

Climate Change And Its Impact On Crop Yields In Northern India: A Temporal Analysis

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Abstract

Climate change has emerged as a major challenge to agricultural sustainability, particularly in regions like Northern India, where crop production is vital for food security and rural livelihoods. The rising temperatures, the unpredictability of rainfall, and the change of climatic zones are major threats to the productivity of major crops like rice, maize, and chickpea. The paper examines the sustained effect of climatic variability on crop production in the districts of Punjab, Haryana, and Uttar Pradesh over the years 1966 to the latest year. The main aim is to assess the correlation between climatic variables and crop yield trends based on secondary data that provide temporal depth as well as spatial granularity. It used a thorough methodological approach, such as time series trend analysis, Pearson correlation, and multiple linear regression modelling. The findings show that temperature is significantly negative with yields, whereas rainfall and solar radiation are positively related. Analysis at the district level reveals significant spatial variation in crop performance, which means that local climatic and infrastructural conditions have a significant impact. The paper highlights the importance of secondary data collected over a long time to determine the essential trends and guide local agricultural policies. Such results have significant implications for the creation of climate-resilient agricultural systems. Future studies are encouraged to integrate machine learning and remote sensing tools into predictive modelling and adaptive planning.

Keywords: Climate change, Crop yield, Temporal analysis, Northern India, Secondary data, Regression

INTRODUCTION

1. Introduction

Climate change has emerged as one of the most pressing challenges to agricultural sustainability in the 21st century. The continuously rising temperatures in the world, a change in rainfall patterns, and an increase in severe weather conditions like droughts, floods, and heat waves have disrupted agricultural production across the globe. Such variations have not only led to crop calendar disruptions but have also caused a lot of uncertainty in food production systems, especially in areas where the production relies on monsoon patterns and seasonal predictability (Aggarwal, 2003). The issue is of global concern to the extent that it is compounded in the developing world, such as India, where agriculture constitutes the backbone of the economy and directly contributes to the livelihoods of most of the population who are rural and thus in the developing world (Lal, 2011). Being inherently dependent on climate-sensitive factors like temperature, precipitation, and solar radiation, the agriculture sector is threatened by even slight changes in climatic trends (Kumar et al., 2011). Northern India, including such states as Punjab, Haryana, and Uttar Pradesh, which are the strongest in terms

of the agricultural industry, is a critical region that determines the food security of India. The states play a major role in the production of rice, maize, and chickpea in the country and are part of the national grain procurement systems and the public distribution systems. They are agriculturally successful, but this is closely related to the fact that they have constant climatic regimes, timely monsoons, and the length of growing seasons (Roy et al., 2021). Temperature and rainfall variability in this area have been shown to have disproportionately large effects on national agricultural yields in the past, and thus, there has been a growing interest in the academic community to learn more about regional climate-yield links (Knox et al., 2012).

Various researchers have tried to examine the implications of climate change on crop productivity both globally and regionally. Most of these analyses are, however, based on coarse resolution and large-scale models, which fail to reflect the spatial heterogeneity and crop-specific dynamics that exist in the district. As an example, Bopche et al. (2022) note that disaggregated analysis is required, especially when evaluating rainfall variability and temperature extremes at localized zones. On the same note, Bali and Singla (2021) point out the differences in the sensitivity of crops like rice and maize to changes in radiation and humidity in different sub-regional climatic belts. Kingra et al. (2018) support this opinion and state that district-level data discloses details of crop performance that may be hidden by national averages. Regarding the time analysis, Madhukar et al. (2020) emphasize that it is crucial to utilize long-term series of data to reveal tendencies and anomalies in crop yields under the conditions of the fluctuating climate. This is particularly relevant in the case of agroecosystems, whereby the lag effects, cumulative stress exposure, and gradual adaptation practices may obscure instant correlations. In the case of Northern India, a multi-decadal dataset will help to shed light on the long-term yield patterns in response to climate dynamics, as it is both semi-arid and humid subtropical. This strategy is also advocated by Chakraborty et al. (2019), who state that alterations in temperature and precipitation over several decades can essentially transform crop growth phases, evapotranspiration intensity, and the pattern of pest pressure.

