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RESEARCH PAPER

Assessing the Impact of Climate and Agricultural Variables on Rice Yield in Punjab

Karnati Kiran Kumar[1]* and Naveen Kumar[2]

[1]School of Economics, University of Hyderabad, Telangana, India
[2]Department of Economic Studies, Central University of Punjab, Punjab, India

*Corresponding author: kirankumarkarnati40@gmail.com (**ORCID ID:** 0000-0003-3843-6398)

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ABSTRACT

Rice is a vital staple crop in India, with Punjab being one of its largest producers and making a significant contribution to the country's food security. In recent years, Punjab has faced several impacts of climate change, such as rising temperatures and fluctuations in rainfall, which affect rice production. In this context, the current study examines the interdependence between climate variables and rice yield in Punjab from 1990 to 2022 by using the Granger causality test and the Vector Autoregressive (VAR) model. The estimated VAR results were then employed for future predictions.

HIGHLIGHTS

- The findings indicate a bidirectional causality between climate variables and rice yield. The VAR estimates suggest that climate factors notably influence rice yield in Punjab.
- In particular, the minimum temperature and precipitation favorably contribute to the yield of rice; the maximum temperature, however, is detrimental
- Additionally, canal water irrigation negatively impacts rice yield.
- This study recommends that, to safeguard rice cultivation in Punjab from climate change, a multifaceted strategy is essential, including diversifying the cropping system, adopting various climate-resilient rice varieties and encouraging sustainable agrarian practices.
- Improved extension services can further enhance farmers' decision–making. Moreover, water–saving techniques such as wetting and drying, direct–seeded rice, and seeding on raised beds can significantly reduce water usage and potentially increase yields.

Keywords: Climate Change, Precipitation, Rice Yield, Temperature

Punjab is situated in northwestern India and has a subtropical monsoon climate, characterised by hot summers, cold winters and a distinct rainy season (Faroda & Poonia, 2012). The area experiences intense summers and bitterly cold winters, with temperature dropping to zero in some regions. Yearly rainfall is unevenly distributed, measuring over 1,000 mm in the north-eastern parts and dropping to beneath 400 mm in the semi-arid south-western zones. Rain is sporadically distributed throughout the year (Kaur and Vatta & Sidhu, 2015). From 1990 to 2022, the average maximum temperature in Punjab was 30.96 degrees Celsius, increasing by 0.37 °C from 30.78 °C in 1990–2006 to 31.15 °C in 2007–2022 (see Figure 1.a for the trend of maximum temperature in Punjab from 1990 to 2022). Similarly, the average minimum temperature from the period 1990-2022 in Punjab was 17.78 °C. It rose by 0.54 °C from 17.52 °C in 1990–2006 to 18.06 °C in 2007–2022 (see Fig. 1.b for the trend of minimum temperature in Punjab from 1990 to 2022), indicating a warming trend in the region. Precipitation also varied, with the average annual rainfall in Punjab

