Impact of Climatic Factors on Rice Yield in Tamil Nadu: An ARDL Approach

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Abstract: *Climate change is one of the most pressing issues nearly all nations face, particularly those in developing and underdeveloped stages. Agriculture is the most vulnerable sector due to its direct and indirect dependence on climatic factors.This study investigates the impact of climate change on rice productivity in Tamil Nadu, spanning from 1990-91 to 2022-23, using the Autoregressive Distributed Lag model. The bounds test was used to test whether minimum temperature, maximum temperature, and rainfall exhibit a long-term cointegration relationship with rice productivity. The bound test result indicates that there exists a cointegration among the climatic variables and rice yield. The adjusted R-squared value of 0.4943 indicates that approximately 49.43 per cent of the variation in the rice yield is explained by the climate factors used in the model. The study provides valuable insights for policymakers to understand the impact of climate change on the agriculture sector, particularly rice production, and supports the development of effective climate mitigation policies.*

Keywords: ADF Test, ARDL, Climate change, Rice yield, Tamil Nadu

I. INTRODUCTION

Climate variability poses a significant challenge globally, with irregular climate conditions adversely impacting various economic activities, particularly the agricultural sector (Ali et al., 2017). Agriculture and its allied activities constitute the backbone of India's economy, supporting the livelihoods of millions across different states (Mariappan, 2024). Most farmers in Tamil Nadu possess small and marginal landholdings (Vincent & Saravanan, 2020). Climatic factors like temperature and precipitation significantly affect the agricultural output of all the nations (Lobell et al., 2007). Extreme weather events have an enormous effect on smallholder farmers in developing nations compared to developed countries (Altieri & Nicholls, 2017).

Tamil Nadu is one of India's most prosperous agricultural states, renowned for its production of rice, bananas, coconuts, sugarcane, pulses, and oilseeds. Geographically, the state is situated at the southern tip of the Indian peninsula, bounded by north latitude 8°52 and 13°352 and east longitude 76°152 and 80°202 . Tamil Nadu comprises 38 districts, spanning an area of 1,30,058 square kilometres, with a population of 7,21,47,030 (Tamil Nadu Government Portal, 2024).Approximately 45 per cent of the rural population in Tamil Nadu depends on agriculture for their livelihood (NABARD, 2024). Changes in rainfall patterns and amounts are likely to impact farmers in the state adversely. Climatic factors, such as rainfall and temperature, significantly influence agricultural activities, including field preparation, sowing, and harvesting. Tamil Nadu is one of the states most vulnerable to climate-related disasters, including droughts and floods (Mohanty & Wadhawan, 2021). Fluctuations in climatic variables disproportionately affect farmers. Variations in temperature and precipitation directly impact crop yields, soil fertility, and water availability. Climatic factors like temperature and precipitation significantly affect the agricultural output of all the nations (Lobell et al., 2007).

Climate change is hurting emerging nations' capacity to attain food security and stable economic growth, as they rapidly expand populations with high food demand. (Rehman et al., 2019). Climate change directly affects the agricultural sector through changes in rainfall patterns and increases the chances of pest and insect attacks (Lama & Devkota, 2009). Climate change is not only a natural phenomenon; human activities are the major suspects of climate change (Praveen & Sharma, 2020). Climate change affects the world's nutritional and food security (Malhi et al., 2021). The concentration of greenhouse gases like methane, carbon dioxide, and nitrous oxide increases in the atmosphere because of anthropogenic activities, which causes ozone depletion (Montzka et al.,2011). Extreme temperature events cause problems with the normal life cycle of plants, leading to a decline in production (Hatfield &Prueger, 2015). Though agriculture is directly influenced by several activities such as Variability in climatic factors (maximum temperature, minimum temperature, precipitation, humidity, solar radiation, sun intensity, drought, flood, wind speed, etc. (Kumar & Sharma, 2014).

II. REVIEW OF LITERATURE

Ozdemir (2021) found that annual rainfall has a negative short-term impact but a positive long-term impact on agricultural output in Asian countries. A study by Chandio et al. (2020) on the link between climate change and agricultural production in China found that climate change was detrimental to agricultural production and rural residents' income. An Indian study by Praveen and Sharma (2020) on the impact of climate change on several crops using multivariate regression found that temperature and rainfall do not significantly impact the production of crops, including wheat, cotton, groundnut, linseed, and arhar. The marginal effects study concluded that the rise in temperature has a detrimental influence on the output of tea, sugar, ragi, wheat, maize, and jowar. Increased rainfall benefits productivity as long as it does not become excessive. Guntukula (2019) examined the effects of climate change on Indian agriculture by analysing seven of the country's most significant crops. According to the study, the effects of various climatic variables on crops differ between food and non-food crops. Saravanakumar et al. (2015) studied the effect of climate change on rice production in various districts of Tamil Nadu. Panel data from 30 districts in Tamil Nadu from 1971 to 2009 were used for the study. A fixed-effect panel data model was utilised to analyse the data. The study finds that climate change negatively influences rice yield, and the forecasted results also show that climate change will cause yield decline in the long run.