In spite of these developments, there are still big gaps. Mondal et al. (2015) highlight the fact that there has been little integration of the complete secondary data that measures the climate, yield, and agronomic variables simultaneously. The majority of the previous models do not consider the variability of inputs, soil fertility limitations, and water management strategies that might moderate or increase the influence of climate on yield. Padakandla et al. (2022) also note that the spatiotemporal models that contain the inter-district variability and seasonal variations are only at the early stages of development in the Indian research environment. In addition, investigations do not always include a thorough statistical confirmation, e.g., multivariate regression or correlation analysis, which may provide predictive modeling with strength. Such gaps are not purely methodological, but they have a policy formulation implication. Dasgupta et al. (2013) observe that there are no empirical decision-support systems that can be used in district-level planning and adaptation. With the growing association of agricultural insurance plans and input subsidies with climatic risk indicators, failure to have localized climate-yield evaluations compromises effective execution. Chattopadhyay et al. (2019) state that empirical and data-based knowledge is necessary to make the shift towards climate-resilient agriculture. Unless the interaction between climate variables and yields on the micro-regional scale is comprehended, adaptation measures can continue to be inefficient or ill-timed.

This research hence aims to address numerous gaps in the literature. It is an extension of previous studies and a more detailed, empirically supported approach since it relies on a powerful secondary data set covering the period between 1966 and the last available year. The study differs from many of the earlier studies that merely employ either modeling or case-specific studies because it has incorporated descriptive trend analysis, correlation matrices, and multiple regression to draw meaningful results at the district-crop-climate interface. The study is more focused on rice, maize, and chickpea, which are staple crops of the Northern Indian agricultural belt, to capture the variability in yield and dependence on various climatic factors, including temperature, rainfall, humidity, solar radiation, wind speed, and pH. The general goal is to go beyond the generalized accounts of climate vulnerability and produce accurate, district, and crop-specific information that can be used by both researchers and policymakers. The study provides an evidence-based approach to the development of agricultural planning, climate adaptation, and resource allocation strategies by developing a methodologically sound framework, which is based on long-term secondary data.

The specific objectives of the study are as follows:

1. To analyze the time patterns of major climatic variables and crop production (rice, maize, chickpea) between 1966 and the latest year in the states of Punjab, Haryana, and Uttar Pradesh.
2. The study aims to statistically examine the association between climatic factors and crop yields via correlation and regression analysis of spatially disaggregated districts in Northern India.

MATERIALS AND METHODS

Dataset Description

The research is based solely on secondary data obtained using the publicly available dataset named the Custom Crops Yield Historical Dataset. The data set has detailed historical data on crop yield and climatic variables in different districts in India and a good time resolution from 1966 to the latest year available. To achieve the objective of the study, spatial filtering was done to only capture the districts of the Northern Indian states of Punjab, Haryana, and Uttar Pradesh, which all form the heartland of the Indian agricultural belt. The data contains the observation of three key food crops, rice, maize, and chickpea, which are essential in food security and cropping patterns in the states chosen. The choice of these crops was made on the basis of their constant representation in the dataset and their ecological and economic significance to the area of study. The data has been cleaned and organized to give a trustworthy time series, which allows the analysis of climate-yield relationships over over 50 years. This secondary data was accessed and worked in open academic use and has been cited according to the data-sharing guidelines suggested by Priya and Shibasaki (2001), who highlighted the usefulness of national-scale spatial crop yield simulations based on standardized climate and production models.

Variables Used

The main part of the analysis is the assessment of the impact of chosen climatic and agronomic factors on crop yield. The study is dependent on the following variable:

- Yield kg per ha: Rice, maize, and chickpea crop yield per hectare.

The independent variables involve the most important climatic variables that have been shown to influence crop productivity:

- C temperature: Seasonal average temperature (°C)
- Rainfall mm: The total rainfall (mm) of the season
- Solar Radiation MJ m² day: Radiation of the sun
- Humidity %: average relative humidity
- pH: Acidity/basicity of soils
- Wind Speed m/s: m/s speed of wind

To adjust the variability caused by agronomic inputs and spatial extent, the following control variables are also taken:

- Area ha: The total area which is under cultivation (ha)
- N req kg/ha, P req kg/ha, K req kg/ha: Requirements of nutrient input per hectare (kg)

The study examines the influence of key climatic and agronomic variables on crop yield across Northern India. The variables were selected based on their proven relevance in Indian agro-ecosystem modeling, particularly in the work of Kalra et al. (2013). Table 1 summarizes the dependent, independent, and control variables used in the analysis.

