is the local coefficient for variable k ; X_{ik} is the k th predictor at location i ; ε_i is the random error term.

Statistical significance of spatially varying coefficients was assessed using adjusted t -values at the 95% confidence level provided by the MGWR framework. Coefficients exceeding the critical threshold were considered statistically significant, indicating meaningful spatial heterogeneity rather than random variation. Significant variables and their adjusted t -values are summarized in Table A3.

2.3.5. Classification of Dominant Driver Zones

To classify prefecture-level units into climate-dominated, anthropogenic-dominated, and dual-dominated (synergistic) zones, we adopted a relative-strength classification approach based on the absolute values of MGWR local regression coefficients. For each city i , the cumulative influence of climatic and anthropogenic factors was calculated as follows. Examples 9 and 10 illustrate the corresponding equations:

$$S_i^{clim} = \sum_{j \in C} |\beta_{i,j}| \quad (9)$$

$$S_i^{anth} = \sum_{k \in A} |\beta_{i,k}| \quad (10)$$

where C represents climatic variables, and A represents anthropogenic variables. $\beta_{i,j}$ and $\beta_{i,k}$ denote MGWR local coefficients for climatic and anthropogenic drivers, respectively.

If $S_i^{clim} \geq 1.10 \times S_i^{anth}$, the city was classified as climate-dominated; if $S_i^{anth} \geq 1.10 \times S_i^{clim}$, the city was classified as anthropogenic-dominated; Otherwise, the city was classified as dual-dominated, indicating comparable influence from both driver groups. The 10% threshold was introduced to reduce sensitivity to marginal differences and emphasize practically meaningful dominance relationships. Absolute coefficient values were used to represent influence magnitude rather than direction. This classification was conducted separately for wheat and maize using crop-specific MGWR coefficients at the prefecture level. GeoDetector q -statistics were employed as global references of explanatory power, while spatial zoning was determined primarily by MGWR-derived local influence strengths.

3. Results

3.1. Spatial Patterns of WP in the NCP

Grain production in the NCP is dominated by wheat and maize. Based on five representative years (2000, 2005, 2010, 2015, and 2019), we calculated the multi-year average WP for both crops across the region (Figure 3). The multi-year average wheat WP ranged from 0.56 to 1.30 kg m⁻³, while maize WP varied from 0.89 to 1.72 kg m⁻³ (Figure 3a,b). The lowest WP values for both crops occurred in Zhangjiakou, northwestern Hebei (0.56 kg m⁻³ for wheat and 0.89 kg m⁻³ for maize). In contrast, the highest wheat WP was observed in Zhoukou, southern Henan (1.30 kg m⁻³), whereas maize reached its maximum in Tai'an, central Shandong (1.72 kg m⁻³). Spatially, higher WP values for both crops were mainly concentrated in the central and eastern parts of the NCP, including most areas of Hebei, Henan, and Shandong, whereas northern regions (northern Hebei and the Beijing–Tianjin area) consistently exhibited lower WP.

At the provincial scale (Figure 3c), wheat WP was lowest in Beijing (0.936 kg m⁻³) and showed comparable levels in Tianjin (1.064 kg m⁻³), Hebei (1.037 kg m⁻³), Henan (1.008 kg m⁻³), and Shandong (1.010 kg m⁻³). For maize, Shandong had the highest WP (1.413 kg m⁻³), Tianjin the lowest (1.042 kg m⁻³), while Beijing, Hebei, and Henan ranged between 1.108 and 1.159 kg m⁻³. Higher multi-year average WP for both wheat and maize

was persistently concentrated in the central–eastern NCP, whereas northern areas exhibited stable low-WP patterns across all five study years.

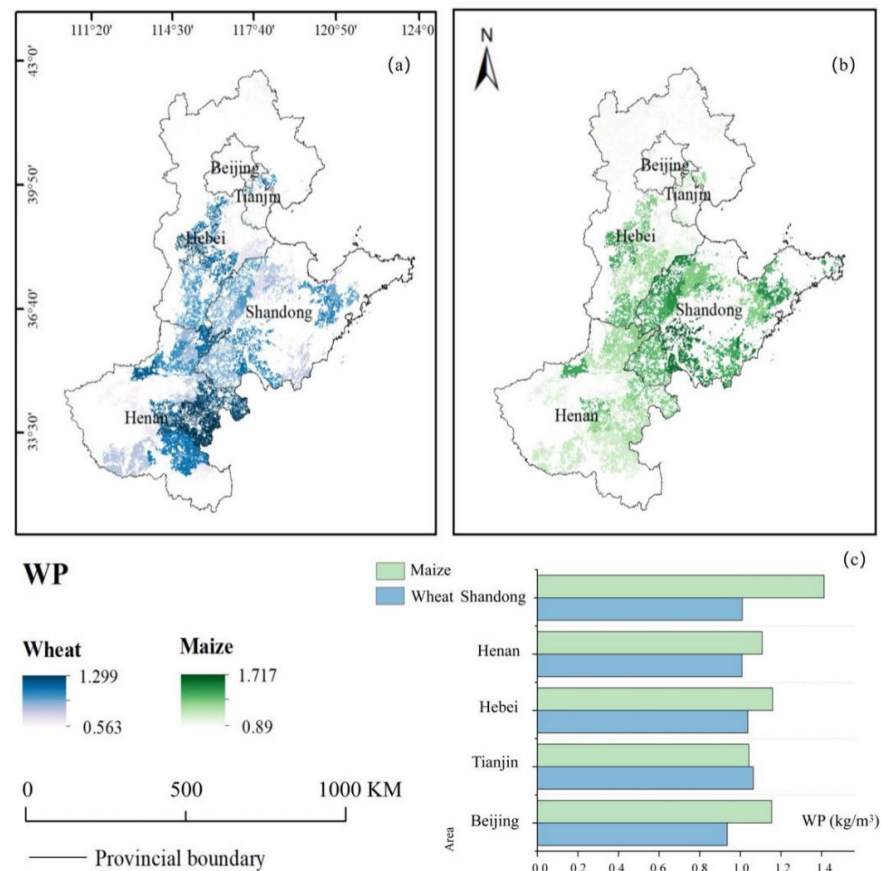


Figure 3. Spatial distribution of multi-year average WP in the NCP. (a) Spatial distribution of the multi-year average WP for wheat; (b) spatial distribution of the multi-year average WP for maize; and (c) provincial averages for wheat and maize WP. Multi-year averages were calculated from the years 2000, 2005, 2010, 2015, and 2019.

