https://doi.org/10.1590/1678-992X-2023-0140

ISSN 1678-992X

Scientia Agricola

Research article

Effects of climate change on grain yield in a major grain producing area of China

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Edited by: Hossein Kazemi

Received June 29, 2023
Accepted December 04, 2024

ABSTRACT: The impact of climate change on food production is evident across most regions of the world, including China, particularly in the Huang-Huai-Hai Plain (HHHP), which is crucial for grain production. Investigating the quantitative effects of climate variables on grain yield is therefore of paramount importance. A study of the HHHP region revealed an upward trend in temperature, along with a downward trend in shortwave radiation and precipitation from 1995 to 2018. During this period, the grain yield exhibited two distinct stages: a decline from 1.1 billion tons in 1995 to 0.96 billion tons in 2003, followed by a period of stable growth from 1 billion tons in 2004 to 1.5 billion tons in 2018. In terms of spatial dynamics, the grain yield in the HHHP transitioned from a pattern of scattered high-yield cities to concentrated high-yield areas. From a single-factor perspective, temperature (q = 0.44) exhibited the most significant impact to grain yield in the HHHP, followed by shortwave radiation (q = 0.28) and precipitation (q = 0.24). The interaction between temperature and precipitation was identified as the primary driver of grain yield in the HHHP and its sub-region, Hebei Province. In contrast, in Henan and Shandong Provinces, the predominant influence was attributed to the interaction of shortwave radiation and temperature. The sensitivity degree model indicates that 87.5 % of cities within the HHHP region are sensitive to cropland with respect to grain yield. The present study demonstrates the multifaceted impacts of climate change on grain yield and provides essential evidence for developing effective strategies to ensure global food security.

Keywords: Huang-Huai-Hai Plain, food security, geographical detectors

Introduction

The Intergovernmental Panel on Climate Change Sixth Assessment Report states that the impact of climate change on crop yield varies geographically; however, with an overall predominantly negative effect (high confidence) (Pörtner et al., 2022). The impact of climate change on food production and food security has become increasingly evident due to global warming, enhanced precipitation, and the frequent occurrence of extreme weather events (Arora, 2019; Donat et al., 2016; Habib-ur-Rahman et al., 2022). Consequently, it is imperative to investigate the impact of climate change on crop production.

Recent research has identified climate change as one of the most unpredictable factors affecting global crop production (Grassini et al., 2013), leading to yield stagnation worldwide (Hochman et al., 2017). In Europe, the average decreases of 9 % and 7.3 % in cereal production are attributed to droughts and heat waves, respectively (Brás et al., 2021). In Iran, for instance, climate change has negatively impacted agricultural practices due to alterations in precipitation, temperature, and carbon dioxide levels (Saei et al., 2018). Climate change has become a significant challenge for agriculture worldwide, with several regions experiencing negative impacts on food production (Hague et al., 2016; Nhamo et al., 2019; Ray et al., 2019). In China, increasing precipitation and decreasing solar radiation have led to a stagnation in grain production (Asai et al., 2021; Chen et al., 2017). The impact of climate change on grain yield in China is primarily attributed to its effect on crop growth and development (Chen et al., 2014). This, in turn, results in changes in cultivation structure (Wang et al., 2018), increases in agricultural pests and diseases (Bajwa et al., 2020), and an escalation in weather-related hazards (Fu et al., 2013; Xiao et al., 2021).

The Huang-Huai-Hai Plain (HHHP) is a major center for grain production in China (Li et al., 2017). Previous studies have demonstrated that temperature influences the phenology of winter wheat in the region (Shirazi et al., 2022). In addition, it has been determined that precipitation plays a crucial role in determining the yield of summer maize in the region (Chen et al., 2012), with optimal growth of this crop occurring with a cumulative precipitation level of 300-500 mm (Wang et al., 2020). Consequently, the growth and development of crops are governed by the intricate interplay among multiple climatic factors, rather than by any individual factor in isolation (Chou et al., 2019).

Despite the abundant academic research on the impact of climate change on agricultural productivity, the quantitative contribution of climate variables to grain yield remains limited. The objective of this study was to 1) map the spatiotemporal changes in climate variables; 2) quantify the spatiotemporal pattern of grain yield influenced by climate variables; and 3) quantitatively evaluate the effects of temperature, precipitation, shortwave radiation, and other climate variables on grain yield.

Materials and Methods

Study site

The HHHP, located in central and eastern China, is a substantial alluvial plain that encompasses the deltas of the Yellow River, Huai River, and Hai River. Topographically, the Taihang Mountains in the west, the Dabie Mountains in the south, and the Yanshan Mountains in the north dominate the study site. Geographically, the region is delineated by latitude coordinates ranging from 31°23′04″ N to 42°37′20″ N and longitude coordinates from 110°21′46″ E to 122°42′43″ E. The altitude in this area varies from 8 m to 2414 m, encompassing an area exceeding 500,000 km^2. This expanse traverses three provinces (Henan, Hebei, and Shandong) and two municipalities (Beijing and Tianjin), thereby playing a pivotal role in sustaining China's agricultural sector (Figure 1).