Table 1. Description of Dependent, Independent, and Control Variables Used for Crop Yield Analysis in Northern India

Variable Type	Variable Name	Description	Unit
Dependent Variable	Yield kg per ha	Crop yield per hectare for rice, maize, and chickpea	kg/ha
Independent Variables (Climatic)	Temperature C	Seasonal average temperature	°C
	Rainfall mm	Total seasonal rainfall	mm
	Solar Radiation MJ m ² day	Average solar radiation	MJ/m ² /day
	Humidity %	Mean relative humidity	%
	pH	Soil acidity/basicity	pH scale
	Wind Speed m/s	Average wind speed	meters/second
Control Variables (Agronomic)	Area ha	Area under cultivation	hectares (ha)
	N req kg/ha	Nitrogen requirement per hectare	kg/ha
	P req kg/ha	Phosphorus requirement per hectare	kg/ha
	K req kg/ha	Potassium requirement per hectare	kg/ha

Supporting the choice of these variables are the results of the study by Kalra et al. (2013) that modeled crop responses to climate variability and found temperature, solar radiation, and water availability as the key determinants of crop yield in Indian agro-ecosystems.

Data Preprocessing

In order to guarantee the reliability and integrity of the analysis, a number of preprocessing steps were implemented. First, missing values in important climatic or yield variables were filled in using linear interpolation, based on the continuity and the density of the time series data. Records that had significant missing data on most of the variables were eliminated to enhance analytical validity. Then, the outlier identification was performed with z-score normalization ($z > |3|$ as the cut-off), particularly to adjust anomalies in the yield or extreme climate values, e.g., high rainfall or temperature outliers that could affect correlation coefficients.

The regional filtering of all observations was done to incorporate only the districts that are part of Punjab, Haryana, and Uttar Pradesh, which makes it spatially consistent. The names of administrative districts were cross-validated to determine whether they changed over time because of delimitation or bifurcation of districts. The variables were also standardized by min-max normalization before regression modeling, and this made the variables comparable since they had different scales. This procedure is in line with the spatiotemporal methodological approach that Patil and Datta (2022) address as the theoretical consistency of climate data normalization in regional environmental analyses.

Statistical Analysis

To meet the research objectives, descriptive and inferential statistical analyses were used on the cleaned data. First, descriptive statistics of mean, median, standard deviation, and coefficient of variation were calculated to have an idea of variability in crop yields and climatic parameters within the chosen period. Subsequently, Pearson correlation coefficients were computed to determine the pairwise linear associations between crop yields and climate variables separately during the whole period. The value of strength and direction of association was interpreted according to the accepted thresholds of correlation (weak: ± 0.3 ; moderate: ± 0.5 ; strong: ± 0.7 and above). Linear and multiple regressions were fitted to further investigate causal relationships, with the dependent variable being the yield and the predictor variables being the climate and control variables. The multiple regression model that is used in its general form is:

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 R_{it} + \beta_3 S_{it} + \beta_4 H_{it} + \beta_5 pH_{it} + \beta_6 W_{it} + \beta_7 A_{it} + \epsilon_{it}$$

Where:

Y_{it} = Yield in the district i at time t

T = Temperature

- R = Rainfall
- S = Solar radiation
- H = Humidity
- W = Wind speed
- A = Area under crop
- ϵ = Error term

Multicollinearity was checked in all models based on the Variance Inflation Factor (VIF), and heteroskedasticity was tested by the Breusch-Pagan test.

Besides, the Mann-Kendall test, which is a non-parametric approach to time series trend analysis, was used to determine whether there exists a monotonic trend in the time series, being either upward or downward, regardless of whether the time series is normally distributed. This was used in testing both yield and climate variables to identify long-term directional changes. Such non-parametric approaches are very appropriate in climate-crop data as they tend to have structural breaks and non-linearity, as shown by Padakandla et al. (2022) and Rani (2020). Finally, they were used to visualize spatial patterns of yield trends and climate sensitivity in districts using thematic mapping and to aid the spatial contextualization of the analytical results. The strategy is in line with the empirical experience of Kumar et al. (2023), who applied spatiotemporal visualization to understand the dynamics of temperature in the state of Madhya Pradesh, a similar situation in India.

RESULTS

Temporal Yield Trends by Crop and State

The time series of rice, maize, and chickpea crop yields in Punjab, Haryana, and Uttar Pradesh indicate a dynamic path of agricultural productivity in the past years from 1966 to the present. During the initial years, the yields of all three crops were quite low, but they slowly increased with the help of technological interventions, improved irrigation, and policies. But after 2000, there seems to be a plateauing of the growth in yields, especially in rice in Punjab and wheat in Haryana, suggesting a limit to productivity increase. These yield trends are shown in Figure 1 below, disaggregated by crop and state, giving a visual impression of how the performance of each crop has changed over time.