3.2. Temporal Trends in WP

Based on five representative years (2000, 2005, 2010, 2015, and 2019), Figure 4a illustrates the spatiotemporal variation in wheat and maize WP across the NCP. Both crops exhibited increasing tendencies in most regions, with pronounced spatial heterogeneity. For wheat, evident increases were observed in southern Hebei, eastern and northern Henan, and western to eastern Shandong, whereas Beijing and Tianjin experienced an initial decline between 2000 and 2005, followed by recovery in subsequent years (Table 3). For maize, increases in WP were mainly concentrated in northern and southern Hebei, northeastern Henan, and western Shandong, while localized decreases occurred in western Henan and northeastern Hebei.

Figure 4b presents boxplots of WP for the five observation years. Wheat WP increased from 0.88 kg m^{-3} in 2000 to a maximum of 1.33 kg m^{-3} in 2015 and then declined to 1.04 kg m^{-3} in 2019, with an overall interannual range of $0.88\text{--}1.33 \text{ kg m}^{-3}$. Maize WP rose from 1.09 kg m^{-3} in 2000 to 1.42 kg m^{-3} in 2010 and subsequently decreased to 1.12 kg m^{-3} in 2019, spanning a range of $1.09\text{--}1.42 \text{ kg m}^{-3}$, indicating substantial temporal variability for both crops. The Mann–Kendall test results are presented in Figure 4c. For wheat, the UF statistic increased progressively from 2000 to 2015 and exceeded the 0.05 significance threshold (± 1.96) in 2015, suggesting an apparent upward tendency during 2000–2015; however, given the limited number of observation points, this pattern should be interpreted

cautiously. In 2019, the UF value decreased below the critical threshold, suggesting that the increasing trend was not significant over the entire study period (2000–2019). The intersection of the UF and UB curves occurred around 2004, and the intersection point was within the confidence interval (± 1.96), indicating that no statistically significant abrupt change point was detected. For maize, the UF statistic showed a gradual increase from 2000 to 2011 but did not exceed the ± 1.96 critical value in any year. Therefore, no statistically significant monotonic trend was detected during 2000–2019 at the 95% confidence level. The UF and UB curves intersected around 2002 within the confidence bounds, further indicating the absence of a significant mutation point.

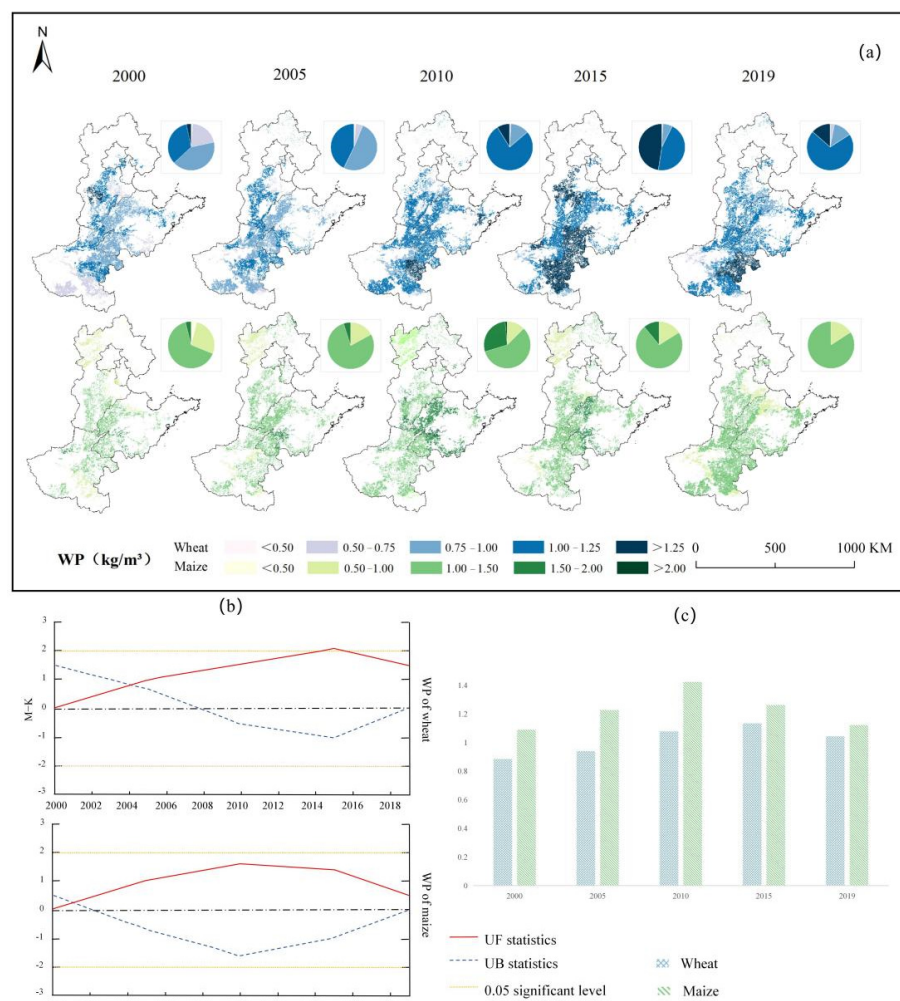


Figure 4. Temporal trends in WP. (a) Spatial distribution of wheat and maize WP in the NCP in 2000, 2005, 2010, 2015, and 2019, and the pie chart in the upper right shows the ratio of high and low WP in each year; (b) marginal boxplot of WP in the NCP; and (c) Mann–Kendall test with mutation analysis.

