



Original Research

Assessing the Comparative Impact of Climate Variability and Irrigation Infrastructure on Rice and Wheat Yield: Evidence from Haryana

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Abstract

This study analyses the impact of irrigation infrastructure and climate variability on rice and wheat yields across 22 districts of Haryana using a panel dataset from 2014-15 to 2022-23, collected from the Department of Economic and Statistical Affairs, Government of Haryana; additionally, data on climate variables such as rainfall, temperature, and relative humidity were collected from the NASA Power Data Access Viewer (DAV). The study integrates agricultural infrastructure, irrigated area by tubewells, canal system, total fertilizer use, area under crop, and climate variables such as temperature, rainfall, and relative humidity. Descriptive statistics were used to summarize the data for both crops, wheat and rice. Diagnostic tests such as the variance inflation factor (VIF), Breusch-Pagan LM test, and Hausman test were performed. The Hausman test was applied to select between random effects and fixed effects methods; the Hausman test failed to reject the null hypothesis, which means that random effects are preferred over fixed effects. So, the main model of the current research for analysis is random effects. Further, the Pesaran CD test was performed and the null hypothesis was rejected, suggesting the presence of cross-sectional dependence among districts. Therefore, the analysis uses Fixed Effects Regression (Driscoll-Kraay SE) for both crops to check robustness. The results illustrate that climatic factors have more influence on wheat production, while rice productivity is primarily associated with cultivated area and input utilization. The analysis recommends that a better future policy should be focused on climate-responsive water management rather than continuing to expand irrigation sources.

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Statement of sustainability: This study contributes to sustainable agricultural development by evaluating the relationship between irrigation infrastructure and crop productivity in Haryana using district-level panel data. The results provide evidence to support efficient water resource management, improved irrigation planning, and evidence-based agricultural policies that enhance food security while promoting the sustainable use of natural resources. The study aligns with the United Nations Sustainable Development Goals, particularly SDG 2 (Zero Hunger) through improved agricultural productivity and food security; SDG 6 (Clean Water and Sanitation) by encouraging efficient and sustainable use of irrigation water; SDG 12 (Responsible Consumption and Production) through improved resource-use efficiency in agricultural production; SDG 13 (Climate Action) by considering the influence of climatic variables on agricultural productivity and supporting climate-resilient farming strategies.

1. Introduction

Agriculture and allied services contributed approximately one-fifth (1/5th) of India's GDP for FY 2023-24 at current prices (GOI, 2026). But nearly half of India's agricultural households earn a total monthly income below the official poverty line (Shukla, 2025). Agriculture ensures employment, food security and overall economic development (Jose, 2025). Agricultural growth mainly depends on sustainable irrigation, efficient use of resources, fertilizers etc. Growth of agriculture infrastructure such as irrigation infrastructure directly affects agricultural productivity (Kumar et al., 2024). In India, the scope for cultivable land expansion is limited. So, crop productivity has emerged as an important factor that may increase the production and yield of a crop and overall agricultural performance. Agricultural productivity and yields mainly depend on sustainable irrigation and irrigation infrastructure. But Indian agriculture depends on groundwater borewells such as diesel pump sets and electric pump sets, as well as rivers,



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canal systems, and rainfall (Kumar et al., 2022). There are 20.3 million electric pump sets, 8.8 million diesel pump sets, and 2.7 million solar pump sets (BEE, 2025; IEA, 2025). Also, irrigation facilities among the 132 million Indian farmers varied across size groups and geographies (Jain & Shahidi, 2018). The estimated Ultimate Irrigation Potential (UIP) for the country is 139.89 Mha (million hectares), but due to underutilization of irrigation resources, only 77.916 Mha (55.7%) of the area is irrigated, which is insufficient to enhance the farmers' living standards (Central Water Commission, 2024; MOSPI, 2012). Irrigation remains the primary consumer of water resources, representing the largest share of total water utilization (Central Water Commission, 2024). The gross irrigated area as a share of the gross cropped area has increased from 41.7 per cent in 2001-02 to 55.8 per cent in 2022-23 (Ministry of Finance, 2026). Irrigation infrastructure is widely recognized as a critical investment for improving agricultural productivity, expanding cultivated land, and strengthening resilience to climate variability (Cisse et al., 2026). Irrigation contributes not only to higher crop yields but also to more intensive land use, reinforcing the need for continued investment in irrigation infrastructure (Jin et al., 2012). Irrigation systems effectively provide water to farmers when needed, improve nutrient uptake, make agriculture more resilient to climate vulnerability, enhance crop diversification, and increase cropping intensity (Molden et al., 2009; Riaz & Ashfaq, 2019). Crop diversification and crop intensity are helping to achieve the goal of sustainable agriculture. The efficient use of inputs such as water, fertilisers, and energy means that sustainable agriculture majorly depends on sustainable irrigation or irrigation infrastructure. To promote sustainable irrigation, the government has launched many schemes such as PMKSY (Pradhan Mantri Kisan Sampada Yojana) which aims to achieve collaborative investment in irrigation infrastructure, increase the net irrigated area, enhance water usage efficiency to minimize water waste, precision irrigation and other water saving techniques, and the use of sustainable water conservation methods. The government also promotes drip irrigation, sprinkler irrigation, and micro-irrigation to enhance water use efficiency and management.