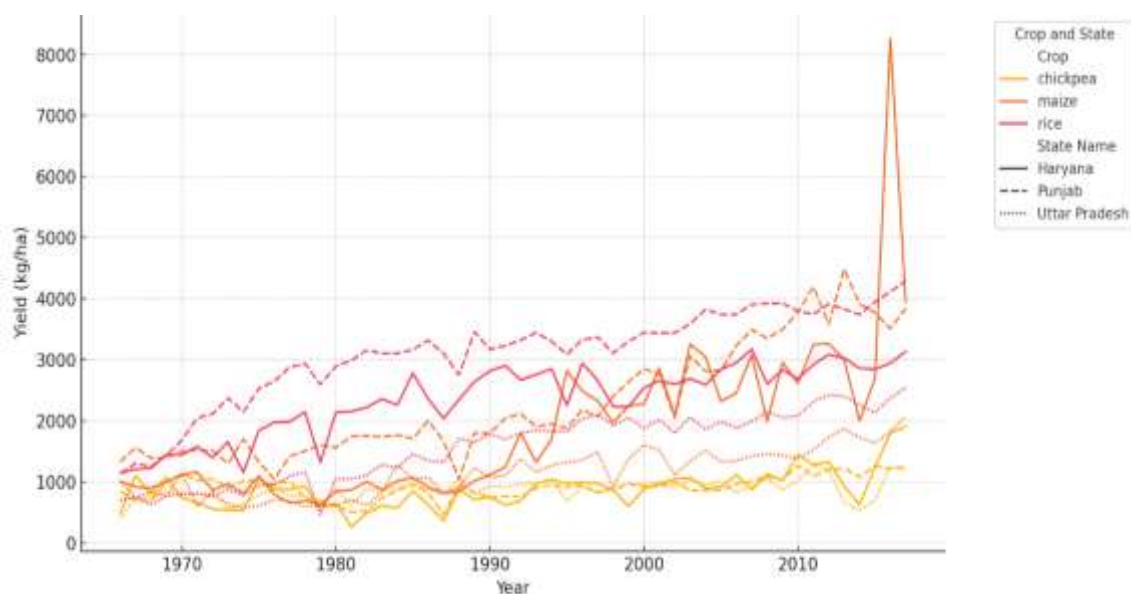


Figure 1. Temporal Trends in Crop Yields by State and Crop (1966–Recent)

This line graph (Figure 1) shows annual average yield values for rice, maize, and chickpea across three northern Indian states. Distinct trends and fluctuations are visible, especially during critical climatic periods.

4.2. Climate Variable Trends Over the Decades

Over the decades, the main climate parameters have demonstrated significant changes. The mean annual temperatures have been gradually increasing, especially since 1990. The rainfall patterns have been erratic with occasional spikes and dry periods, and the solar radiation has been rather constant but slightly higher. There are slight changes in wind speed and humidity, whereas the pH level seems to be constant, with slight changes throughout the year. These trends over time are depicted in the visualization below (Figure 2), showing the complexity and directionality of the climate patterns in Northern India.