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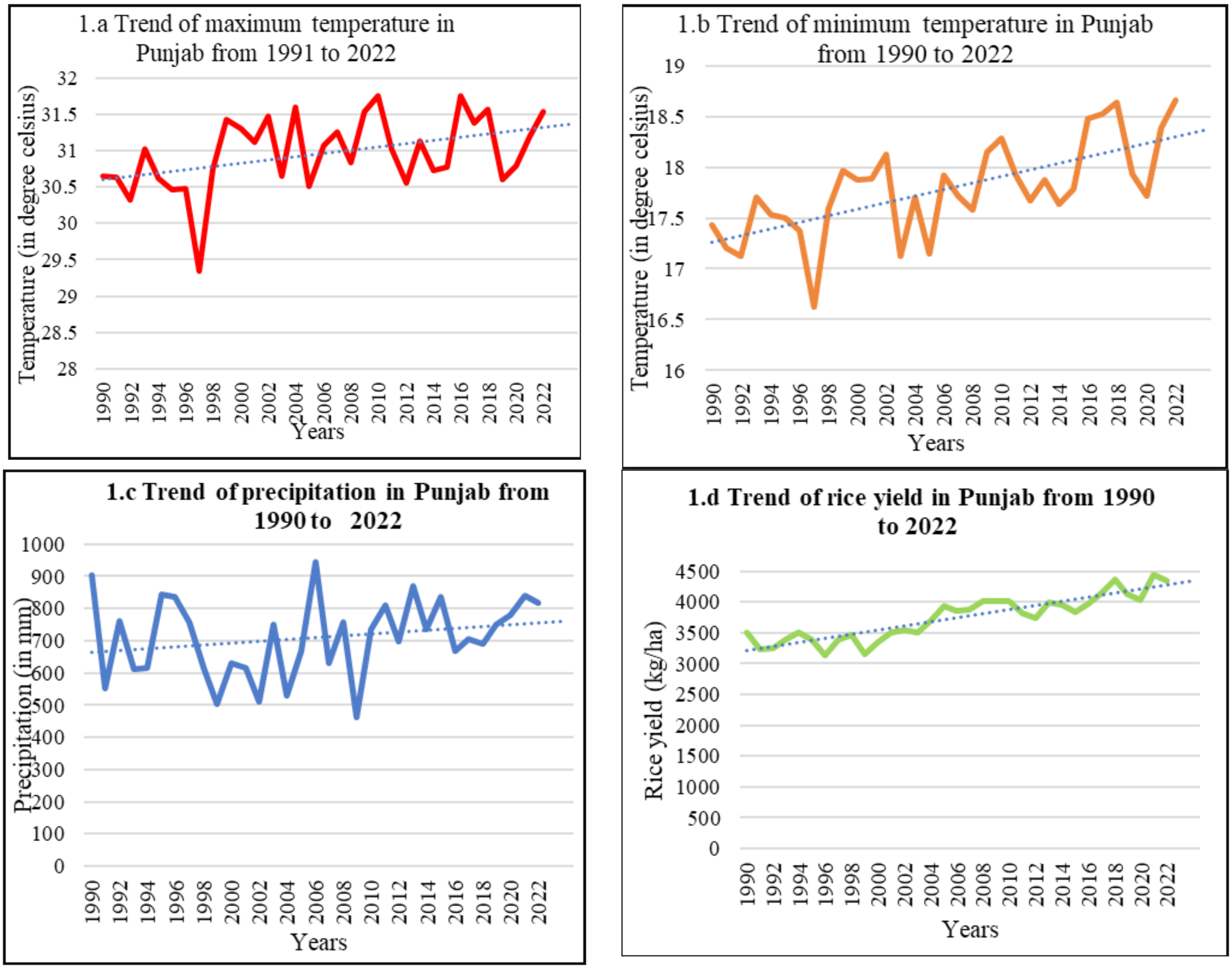
being 710.11 mm, increasing from 685.20 mm in 1990–2006 to 736.57 mm in 2007–2022 (see Fig. 1.c for the trend of precipitation in Punjab from 1990 to 2022). These changes suggest a warming and wetter climate in recent decades, although rainfall remains highly unpredictable and unevenly distributed. This climatic variability in precipitation has contributed to Punjab's heavy dependence on groundwater for irrigation and cultivation (Singh, 2011).

Rice and wheat are the most important staple crops in Punjab, contributing substantially to both regional food security and the agrarian economy. Punjab is often referred to as the "Granary of India," because of the significant share of the country's rice and wheat output, thereby ensuring national food self-sufficiency. However, rice cultivation in the state is increasingly threatened by changes in the climate, as evidenced by intensifying temperatures, changed precipitation patterns, and more frequent life-threatening weather events (IPCC, 2021). Since rice cultivation in Punjab is highly dependent on groundwater irrigation and the monsoonal cycle, climatic changes pose critical risks to its productivity and sustainability (Singh, 2011). Climate change affects rice yield in Punjab through both direct and indirect pathways. Directly, higher maximum and minimum temperatures shorten the rice growth cycle, adversely affecting sensitive stages such as flowering and grain filling (Lobell *et al.* 2012). Indirectly, changing rainfall patterns and increased irrigation demand exert pressure on water resources, undermining long-term sustainability (Aggarwal & Sivakumar, 2011). Several studies in South Asia confirm that even marginal increases in



Source: *Climate Change Knowledge Portal and EPWRF.*

Fig. 1: Trends of Maximum and Minimum temperature, Precipitation and Rice Yield in Punjab from 1990 to 2022

temperature reduce rice productivity (Krishnan *et al.* 2011; Auffhammer *et al.* 2012).