The HHHP is characterized by a dual temperate and subtropical monsoon climate, with relatively dry and cold winters, and hot and humid summers with heavy rains that frequently result in flooding. The region is traversed by numerous rivers, with the Yellow, Huai, and Hai rivers being of particular significance due to their profound influence on the region's ecological and economic systems. The region boasts a rich agricultural history spanning millennia and currently encompasses one-fourth of China's cropland, covering an area of 304,104 km^2 in 2020. The region's predominant food crops include wheat (*Triticum aestivum* L.), rice (*Oryza sativa* L.), corn (*Zea mays* L.), sorghum [*Sorghum bicolor* (L.) Moench], foxtail millet [*Setaria italica* (L.) P. Beauv.],

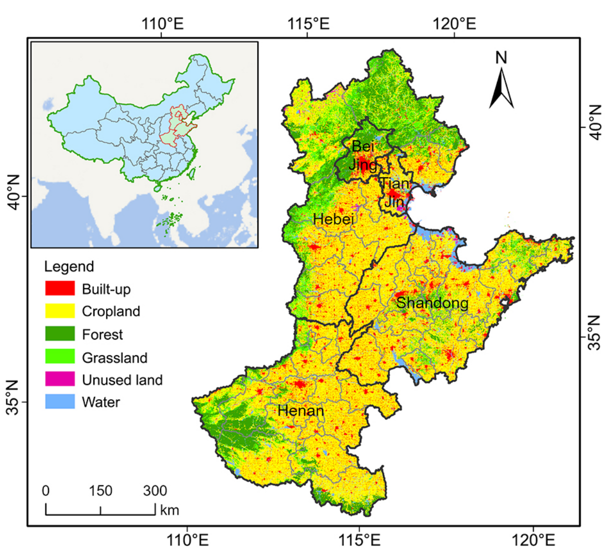

Figure 1 – Geographical location of the Huang-Huai-Hai Plain.

and sweet potatoes [*Ipomoea batatas* (L.) Lam.]. A significant proportion of the grain production structure comprises wheat and corn, with the predominant planting pattern being double cropping within a year (Zhou et al., 2020). The HHHP is distinguished by its production of cash crops, including cotton (*Gossypium hirsutum* L.), peanuts (*Arachis hypogaea* L.), rapeseed (*Brassica napus* L.), sesame (*Sesamum indicum* L.), and soybeans [*Glycine max* (L.) Merr.]. This renders it a prominent site for grain, cotton, and oil production in China.

Datasets

The data utilized in this study on grain production and arable land in the HHHP region were obtained from the statistical yearbooks of Hebei, Shandong, Henan Provinces, Tianjin Municipality, and Beijing Municipality, published by the China Statistics Bureau from 1995 to 2018. The statistics encompass total food production and the planted area of food crops among the HHHP municipalities during the specified period. The grain crops examined in this study primarily encompassed rice, wheat, corn, and soybeans.

The land use/cover data for 1995, 2018, and 2020 in the HHHP were utilized to analyze changes in land use from 1995 to 2018, and land cover distribution in 2020. These land use/cover data were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). The land use/cover data, with a spatial resolution of 1 km, was subjected to manual visual interpretation of Landsat images to ensure high classification accuracy. The land use categories primarily comprised forest, grassland, cropland, built-up, water, and unused land (Liu et al., 2014).

The climate variables employed in this study, including precipitation, temperature, and shortwave radiation, were sourced from the China Meteorological Forcing Dataset (CMFD), obtained from the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/). The CMFD comprises seven near-surface meteorological elements, such as precipitation rate, air temperature, wind speed, surface pressure, specific humidity, downward longwave radiation, and downward shortwave radiation. The period of this dataset is from 1979 to 2018, with a spatial resolution of 0.1° and a temporal resolution of 3 h. The CMFD dataset is highly accurate because it integrates meteorological observation data and a series of gridded datasets, including Tropical Rainfall Measuring Mission precipitation data, global land data assimilation system data, global energy and water cycle experiment surface radiation budget radiation data, and international Princeton reanalysis data (He et al., 2020). The monthly precipitation, temperature, and shortwave radiation of HHHP in 1995-2018, and the annual values of each city in HHHP, were extracted using Matlab and ArcGIS platforms.

Methods

Theil-Sen median method

Theil-Sen median (TS) method is a non-parametric statistical approach that utilizes the median to estimate trends. It is resistant to the impact of observational errors and anomalous data. The TS method is highly efficient regarding computational speed and frequently analyzes trends in long-term meteorological data. The formula for this method can be expressed as follows:

$$\beta = Median\left(\frac{x_j - x_i}{j - i}\right), \forall j > i \tag{1}$$

where x_j and x_i refer to the elements of the time series, arranged in a chronological order. Median is the function that indicates an ascending trend when $\beta > 0$, and a descending trend when $\beta < 0$ (Wu et al., 2021).

Geographical detector model

The geographical detector model (GeoDetector) is a geostatistical method that examines spatial divisions and identifies the driving factors (Wang and Xu, 2017). The GeoDetector model comprises four components: factor detection, interaction detection, risk detection, and ecological detection. The present study employs factor detection and interaction detection to investigate the influence of climate variables on grain yield. The independent variable X (climate variables) should be a classification layer or require partitioning. This study partitions the temperature, precipitation, and shortwave radiation by natural breaks (Jia et al., 2021).