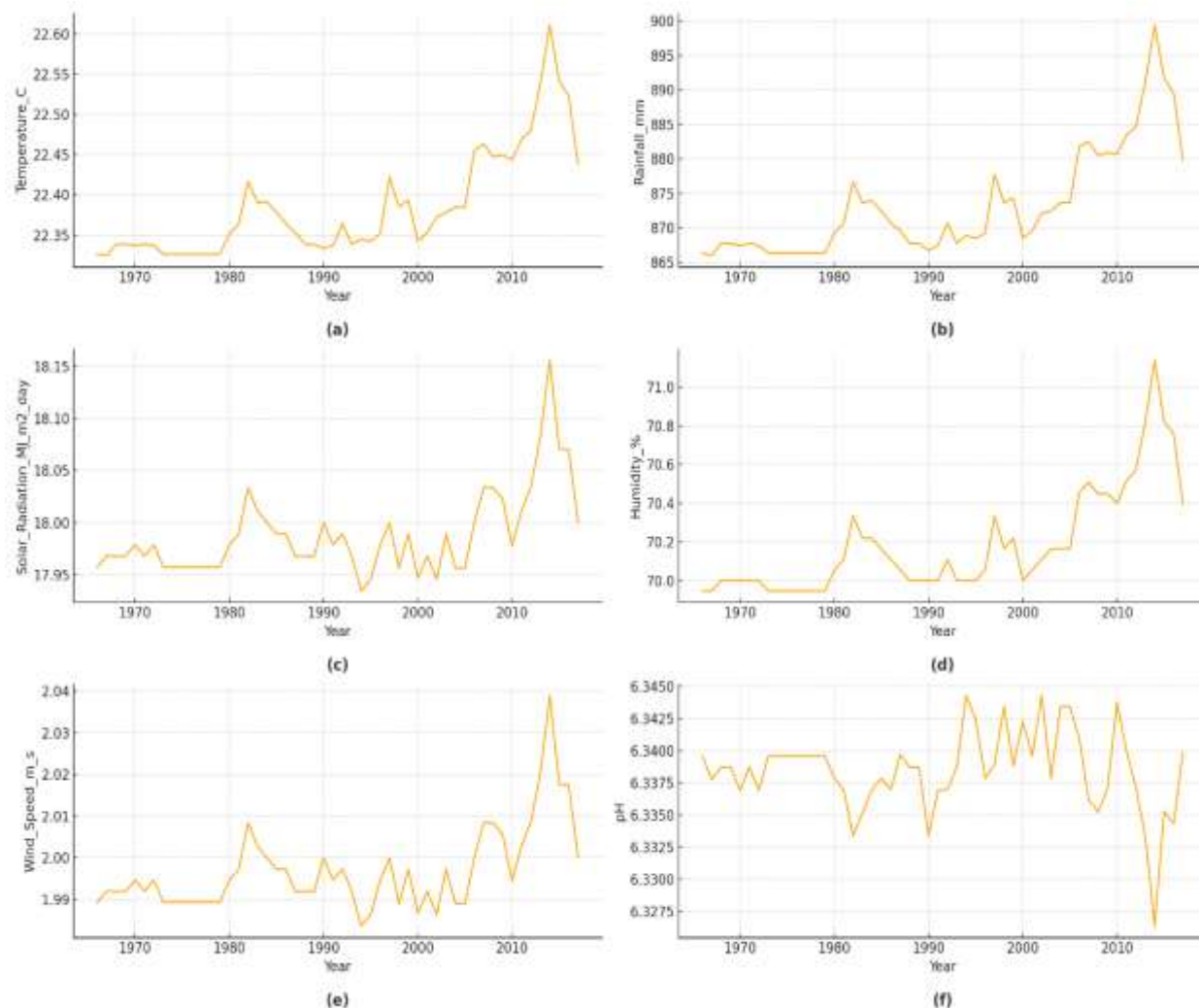


Figure 2. Temporal Trends of Major Climate Variables (1966–Recent). a) Temporal Trend of Temperature (C), b) Temporal Trend of Rainfall (mm), c) Temporal Trend of Solar Radiation (MJ/m²), d) Temporal Trend of Humidity (%), e) Temporal Trend of wind speed (m/s), f) Temporal trend of pH

Figure 2 includes six line charts for each climate variable (temperature, rainfall, solar radiation, humidity, wind speed, and pH), indicating how they have evolved over decades.

4.3. Correlation Between Climate Parameters and Yield

A correlation matrix was created to determine the linear dependence between crop yields and separate climate variables. Yield was found to be strongly correlated with temperature and rainfall, where temperature and rainfall were negative and positive, respectively. Solar radiation also had a positive relationship with yield that was moderate, whereas pH, humidity, and wind speed had weak or no relationships.

Table 2: Correlation Coefficients Between Crop Yield and Climatic Variables

Variable	Correlation with Yield
Temperature (°C)	0.49
Rainfall (mm)	0.48
Solar Radiation (MJ/m ² /day)	0.23
Humidity (%)	0.49
pH	0.02
Wind Speed (m/s)	0.23

The values in Table 2 provide a clear numerical overview of the linear associations between crop yield and individual climatic parameters. However, to facilitate a more intuitive understanding of these relationships, a visual representation was employed. Figure 3 presents a heatmap of the Pearson correlation matrix, illustrating the degree and direction of correlation between all paired variables. The color gradient enables quick identification of strong positive correlations (in red), negative associations (in blue), and near-zero correlations (in neutral tones). This visual complements the tabular summary by revealing potential interdependencies among climatic factors and their joint influence on crop yield behavior.