Climate change is a prominent obstacle to global food security, and its consequences are more severe in agricultural economies such as India. It's position as the one of the largest rice producers in the world makes the country's food security and rural economy vitally influenced by the stability of its rice production system (Faroda & Poonia, 2012). In this context, Punjab plays a crucial role in maintaining national food security (Singh and Awais, 2019). However, rice farming is highly susceptible to climate fluctuations, such as temperature variations, rainfall patterns, and an increase in severe weather conditions (Hanif *et al.* 2010). Various studies consistently demonstrate that rising temperatures negatively impact rice yields. Saseendran *et al.* (2000) suggested a negative effect of rising temperatures on rice yield in Kerala and also found that a 1-degree rise in temperature could decrease rice yield by 6 per cent. Palanisami's (2017) research showed that elevated maximum temperatures positively influence rice production in 13 key rice-growing states in India. In contrast, lower minimum temperatures negatively affect yield, probably due to increased respiration rates and higher energy usage. Furthermore, Anand & Dhaliwal (2024) confirmed that increases in maximum and minimum temperatures during the tillering and flowering stages of rice are major reasons for reduced yields. This is particularly problematic in many rice-growing regions of India where temperatures are already high. Rice is a water-intensive crop, and its cultivation is highly sensitive to changes in precipitation. Erratic rainfall patterns, including prolonged dry spells and heavy rainfall events, significantly affect rice productivity. Das & Baruah (2008) suggested that the primary reason for crop failure in large parts of rainfed areas in India is drought, which reduces the availability of irrigation water. Conversely, Dass *et al.* (2015) found that extreme rainfall and flooding can cause crop submergence, soil erosion, and nutrient leaching, resulting in low yields. Singh & Awais (2019) observed a decline in monsoon rainfall over recent decades, though tube wells help compensate; however, this leads to a severe drop in the groundwater table. Anand & Dhaliwal (2024) disclosed that unexpected heavy rains, particularly during ripening and harvesting stages in September, cause lodging, reduce grain quality, and lead to significant crop damage, thereby lowering yields. Increasing rainfall variability, with prolonged dry spells and intense downpours, remains a major concern. A study by Hari (2024) reveals that the intensive rice-wheat cropping system in Punjab has led to substantial depletion of groundwater resources, a situation further exacerbated by climate change. The prevailing literature highlights the vulnerability of a state's rice economy due to rising temperatures and erratic rainfall leading to food security issues and significant socio-economic challenges for farming communities.

In the context of Punjab, the dual reality of increasing rice yield trend (See figure 1.d) alongside intensifying climate pressures, Punjab presents a complex case of agricultural resilience and vulnerability. While technological advances, improved crop varieties and agricultural policies have contributed to yield improvements, the state's climate trajectory indicates mounting risks for the future. Moreover, the unsustainable groundwater use poses a long-term threat to the region's agricultural sustainability. So, it becomes imperative to understand the interaction between climate change and rice yields for designing adaptation strategies, including crop diversification, efficient irrigation technologies and the adoption of climate-resilient rice varieties. Such efforts are essential to ensure the sustainability of rice cultivation in Punjab's changing climatic landscape.

MATERIALS AND METHODS

This study intends to evaluate how climate and agricultural factors affect rice production in the Punjab region of India. For this purpose, secondary data regarding rice yield, rice area, maximum temperature, minimum temperature, precipitation, canal water irrigation and fertilizer consumption were extracted from the Climate Change Knowledge Portal, EPWRF, and Open Government Data (OGD) Platform India, from 1990 to 2022 (See Table 1). For data analysis, statistical and econometric methods were used, such as descriptive statistics and a correlation matrix. The Dickey-Fuller test is used to determine the stationarity of the series while the Johansen test is used to determine the long-run cointegration. After that, the dataset was tested for heteroskedasticity, autocorrelation, and multicollinearity. Variable interdependency was confirmed using the Granger causality test. The impact assessment was done through the VAR model while the rice yield prediction was done using the model's projected values.

Table 1: Variable list

Type of variable	Variables	Source
Dependent Variable	Rice yield	Open Government Data Platform India and EPWRF
Independent Variables	Rice area	
	Canal water irrigation	
	Fertilizer consumption	
	Maximum temperature	Climate Change Knowledge Portal
	Minimum temperature	
	Precipitation	

The function form for the variables used in the present study *ia* as follow,

$$ry = f(ra, cwi, fc, tmax, tmin, prec)$$

Here, *ry* (rice yield), *ra* (rice area), *cwi* (canal water irrigation), *fc* (fertilizer consumption) *tmax* (maximum temperature), *tmin* (minimum temperature) and *prec* (precipitation).