The GeoDetector's core principle is its capacity for factor detection, which methodically quantifies the independent influence of each factor on the spatial distribution of grain yield. This analysis is achieved by comprehensively examining variability in each influencing factor's dispersion variability across sub-regions and inter-regions. The spatial heterogeneity of the dependent variable Y, representing grain yield, manifests in various distribution patterns. The critical task is to evaluate the extent to which the detection factors elucidate the underlying spatial variations observed in the dependent variable Y. The q value ($q \in [0,1]$) expresses the impact of climate variables on grain yield, and the equations of q value can be expressed as:

$$q = 1 - \frac{SSW}{SST} \tag{2}$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2 \tag{3}$$

$$SST = N\sigma^2 \tag{4}$$

where h = 1, 2, ..., L signifies the number of categories correlated with the independent variable X. N_h denotes the number of units within the zone h, while N refers to the total number of units within the entire region. σ_h^2 signifies the variance of Y within the zone h, and σ^2 represents the global variability of Y across the entire region. The sum of squares (SSW) indicates the weighted sum of the local variabilities, where the respective number of samples within each zone determines the weights. The total sum of squares (SST) is representative of the overall variance spanning the entire region. The value range of q is [0, 1], where a higher value indicates a more pronounced spatial differentiation of the dependent variable Y. When the stratification is induced by the independent variable X, a higher q value indicates a stronger explanatory power of the independent variable X in relation to the attribute Y. Conversely, a lower q value signifies a weaker influence of the attribute Y on the independent variable X.

A notable point is that the independent variables (i.e., climatic variables) may not be independent of each other in terms of their effect on grain yield. Consequently, an interaction detector was employed to explore whether an interaction exists between the effects of multiple factors on grain yield and, in case the interaction exists, to assess this relationship's intensity and nature (linear or non-linear). This enables the detection of two-factor superimposed multiplications and any other relationships. The observed interactions are outlined in Table 1.

Sensitivity degree model

In order to evaluate the sensitivity of food production to changes in cultivated land, we developed a model for quantifying this relationship (Liu et al., 2009). The primary objective was to measure the extent to which variations in cultivated land impact food production.

Table 1 – Types of interaction between two covariates.

Criterion	Type of interaction
$q(X1 \cap X2) < \text{Min}(q(X1), q(X2))$	Nonlinear weakened
$\text{Min}(q(X1), q(X2)) < q(X1 \cap X2) < \text{Max}(q(X1), q(X2))$	Univariate nonlinear weakened
$q(X1 \cap X2) > \text{Max}(q(X1), q(X2))$	Bivariate enhancement
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinear enhancement

Min = minimum; Max = maximum.

$$\beta = \frac{\left[\left(G_{t+1} - G_t\right) / G_t\right]}{\left[\left(L_{t+1} - L_t\right) / L_t\right]} \quad (5)$$

where G_t and G_{t+1} represent food production in the base and final stages, respectively, while L_t and L_{t+1} denote the cultivated area in the base and final stages. When $\beta < 0$, the grain yield changes are in the reverse direction with the cultivated land area, suggesting a lack of sensitivity of food production to changes in cultivated land area. Conversely, $\beta > 0$ indicates a direct relationship between food production and changes in cultivated land area, suggesting that grain yield is sensitive to such changes. As the value of β increases, the sensitivity of grain yield to changes in cultivated land area also increases, indicating that minor changes in cultivated land can significantly impact grain yield fluctuations. The sensitivity of grain yield to changes in cultivated land was evaluated using Eq. (5) for the period from 1995 to 2018. The sensitivity was categorized into four levels: when $\beta \leq 0$ is non-sensitivity, $0 < \beta \leq 5$ is defined as low-sensitivity, $5 < \beta \leq 10$ as mid-sensitivity, and $\beta > 10$ is high-sensitivity.

Results

Spatiotemporal patterns of climate variables in the HHHP

Temporal characteristics of climate variables in the HHHP

The annual temperature range, precipitation, and shortwave radiation for the HHHP from 1995 to 2018 exhibited significant fluctuations over time. Before 2003, the fluctuations were substantial, while after 2003, they tended to be moderate, as illustrated in Figure 2A-C. Consequently, the research period was divided into two phases: 1995-2003 constituted the first stage, and 2004-2018 comprised the second stage.

From 1995 to 2018, the HHHP's mean annual temperature fluctuated between 11.47 and 13.14 °C, with a multi-year mean of 12.24 °C (Figure 2A). During the first stage, the temperature exhibited an upward trend with an increase rate of 0.045 °C yr^{-1} (p = 0.47). A similar upward trend was observed in the second stage, with an increase rate of 0.044 °C yr^{-1} ($p < 0.10$).

From 1995 to 2018, the solar radiation fluctuated between 147.97 and 171.37 W m^{-2}, with a multi-year average value of 157.82 W m^{-2} (Figure 2B). During the first stage (1995-2003), the solar radiation exhibited significant variability, with the maximum and minimum values recorded. This stage demonstrated a pronounced downward trend in solar radiation, with an overall decrease of −1.41 W m^{-2} yr^{-1} ($p < 0.10$). In the second stage (2004-2018), solar radiation exhibited an upward trend, with a rate of change of 0.11 W m^{-2} yr^{-1} (p = 0.64).

The inter-annual precipitation variation was substantial, fluctuating within the 472.11 to 871.49 mm range. The multi-annual average precipitation was 659.40 mm (Figure 2C). In the first stage, precipitation exhibited regular fluctuations, alternating dry and wet years. The linear regression analysis of precipitation data from 1995 to 2003 indicated a slope of 0.18 mm yr^{-1} (p = 0.99). In the second stage (2004-2018), a discernible downward trend for precipitation was observed, with a change rate of −7.33 mm yr^{-1} ($p < 0.10$).