Research Gap and Objective of the Study

The existing literature on the impact of climate change on agriculture primarily addresses the broader Indian context, with very few studies focusing on specific states, particularly Tamil Nadu. As a region with distinct agro-climatic characteristics and high productivity in various crops, including rice, a study on Tamil Nadu will provide more localised insights into how climate variability affects the rice yield.

This study aims to examine the impact of climate factors on rice yield in Tamil Nadu, focusing on climatic factors such as minimum temperature, maximum temperature, and rainfall. This study utilises the latest and most comprehensive data from 1990-91 to 2022-23 and employs time series econometric methodologies to provide precise and reliable findings.

III. ECONOMETRIC METHODOLOGY

SOURCE OF DATA

Data on the research variables was gathered from several reliable sources spanning 1990-91 to 2022-23. The Rice Yield (RY) data were obtained from the Database on Indian Economy, Reserve Bank of India. Climatic variables included in the model were minimum annual temperature, maximum annual temperature, and annual rainfall. This data was sourced from the India Meteorological Department, the Ministry of Earth Sciences, Government of India.

Measurement of Variables

The present study takes the Rice Yield as the dependent variable, which was measured in Kilograms per Hectare. Independent variables, including Minimum Annual Temperature (Min-Tem) and Maximum Annual Temperature (Max-Tem), were measured in Degrees Celsius, and Annual rainfall was measured in millimetres.

Econometric Application

Appropriate time-series econometric models, including the Augmented Dickey-Fuller (ADF) test and the Auto Regressive Distributed Lag (ARDL) model, were employed to examine the impact of climate factors on rice yield. Both short-run and long-run analyses were conducted using EViews software.

Unit Root Test

The estimated results of an OLS regression involving non-stationary variables can lead to unreliable economic interpretations and obscure the natural relationships among variables. This issue is characteristic of spurious regression problems among non-stationary variables (Muftaudeen& Bello, 2014). To address this concern, a unit root test was applied to ensure the stationarity of the variables used in this analysis. In this study, the Augmented Dickey-Fuller (ADF) test was applied to evaluate the stationarity of the variables (Dickey & Fuller, 1979). The ADF unit root test is widely used in empirical research to examine the stationarity of variables. The unit root tests for all the time series were specified as:

$$\Delta X_t = \beta_1 + \alpha X_{t-1} + \sum_{i=1}^{k} \gamma i\, \Delta X_{t-1} + e_t \quad \text{(Model-I: Constant)} \quad (1)$$

$$\Delta X_t = \beta_1 + \beta_{2t} + \alpha X_{t-1} + \sum_{i=1}^{k} \gamma i\, \Delta X_{t-1} + e_t \quad \text{(Model-2: Constant \&Trend)} \quad (2)$$

$$\Delta X_t = \alpha Y_{t-1} + \sum_{i=1}^{k} \gamma i\, \Delta X_{t-1} + e_t \quad \text{(Model-3: None)} \quad (3)$$

Where t denotes any time trend, k denotes the number of lagged differences, and the parameters called α β, and γ were estimated, e denotes the error term, which was assumed to be normally distributed, Δ denotes by the difference operator, and X denotes all the time series variables. The Null hypothesis (H_0): $\alpha = 0$ Data were non-stationary. The Alternative hypothesis (H_1): $\alpha \neq 0$ Data were stationary.

The Lag Length Criterion

In time series analysis, the standard Akaike's Information Criterion (AIC), Schwarz's Bayesian Information Criterion (SBIC), and Hannan-Quinn Information Criterion (HQIC) are commonly employed to determine the optimal lag length of variables. The optimal lag length criteria were specified as:

$$AIC = -2T\, [\ln (\hat{R}^2\rho)] + 2p \quad (4)$$

$$SBIC = \ln (\hat{R}^2\rho) + [\rho \ln (T)] / T \quad (5)$$

$$HQIC = \ln (\hat{R}^2\rho) + 2\, T^{-1}\rho \ln[\ln (T)] \quad (6)$$

Where ρ represents the lag length to determine the time series model, R represents the estimation of the residuals from the model, and T represents the number of observations.

ARDL Short-run and Long-run

The following model specification was used to examine the association of climate factors, that is, rainfall and the minimum and maximum temperature, with Rice yield the state of Tamil Nadu over the period 1990-91 to 2022-23.

$$\Delta lnRY_t = \lambda_0 + \sum_{i=1}^{L} \lambda_{1j} \Delta lnRY_{t-k} + \sum_{i=1}^{L} \lambda_{2j} \Delta lnARF_{t-k} + \sum_{i=1}^{L} \lambda_{3j} \Delta lnAMin.Tem_{t-k} + \sum_{i=1}^{L} \lambda_{4j} \Delta lnAMax.Tem_{t-k} + \delta_1 lnTFGY_{t-1} + \delta_2 lnARF_{t-1} + \delta_3 lnAMin.Tem_{t-1} + \delta_4 lnAMax.Tem_{t-1} + \epsilon_t \quad (7)$$

Where lnRYis the natural logarithm of Rice Yield, lnARFis the natural logarithm of annual rainfall, lnAmin.Temis the natural logarithm of the annual minimum temperature, lnAmax.Temis the natural logarithm of the annual maximum temperature λ is the intercept, λ_1, λ_2, λ_3, and λ_4 are the short-run coefficients, δ_1, δ_2, δ_3, and δ_4 are long-run coefficients, L is the lag order, Δ is the first difference operator, t-1 is the time lag, and ϵ_t is the error term.