According to Economic Survey, "Haryana has 4.42 million hac total area, 1.34% of India's geographical area. But Haryana plays a crucial role in the country's agricultural production. The state contributes a disproportionately high share of national foodgrain and wheat production owing to its high agricultural productivity. Total cultivable areas dominate nearly 83.6% of the state's land. The net sown area is 97% of the total agricultural land, with a cropping intensity of 183.2%. And 94.9% of the net sown area is irrigated with an irrigation intensity of 176.7%". Moreover, nearly 95% of the net sown area is already irrigated, leaving very limited scope for expanding agricultural production through additional cultivated or irrigated land. Consequently, future growth in agricultural output cannot rely on area expansion. It depends on improvements in productivity and the efficient use of existing irrigation resources. But 65% of irrigation is provided by tubewells, and only 35% by canals (Haryana agriculture statistics, 2024). In 2022-23, 8.32 lac pump sets were reported, of which 2.79 lac were diesel-based and 5.53 lac were electric (Govt of Haryana, 2025). It shows that Haryana relies more on diesel and electric-powered pump sets. From 1975 to 2013, the density of tube wells per thousand hectares and their number have grown by more than 250 and 300 per cent, respectively, in Haryana (Kasana & Singh, 2017). In this context, promoting sustainable irrigation infrastructure and enhancing water use efficiency and management have become essential for sustainable agricultural productivity and sustainable irrigation in Haryana.

2. Literature Review

2.1. Irrigation Infrastructure, Water Availability and Crop Productivity

Agricultural productivity majorly depends on sustainable irrigation sources because it reduces dependence on uncertain rainfall and ensures water availability during critical crop-growth stages. Groundwater has become an increasingly important source of irrigation for wheat and rice crops in Haryana and Punjab, and groundwater is helping in mass-scale cereal production, but this dependency has created pressure on groundwater resources (Erenstein, 2010). In Haryana, it was found that paddy and wheat crops effectively used only approximately 62% of irrigation water, which shows that there is a need to enhance water-use efficiency rather than simply expand irrigation infrastructure (Singh et al., 2023). In Haryana, the groundwater system also shows a decline of approximately 5 metres in groundwater levels between 2004 and 2017, highlighting the environmental limitations of continued groundwater-dependent irrigation (Khara & Ghuman, 2024). Irrigation sustainability positively enhances wheat yields, and reductions in irrigation availability increase wheat yield losses from 1-8% to 4-36%, which makes the wheat crop's yield more climate vulnerable in Indo-Gangetic plains (Daloz et al., 2021). The literature demonstrates that irrigation remains essential for crop productivity, but its marginal contribution depends on existing irrigation coverage, water-use efficiency and the sustainability of available water resources.

2.2. Climate Variability, Temperature and Rice-Wheat Yield

Crop yields are adversely affected by a rise in maximum temperature and positively affected if there is an upsurge in minimum temperature while the study calculates that rice yield reduces by approximately 15% and wheat yield reduces by 22% (Birthal et al., 2014). Climate variability represents another important determinant of agricultural productivity, particularly through changes in temperature and rainfall during crop-sensitive growth periods. Increasing temperature, declining rainfall and changes in water availability negatively impact the wheat yield, again showing that if irrigation infrastructure assured a sustainable irrigation, it makes the wheat yield more climate vulnerable in northwest India (Mukherjee et al., 2019). A study conducted in Haryana cov-



ering the 1991–2020 period found significant relationships between rice and wheat production and climatic variables including minimum and maximum temperature, rainfall, relative humidity and wind speed (Awasthi et al., 2023). A study of the rice and wheat system in Haryana further found that wheat grain yield was associated with temperature conditions during the winter growing season, with approximately 21°C maximum and 6.5°C minimum temperature identified as favourable conditions during December–February (Sendhil et al., 2015). Rainfall patterns during critical rice growth stages affect the crop yield, demonstrating that the timing of climatic exposure can be as important as total seasonal rainfall (Rana et al., 2019). A study in India also reveals considerable spatial variation, with Punjab and Haryana showing the highest irrigation coverage and lowest wheat-yield variability, while less-irrigated regions face more yield variability (Madhukar et al., 2026). These studies reveal that climate effects are crop and location specific. It provides justification for separately estimating rice and wheat yield responses to rainfall and temperature.

2.3. Irrigation as Climate Adaptation and Agricultural Resilience

Irrigation serves not only as a direct production input but also as an adaptation mechanism that can reduce the vulnerability of crops to climatic variability. This adaptation mechanism is particularly evident in the Indo-Gangetic Plains, where Daloz et al. (2021) estimated that direct climate effects could reduce wheat yields by 1–8%, but the potential loss increased to 4–36% when reductions in irrigation availability were incorporated. BIRTHAL et al. (2014) identified irrigation as an important factor in reducing the adverse effects of higher temperatures on Indian agricultural production. Similarly, evidence from northwest India shows that wheat production is highly dependent on irrigation because winter rainfall is relatively limited, making changes in both temperature and water availability important determinants of yield performance (Mukherjee et al., 2019). In Haryana, the intensive rice and wheat system depends heavily on groundwater irrigation to maintain production despite variable climatic conditions, which reinforces this relationship between irrigation and crop production (Erenstein, 2010). However, irrigation-based adaptation has a sustainability limit, as groundwater depletion in Haryana has reduced the long-term reliability of groundwater as an adaptation resource (Khara & Ghuman, 2024). The literature suggests that irrigation can strengthen agricultural resilience to climatic stress, but its effectiveness is conditional on water availability and efficient resource management.

2.4. Agricultural Intensification, Complementary Inputs and Productivity

Crop productivity is not determined by irrigation and climate alone; irrigation operates within a broader agricultural production system involving cultivated area, fertilizer, improved varieties and other complementary inputs. The development of the north-western Indian rice–wheat system demonstrates that productivity growth resulted from the combined expansion of irrigation, improved seed varieties, fertilizer use and other Green Revolution technologies rather than from irrigation alone (Erenstein, 2010). Evidence from Haryana similarly characterizes the rice–wheat system as a high-input, high-output production system in which irrigation, fertilizer and modern crop technologies jointly contributed to high productivity (Erenstein, 2010). At the same time, intensive input use can generate environmental and resource costs; groundwater depletion and waterlogging in parts of Haryana demonstrate that productivity gains from intensive agricultural systems may involve significant resource trade-offs (Khara & Ghuman, 2024; Mukherjee et al., 2019). This literature therefore suggests that crop yield should be examined within a broader production framework in which irrigation, cultivated area, fertilizer use and climatic conditions operate simultaneously. This provides the rationale for including both production inputs and climatic variables in the present district-level panel model rather than attributing changes in crop yield to irrigation or climate alone.