Spatiotemporal characteristics of climate variables in the HHHP

The majority of the region demonstrated an increase in temperature, with observed trends ranging from −0.06 to 0.09 °C yr^{-1} (Figure 3A). However, the mountainous regions of northeastern Hebei and southwestern Henan, as well as the eastern coastal area of Shandong exhibited

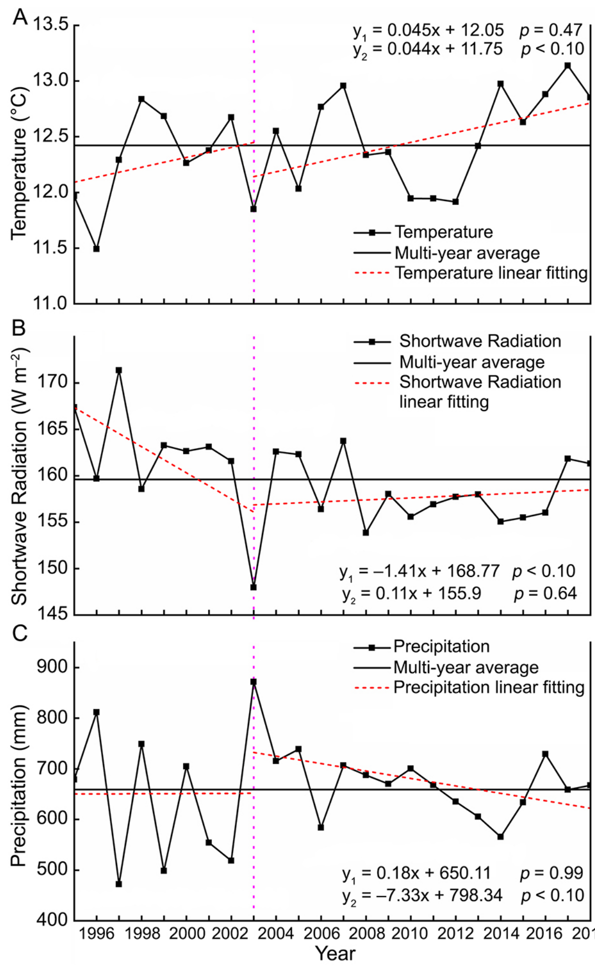

Figure 2 – A) Temporal distribution of temperature, B) shortwave radiation, and C) precipitation in the Huang-Huai-Hai Plain from 1995 to 2018. The dashed line in pink is the dividing line occurring in 2003.

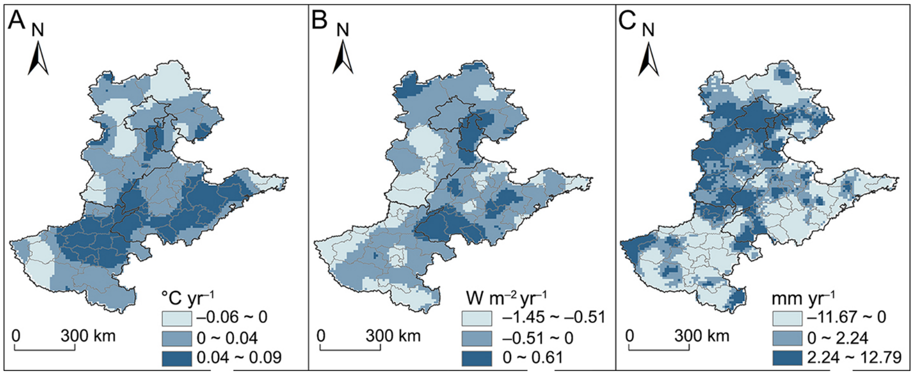

Figure 3 – A) Spatiotemporal change trend of annual temperature, B) shortwave radiation, and C) precipitation in the Huang-Huai-Hai Plain from 1995 to 2018.

a decreasing trend in temperature. The shortwave radiation in most areas of the HHHP (Figure 3B) exhibited a decreasing trend over the study period, with only the following areas showing an increasing trend: Tianjin, Heze, Jining, Zaozhuang, the junction of Weifang, Zibo, and Laiwu, and the northwest of Zhangjiakou. The precipitation trend within the HHHP (Figure 3C) revealed a variation range from –11.67 to 12.79 mm yr^{-1}. The precipitation levels in Hebei Province, Beijing, and Tianjin exhibited an upward trend, while Henan and Shandong Provinces demonstrated a downward trend.

Spatiotemporal patterns of grain yield in the HHHP

Temporal distribution of grain yield in the HHHP

The total food production of the five sub-regions within the HHHP exhibited a consistent upward trend from 1995 to 2018 (Figure 4). The temporal progression of this production can be divided into two distinct phases: a decline phase (1995-2003) and a stable growth phase (2004-2018). In the first stage, grain yield exhibited fluctuations, with a decline observed yearly from 2000 to 2003, reaching its lowest value in 2003. After 2004, grain yield steadily increased, reaching a peak in 2017. Concerning provinces and cities, Henan, Shandong, and Hebei Provinces contributed the most to the total grain production of the HHHP. The trend in grain production in these provinces was consistent with the total grain production in the HHHP. However, the total grain production of Beijing and Tianjin only represented a small fraction of the HHHP's overall output. The food production in Beijing exhibited a fluctuating downward trend, while Tianjin's was unremarkable during the study period.