The linear regression equation for the present study is as follows,

$$Y_i = \alpha + \beta_1 X_{t-1} + \cdots + \beta_n X_{t-n} + \varepsilon_t \quad \ldots(1)$$

$$ry_{it} = \alpha + \beta_1 ra_{t-1} + \beta_2 cwi_{t-1} + \beta_3 fc_{t-1} + \beta_4 tmax_{t-1} + \beta_5 tmin_{t-1} + \beta_6 prec_{t-1} + \varepsilon_t \quad \ldots(2)$$

The logarithmic (ln) equation is as follows,

$$lnry_{it} = \alpha + \beta_1 lnra_{t-1} + \beta_2 lncwi_{t-1} + \beta_3 lnfc_{t-1} + \beta_4 lntmax_{t-1} + \beta_5 lntmin_{t-1} + \beta_6 lnprec_{t-1} + \varepsilon_t \quad \ldots(3)$$

For the impact assessment, the Vector Autoregression (VAR) method was executed. It is a multivariate time series model that captures the dynamic interrelationships among multiple variables and treats all the variables as jointly dependent (Sims, 1980). As per Lutkepohl (2005), VAR is expressed as,

$$y_t = AY_{t-1} + B_0 x_t + u_t \quad \ldots(4)$$

Afterward, estimates from the VAR model were used to generate multi–step–ahead forecasts of rice yield in Punjab, with the results presented in graphical form to illustrate the dynamic projections. As per StataCorp (2021), the forecasting equations are expressed as,

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + u_t \quad \ldots(5)$$

Here, y_t is the vector of the dependent variable, v is the vector of intercept term, A_1, $A_2 \ldots A_p$ represent the coefficient matrix of the dependent variable upto the lag p, $y_{t-1} \ldots y_{t-p}$ are the lagged values of the dependent variable's vector. B here is the coefficient matrix of the independent variables, x_t is the vector of the independent variables and u_t is the vector of the structural disturbances.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 2 displays the descriptive statistics of Punjab from 1990 to 2022. Average rice yield in Punjab was 3743.636 kg/ha and rice area was 2547.69. Mean canal water irrigation was 1884.826. Average fertilizer consumption was 215.3026 kg/ha. The average maximum was 30.96 °C , ranging from 29.34 °C to 31.76 °C, and the minimum temperature was 17.78 °C, ranging from 16.63 °C to 18.66 °C. Average precipitation was 710.1109 mm.

Table 2: Descriptive statistics

Variables	Mean	Std. dev.	Minimum	Maximum
ry	3743.636	362.2931	3132	4443
ra	2547.69	347.2963	1905	3064
cwi	1884.826	244.0491	1327	2266
fc	215.3026	28.2746	161.84	250.6
tmax	30.96485	0.5080854	29.34	31.76
tmin	17.78182	0.4682978	16.63	18.66
prec	710.1109	122.4042	463.71	946.45

Source: *Calculated by author.*

Correlation Matrix

Table 3 explains the correlation matrix. The rice area has a low positive correlation (0.1338) with the rice yield. Canal water irrigation has a weak-to-moderate positive correlation (0.3846) with rice yield. Fertilizer consumption has a moderate negative correlation (-0.3711) with rice yield. Maximum temperature has a low positive correlation (0.1830) with rice yield, and minimum temperature has a low positive correlation (0.1451) with rice yield. Precipitation has a low negative correlation (-0.0050) with rice yield.

Table 3: Correlation matrix

Variables	*lnry*	*lnra*	*lncwi*	*lnfc*	*lntmax*	*lntmin*	*lnprec*
lnry	1.0000						
lnra	0.1338	1.0000					
lncwi	0.3846	-0.1725	1.0000				
lnfc	-0.3711	-0.1495	-0.1065	1.0000			
lntmax	0.1830	0.0564	0.4877	-0.2829	1.0000		
lntmin	0.1451	0.0781	0.4587	-0.2613	0.8961	1.0000	
lnprec	-0.0050	0.0197	-0.3058	-0.1615	-0.4127	-0.2708	1.0000

Source: *Calculated by author.*

Result of unit root test

To assess the stationarity of the time series dataset, the Augmented Dickey-Fuller (ADF) test was executed. Dickey and Fuller (1979) developed the procedure for testing the unit root. It was further developed by Said and Dickey (1984) and Mackinnon (1994). The basic Dickey–Fuller test considered the following autoregressive model equation,

$$y_t = \rho y_{t-1} + \epsilon_t$$

Where, ε_t are independent and identically distributed as $N(0, \sigma^2)$ and $y_t = 0$, the OLS estimate based on an n-observation time series of the autocorrelation parameter ϱ, which is given by;

$$\widehat{\rho_n} = \frac{\sum_{t=1}^{n} y_{t-1}\, y_t}{\sum_{t=1}^{n} y_t^2}$$

In dealing with autocorrelation and the calculation of the test statistics, the Augmented Dickey-Fuller regression fits in the form of;

$$\Delta y_t = \alpha + \beta y_{t-1} + \gamma t + \sum_{i=1}^{n} \delta_i \Delta y_{t-i} + u_i$$

Using OLS, the constant term α or the time trend δ_t can be omitted based on the specified options, and n represents the number of lags.