Many studies have discussed agricultural productivity, irrigation development, and groundwater use in Haryana (Archana, 2022; BIRTHAL et al., 2014; Erenstein, 2010; Gautam, 2022; Klinnert et al., 2025; Madhukar et al., 2026; Perna & Singh, 2024; Rani, 2024). However, there is limited empirical evidence quantifying the district-level effects of canal irrigation, tubewell irrigation, and irrigation pumping infrastructure on crop yields and linking them with climate variables such as temperature, rainfall and humidity. Previous studies examined the impacts of irrigation infrastructure on crop yields and productivity and the impacts of climate on crop yield separately. This study combines both sets of variables for analysis. Existing studies are mainly descriptive and focused on groundwater depletion, energy use, climate change and irrigation efficiency separately rather than estimating the contribution of different irrigation sources and climate variability combined (Daloz et al., 2021; Khara & Ghuman, 2024; Mukherjee et al., 2019; Rana et al., 2019; Riaz & Ashfaq, 2019; Sendhil et al., 2015). This study addresses this gap by employing district-level panel data to examine how irrigation infrastructure and climate variability influence crop yields in Haryana.

So, the current research mainly focuses on examining the effects of both irrigation infrastructure and climate variables on yield of rice and wheat in Haryana. In this research, the impacts of irrigation and climate factors on crop yield are examined together.

3. Materials and Methods

3.1. Study Area

Haryana is situated in northern India between approximately 27°39' N and 30°35' N latitudes and 74°28' E and 77°36' E longitudes, covering an area of approximately 44,212 km². Haryana is one of India's leading agricultural states and a major contributor to the national food security system. In Haryana's agriculture, rice and wheat are the major crops, which have the largest share



of cultivated cereal area and production. Wheat is the principal rabi crop, while rice is the major kharif crop. These two crops account for the majority of cereal production and public procurement in Haryana. This makes them appropriate indicators for analysing district-level agricultural productivity. Consequently, the present study limits its empirical analysis to wheat and rice using a balanced panel dataset covering all districts of Haryana over a ten-year period (2014-15 to 2022-23). The long panel enables examination of temporal as well as spatial variations in crop productivity, irrigation infrastructure, and climatic influences. Figure 1 presents the district map of Haryana.