Spatial characteristics of grain yield in the HHHP

The objective of this study was to investigate the spatial distribution characteristics of food production in the HHHP. To this end, the cities in the region were classified

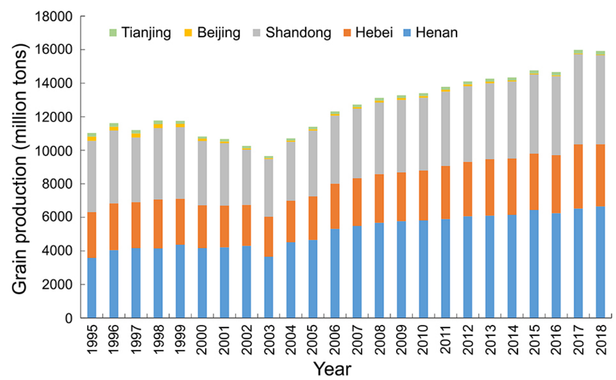

Figure 4 – Temporal change of total grain production in Huang-Huai-Hai Plain from 1995 to 2018.

into six categories based on their grain production. The categories were as follows: less than 1 million tons, 1 to 2 million tons, 2 to 3 million tons, 3 to 4 million tons, 4 to 5 million tons, and more than 5 million tons. This analysis was conducted across six different time points ranging from 1995 to 2018.

A significant spatial variation in grain yield was observed for each city within the HHHP region (Figure 5). The overall trend in grain production increased, transitioning from scattered high-yield cities to concentrated contiguous high-yield areas. Specifically, in 1995, only Weifang and Baoding attained grain yields exceeding 5 million tons. By 2000, this had expanded to include Baoding and Zhoukou. By 2005, the distribution had shifted primarily to Zhoukou and Zhumadian. A notable increase in the number of cities with grain yield exceeding 5 million tons was observed in 2010, including 11 cities such as Baoding, Shijiazhuang, Dezhou, Liaocheng, Weifang, Heze, Shangqiu, Zhoukou, Zhumadian, Nanyang and Xinyang. This development has led to the formation of a region characterized by high grain yield. In 2015, Handan City was added to the list of cities with grain exceeding 5 million tons, while Weifang experienced a decline in yield by one grade. In 2018, compared to 2015, the number of cities with grain output exceeding 5 million tons decreased by one city, reaching ten cities. The distribution of grain yield within the HHHP region reveals a concentration of high-value production areas in the central and southern parts, particularly in the southeast of Henan Province, the south of Hebei Province, and the southwest of Shandong Province. These three provinces form the 'Gong'-shaped region of high-yield production. In contrast, low-yield areas are predominantly situated on the periphery of the HHHP, encompassing the northern part of Hebei Province, Beijing, Tianjin, the central and western parts of Henan Province, and the eastern coastal area of Shandong Province. From 1995 to 2018, the growth of low-yield areas was modest, remaining below 2 million tons.

Influence of climate change on grain yield in the HHHP

Single factor analysis of climate variables on grain yield

Utilizing GeoDetector models was instrumental in elucidating the impact of climatic variables on grain production within the HHHP. The present study's findings indicated that temperature exhibited a significant influence on food production (Table 2). The analysis further delineated the relative explanatory powers of various driving factors on grain yield change. The ranking was as follows: temperature (q = 0.44), shortwave radiation (q = 0.28), and precipitation (q = 0.25). The

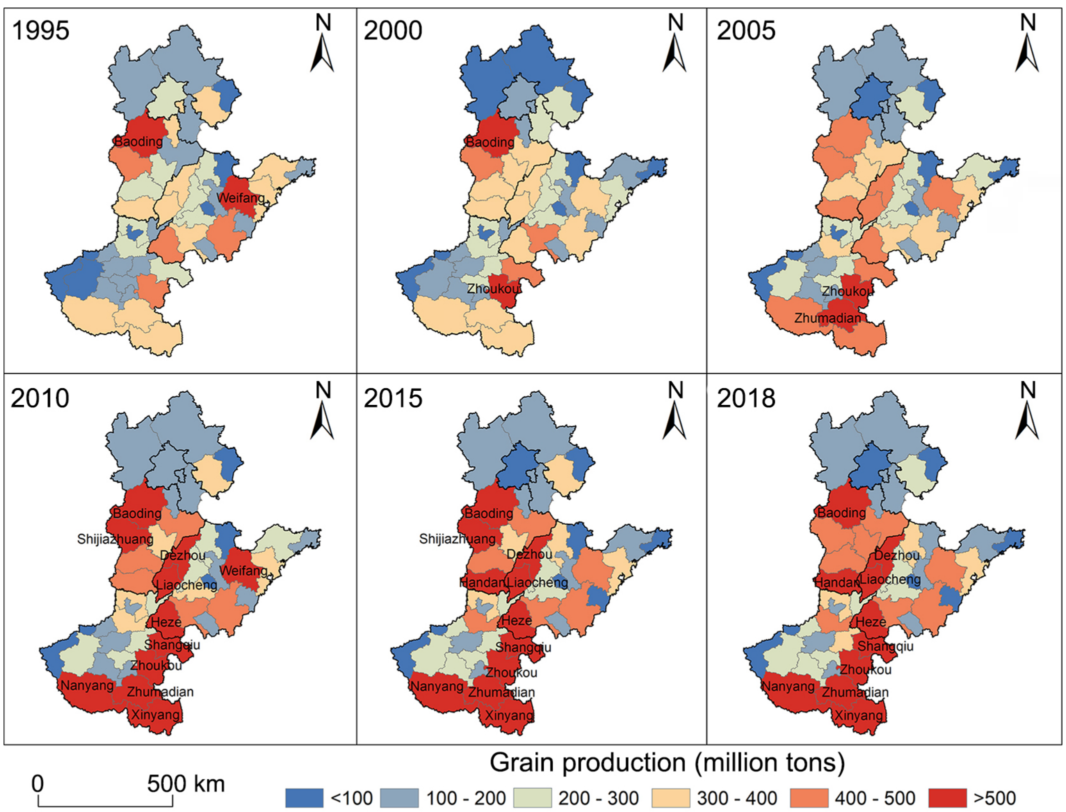

Figure 5 – Spatial distribution of grain production in the Huang-Huai-Hai Plain.