The test statistic Z_t is obtained using the following formula;

$$Z_t = \frac{\hat{\beta}}{\widehat{\sigma_\beta}}$$

Here, $\widehat{\sigma_\beta}$ is the standard error of $\hat{\beta}$. Also, Z_t is computed against the null hypothesis (H_0): Variables are not stationary and the alternative hypothesis (H_a): Variables are stationary.

All the variables, i.e., rice yield, rice area, canal water irrigation, fertilizer consumption, maximum temperature, minimum temperature, and precipitation, were tested for stationarity at the level. Table 4 reveals the results of the stationarity test. Maximum temperature, minimum temperature, and precipitation were found to be stationary at the level. All the other variables, i.e., rice yield, rice area, canal water irrigation and fertilizer consumption, were found to be stationary at first difference.

Table 4: Dickey–Fuller test for unit root

Variable	At level Test Statistic (P-Value)	At first difference Test Statistic (P-Value)
lnry	-1.039 (0.7386)	-6.672 (0.0000)
lnra	-1.747 (0.4070)	-4.321 (0.0004)
lncwi	-2.557 (0.1022)	-4.775 (0.0001)
lnfc	-1.366 (0.5984)	-5.239 (0.0000)
lntmax	-4.166 (0.0008)	-8.360 (0.0000)
lntmin	-2.905 (0.0448)	-7.419 (0.0000)
lnprec	-5.564 (0.0000)	-10.871 (0.0000)

Source: *Calculated by author.*

Johansen Cointegration Test Results

To test the long-run cointegration of the rice yield with other variables, Johansen (1988; 1991) cointegration test was conducted. The test follows the Vector Autoregression (VAR),

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_n Y_{t-n} + \mu + \varepsilon_t$$

Where A_i are the coefficient matrices, μ is the deterministic term, and ε_t is the white-noise error term. This VAR equation is reparametrized into the Vector Error Correction Model (VECM) equation,

$$\Delta Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \tau_i \Delta T_{t-i} + \mu + \varepsilon_t$$

Where π is αβ′ having the long–run information, α is the adjustment coefficient, β is the cointegration vector, and τ captures the short–run dynamics.

The Trace and maximum eigenvalue statistics were calculated in relation to the alternative hypothesis (Ha) that there is cointegration and the null hypothesis (H_0) that there is no cointegration. Formula for Trace statistics,

$$LR_{trace}(r) = -T \sum_{i=r+1}^{k} ln\left(1 - \widehat{\lambda_\iota}\right)$$

Formula for the Maximum eigenvalue statistics,

$$LR_{max}(r, r+1) = -T\ ln\left(1 - \widehat{\lambda_{r+1}}\right)$$

Where T is the sample size, and $\widehat{\lambda_\iota}$ is the estimated eigenvalue.

Table 5 displays the results of the cointegration test. At maximum rank 0 and 1, the trace statistic is greater than the critical value (5%), hence H_0 of no cointegration was rejected. However, at maximum rank 2, the trace statistic was less than the critical value (5%). Therefore, H_0 of no cointegration was not rejected, which indicates only one long-term equilibrium relationship between the variables, with an ideal cointegration rank of one. The Vector Error Correction Model (VECM) estimate found a single cointegration equation, _ce1, which corresponds to the Johansen cointegration test of rank 1. This equation represents the long-run relationship between the variables. P-value in this equation is less than 0.05 (P-value <0.05), suggesting that the long-run equation is statistically significant (Table 6).

Results of Heteroskedasticity, Autocorrelation and Multicollinearity Tests

Table 7 reveals the results of heteroskedasticity, autocorrelation and multicollinearity tests. For testing heteroskedasticity, White's test was conducted with the null hypothesis (H_0): Homoskedasticity and alternative hypothesis (H_a): Unrestricted heteroskedasticity. *P*-Value for the test was greater than 5 per cent level (*P*-Value>0.05), hence accepting H_0 i.e., data set is homoskedastic. For testing autocorrelation, the Breusch–Godfrey LM Test was executed with null hypothesis (H_0): No serial autocorrelation and alternative hypothesis (H_a): Serial autocorrelation. We accept H0, which states that there is no serial autocorrelation in the dataset, because the test's P-Value was higher than 0.05 (*P*-Value>0.05) (0.9785). VIF, or the Variance Inflation Factor, was employed for multicollinearity. There is no possible risk of multicollinearity in the dataset, as indicated by the mean VIF of 2.87 (Mean VIF>5).