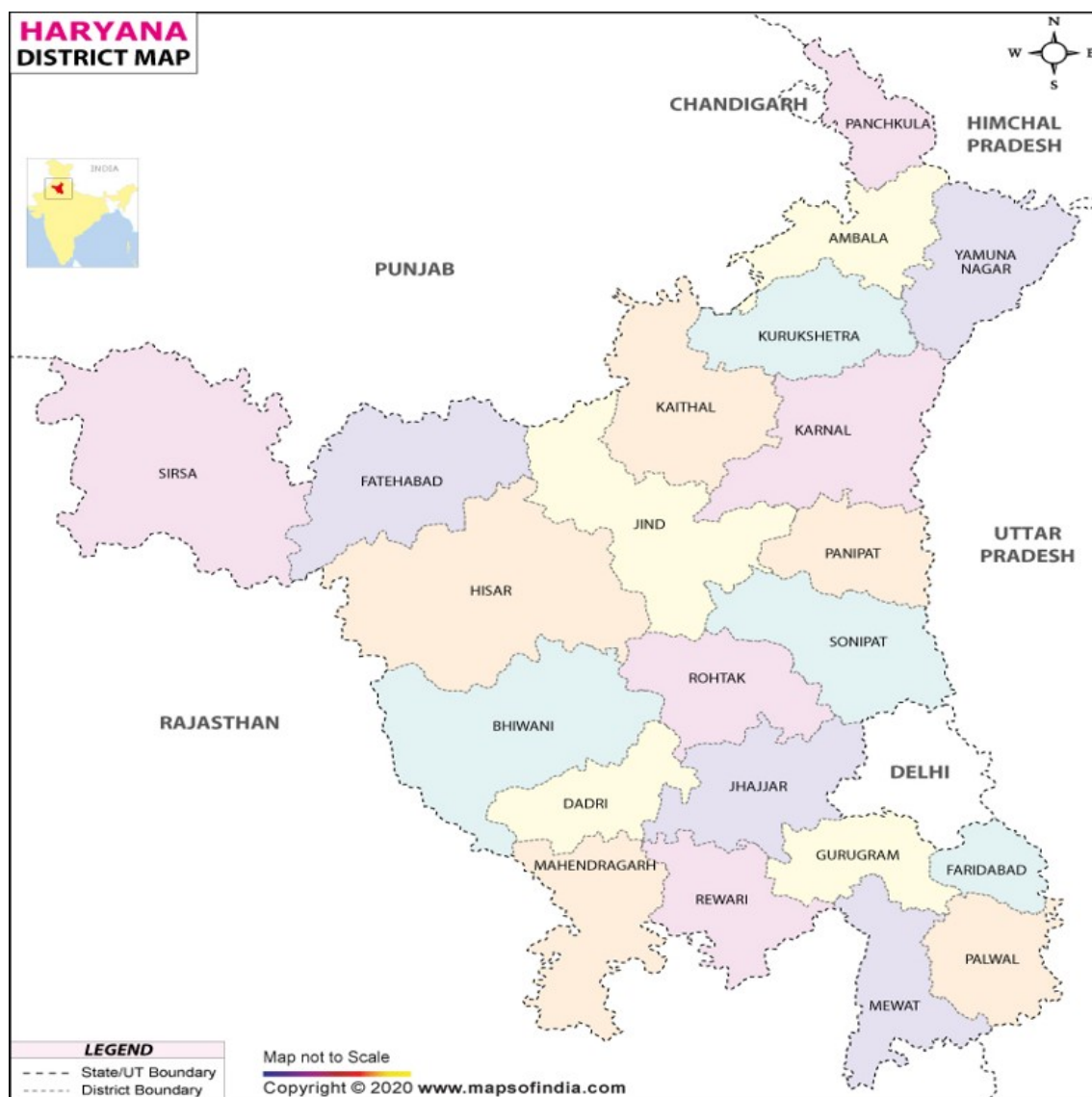


Figure 1. District map of Haryana (Source: www.mapsofindia.com).

3.2. Data Sources

District-level data on the dependent variable (crop yield) (in kg/ha) and the agricultural and input covariates—irrigated area by tubewells (IAT) (000 ha), irrigated area by Government canals (IAGC) (000 ha), total fertilizer use (TFU)(tonnes), and area under crop (AUC) (000 ha)—were compiled year-wise from the Statistical Abstract of Haryana , issued by the Department of Economic and Statistical Affairs, Government of Haryana (2024). The three climate variables—rainfall (mm), temperature (degree Celsius), and relative humidity (RH) (%)—were sourced from the NASA POWER website . For analysis, the current research used Excel, R software, and Python. Table 1 presents the description of the variables along with their units and sources.



Table 1. District-level data on irrigation, crop area, yield, rainfall, and fertilizer consumption in Haryana.

Variable type	Variable	Unit	Source
Dependent variable	Crop Yield	Kg/ha	Statistical abstract of Haryana
Independent variables	Area under crops (AUC)	000'ha	Statistical abstract of Haryana
	Irrigated area by tubewell (IAT)	000'ha	Statistical abstract of Haryana
	Irrigated area by Government canals (IAGC)	000'ha	Statistical abstract of Haryana
	Total fertilizer use (TFU)	Tonnes	Statistical abstract of Haryana
	Temperature	Degree Celsius	NASA POWER official website
	Rainfall	Mm	Statistical abstract of Haryana
	Relative humidity (RH)	Percentage	NASA POWER official website

3.3. Methods

The study uses a district-level panel dataset covering a 10-year period to analyze the impact of irrigation infrastructure and climate on crop yield. The study chooses two crops for analysis, wheat and rice, because in the rabi season wheat is the dominant crop in Haryana overall and in the kharif season rice has a major share in total cereal crops in Haryana. The study first calculates the descriptive statistics for both crops. After that, the study applies the VIF test to check multicollinearity in the dataset and finds that there is no risk of multicollinearity. To check exogeneity, the study applied the Durbin–Wu–Hausman (DWH) exogeneity test. The study applied the main model “Random effects regression (Rice and Wheat)” on the basis of the Hausman test. For a robustness check, the current research applied Fixed Effects, Two-Way, with Driscoll–Kraay SE (Rice and Wheat). To check endogeneity for AUC, the study applied the IV-2SLS Estimation (Rice and Wheat). Figure 2 presents the model framework followed in the analysis.

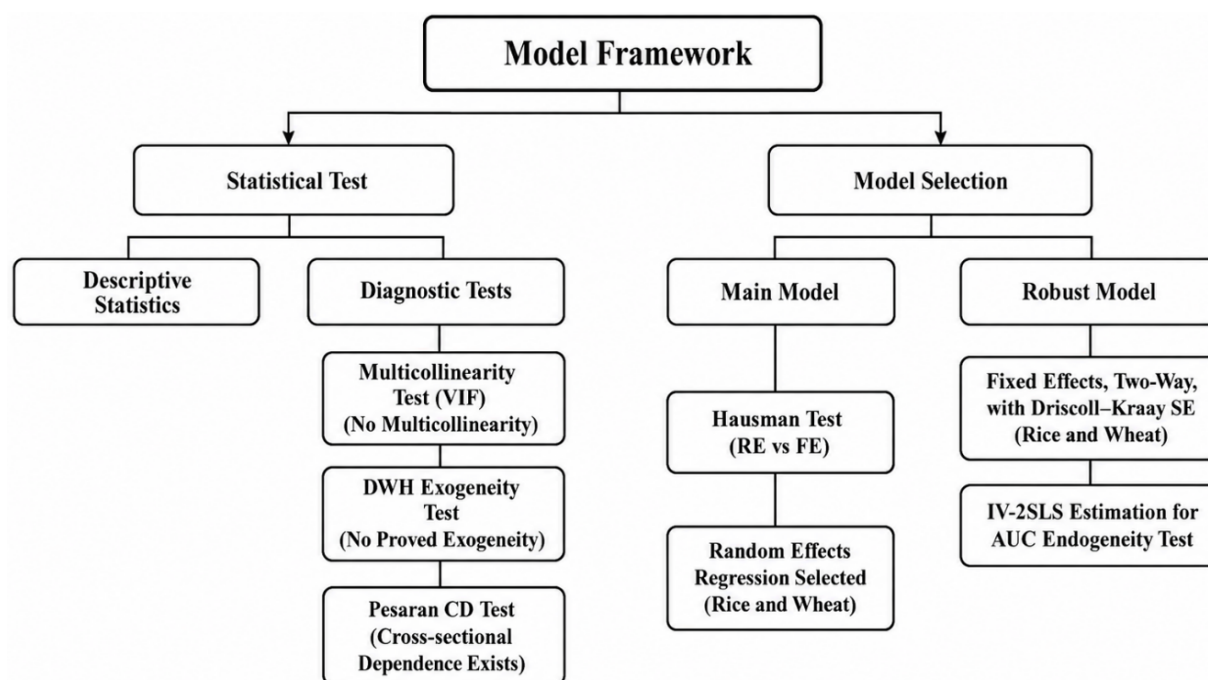


Figure 2. Statistical framework for robust modelling of rice and wheat yield in Haryana.