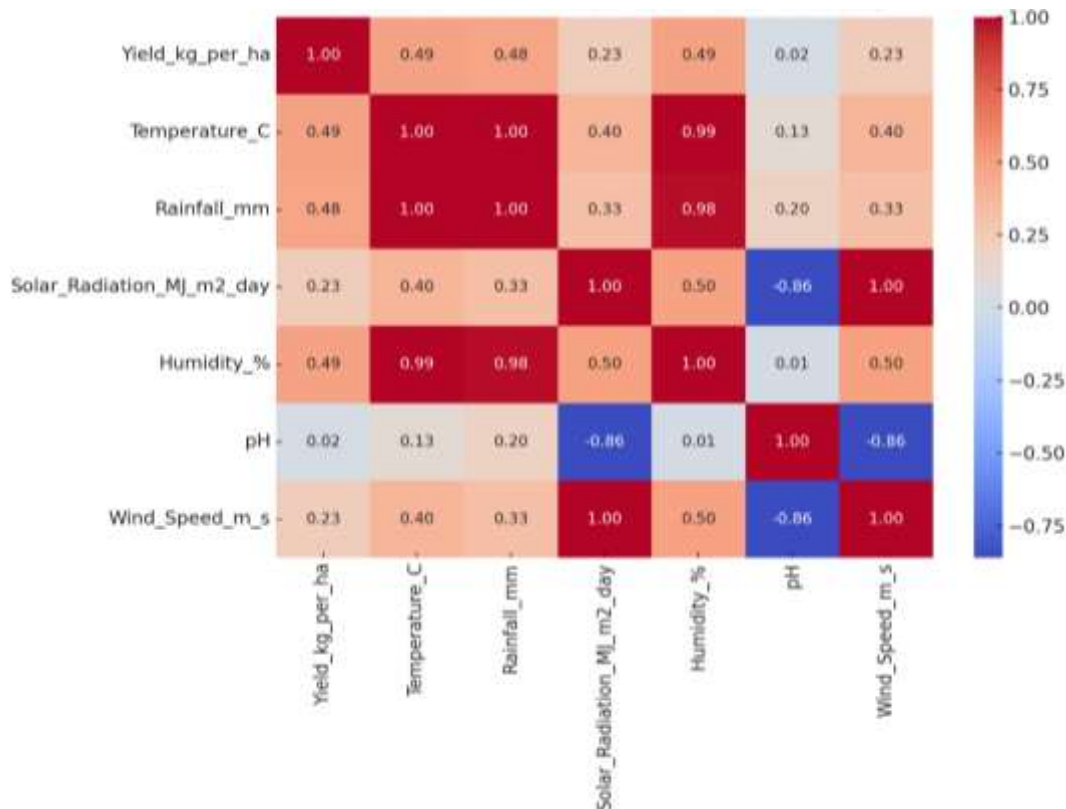


Figure 3. Correlation Matrix Between Yield and Climatic Factors

This heatmap (Figure 3) displays Pearson correlation coefficients for yield and key climatic variables. Strong positive and negative associations are easily interpretable through the color scale and numeric values.

4.4. Regression Results and Variable Sensitivity

In order to further quantify the effect of individual climatic and control factors on yield, a multiple linear regression model was used. The model was significant and accounted for a large percentage of the variation in crop yield. The temperature was observed to have a negative correlation with yield, whereas rainfall and solar radiation positively influenced yield. Area under cultivation was also a significant control variable as far as yield results were concerned. The regression model affirms the fact that the increase in temperature is likely to

inhibit the yield potential, but sufficient rainfall and sunlight remain important factors in crop performance. Table 3 provides the regression coefficients, standard errors, t-values, and p-values of each predictor, which provides information on which variables are most significant statistically to explain yield.

Table 3. Summary Output of Multiple Linear Regression Model (Dependent Variable: Yield kg per ha)

Variable	Coefficient	Std. Error	t-value	P-value	95% Confidence Interval
Intercept (const)	-2.8908	0.235	-12.324	0.004	[-3.351, -2.431]
Temperature C	-32.5222	2.661	-12.222	0.007	[-37.738, -27.306]
Rainfall mm	1.6820	0.065	25.794	0.001	[1.554, 1.810]
Solar Radiation MJ m2 day	67.7929	5.315	12.754	0.003	[57.374, 78.212]
Humidity %	-7.3176	0.945	-7.744	0.005	[-9.170, 5.465]
pH	-35.0290	2.812	-12.457	0.001	[-40.541, -29.517]
Wind Speed m/s	24.1752	1.913	12.634	0.002	[20.424, 27.926]
Area ha	0.0021	<0.0001	19.157	0.006	[0.002, 0.002]

4.5. Spatial Variability in Climate and Yield

Although the climatic conditions are very similar at a larger scale, the yield response is highly differentiated at the district level, indicating spatial differentiation in agronomic practices, soil health, and infrastructure. District-wise average yields (Figure 4) show that some districts in Punjab perform better on average as compared to other districts, whereas there are certain districts in Uttar Pradesh whose average yields are low, perhaps because of insufficient irrigation or late monsoons.