Table 5: Johansen test for cointegration

Maximum rank	Params	LL	Eigenvalues	Trace statistic	Critical value (5%)
0	7	-17.136896	—	201.9691	124.24
1	20	16.250726	0.97552	135.1939	94.15
2	31	40.240806	0.93044	87.2137	68.52
3	40	53.833575	0.77916	60.0282	47.21
4	47	65.200819	0.71720	37.2937	29.68
5	52	73.689364	0.61061	20.3166	15.41
6	55	79.268383	0.46200	9.1586	3.76
7	56	83.847673	0.39879	—	—

Source: *Calculated by author.*

Table 6: VECM cointegration equations

Equation	Parms	Chi2	P-Value
_ce1	6	637.7457	0.0000

Source: *Calculated by author.*

Table 7: Diagnostic test

White's Test				
Source	**chi²**	***df***	**P–Value**	**Result**
Heteroskedasticity	19.00	18	0.3918	Homoskedasticity
Skewness	7.02	6	0.3194	
Kurtosis	1.28	1	0.2585	
Total	27.29	25	0.3415	
Breusch–Godfrey LM Test				
Autocorrelation	0.001	1	0.9785	No serial autocorrelation
Multicollinearity				
Mean VIF	2.87			No multicollinearity

Source: *Calculated by author.*

The Granger Causality Test Results

To determine the causal links between the independent variables (X_i) and the dependent variable (Y_i), the Granger causality test was conducted. The null hypothesis (H0) for the test stated that X_i does not Granger cause Y_i, while the alternative hypothesis (Ha) proposed that X_i does Granger cause Y_i. The results of the Granger causality test are shown in Table 8. Rice area, canal water irrigation, maximum and minimum temperatures, and precipitation are examples of independent variables with P-values below 0.05. Therefore, the alternative hypothesis (Ha) can be accepted, and the null hypothesis (H0) rejected. This indicates that rice area, canal water irrigation, maximum temperature, minimum temperature, and precipitation Granger cause rice yield. Conversely, for fertilizer consumption, $P > 0.05$. Thus, the null hypothesis (H0) is accepted, suggesting that fertilizer consumption does not Granger cause rice yield. For all variables combined, P-value < 0.05, indicating that collectively, all the variables Granger cause rice yield. Additionally, there is reverse causation with fertilizer consumption and rice yield. Meanwhile, canal water irrigation and climate variables (maximum temperature, minimum temperature, and precipitation) exhibit bidirectional causal relationships with rice yield (see Table 9 and Table 1A in the Appendix).

Estimates of Vector Auto Regression (VAR) And Forecast Results

Table 10 displays the results of the Vector Auto Regression (VAR) model at immediate lag 1 and delayed lag 2.

At immediate lag 1, the rice area has a positive impact on rice yield, but it is statistically insignificant

Table 8: Results of the Granger causality test

Dependent variable (Y_i)	Independent variables (X_i)	chi²	*df*	P–Value	Result
	Rice area	15.793	2	0.000	Reject H_0
	Canal water irrigation	6.2715	2	0.043	Reject H_0
	Fertilizer consumption	5.5665	2	0.062	Accept H_0
Rice yield	Maximum temperature	25.785	2	0.000	Reject H_0
	Minimum temperature	11.708	2	0.003	Reject H_0
	Precipitation	25.546	2	0.000	Reject H_0
	ALL	61.358	12	0.000	Reject H_0

Source: *Calculated by author.*

Tables 9: Type of causal relationship between variables

Dependent variable (Y_i)	Independent variables (X_i)	Causal relationship
	Rice area	Unidirectional
Rice yield	Canal water irrigation	Bidirectional
	Fertilizer consumption	Reverse causation
	Maximum temperature	Bidirectional
	Minimum temperature	Bidirectional
	Precipitation	Bidirectional