3. Results

3.1. Descriptive Statistics

The descriptive statistics indicate substantial variation in agricultural productivity, irrigation infrastructure, input use, and climatic conditions across the 196 district-year observations for both rice and wheat (Table 2). Wheat recorded a higher average yield (3,912.50 kg/ha) than rice (2,999.85 kg/ha), although both crops show significant yield variability, as reflected by their standard deviations of 927.57 and 969.81 kg/ha, respectively. The average area under wheat (111.53) was also larger than that under rice (74.68), suggesting greater spatial and temporal coverage of wheat cultivation in the study districts. For both crops, tubewell-irrigated area exceeded government canal-irrigated area, highlighting the relatively greater presence of tubewell-based irrigation infrastructure. The particularly high standard deviations for canal-irrigated area indicate substantial differences in irrigation infrastructure across



districts. Climatic conditions were broadly similar for the two crops, with mean rainfall of 530.76 mm for rice and 515.98 mm for wheat, mean temperature of approximately 25.1°C, and mean relative humidity of approximately 47.5%. Fertilizer use was higher on average for wheat (78,968.68) than rice (71,271.22) and displayed considerable variation, indicating differences in input intensity across district-year observations. Overall, the descriptive evidence suggests that wheat had higher average productivity and cultivated area, while tubewell irrigation represented a more prominent irrigation source for both crops; at the same time, substantial spatial and temporal heterogeneity in irrigation, fertilizer use, yield, and rainfall provides meaningful variation for the subsequent panel regression analysis. These descriptive statistics, however, represent associations and distributions rather than causal effects; the independent contribution of irrigation, fertilizer, and climate variables is assessed through the econometric models.

Table 2. Descriptive statistics of agricultural inputs, crop yield, and climatic variables for rice and wheat in Haryana.

Variable	N		Mean		Std. Dev		Min		Max	
	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat
Yield	196	196	2999.85	3912.50	969.81	927.57	0.00	1434.00	4962.00	5643.00
AUC	196	196	74.68	111.53	55.66	64.06	0.00	2.00	189.20	304.40
IAGC	196	196	61.38	70.28	75.93	77.61	0.00	1.00	287.00	287.00
IAT	196	196	97.36	101.76	42.71	41.20	5.00	5.00	223.00	223.00
Rainfall	196	196	530.7	515.98	249.84	249.94	115.0	115.0	1403.0	1403.0
Temperature	196	196	25.11	25.13	0.78	0.78	22.92	22.92	26.95	26.95
RH	196	196	47.73	47.47	6.22	6.26	35.27	35.27	62.00	62.00
TFU	196	196	71271.22	78968.68	39794.25	36500.25	0.00	996.00	203890.00	203890.00

Source: Author's own calculations based on data from Haryana Statistical Abstract.

3.2. Diagnostic Tests

Hausman test: For the rice crop, the Hausman test provides a chi-square statistic of 11.3603 with 8 degrees of freedom and a p-value of 0.1821. Since the p-value is greater than the 5% significance level, the null hypothesis that the Random Effects (RE) estimator is consistent and efficient cannot be rejected. Therefore, the Random Effects model is preferred over the Fixed Effects model for the analysis. For the wheat crop, the Hausman test gives a chi-square statistic of 12.0695 with 8 degrees of freedom and a p-value of 0.1481. Since the p-value is greater than the 5% significance level, the null hypothesis that the Random Effects (RE) estimator is consistent and efficient cannot be rejected. Therefore, the Random Effects model is preferred over the Fixed Effects model for the analysis, implying that the unobserved district-specific effects are not sufficiently correlated with the explanatory variables to justify the fixed-effects specification.

Pesaran test: For the rice crop, the Pesaran CD test produces a CD statistic of 3.4767 and a p-value of 0.0005. The p-value is again substantially below the 5% significance level, leading to rejection of the null hypothesis of cross-sectional independence. Thus, the districts show statistically significant cross-sectional dependence. For the wheat crop, the Pesaran Cross-Sectional Dependence (CD) test gives a CD statistic of 22.7547 with a p-value of 0.0000. Since the p-value is well below the 5% significance level, the null hypothesis of cross-sectional independence is rejected. This indicates that the observations across districts are not independent; rather, economic, agricultural, climatic, policy, or other common factors may generate interdependence among districts.

Durbin–Wu–Hausman (DWH) exogeneity test: For rice, the Durbin test reports a statistic of 0.4080 with a p-value of 0.5230, while the Wu–Hausman test reports a statistic of 0.3840 with a p-value of 0.5365. Since both p-values are greater than the 5% significance level, the null hypothesis of exogeneity cannot be rejected. This indicates that AUC does not show statistically significant endogeneity; therefore, AUC can be treated as an exogenous explanatory variable in the rice analysis. For wheat, the Durbin test produces a statistic of 1.3713 with a p-value of 0.2416, while the Wu–Hausman test gives a statistic of 1.3032 with a p-value of 0.2555. Both p-values exceed 0.05, so the null hypothesis of exogeneity cannot be rejected. Thus, there is no statistically significant evidence that AUC is correlated with the regression error term. The results indicate that AUC can be treated as exogenous.