Table 3. Regional trends in WP in the NCP.

Year	Crop Type	Beijing	Tianjin	Area Hebei	Henan	Shandong
2000	Wheat	1.0801	1.1262	0.9308	0.8484	0.8665
	Maize	0.8626	0.6310	0.8811	1.0885	1.2739
2005	Wheat	0.8519	0.9563	0.9758	0.9285	0.9327
	Maize	1.0941	1.1541	1.2460	1.0604	1.4098
2010	Wheat	0.7806	1.0289	1.1244	1.0446	1.1037
	Maize	1.1934	1.2003	1.3810	1.2276	1.6991

Table 3. Cont.

Year	Crop Type	Beijing	Tianjin	Area Hebei	Henan	Shandong
2015	Wheat	0.8107	1.1181	1.0930	1.1747	1.1360
	Maize	1.3529	1.0244	1.1858	1.1472	1.4525
2019	Wheat	1.1554	1.0922	1.0604	1.0461	1.0160
	Maize	1.2679	1.2009	1.1020	1.0142	1.2406

3.3. Factors Affecting WP in Different Crops

3.3.1. Contributions of Climate Change and Anthropogenic Factors

Figure 5 illustrates the temporal variation in the explanatory power (q values) of climatic and anthropogenic variables for wheat and maize WP. In 2000, wheat WP was primarily influenced by SH ($q = 0.434$) and MinT (0.355), whereas maize WP was dominated by SH (0.401) and P (0.341). In 2005, FA (0.223) and EIA (0.220) showed relatively higher explanatory power for wheat, while MaxT (0.371) and SH (0.260) were the leading factors for maize. In 2010, PU (0.311) and EIA (0.244) became more influential for wheat, whereas maize WP was strongly controlled by MaxT (0.476) and SH (0.411), with MaxT reaching the highest q value observed across all years. In 2015, FA (0.317) and RH (0.298) were dominant for wheat, while PU (0.238) and SH (0.219) showed comparatively stronger effects for maize. By 2019, SH exhibited the highest explanatory power for both wheat (0.240) and maize (0.374), with MinT (0.240) also showing comparable importance for wheat.

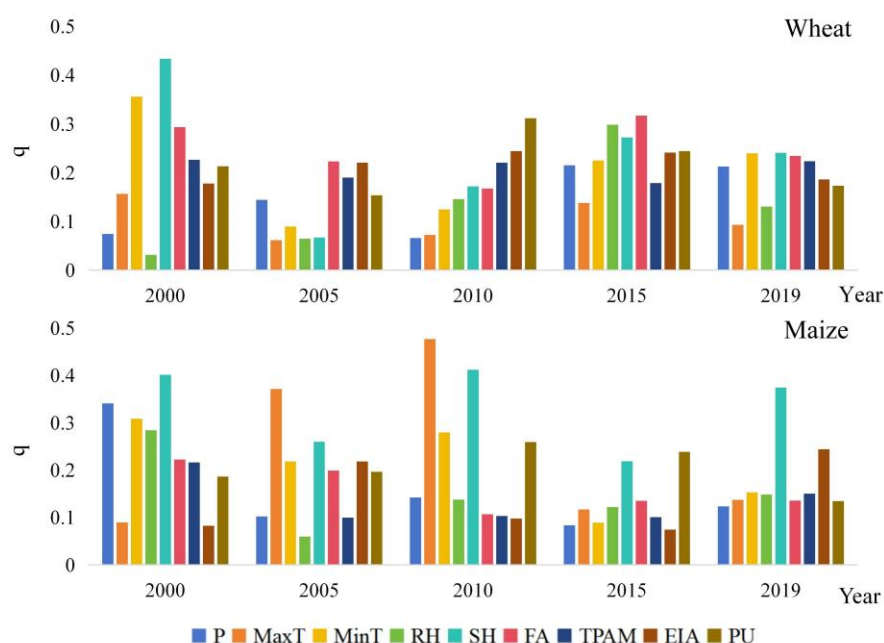


Figure 5. Key drivers of WP in major crops. P, Precipitation; MaxT, Maximum temperature; MinT, Minimum temperature; RH, Relative humidity; SH, Sunshine hours; FA, Fertilizer application; TPAM, Total power of agricultural machinery; EIA, Effective irrigated area; PU, Pesticide use. q represents the factor explanatory power.

Figure 6 summarizes the relative contributions of individual factors. Compared with wheat, maize WP exhibited stronger associations with temperature-related variables, whereas wheat WP showed higher sensitivity to irrigation-related indicators. These patterns highlight crop-specific differences in the statistical relationships between WP and its potential drivers.



Figure 6. Contributions of individual drivers to WP in wheat and maize. P, Precipitation; MaxT, Maximum temperature; MinT, Minimum temperature; RH, Relative humidity; SH, Sunshine hours; FA, Fertilizer application; TPAM, Total power of agricultural machinery; EIA, Effective irrigated area; PU, Pesticide use. q represents the factor explanatory power.

3.3.2. Results of the MGWR

MGWR revealed pronounced spatial heterogeneity in the relationships between WP and explanatory variables for both crops (Table A4). For wheat, P, SH, FA, TPAM, EIA, and PU were retained in the final model, whereas maize WP was associated with P, MaxT, RH, SH, FA, and PU.

The spatial variation in MGWR local coefficients is shown in Figure 7. For wheat, FA and EIA exhibited predominantly negative coefficients across most of the NCP, whereas SH, TPAM, and PU were mainly positive. The strength of FA effects increased from south to north, while EIA showed stronger associations in western regions. For maize, MaxT, FA, and PU generally displayed negative coefficients, whereas SH showed both positive and negative values, ranging from -0.374 to 0.837 . Precipitation exhibited bidirectional associations with WP for both crops, with coefficient ranges of -1.848 to 0.073 for wheat and -0.201 to 0.556 for maize, indicating strong spatial variability. PU showed positive coefficients for wheat across most areas (0.203 – 0.204) but negative coefficients for maize (-0.024 to -0.024). These results indicate substantial spatial heterogeneity in the statistical relationships between WP and its climatic and anthropogenic correlates.