Table 2 – q-statistic between climate variables on grain yield in Huang-Huai-Hai Plain (HHHP) and its sub-regions. The maximum value of q-statistic is highlighted in bold.

Region	Significant	Temperature	Precipitation	Shortwave radiation
HHHP	q-statistic	**0.440**	0.250	0.280
	p-value	0.000	0.000	0.000
Henan	q-statistic	0.570	**0.680**	0.380
	p-value	0.000	0.000	0.000
Hebei	q-statistic	0.750	0.420	**0.760**
	p-value	0.000	0.000	0.000
Shandong	q-statistic	0.360	0.560	**0.710**
	p-value	0.000	0.000	0.000

findings underscore the pivotal function of temperature in modulating grain yield fluctuations within the HHHP, underscoring its paramount importance in understanding the dynamics of agricultural production in this region.

The Henan, Hebei, and Shandong Provinces are the primary regions for grain production within the HHHP region. In Henan Province, precipitation significantly influenced grain yield, indicating a q value of 0.68. The explanatory power values for temperature and shortwave radiation were 0.57 and 0.38, respectively. Conversely, shortwave radiation and temperature exhibited the highest contribution to grain yield in Hebei Province, with q values of 0.76 and 0.75, respectively. Precipitation exhibited a negligible impact on grain yield, with a q value of 0.42. In Shandong Province, shortwave radiation predominantly influenced grain yield, with a q value of 0.71, followed by precipitation (q = 0.56), and temperature (q = 0.36). These findings imply regional differences in the primary factors influencing grain yields within the HHHP region. While precipitation plays a pivotal role in Henan Province, shortwave radiation is the predominant factor affecting grain production in Hebei and Shandong Provinces.

Interaction analysis of climate variables on grain yield

The interaction of multiple climatic variables engenders a high degree of vulnerability in food crops to climate change, with the potential for substantial impact on their growth and development. The positive effects of one or more factors on crop growth may be amplified, weakened, or even offset by other factors (Chou et al., 2019; Lobell and Field, 2007). Consequently, examining the interaction between temperature, precipitation, and shortwave radiation on food production is imperative. The study site demonstrates a nonlinear/bilinear enhanced and a double-factor relationship between grain yield and climate variables, indicating the absence of an independent factor.

The comprehensive interaction matrix encompassing the grain yield and climatic variables within the HHHP and its sub-regions are delineated in Table 3. The outcomes of this study demonstrate that the manifestation of the interaction effect is characterized by bilinear enhancement or nonlinear enhancement, thereby signifying that the interaction of two factors results in an enhancement of grain yield changes. Among the array of interaction pairs, bilinear enhancement interactions are predominantly observed between temperature and precipitation, as well as between shortwave radiation and temperature. Notably, the interaction q values exhibited substantial variation among different interaction pairs and regions. For the entire HHHP, the explanation rates of the interaction between the two variables were as follows: temperature ∩ precipitation (q = 0.67) > shortwave radiation ∩ precipitation (q = 0.66) > shortwave radiation ∩ temperature (q = 0.62). The findings indicated that the interaction between temperature and precipitation significantly influenced food production within the HHHP.

Table 3 – The q-values of the interactive pairs on grain yield. The maximum value of q-value is highlighted in bold.

Interaction factor	HHHP	Henan	Hebei	Shandong
Precipitation ∩ Temperature	**0.67**	0.90	**0.86**	0.75
Precipitation ∩ Shortwave radiation	0.66	0.92	0.84	0.96
Temperature ∩ Shortwave radiation	0.62	**1.00**	0.76	**0.99**

HHHP = Huang-Huai-Hai Plain.

In Henan Province, an investigation was conducted into the interplay between the two variations, resulting in the following rates of explanation: shortwave radiation ∩ temperature (q = 1.00) > shortwave radiation ∩ precipitation (q = 0.92) > precipitation ∩ temperature (q = 0.90). The interplay between shortwave radiation and temperature was found to be a nonlinear enhancement. The most significant impact on the variation of grain yield in Henan Province can be attributed to the interplay between shortwave radiation and temperature, which was different from the dominant factor identified in the univariate analysis of climatic variables affecting grain yield variation in the region. The interaction rate of the three influencing factors was more than 90 %, indicating that food production in Henan Province was greatly affected by shortwave radiation, temperature, precipitation, and the interaction among them. A comparative analysis of the spatial patterns of grain yield and climate variables in Henan Province revealed that regions exhibiting significant increases in grain yield were also characterized by elevated temperatures, decreased shortwave radiation, and reduced precipitation.

In Hebei Province, the explanation rates of the interplay between the two variables were as follows: temperature ∩ precipitation (q = 0.86) > shortwave radiation ∩ precipitation (q = 0.84) > shortwave radiation ∩ temperature (q = 0.76). The interplay between the three variables showed a bivariate enhancement. These findings imply that the interplay between temperature and precipitation strongly affected grain production in Hebei Province. By observing the spatial characteristics of climate variables in the HHHP, it was found that the temperature and precipitation of Hebei Province showed an upward trend.