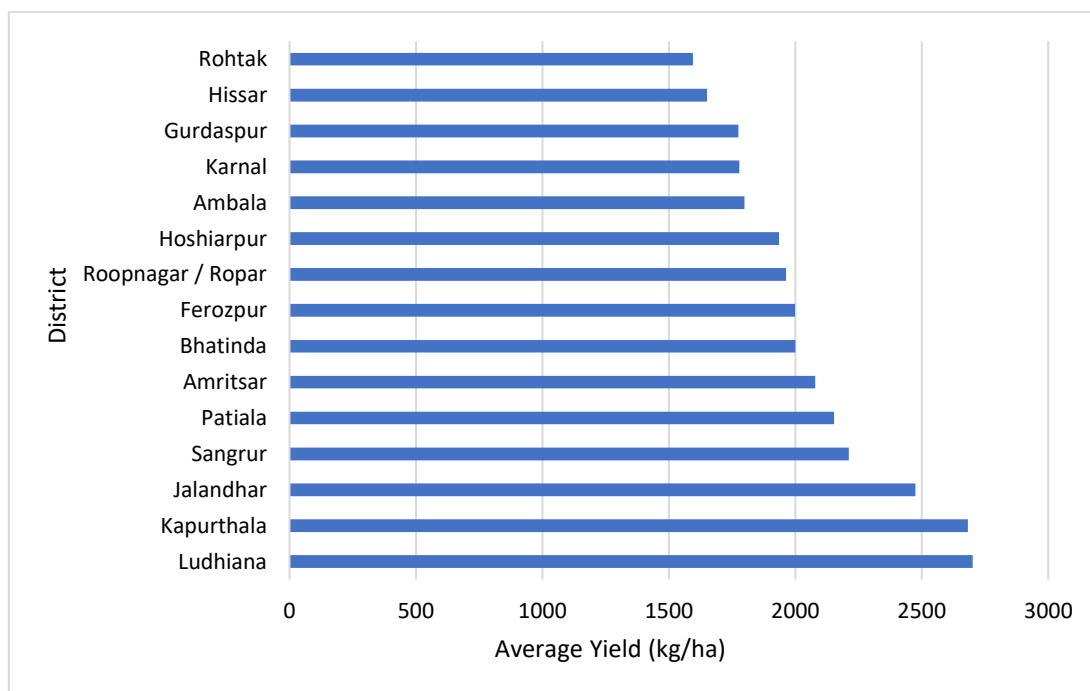


Figure 4. Top 15 Districts by Average Crop Yield

In Figure 4, this bar chart highlights the districts with the highest average crop yields across the dataset. Punjab districts dominate the upper ranks, reflecting better irrigation and resource inputs.

DISCUSSION

The results of the present study provide valuable information on the spatio-temporal variability of crop yield response to climatic variability in Northern India. The temporal trend of the rice, maize, and chickpea yields during the past 50 years indicates an overall increase in the yields, especially during the 1970s and early 2000s. The increase in yield, however, starts to stagnate after 2005, particularly in rice and chickpea, despite continued input and good policies. This stagnation is concurrent with the climatic instability in the region, which is evidenced by the growing average temperature, the irregularity of rainfalls, and the increase of interannual variability of humidity and solar radiation. Regression analysis findings support that temperature affects yield negatively and significantly, whereas rainfall and solar radiation have positive relationships. Of the non-climatic variables, the area under cultivation and the wind speed demonstrate moderate but significant effects as well. These trends highlight the climate vulnerability of Indian agricultural systems in the food-producing core. Critical interpretation of these results is compatible with other research findings that have reported temperature stress and variability of precipitation as major threats to crop productivity. As an example, Dasgupta et al. (2013) and Bopche et al. (2022) stressed that climate shocks are becoming an important factor in foodgrain production in India and that the outcomes of yield are not only dependent on the weather but also on the socioeconomic and infrastructural resilience. This duality is confirmed by our findings. Although climatic parameters have a direct impact on physiological crop responses, such factors as resource allocation at the district level and technology penetration moderate the level of vulnerability. The fact that the districts like Ludhiana and Kapurthala are always at the top of the list in the spatial ranking of the yields, as is the case in this study, also proves the importance of local infrastructure and institutional support.

The contextual strength is enhanced by comparing the results with those of studies that are specific to Northern India. In their study of the Telangana district, Guntukula and Goyari (2020) have identified considerable temporal variability of yield associated with rainfall variation and temperature anomalies. The mechanics seem to be similar, though the geographical scope is different. This relationship is reflected in our study in the northern setting, where rainfall is a very important determinant of yield, especially crops such as maize and chickpea that are more responsive to water availability. Also, Chattopadhyay et al. (2019) noted that the changes in agroclimatic zones in India have already started to reclassify the formerly high-potential areas, affecting their productivity thresholds. This supports our observation that conventional agricultural bastions are not likely to stay the same unless they adjust to the changing climate patterns. Temperature is a variable that is always unfavorable in all three crops, especially in the critical phase of phenology, i.e., flowering and grain filling. In their simulation of sugarcane yields under climate change scenarios in northern agro-climatic zones, Sonkar et al. (2020) indicated that there would be high productivity losses in warming trends. Although our study did not involve any future projections, the negative regression coefficients related to temperature reflect the findings of Sonkar et al. (2020) and Madhukar et al. (2020), which indicate that the current trends of warming are already offsetting the yield advantages. Conversely, the solar radiation had a positive impact on yield, probably because it has an impact on photosynthetic efficiency. Such trends align with Mall et al. (2017), who observed that although radiation improves the productivity of crops when moisture is sufficient, its positive effects are neutralized by evapotranspiration stress due to temperature when rainfall is low.