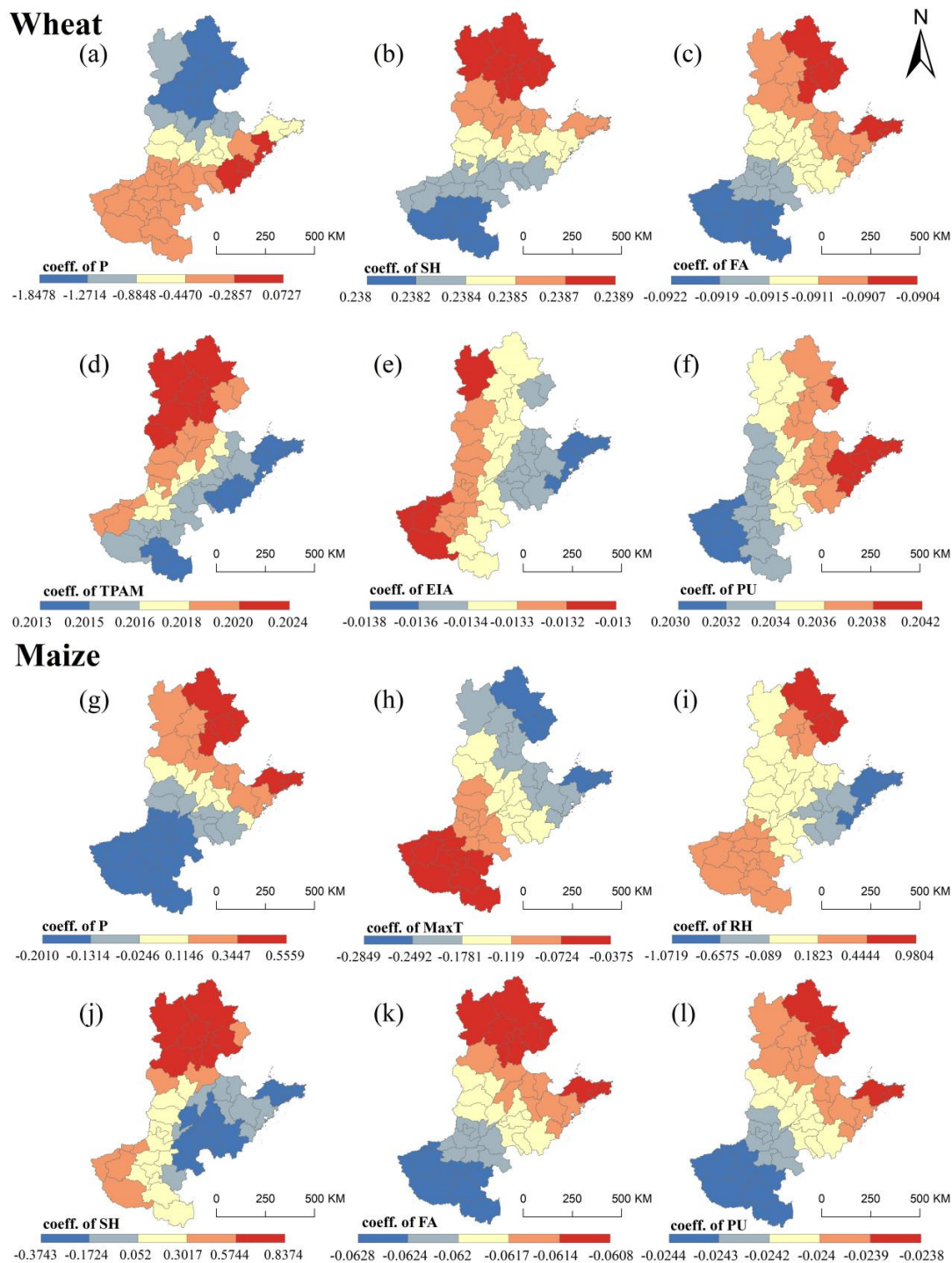


Figure 7. Spatial distribution of correlation coefficients for factors affecting WP in wheat and maize. The figure shows the climate change and human activity drivers with high explanatory power affecting changes in WP in wheat and maize during 2000–2019. In particular, (a–f) are drivers affecting wheat, and (g–l) are drivers affecting maize.

3.4. Dominant Factor Zones

Figure 8a illustrates the spatial partitioning of wheat and maize WP into Climate-dominated, Anthropogenic-dominated, and Dual-dominated zones across the NCP. For wheat, Climate-dominated zones comprised 12 cities, mainly located in eastern Shandong and northern Hebei (e.g., Chengde, Qingdao, Weifang, Weihai). Anthropogenic-dominated zones included 16 cities, distributed across most of Hebei and northwestern Shandong (e.g., Beijing, Tianjin, Shijiazhuang, Dezhou, Liaocheng). Dual-dominated zones covered

20 cities, primarily concentrated in Henan and southwestern Shandong (e.g., Zhengzhou, Kaifeng, Shangqiu, Jining, Heze).