Source: *Based on Granger causality test results.*

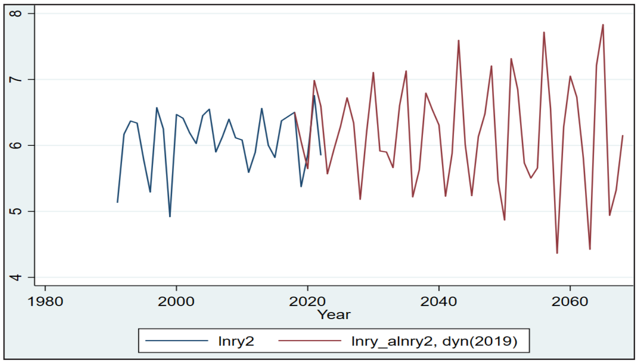
(*P*-value > 0.05). The coefficient value of canal water irrigation suggests a positive and statistically significant (*P*-value < 0.05) impact on rice yield at lag one. A one percent rise in canal water irrigation is expected to increase the rice yield by 0.31 percent. The fertilizer consumption at immediate lag one has a positive impact on rice yield, but is statistically insignificant (*P*-value > 0.05). The rice yield is negatively impacted by the highest temperature, with the coefficient value of -9.731362, statistically significant at 5 per cent (*P*-value < 0.05). This result aligns with the study of Anand and Dhaliwal (2024). The possible reason for this negative impact could be a rise in the maximum temperature during the tillering and the flowering stages, affecting the phenology of the crop and reducing the quality and quantity of the crop. Whereas, minimum temperature has a positive impact on the rice yield at immediate lag one and is statistically significant (*P*-value < 0.05), the result is in tune with Chowdhury and Rahman (2015); Bal *et al.* (2023); Nguyen *et al.* (2024). A moderate increase in the night time minimum temperature during the summer–autumn is conducive to rice growth. The coefficient value of minimum temperature suggests that a rise in minimum temperature by one degree celsius will increase the rice yield by 11.38 percent. The coefficient value precipitation (0.1561204) is also reflecting a positive impact on the rice yield but is statistically insignificant (*P*-value > 0.05) at immediate lag one.

At delayed lag two, the rice area has negative impact on rice yield with the coefficient value of -0.6306091, and is statistically significant at 5 per cent (*P*-value < 0.05). The coefficient value of canal water irrigation suggests a positive and statistically significant (*P*-value < 0.05) impact on wheat yield at lag two. A one per cent rise in canal water irrigation is expected to increase the rice yield by 0.17 per cent. The fertilizer consumption at delayed lag two has a positive impact on rice yield, but is statistically insignificant (*P*-value > 0.05). The maximum temperature has a positive impact on the rice yield with the coefficient value of 1.104813, but it is statistically insignificant (*P*-value > 0.05). Whereas, minimum temperature has a negative impact on the rice yield at delayed lag two and is also statistically insignificant (*P*-value > 0.05). Precipitation reflects a positive impact on the rice yield and is statistically significant (P-value < 0.05) at a delayed lag two, the result aligns with Dkhar *et al.* (2017); Kumar *et al.* (2025). As rice is a water intensive crop so rainfall during *kharif* season especially between June and July positively affect the rice yield. The coefficient value of precipitation suggests that a one percent rise in precipitation is expected to increase the rice yield by 0.47 percent.

Table 10: Result of Vector Auto Regression (VAR) model

Variables	Coefficient	Std. err.	P-Value
lnry			
L1.	0.492117	0.2101385	0.019
L2.	-1.149842	0.2023981	0.000
lnra			
L1.	0.134994	0.1287826	0.295
L2.	-0.6306091	0.2331734	0.007
lncwi			
L1.	0.3171969	0.1307648	0.015
L2.	0.1788049	0.083888	0.033
lnfc			
L1.	0.2171724	0.2082426	0.297
L2.	0.2086415	0.212402	0.326
lntmax			
L1.	-9.731362	1.916699	0.000
L2.	1.104813	1.821372	0.544
lntmin			
L1.	11.38582	3.589808	0.002
L2.	-0.9482045	2.117659	0.654
lnprec			
L1.	0.1561204	0.1032543	0.131
L2.	0.4718615	0.1024836	0.000
_cons	0.3012744	8.907792	0.973

Source: *Calculated by author.*



Source: *Prepared by author using predicted values from VAR model.*

Fig. 2: Rice yield forecast

Fig. 2 represents the log-transformed historical trend (lnry2/blue line) and forecasted trend (lnry_blnry2, dyn (2021)/brown line) of rice yield. The historical trend shows a considerable variability with notable ups and downs, reflecting fluctuations in the rice yield. The dynamic forecast/brown line/lnry_blnry2, dyn (2021) has been generated using the predicted values from the VAR model. The forecasted line suggests an increasing volatility in the rice yields with relatively larger oscillations compared to the historical trend. This implies that in the long term, the average rice yield is expected to improve slightly, and the inter-annual variability is expected to intensify. While the prediction shows upward and downward shifts, the stability should be interpreted cautiously, as the actual future yields may deviate due to unmodeled shocks such as extreme and unpredictable weather events, pest outbreaks, or policy changes.