The implications of these findings on policy are huge. National strategies might be inadequate as the effects of climate change are becoming more localized and multifaceted. The uneven performance of the districts demands local adaptation measures which are specific to the micro-climatic and resource reality of each region, Padakandla et al. (2022). It is important to invest in drought-resistant varieties, agro-advisory systems specific to districts, and irrigation practices that are sensor-based. Feedback loops should also be integrated into climate-smart agriculture (CSA) frameworks by including farmers, extension workers, and localized data sources. Also, nutrient management should be given a second chance. Bode et al. (2023) and Chakraborty et al. (2019) demonstrated the environmental expenditures of nutrient inefficiencies in Indian agriculture and revealed that spatial misalignments in fertilizer application can exacerbate climate risks. The macro-nutrient requirements (N, P, K) were also captured in our dataset, which presents the possibility of incorporating nutrient balance as a co-variable in future predictive models. Also, socioeconomic constraints are a major factor that restricts the adaptive capacity of farming households. In her thesis, Kaur (2017) on agricultural productivity and food security in India, emphasized the compounding nature of climate uncertainty on poverty and female-headed

farming households in India. Despite the fact that our research was based on climatic data, the spatial differences in yield suggest that structural inequalities can be a barrier to even adaptation. Similar climatic conditions and different yields probably indicate the variation in policy implementation, landholding patterns, and access to technology, which should be further investigated.

Although such a study can give useful information, some limitations have to be admitted. Although the secondary data is vast, it is limited by the possibility of missing information on the district level and uniformity over decades. Aggregation of climate and yield data at the annual level can also hide intra-seasonal patterns, which can also have important yield implications, e.g., late monsoons or mid-season droughts. Moreover, although the regression models give statistical precision regarding the impact of variables, they fail to capture the non-linear and lagged effects, which are increasingly being identified in climate-agriculture studies. The future studies should thus focus on incorporating more detailed time-based information, investigating alternative machine learning approaches to non-linear relationships, and including socioeconomic factors like access to credit, insurance coverage, and market connections. Also, the risk hotspots can be visualized with the help of spatial overlays with GIS and inform interventions on a geographic basis. Overall, the findings of this paper highlight the necessity of localized, data-based, and inclusive agricultural planning in the climate change scenario. The historical agricultural success notwithstanding, Northern India is experiencing a growing number of challenges that require a transition to anticipatory climate governance.

CONCLUSION

The paper has given an in-depth temporal evaluation of the effects of climate change on crop production in Northern India, particularly rice, maize, and chickpea in the states of Punjab, Haryana, and Uttar Pradesh. The results indicate that there is a clear indication of sensitivity of yields to climatic changes, especially temperature, rainfall, and solar radiation. Although the overall change in yields has been positive in the last 50 years, the growth has slowed down, which is an indication of a saturation point due to unfavorable climatic conditions. Of the climatic variables studied, temperature was found to have a negative, consistent effect on yield, and rainfall and solar radiation had a positive correlation. The findings indicate the increased fragility of conventional farming systems in the area. An important contribution of this study is that it employed long-term secondary data, which allowed performing a strong analysis of the relationships between climate and yields over time. The diversity and the history of the data set enabled identifying the slight yet meaningful trends that would not be identified with a shorter data set or a local survey. This supports the usefulness of secondary data in carrying out large-scale longitudinal climate impact studies in data-scarce areas. The findings necessitate an immediate need for region-specific adaptive strategies. These can be promotion of drought and heat-tolerant crop varieties, efficiency in irrigation, and better agro-advisory systems. The policymakers must also think of incorporating local climatic analytics into crop planning and farmer support services to develop grassroots resilience. Moving ahead, in the future, the application of machine learning methods to model non-linear and lagged climate-yield relationships should be examined. Moreover, remote sensing data could be integrated to increase spatial accuracy as well as real-time crop health and climatic stress monitoring. These innovations will play an important role in developing predictive agricultural systems capable of proactively responding to changing climate challenges.

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