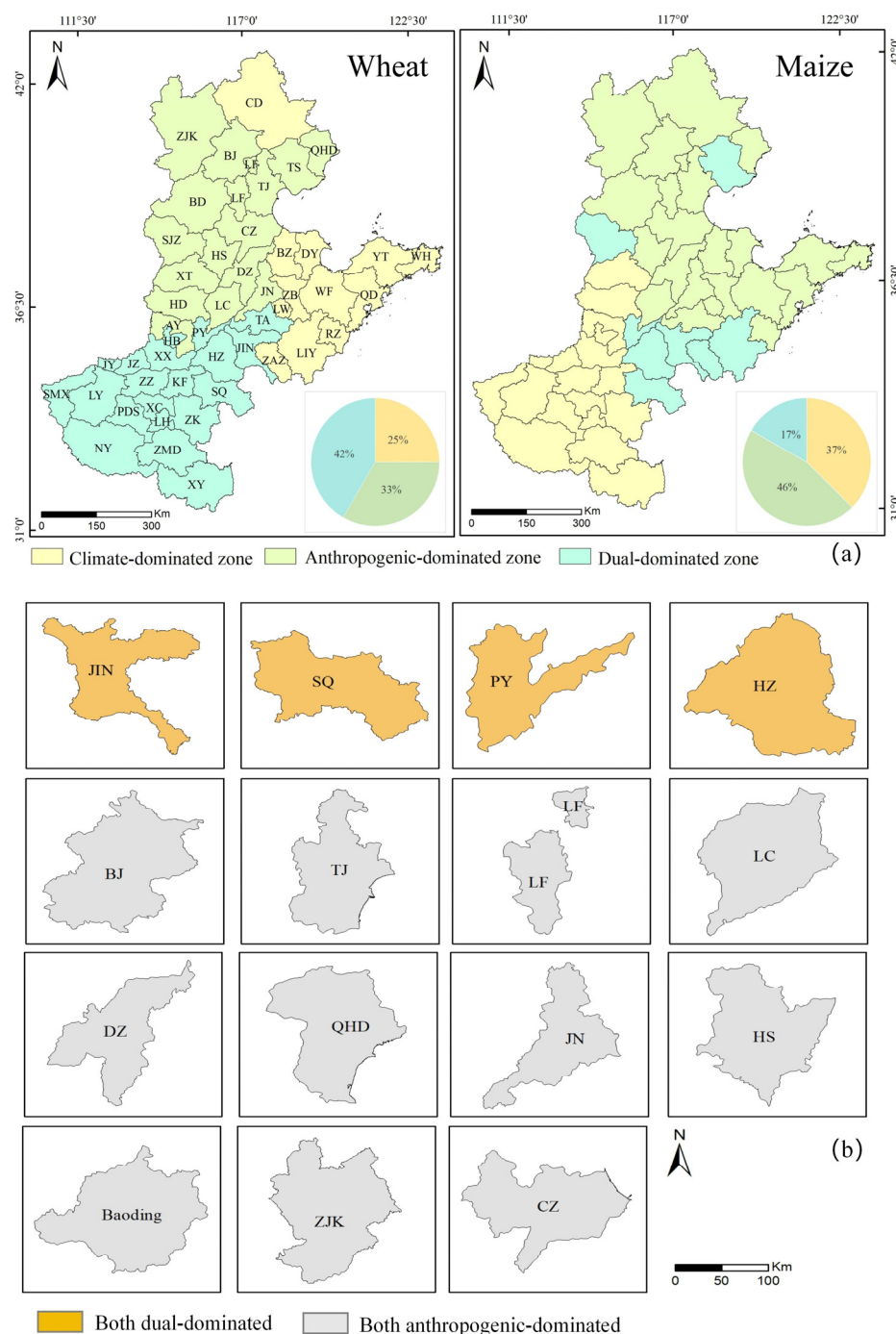


Figure 8. Spatial classification of dominant driving types for wheat and maize WP. **(a)** Regions classified separately for wheat and maize into climate-dominated, anthropogenic-dominated, and dual-dominated zones; **(b)** regions where wheat and maize share the same dominant type, including both anthropogenic-dominated and dual-dominated zones. BJ, Beijing; TJ, Tianjin; SJZ, Shijiazhuang; TS, Tangshan; QHD, Qinhuangdao; HD, Handan; XT, Xingtai; BD, Baoding; ZJK, Zhangjiakou; CD, Chengde; CZ, Cangzhou; LF, Langfang; HS, Hengshui; ZZ, Zhengzhou; KF, Kaifeng; PDS, Pingdingshan; LY, Luoyang; SQ, Shangqiu; AY, Anyang; XX, Xinxiang; XC, Xuchang; HB, Hebi; JZ, Jiaozuo; PY, Puyang; LH, Luohe; SMX, Sanmenxia; ZK, Zhoukou; ZMD, Zhumadian; NY, Nanyang; XY, Xinyang; JY, Jiyan; JN, Jinan; QD, Qingdao; ZB, Zibo; ZAZ, Zaozhuang; DY, Dongying; YT, Yantai; WF, Weifang; JIN, Jining; TA, Tai'an; WH, Weihai; RZ, Rizhao; BZ, Binzhou; DZ, Dezhou; LC, Liaocheng; LIY, Linyi; HZ, Heze; LW, Laiwu.

For maize, Climate-dominated zones encompassed 18 cities, mainly in Henan and southern Hebei (e.g., Handan, Zhengzhou, Xinxiang, Nanyang, Xinyang). Anthropogenic-dominated zones comprised 22 cities, concentrated in the Beijing–Tianjin–Hebei region and central–eastern Shandong (e.g., Beijing, Tianjin, Baoding, Qingdao, Weifang, Dezhou). Dual-dominated zones included 8 cities, such as Shijiazhuang, Tangshan, Shangqiu, Linyi, and Heze. Comparison between wheat and maize zoning (Figure 8b) shows that Shangqiu, Puyang, Jining, and Heze were classified as Dual-dominated for both crops, whereas Beijing, Tianjin, and Jinan were consistently categorized as Anthropogenic-dominated. Several cities exhibited crop-specific zoning patterns.

4. Discussion

4.1. Temporal Shifts and Spatial Persistence of WP

Between 2000 and 2019, WP of winter wheat and summer maize in the NCP increased until 2010 and declined thereafter (Figure 3). As the analysis was conducted at five-year intervals, the pattern represents stage-wise shifts rather than continuous annual dynamics. Spatial distributions remained relatively stable, with higher WP concentrated in the central and eastern NCP and persistently lower values in northern areas. This stability suggests that background climatic conditions, irrigation infrastructure, and soil properties impose structural constraints on regional WP [51–54].