CONCLUSION

The present study's primary goal was to determine the influence of climate change on rice output in Punjab from 1990 to 2022. Punjab is one of the largest rice-producing states in India and contributes significantly to the national food security. However, in the past few years, the state has been experiencing several climatic events such as rising temperatures, erratic rainfall and delayed or early monsoons. Apart from these climatic events, it is also facing the problem of groundwater depletion. These combined problems seriously threaten rice cultivation in the Punjab state, leading to the problem of national food security and creating significant socio–economic challenges for the farming community. The results of the present study reveal that the climate variables significantly affect the rice yield in Punjab. A moderate rise in the night time minimum temperature during the growing rice season affects the crop positively, leading to a higher yield. The rainfall during June and July is also favourable for rice cultivation.

Meanwhile, the rise in the maximum temperature during the rice season seriously affects the crops' phenology and growth, reducing output and quality. Furthermore, the groundwater level in Punjab is low. If the monsoon is not on time, then the farmers have to depend heavily on the canal water, which is not sufficient and as rice is water–intensive, a lack of access to water leads to reduced rice yield. The study's findings show that Punjab's rice farming is a case that demands a multi-pronged approach to its sustenance against climate change. This approach should consist of climate-resilient rice varieties, diversified cropping, and promotion of sustainable agricultural practices. Proper extension service facilities would enable farmers to make better choices in the context of selecting seed varieties, fertilizer application and watering the field efficiently. Water-saving techniques such as direct-seeded rice, soaking and drying, and raised-bed seeding can substantially improve yield while reducing water use. Additionally, the canal irrigation system should be modernized for efficient management. By ensuring equitable distribution and efficient use of canal water, dependency on groundwater can be reduced and long-term rice productivity can be enhanced and sustained.

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Appendix

Table 1A: Results of Granger causality test

Dependent variable (Y_i)	Independent variables (X_i)	chi²	*df*	P–Value	Result
	Rice yield		2	0.799	Accept H_0
Rice area	Canal water irrigation		2	0.227	Accept H_0
	Fertilizer consumption		2	0.123	Accept H_0
	Maximum temperature		2	0.627	Accept H_0
	Minimum temperature		2	0.929	Accept H_0
	Precipitation		2	0.481	Accept H_0
	ALL		12	0.610	Accept H_0
	Rice yield		2	0.005	Reject H_0
Canal water irrigation	Rice area		2	0.179	Accept H_0
	Fertilizer consumption		2	0.038	Reject H_0
	Maximum temperature		2	0.001	Reject H_0
	Minimum temperature		2	0.001	Reject H_0
	Precipitation		2	0.000	Reject H_0
	ALL		12	0.000	Reject H_0
	Rice yield		2	0.000	Reject H_0
Fertilizer consumption	Rice area		2	0.000	Reject H_0
	Canal water irrigation		2	0.000	Accept H_0
	Maximum temperature		2	0.000	Reject H_0
	Minimum temperature		2	0.000	Reject H_0
	Precipitation		2	0.000	Reject H_0
	ALL		12	0.000	Reject H_0
	Rice yield		2	0.000	Reject H_0
Maximum temperature	Rice area		2	0.000	Reject H_0
	Canal water irrigation		2	0.232	Accept H_0
	Fertilizer consumption		2	0.000	Reject H_0
	Minimum temperature		2	0.000	Reject H_0
	Precipitation		2	0.007	Reject H_0
	ALL		12	0.000	Reject H_0
	Rice yield		2	0.000	Reject H_0
Minimum temperature	Rice area		2	0.000	Reject H_0
	Canal water irrigation		2	0.000	Accept H_0
	Fertilizer consumption		2	0.000	Reject H_0
	Maximum temperature		2	0.000	Reject H_0
	Precipitation		2	0.000	Reject H_0
	ALL		12	0.000	Reject H_0
	Rice yield		2	0.000	Reject H_0
Precipitation	Rice area		2	0.000	Reject H_0
	Canal water irrigation		2	0.000	Accept H_0
	Fertilizer consumption		2	0.000	Reject H_0
	Maximum temperature		2	0.000	Reject H_0
	Minimum temperature		2	0.000	Reject H_0
	ALL		12	0.000	Reject H_0

Source: *Calculated by author.*