In Shandong Province, the explanation rates of the interplay between the two variables were as follows: shortwave radiation ∩ temperature (q = 0.99) > shortwave radiation ∩ precipitation (q = 0.96) > precipitation ∩ temperature (q = 0.75), and the interplay between the three variables showed bivariate enhancement. Among the interactions between climatic variables in Shandong Province, shortwave radiation and temperature were the most impactful factors influencing grain yield changes. Spatial analyses of climate variables in the HHHP showed that although precipitation tended to decrease during the study period, Shandong Province, located at the junction of the Yellow, Huai, and Hai rivers, had abundant water resources for irrigation. Agriculture accounted for approximately 70 % of the total water consumption in Shandong Province, where over 50 % of the crop sown area was effectively irrigated, thereby mitigating the drought event caused by reduced precipitation. Consequently, compared to precipitation, shortwave radiation and temperature had a more pronounced impact on grain production in this region.

Sensitivity analysis of grain yield to changes in the cropland area

Significant changes in the cultivated land area have exacerbated climate change's impact on food production in the region. Since the initiation of the reform and opening-up policies, there has been a considerable loss of cultivated land resources in the region (Peng et al., 2020). In addition, studies have shown that the sensitivity of food production to changes in arable land has been increasing over time (Wang et al., 2022b). The region has experienced mounting pressure from population growth and increased grain consumption, further exacerbating land degradation (Li et al., 2022a). Ensuring sufficient cultivated land is imperative to maintain adequate food production, as China's grain output is significantly influenced by the area dedicated to cultivation (Wang and Cheng, 2022). The use of sensitivity evaluation models to assess the impact of changes in cultivated land on grain yield is illustrated in Figure 6. From 1995 to 2018, we found that the sensitivity of grain production to changes in arable land was high in four cities, namely Zhangjiakou, Sanmenxia, Luoyang, and Jiaozuo. Among the remaining cities, Xingtai, Handan, Jiyuan, and Luohe exhibited moderate sensitivity, while 34 cities showed low sensitivity. The analysis revealed that 87.5 % of the cities in the HHHP demonstrated sensitivity to changes in arable land. The cities demonstrating high sensitivity were predominantly located in the western mountainous and hilly regions of the HHHP, which are distinguished by substantial undulations, severe soil erosion, limited arable land, deficient farmland infrastructure, and diminished comprehensive production capacity. Minor changes in cultivated land within this region can result in fluctuations in grain production, underscoring the imperative for safeguarding arable land and implementing effective management strategies for grain bases in high-sensitivity areas. Achieving this objective necessitates the strict implementation of the "occupation-compensation balance" policy in conjunction with the overarching goal of preserving cropland and ensuring long-term food security.

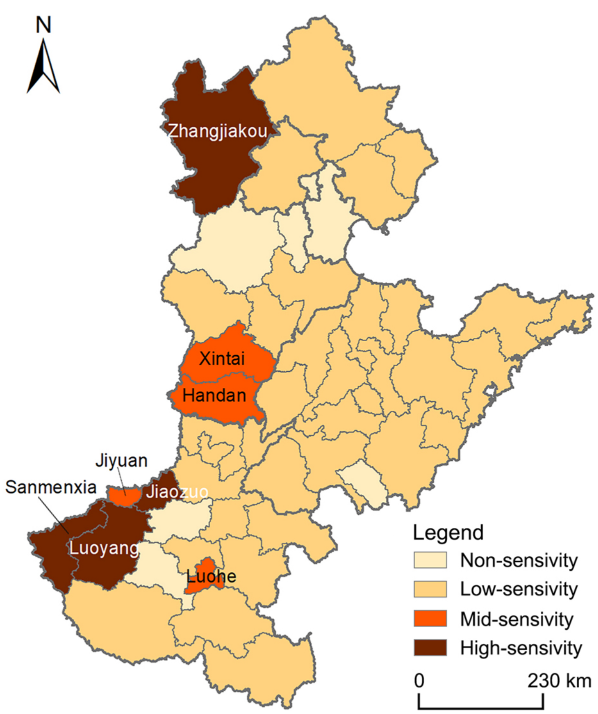

Figure 6 – Spatial distribution of sensitivity of grain yield to cultivated land area in the Huang-Huai-Hai Plain.

Discussion

A single-factor analysis determined the primary climate variables affecting grain yield in the HHHP (Table 2). The results indicated that temperature was the predominant factor, with an overall increasing trend observed across most regions of the HHHP, except for the western and northern mountainous regions. These findings are consistent with previous studies (Li et al., 2022b). A single-factor analysis conducted in Henan Province, a major grain-producing province located in the low altitudes of the HHHP, revealed that precipitation had the greatest impact on grain yields. Henan Province is greatly influenced by the monsoon climate, experiencing frequent droughts and floods. In 2003, precipitation levels exceeded the annual average, reaching the highest value during the study period. The 2003 flood triggered by a rainstorm, caused significant crop failure in Henan Province (Guo et al., 2019). Single-factor analyses conducted in Hebei and Shandong Provinces indicated that shortwave radiation was the most substantial explanatory factor for grain yield. The impact of on grain yield is predominantly attributed to its role in facilitating photosynthesis, thereby influencing the growth and quality of grain crops. Hebei and Shandong are in a temperate monsoon climate city characterized by abundant light and heat conditions, leading to more sunny days during crop growth periods. This results in an increased intensity of shortwave radiation received by the soil. This phenomenon has been previously documented in studies conducted in the HHHP region (Tang and Liu, 2021).