The post-2010 decline coincided with multiple extreme events. Heavy rainfall in 2012 [55], a severe drought in 2015 across Hebei, Henan, and Shandong [56], flooding in 2016 [57], and the wheat stripe rust outbreak in 2017 [58] overlapped with reductions in maize and wheat WP (Figure 3). These correspondences indicate that climatic extremes and biological disturbances contributed substantially to interannual variability.

The pre-2010 increase is consistent with evidence that improvements in irrigation management and agronomic practices can enhance WP under favorable climatic conditions [9,10,16]. Similar medium-term fluctuations have been reported in semi-arid agricultural systems, where technological progress and climate variability jointly shape productivity dynamics [12,18]. The trajectory observed in the NCP therefore reflects the combined influence of environmental variability and management adjustment rather than a monotonic improvement trend. Given the strong climate-management interactions identified in Section 4.3, future WP dynamics in the NCP will likely depend on the extent to which adaptive management can offset increasing climatic variability.

4.2. Spatially Heterogeneous and Crop-Specific Drivers of WP

The MGWR results (Figure 7; Table A4) reveal pronounced spatial heterogeneity in the associations between WP and climatic or anthropogenic variables. Because MGWR estimates local conditional relationships, the signs of the coefficients represent context-dependent statistical associations rather than direct causality. Variations in sign and magnitude, therefore, reflect differentiated production environments across the NCP.

FA exhibited predominantly negative coefficients for both crops across large areas. Although fertilization generally promotes yield, WP measures grain output per unit water consumed. In high-input systems, additional fertilization may stimulate vegetative growth and transpiration without proportional yield gains, leading to diminishing marginal returns [9,10]. Nutrient losses under conventional irrigation can further reduce uptake efficiency, and long-term over-application may induce soil salinization or nutrient imbalance, constraining root water absorption. Experimental evidence shows that combined water–salt stress significantly reduces maize WP [11]. The stronger negative FA effects observed in intensively cultivated northern counties, therefore, likely reflect declining input efficiency rather than a direct inhibitory effect of fertilizer.

Crop-specific climatic sensitivities further explain the heterogeneous patterns. Maize, as a thermophilic crop, requires relatively high temperatures for optimal development, making it more vulnerable to excessive heat. The predominantly negative MaxT coefficients for maize indicate that elevated temperatures shorten grain filling duration and increase transpiration demand. Wheat, with a longer growth cycle and greater cold tolerance, exhibits broader thermal adaptability, resulting in weaker temperature sensitivity in many regions.

Seasonal water availability further differentiates winter wheat and summer maize. Most rainfall in the NCP occurs between June and August, coinciding with the maize-growing season. Winter wheat, in contrast, receives only 174–261 mm of precipitation during its growth period, representing roughly 20–30% of the annual total [35]. This amount is insufficient to meet crop water demand, making wheat production structurally reliant on groundwater irrigation, which accounts for nearly 70% of total regional irrigation [51,52]. These structural water constraints help explain the stronger spatial correlation between EIA and wheat WP observed in western counties.

4.3. Climate–Management Interactions and Coupled Regulation

Beyond individual effects, the OPGD results (Figure 9) demonstrate that interactions between variables substantially increase explanatory power. In several years, interaction terms explained considerably more variance in WP than single factors, indicating coupled regulation mechanisms. For wheat and maize in certain years, interactions between climatic variables dominated. The $SH \times RH$ interaction for wheat and $SH \times P$ for maize each explained more than 70% of WP variation. Radiation promotes biomass accumulation, but its effectiveness depends on atmospheric moisture conditions that regulate evaporative demand. These results suggest that energy and moisture availability jointly determine crop water-use efficiency.

In other years, climate–management interactions became more influential. For wheat, the $EIA \times RH$ interaction explained over 60% of WP variation in 2010 and 2015. Under structurally water-limited conditions [35], irrigation alone does not determine WP outcomes. Relative humidity regulates transpiration demand, while irrigation controls soil moisture supply. When atmospheric demand is moderated, irrigation inputs can be utilized more efficiently under groundwater constraints [51,52], resulting in enhanced WP.

For maize, strong interactions between MaxT and FA or PU highlight the coupling between thermal stress and input intensity. Elevated temperatures accelerate phenological development and increase metabolic demand [59]. Adequate nutrient supply may partially compensate for heat stress, whereas insufficient inputs can amplify yield reductions relative to water consumption. Higher temperatures can also intensify pest and disease pressure, increasing the relative importance of pesticide application in sustaining grain yield [60,61].

These interaction patterns indicate that WP is governed by an integrated climate–management system. Wheat exhibits stronger coupling between atmospheric moisture and irrigation management, whereas maize shows a tighter linkage between thermal conditions and input intensity. Such crop-specific coupling structures underpin the differentiated spatial responses identified in Section 4.2.

4.4. Recommendations for Differentiated Management by Zone

The zonation analysis shows that, under the winter wheat–summer maize system, the dominant drivers of WP vary markedly across the NCP. This heterogeneity indicates that management strategies should be aligned with region-specific controlling mechanisms rather than applied uniformly.