3.3. IV-2SLS Estimation (Rice and Wheat) (endogeneity test for AUC)

Model Estimation: The IV-2SLS models are used to address the potential endogeneity of AUC, using its lagged value (AUC_lag) as the instrument (Table 3). Both models are statistically significant overall, with F-statistics of 197.11 ($p < 0.001$) for rice and 59.634 ($p < 0.001$) for wheat. The models explain approximately 56.57% of the variation in rice yield and 27.59% of the variation in wheat yield. Thus, the IV specification provides substantial explanatory power for rice, while its explanatory power for wheat is comparatively lower. However, these R^2 values should not by themselves be interpreted as evidence of causal validity; the credibility of the IV results also depends critically on the relevance and exogeneity of AUC_lag as an instrument.

Parameter Estimates: The IV-2SLS parameter estimates are reported in Table 4. After instrumenting AUC, the estimated effect of AUC is positive and statistically significant for rice ($\beta = 4.9106$, $p < 0.001$), indicating that a one-unit increase in the instrumented AUC is associated with approximately 4.91 additional yield units, holding other variables constant. In contrast, the AUC coeffi-



cient for wheat ($\beta = 1.4957$, $p = 0.3874$) is statistically insignificant, indicating no reliable evidence of an independent AUC–yield relationship after addressing potential endogeneity. TFU is positive and statistically significant for both rice ($\beta = 0.0081$, $p = 0.0016$) and wheat ($\beta = 0.0057$, $p = 0.0014$), showing a positive association between fertilizer use and yield. IAGC is significantly negative for rice ($\beta = -2.8807$, $p = 0.0069$), while its wheat estimate is statistically insignificant. The remaining irrigation and climate variables are statistically insignificant at the 5% level. Overall, the IV results provide stronger evidence for a positive AUC–yield relationship in rice, but not in wheat, while fertilizer use remains a statistically significant positive correlate for both crops. These estimates should be interpreted as IV-based conditional effects rather than automatically as causal effects unless the instrument satisfies both relevance and the exclusion restriction.

Table 3. IV-2SLS estimation (rice and wheat): model estimation.

Metric	Rice	Wheat
Dependent variable	Yield	Yield
Estimator	IV-2SLS	IV-2SLS
No. of observations	146	155
R-squared	0.5657	0.2759
Adjusted R-squared	0.5437	0.2414
F-statistic	197.1100	59.6340
F-statistic (p-value)	0.0000	0.0000
Covariance estimator	Robust	Robust
Endogenous regressor	AUC	AUC
Instrument	AUC_lag	AUC_lag

Table 4. IV-2SLS estimation (rice and wheat): parameter estimates.

Variable	Parameter		Std. Err.		T-statistic		P-value	
	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat
Intercept	5456.8	5766.5	2884.9	2174.1	1.8915	2.6523	0.0586	0.0080
IAGC	-2.8807	-1.9287	1.0659	1.0838	-2.7026	-1.7796	0.0069	0.0751
IAT	0.1532	-1.6408	1.3089	0.9682	0.1170	-1.6946	0.9068	0.0901
Rainfall	0.3683	-0.0481	0.2126	0.1302	1.7325	-0.3694	0.0832	0.7119
Temperature	-148.26	-48.811	95.501	71.323	-1.5524	-0.6844	0.1206	0.4937
RH	7.6546	-3.5612	11.207	8.2853	0.6830	-0.4298	0.4946	0.6673
TFU	0.0081	0.0057	0.0026	0.0018	3.1537	3.2027	0.0016	0.0014
AUC (instrumented)	4.9106	1.4957	1.2761	1.7304	3.8482	0.8644	0.0001	0.3874

Source: Author's own calculations based on data from Haryana Statistical Abstract and NASA POWER.

3.4 Random Effects Regression (Rice and Wheat)

Model Estimation: The Random Effects estimates are reported in Table 5. For the rice crop, the Random Effects model explains 48.12% of the overall variation in rice yield ($R^2 = 0.4812$), with the model explaining 33.49% of within-district variation and 44.68% of between-district variation. The overall F-statistic (15.054, $p < 0.001$) and robust F-statistic (12.083, $p < 0.001$) confirm that the explanatory variables are jointly significant. For the wheat crop, the Random Effects model explains 27.25% of the overall variation in wheat yield ($R^2 = 0.2725$). The within-district R^2 of 0.1181 indicates relatively limited explanatory power for year-to-year changes within districts, whereas the between-district R^2 of 0.6527 shows that the model explains a substantial 65.27% of the differences in average wheat yield across districts. The overall F-statistic (7.3234, $p < 0.001$) and robust F-statistic (6.2674, $p < 0.001$) indicate that the explanatory variables are jointly statistically significant. Thus, the model is more effective in explaining differences between districts than changes within districts over time.

Parameter Estimates: The Random Effects parameter estimates are reported in Table 6. For the rice crop, among the explanatory variables, AUC shows the strongest positive association with rice yield ($\beta = 7.840$, $p < 0.001$), indicating that a one-unit increase in AUC is associated with approximately 7.84 additional yield units, ceteris paribus. RH ($\beta = 16.952$, $p = 0.071$) and TFU ($\beta = 0.0038$, $p = 0.083$) are positive but only weakly significant at the 10% level. IAGC, IAT, rainfall, and temperature are statistically insignificant, indicating insufficient evidence of independent associations with rice yield in this specification. Overall, AUC is the principal statistically supported correlate of rice yield, while the remaining variables show weaker or statistically uncertain relationships. These results represent conditional associations rather than causal effects.