An inflection point in the time series distribution of grain yield was observed in the HHHP region in 2003 (Figure 4). Before 2003, grain yield exhibited instability;

however, after 2003, it rapidly increased. In 2003, grain yield was markedly lower than in other years, coinciding with outlier climate variables. From 1995 to 2003, temperature, precipitation, and shortwave radiation exhibited significant fluctuations, with 2003 recording the lowest temperatures and shortwave radiation, and precipitation reaching its highest level during that same period. The observed change in consistency between climate variables and grain yield in 2003 underscores the substantial impact of climatic variables on grain production in the HHHP region. Previous studies have shown that meteorological disasters in the HHHP region reached their peak in 2003 compared to previous years (Wang et al., 2022a). From June to Oct 2003, the Huang-Huai area experienced frequent floods that disrupted light and heat, directly impacting the maturation and harvest of summer grain. Furthermore, the floods delayed in the autumn sowing and harvest, which ultimately resulted in a record-low grain yield in the HHHP region for that year (Li and Lei, 2022). In conclusion, it is evident that climate change, particularly manifested through extreme weather events such as the heavy precipitation in 2003, exerted a substantial influence on grain yield within the HHHP region.

Regarding the role of climate factors in determining grain yield, this study posits that temperature emerges as the predominant factor influencing grain production within the HHHP. This notion finds substantiation in the observed uncertainty in crop yields in irrigated regions attributable to temperature fluctuations (Sun and Wang, 2024). Previous studies further corroborate the notion that temperature exerts a substantial influence on the potential for grain production in China (Li et al., 2020). However, other regions exhibit different responses of temperature variations regarding grain production. For instance, rising temperatures in Turkey had a negative effect on wheat production, whereas higher temperatures in Bangladesh reduced rice yields (Chandio et al., 2021; Sarker et al., 2014). Consequently, the strategy to prevent a decline in grain yield in the context of future temperature increases should be the selection of less sensitive varieties to temperature fluctuations (Zhang et al., 2022).

Sensitivity analysis indicated that cropland area was a significant factor influencing grain yield in the HHHP, in addition to climate variables (Figure 6). The reduction of cropland area has been identified as a significant factor impacting crop yields, even when considering the influence of climate conditions on food production (Liu et al., 2015). A notable example is the impact of changes in cropland area on grain production in 18 municipalities downstream of the Yellow River in China (Wang and Cheng, 2022). A similar relationship has been observed in Brazil, where cropland expansion has been linked to a significant increase in soybean and corn production (Xu et al., 2021). Previous research consistently demonstrates a strong correlation between cropland fluctuations and crop yield changes. Consequently, to ensure a country's food security, consideration must be given to both climate variables and the preservation of cropland areas.

The intricate relationship between climate variables and grain yield has promoted the development of two primary methodologies: crop growth models and statistical methods. Climate change has the potential to impact various stages of crop growth, leading to an increased focus on simulating its effects on crop growth mechanisms. Previous studies have projected the impact of climate change on crop yields, employing diverse crop models, such as the CROPGRO model (Antolin et al., 2021; Silva et al., 2021), the LPJmL model (Fei et al., 2023), and the World Food Studies (WOFOST) crop model (Siatwiinda et al., 2021). However, the response of different crops to climate change varies significantly. For instance, projections in the Banas River Basin, suggest an increase in wheat, barley, and corn yields under future climate change conditions (Dubey and Sharma, 2018). Conversely, using the WOFOST crop model suggests a potential decline in maize yields in the Zambia region under the Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 scenarios (Siatwiinda et al., 2021). The inherent complexity of crop growth environments, coupled with the uncertainty surrounding climate change predictions, poses significant challenges in anticipating the impact on grain production. These include climate forecasts, crop model parameters, and crop model structures (Tao et al., 2020; Wallach et al., 2017). These factors can contribute to the inaccuracy of forecast results. Consequently, the analysis of climate change on grain yield by crop models is crucial for the development of effective adaptations to cope with future climate risks. However, the existing crop models' predictions regarding the influence of climate change differ substantially (Tao et al., 2020).

The relationship between climate variables and crop yields can be explored using traditional statistical methods, except crop models. These statistical methods, including the geographical detector model (Chou et al., 2019) and the geographically weighted regression model (Yao et al., 2023), are favored by scholars due to their advantages of data availability and simplicity of models. The geographical detector model method revealed a more pronounced impact of climate change in the southwest than in northeast China (Chou et al., 2019). However, the multi-scale geographically weighted regression method (Yao et al., 2023) is more localized and less extensive in analyzing the impact of temperature change, drought, and COVID-19 pandemic on crops. Consequently, the utilization of statistical methods for quantitative assessments of the impact of climate change on grain yield remains a viable approach.

Research into the impacts of climate change on food production is imperative for the development of effective disaster prevention and mitigation strategies in the context of climate change, as well as for ensuring food security. While climate variables significantly influence grain yield, they are not the sole determining factors. Farming technology and mechanization levels also affect grain yield. Therefore, it is recommended that future studies incorporate socio-economic factors alongside climate variables for a comprehensive analysis utilizing complex mechanistic models.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (NSFC, U21A2014 and 41701503) and Natural Science Foundation of Henan Province (232300420160).

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Conceptualization: Cao Y, Huang X. **Data curation**: Huang X, Cao Y, Cui M, Li Q. **Formal analysis**: Huang X, Cao Y. **Founding acquisition**: Cao Y. **Investigation**: Huang X, Cui M. **Methodology**: Cao Y, Li Q, Huang X. **Project administration**: Cao Y. **Resources**: Cao Y. **Supervision**: Cao Y. **Writing-original draft**: Huang X, Cao Y. **Writing-review & editing**: Huang X, Cao Y, Cui M, Li Q.

Conflict of interest

The authors declare no conflict of interest.

Data availability statement

The data supporting this study's findings are available upon reasonable request to the corresponding author.

Declaration of use of AI Technologies

Artificial intelligence (AI) technologies were not used.

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