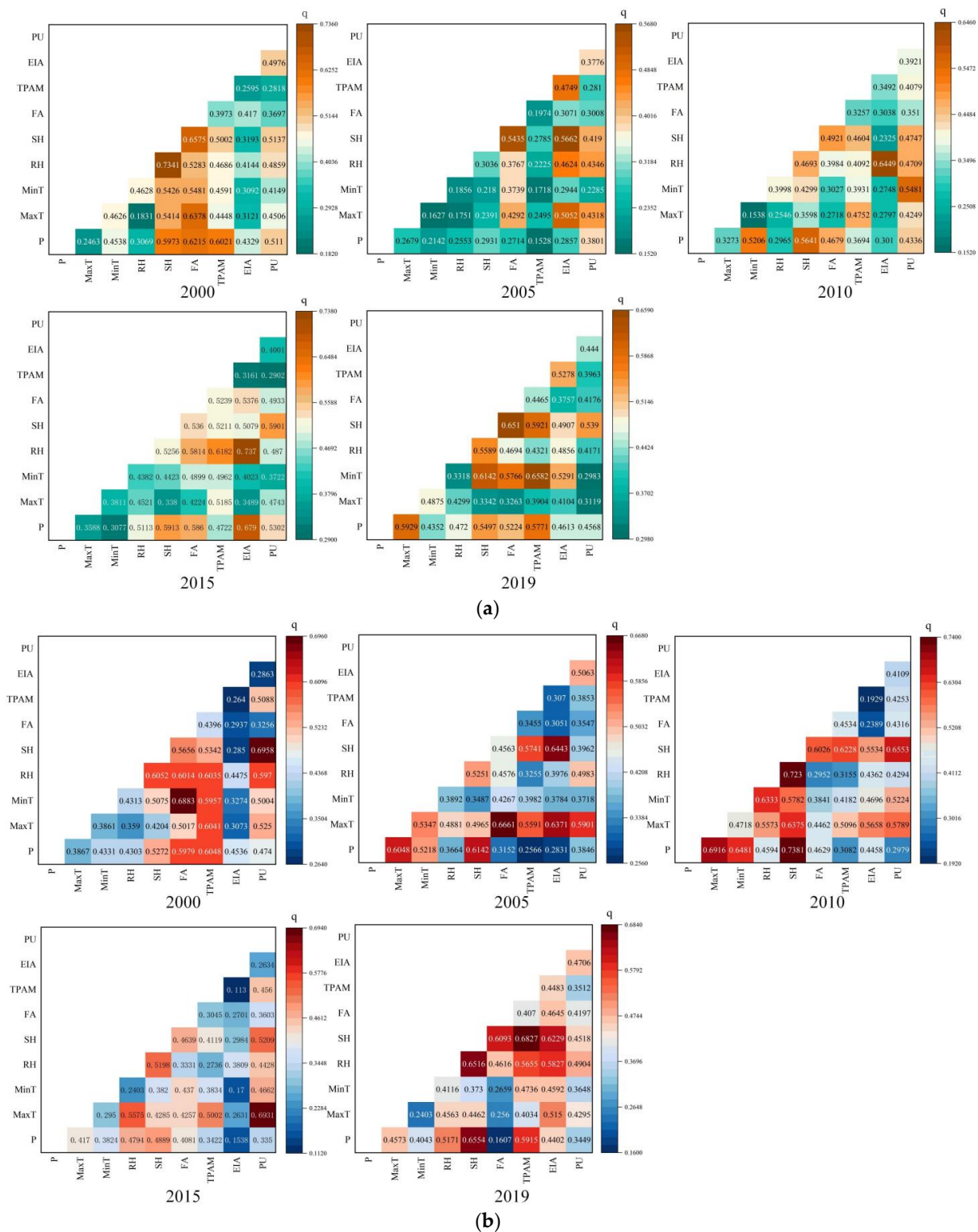


Figure 9. (a) Interaction effects between driving factors influencing WP in wheat. (b) Interaction effects between driving factors influencing WP in maize. q represents the factor explanatory power.

In anthropogenic-dominated zones (e.g., Beijing and Tianjin), WP variation is primarily linked to irrigation intensity and input management. Under groundwater constraints, improving WP relies on increasing water- and nutrient-use efficiency through optimized irrigation scheduling and reduced excessive fertilization. In Climate-dominated zones (e.g., Qingdao and Chengde), WP is mainly controlled by precipitation and temperature variability. Here, adaptive measures—such as adjusting sowing dates and enhancing soil

moisture conservation—are more effective than increasing management inputs in stabilizing WP. In Dual-dominated zones (e.g., Zhengzhou and Jining), both climatic variability and management practices substantially influence WP. Coordinating climate adaptation with improvements in input efficiency and adjusting cropping structures according to the relative WP advantages of wheat and maize may enhance system-level WP under climatic uncertainty.

Zoning differences between wheat and maize within the same region further indicate crop-specific sensitivities. For example, in Qingdao and Weifang, wheat is climate-dominated, whereas maize is anthropogenic-dominated. Such contrasts suggest that differentiated management should operate not only across regions but also between crops within the same double-cropping system.

4.5. Limitations and Future Directions

Several limitations of this study should be acknowledged. First, WP and related analyses were conducted for five representative years (2000, 2005, 2010, 2015, and 2019) rather than using a continuous annual time series. This interval-based design was adopted to ensure spatial data consistency across prefecture-level units while capturing medium-term variability over two decades. However, the Mann–Kendall test is traditionally applied to continuous time series, and using only five discrete points may substantially reduce the statistical power and sensitivity of trend detection. Consequently, the observed temporal patterns should be interpreted as indicative medium-term changes rather than strict monotonic trends. Second, the data series ends in 2019. In recent years, major policy interventions, such as the implementation of the *Groundwater Overdraft Control Plan*, along with rapid improvements in irrigation technologies and agricultural management, may have influenced water use patterns in the NCP. Although the structural relationships identified here reflect long-term climatic and human-driven interactions, future studies using post-2019 data would help assess the persistence and evolution of these mechanisms. Third, seasonal-average crop coefficients were adopted instead of stage-specific dynamic K_c values. This approach improves methodological consistency and spatial comparability at the regional scale, but it does not explicitly capture intra-seasonal physiological variations. Nevertheless, given the use of prefecture-level aggregated yield data and the aim of large-scale comparative analysis, this simplification provides a reasonable approximation of seasonal crop water demand.