For the wheat crop, the coefficient results show that Temperature ($\beta = 190.840$, $p = 0.034$), RH ($\beta = 29.017$, $p = 0.003$), and TFU ($\beta = 0.0055$, $p = 0.012$) have statistically significant positive associations with wheat yield. In practical terms, a one-unit increase in temperature is associated with approximately 190.84 additional yield units, while a one-unit increase in RH is associated with



about 29.02 additional yield units, holding other variables constant. A one-unit increase in TFU is associated with approximately 0.0055 additional yield units, with its practical magnitude depending on the measurement unit of fertilizer use. AUC ($\beta = 1.056$, $p = 0.471$), IAGC ($\beta = -0.511$, $p = 0.680$), IAT ($\beta = 0.527$, $p = 0.655$), and rainfall ($\beta = 0.231$, $p = 0.192$) are statistically insignificant. Overall, temperature, relative humidity, and fertilizer use are the main statistically supported correlates of wheat yield in the Random Effects model, whereas cultivated area and irrigation variables do not show statistically reliable independent associations. These findings indicate conditional associations rather than causal effects.

Table 5. Random effects regression (rice and wheat): model estimation.

Metric	Rice	Wheat
Observations	165	175
Districts	19	20
Time periods	10	10
R ² (Overall)	0.4812	0.2725
R ² (Within)	0.3349	0.1181
R ² (Between)	0.4468	0.6527
F-statistic	15.0540	7.3234
F-statistic p-value	0.0000	0.0000
Robust F-statistic	12.0830	6.2674
Robust F-statistic p-value	0.0000	0.0000
Estimator	Random Effects	Random Effects

Table 6. Random effects regression (rice and wheat): parameter estimates.

Variable	Parameter		Std. Er.		T-statistic		P-value	
	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat
Intercept	2453.4	-2290.4	2595.2	2647.1	0.9454	-0.8652	0.3459	0.3881
AUC	7.8400	1.0555	1.9781	1.4610	3.9634	0.7224	0.0001	0.4710
IAGC	-1.9712	-0.5107	1.6059	1.2351	-1.2275	-0.4135	0.2215	0.6798
IAT	-0.8376	0.5272	1.2076	1.1790	-0.6936	0.4471	0.4890	0.6554
Rainfall	0.0731	0.2314	0.1627	0.1768	0.4495	1.3091	0.6537	0.1923
Temperature	-32.5240	190.8400	88.934	89.494	-0.3657	2.1324	0.7151	0.0344
RH	16.9520	29.0170	9.3238	9.4963	1.8182	3.0557	0.0709	0.0026
TFU	0.0038	0.0055	0.0022	0.0022	1.7477	2.5541	0.0825	0.0115

Source: Author's own calculations based on data from Haryana Statistical Abstract and NASA POWER.

3.5. Robustness of Model

Fixed Effects, Two-Way, with Driscoll–Kraay SE (Rice and Wheat)/Model Estimation: The Fixed Effects models with Driscoll–Kraay standard errors provide a robustness check by controlling for district-specific characteristics and, for rice, common time effects (Table 7). For rice, the within R² of 0.3421 indicates that the model explains about 34.21% of the variation in yield within districts over time. Although the conventional F-statistic is not significant (1.6620, $p = 0.1239$), the robust F-statistic is highly significant (13.603, $p < 0.001$), supporting the joint significance of the explanatory variables under robust inference. The poolability test is also significant ($p < 0.001$), indicating that pooled OLS is inappropriate and that district-specific effects are important. For wheat, the within R² is 0.1524, meaning that approximately 15.24% of within-district changes in yield are explained by the model. Both the conventional F-statistic (3.8022, $p = 0.0008$) and robust F-statistic (65.201, $p < 0.001$) are significant, while the poolability test ($p = 0.0004$) supports the presence of district-specific effects. Overall, the robustness models confirm that unobserved district characteristics should be accounted for when analysing yield differences.

Parameter Estimates: The robustness parameter estimates are reported in Table 8. For rice, AUC remains positively and strongly associated with yield ($\beta = 7.3358$, $p = 0.0009$), while IAGC also becomes positive and statistically significant ($\beta = 5.2680$, $p = 0.0015$). This means that, after controlling for district and time effects and using Driscoll–Kraay standard errors, increases in cultivated area and canal-irrigated area are associated with higher rice yield. IAT, rainfall, temperature, RH, and TFU are statistically insignificant, indicating insufficient evidence of independent relationships in this specification. For wheat, IAGC ($\beta = 9.6376$, $p = 0.0292$), IAT ($\beta = 2.5011$, $p = 0.0260$), and TFU ($\beta = 0.0050$, $p = 0.0022$) are statistically significant and positive. Thus, the robustness results provide evidence that irrigation infrastructure and fertilizer use are more consistently associated with wheat yield, whereas AUC is not statistically significant. Importantly, the change in significance and coefficient size relative to the Random Effects results demonstrates why the robustness specification is useful; the estimates should still be interpreted as conditional associations rather than causal effects.



Table 7. Fixed effects, two-way, with Driscoll–Kraay SE (rice and wheat): model estimation.

Metric	Rice	Wheat
Dependent variable	Yield	Yield
Estimator	PanelOLS (Entity + Time effects)	PanelOLS (Entity effects)
Covariance estimator	Driscoll–Kraay	Driscoll–Kraay
No. of observations	165	175
Entities (districts)	19	20
Time periods (years)	10	10
R-squared (Overall)	–0.1649	–2.5321
R-squared (Within)	0.3421	0.1524
F-statistic	1.6620	3.8022
F-statistic (p-value)	0.1239	0.0008
F-statistic (robust)	13.6030	65.2010
Robust F-statistic (p-value)	0.0000	0.0000
F-test for poolability	13.9380	2.7251
Poolability test (p-value)	0.0000	0.0004

Table 8. Fixed effects, two-way, with Driscoll–Kraay SE (Rice and Wheat): parameter estimates.