Future research should extend temporal coverage to continuous annual datasets to enhance the robustness of trend detection and to evaluate the impacts of policies implemented after 2019. In addition, incorporating stage-specific or dynamically calibrated crop coefficients, remote-sensing-based evapotranspiration products, and process-based crop models such as AquaCrop or DSSAT would improve the representation of crop physiological processes and water balance dynamics. The spatial heterogeneity patterns and dominant driver zones identified in this study offer valuable guidance for configuring process-based models.

5. Conclusions

This study quantitatively analyzed the spatial patterns and stage-wise changes in WP for winter wheat and summer maize in the NCP using five representative years: 2000, 2005, 2010, 2015, and 2019. Winter wheat WP ranged from 0.56 to 1.30 kg m^{−3}, while maize ranged from 0.89 to 1.72 kg m^{−3}. Relatively high WP was consistently observed in central and eastern areas, whereas northern regions exhibited lower values. Winter wheat WP showed an increasing tendency during the study period. Climatic factors, particularly sunshine duration and temperature variables, explained a substantial portion

of WP variability for both crops. Anthropogenic factors displayed pronounced spatial heterogeneity. Fertilizer application was negatively correlated with WP in several regions, suggesting diminishing efficiency under high-intensity management. Zoning analysis revealed that dominant drivers varied across cities and crops, highlighting the clear spatial differentiation in WP regulation.

These spatially differentiated patterns provide a scientific basis for region-specific water management strategies. Improving fertilizer use efficiency, optimizing irrigation allocation, and enhancing climate adaptation capacity are key measures to increase WP and promote sustainable intensification in agriculture. Such interventions also contribute to achieving the water-related Sustainable Development Goals (SDG 6) and the food security objectives (SDG 2). Overall, this study offers empirical support for differentiated regional decision-making regarding water allocation and agricultural input management.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

Abbreviations

The following abbreviations are used in this manuscript:

WP	Water Productivity
NCP	North China Plain
OPGD	Optimal Parameter-Based Geographical Detector
MGWR	Multi-scale Geographically Weighted Regression
OLS	Ordinary Least Squares
VIF	Variance Inflation Factor

Appendix A

Table A1. VIF of explanatory variables used in MGWR modeling.

Driving Factor	VIF		Driving Factor	VIF	
	2000	2019		2000	2019
Climate change			Human activity		
P	6.083758	1.981733	FA	8.533671	7.157514
MaxT	8.863412	7.221101	TPAM	4.91698	5.731546
MinT	12.211078	8.906321	EIA	5.545492	5.816854
RH	7.579741	4.096501	PU	4.370615	4.185378
SH	8.255103	6.306195			

Note: VIF, Variance Inflation Factor; P, Precipitation (mm yr^{−1}); MaxT, Maximum temperature (°C); MinT, Minimum temperature (°C); RH, Relative humidity (%); SH, Sunshine hours (h yr^{−1}); FA, Fertilizer application (t yr^{−1}); TPAM, Total power of agricultural machinery (kW); EIA, Effective irrigated area (ha); PU, Pesticide use (t yr^{−1}).

Table A2. MGWR model configuration and diagnostic statistics for wheat and maize.

Item	Wheat	Maize
MGWR version	2.2.1	2.2.1
Kernel type	Fixed Gaussian	Fixed Gaussian
Model family	Gaussian	Gaussian
Bandwidth selection	Golden section (AICc)	Golden section (AICc)
Variable standardization	On	On
Convergence algorithm	SOC-f	SOC-f
Convergence threshold	1×10^{-5}	1×10^{-5}
Number of observations	48	48
R ² (OLS)	0.48	0.272
R ² (MGWR)	0.85	0.771
AICc (MGWR)	125.96	125.348

Note: R², Coefficient of determination; AICc, corrected Akaike Information Criterion; OLS, Ordinary Least Squares; MGWR, Multi-scale Geographically Weighted Regression; SOC-f, Second-order cone programming-fast algorithm.

Table A3. Adjusted t-values of MGWR coefficients at the 95% confidence level.

Variable	Wheat (Adjusted t)	Maize (Adjusted t)
P	2.548	2.275
MaxT	2.014	2.152
RH	2.978	2.676
SH	2.015	2.681
FA	2.014	2.014
TPAM	2.015	2.016
EIA	2.017	2.018
PU	2.015	2.016

Note: P, Precipitation; MaxT, Maximum temperature; MinT, Minimum temperature; RH, Relative humidity; SH, Sunshine hours; FA, Fertilizer application; TPAM, Total power of agricultural machinery; EIA, Effective irrigated area; PU, Pesticide use.

Table A4. Summary statistics of MGWR local parameter estimates for wheat and maize.

Variable	Mean		STD		Min		Median		Max	
	Wheat	Maize	Wheat	Maize	Wheat	Maize	Wheat	Maize	Wheat	Maize
P	−0.625	0.036	0.471	0.234	−1.848	−0.201	−0.396	−0.052	0.073	0.556
RH	−0.1	0.097	0.00	0.397	−0.101	−1.072	−0.1	0.141	−0.099	0.98
SH	0.504	0.173	0.603	0.34	−0.101	−0.374	0.259	0.156	3.125	0.837
FA	0.238	−0.062	0.00	0.001	0.238	−0.063	0.238	−0.062	0.239	−0.061
TPAM	−0.091	−0.084	0.001	0.001	−0.092	−0.086	−0.091	−0.084	−0.09	−0.083
EIA	0.202	0.014	0.00	0.001	0.201	0.012	0.202	0.013	0.202	0.015
PU	−0.013	−0.024	0.00	0.00	−0.014	−0.024	−0.013	−0.024	−0.013	−0.024
MaxT	0.204	−0.135	0.00	0.071	0.203	−0.285	0.204	−0.124	0.204	−0.038

Note: Mean, Arithmetic mean; STD, Standard deviation; Min, Minimum value; Median, Median value; Max, Maximum value. P, Precipitation; MaxT, Maximum temperature; RH, Relative humidity; SH, Sunshine hours; FA, Fertilizer application; TPAM, Total power of agricultural machinery; EIA, Effective irrigated area; PU, Pesticide use.

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