Variable	Parameter		Std. Err.		T-statistic		P-value	
	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat
Intercept	4084.3	–4904.8	12150	11180	0.3361	–0.4386	0.7373	0.6616
AUC	7.3358	0.4396	2.1559	1.2315	3.4027	0.3570	0.0009	0.7216
IAGC	5.2680	9.6376	1.6204	4.3773	3.2510	2.2017	0.0015	0.0292
IAT	0.1421	2.5011	0.8617	1.1123	0.1649	2.2485	0.8693	0.0260
Rainfall	–0.0881	0.1862	0.0790	0.1746	–1.1160	1.0666	0.2665	0.2879
Temperature	–105.15	261.02	417.89	375.12	–0.2516	0.6958	0.8017	0.4876
RH	11.973	31.405	40.998	35.307	0.2920	0.8895	0.7707	0.3752
TFU	0.0022	0.0050	0.0019	0.0016	1.1418	3.1101	0.2556	0.0022

Source: Author’s own calculations based on data from Haryana Statistical Abstract and NASA POWER.

Finally, rice yield mainly depends on the area sown to the crop, and this relationship is also sustained when farmers grow the crop in different climatic conditions. Fertilizer use improved rice yield only slightly, but it always shows a positive relationship with crop yield. Wheat crop showed that the yield didn’t depend on area under crop while fertilizer use increased wheat yield consistently. Relative humidity has a positive relation with higher yield for both crops, more clearly for wheat than rice, while rainfall showed no significant link to yield for both crops. Temperature is linked to higher wheat yield, but this relationship didn’t sustain longer. Canal-based and tubewell-based irrigation areas have a weaker relationship with higher yield. Overall, rice yield depends mainly on how much land is under crop, wheat yield mainly relates to how much fertilizer is applied, and irrigation source and rainfall show no dependable role for both crops.

4. Discussion

The findings show that, after controlling for irrigation, climate and fertilizer factors, rice yield in Haryana is more strongly associated with the area under rice cultivation than with further expansion of irrigation infrastructure. For the rice crop, government canal irrigation is significant and tubewell irrigation is insignificant in Haryana. But for the wheat crop, government canal irrigation and tubewell irrigation are generally statistically insignificant, which means that yield does not depend on irrigation. This does not mean that irrigation is unimportant for rice production; it means that in Haryana, irrigation has already reached saturation point. Thus, further improvements in irrigation infrastructure do not lead to a significant increase in crop yield (Kijne et al., 2003; Molden et al., 2009; Seckler et al., 2003). In such circumstances, yield enhancement is determined by cultivated area, soil conditions, climatic conditions, input intensity, crop management, and technology. For wheat, the results indicate a different production pattern in which yield is more closely associated with climatic conditions, fertilizer use and irrigation infrastructure than with the area under wheat cultivation. Temperature, relative humidity and total fertilizer use show statistically significant positive associations with wheat yield, while AUC, rainfall and the irrigation variables are statistically insignificant. However, government canal irrigation and tubewell irrigation are positively associated with wheat yield, while fertilizer use remains positive and statistically significant. This suggests that unobserved district characteristics such as soil quality, cropping practices, infrastructure, technology adoption and long-standing differences in agricultural management may influence the observed relationship between irrigation and wheat yield. Overall, the wheat results suggest that productivity is determined by a combination of irrigation availability, fertilizer intensity and climatic conditions, rather than simply by expanding the cultivated area. This is consistent with the broader agricultural productivity literature, which emphasizes that yield improvements depend on complementary inputs and technologies, including



improved production practices, quality inputs, irrigation management, climate conditions and farm-level management (Ali & Shumila, 2026; Fan et al., 2000). Thus, the results imply that future productivity improvements in Haryana are likely to depend less on simply expanding cultivated or irrigated area and more on improving input efficiency, irrigation management, climate resilience and agricultural technology.

4. Conclusion

This study examined first, the relationship between crop yield and irrigation infrastructure in Haryana, and second, how climate variability impacts the farmers' crop yield. The results show that irrigation infrastructure has no statistically significant influence on crop yield over a long period, while climate variables such as temperature remain significant determinants. This indicates that Haryana's irrigation system has reached a stage where further physical expansion of irrigation infrastructure gives less or negative impacts on crop yield. But climate variables have positively affected the crop yield. Previous study also proved that after a limit of expansion in irrigation infrastructure didn't provide a significant enhancement in crop yield and crop production. But if farmers focus on other inputs such as seeds, machinery, technology, water management and efficiency, then this may show an increment in crop yield, because irrigation is not the sole determinant of crop yield.

4.1. Limitations of the Study

This study is not without limitations. The study examined irrigation infrastructure and crop yield relation only for two crops, wheat and rice, with a short time period of 10 years only. Also, the study did not include some important variables that affect crop yield, such as HYV seeds, financial facilities, machinery, groundwater depth etc. Future research could usefully extend this analysis by directly testing the moderating role of groundwater access on the infrastructure-yield relationship, and by incorporating farmer-level survey data to better capture the decision-making process behind the shift toward borewell irrigation during deficit-rainfall years.

4.2. Recommendations

Future investment should be directed toward climate-responsive water management that responds to seasonal rainfall conditions and closer monitoring of agricultural water use specifically during years of rainfall shortfall.

The final conclusion is that physical expansion of irrigation infrastructure is no longer the most effective lever; what the state needs instead is a management framework built around variability in rainfall, not around adding more infrastructure.

Author Contributions

Jagjeet Singh: Conceptualization; Data curation; Resources; Visualization; Writing – original draft; Anish Kumar: Investigation; Methodology; Resources; Software; Visualization; Pullaiah Cheepi: Supervision; Validation; Writing – review & editing; All authors: Funding acquisition. This research received no external funding.

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Declarations

Conflicts of interest: There are no commercial or financial interests, and no organization influenced the research findings. So, there is no conflict of interest in current research.

Institutional/Ethical Approval: This study involved the analysis of secondary data and did not involve experiments on humans or animals. Therefore, institutional ethical approval was not required.

Supplementary Information Availability: Not applicable.

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