Short-Run with Error Correction Term (ECT)

To identify the short-run association between the variables, the following ECM of the ARDL model can be specified:

$$\Delta lnRY_t = \lambda_0 + \sum_{i=1}^{L} \lambda_{1j} \Delta lnRY_{t-k} + \sum_{i=1}^{L} \lambda_{2j} \Delta lnARF_{t-k} + \sum_{i=1}^{L} \lambda_{3j} \Delta lnAMin.Tem_{t-k} + \sum_{i=1}^{L} \Delta lnAMax.Tem_{t-k} + \theta ECT + u_t \quad (8)$$

Where $\boldsymbol{\varnothing}$ represents the speed of adjustment (Error Correction Model) and its value should be negative and statistically significant (Granger, 1988). It represents the speed with which the dependent variable and independent variable adjust from the short run to the long run.

Estimation of Error Correction Term

The error correction term (ECT) is obtained through equations (8)

$$\theta ECT = \Delta lnRY_t - \lambda_0 - \sum_{i=1}^{L} \lambda_{1j} \Delta lnTFGY_{t-k} - \sum_{i=1}^{L} \lambda_{2j} \Delta lnARF_{t-k} - \sum_{i=1}^{L} \lambda_{3j} \Delta lnAMin.Tem_{t-k} - \sum_{i=1}^{L} \lambda_{4j} \Delta lnAMax.Tem_{t-k} - u_t \quad (9)$$

IV. RESULT AND DISCUSSION

Results of Descriptive Statistics

Table 1 represents the descriptive statistics of the variables used in the model. The Jarque-Bera test statistics deal with the normality of variables in the study. It shows that all the variables except rainfall were normally distributed. The kurtosis values of the variables below three indicate moderate distributions, except for maximum temperature and where the kurtosis is slightly above three, indicating that these variables have a few more extreme values or outliers than others. However, the effect is not very strong. The skewness values indicate that maximum temperature is positively skewed, while rice yield, minimum temperature, and rainfall are negatively skewed.

Table 1. Estimated results of descriptive statistics

	ln RY	lnMAX_TEM	lnMIN_TEM	lnRF
Mean	8.058356	3.630778	2.854137	6.758285
Median	8.044305	3.627330	2.850056	6.832924
Maximum	8.395929	3.670564	2.956994	7.229766
Minimum	7.744137	3.601065	2.750903	5.762051
Std. Dev.	0.162542	0.014865	0.044763	0.357790
Skewness	-0.103260	0.185811	-0.029348	-1.414026
Kurtosis	2.307576	3.223403	2.915168	4.352451
Jarque-Bera	0.717890	0.258517	0.014632	13.51212
Probability	0.698413	0.878747	0.992711	0.001164
Sum	265.9257	119.8157	94.18651	223.0234
Sum Sq. Dev.	0.845433	0.007071	0.064121	4.096433
Observations	33	33	33	33

Source: Authors' calculation

The trends of RF, Min-Tem and Max-Tem of time series variables were presented in Figures 1 to 4.

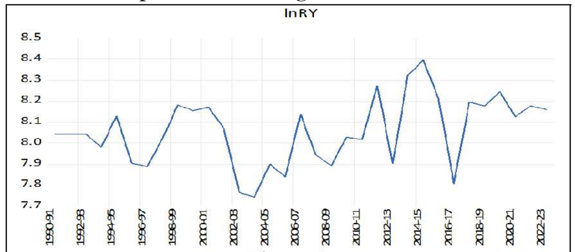

Figure 1

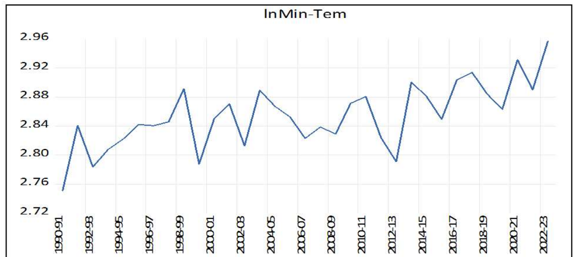

Figure 2

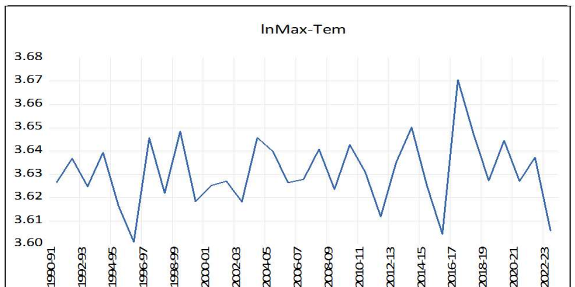

Figure 3

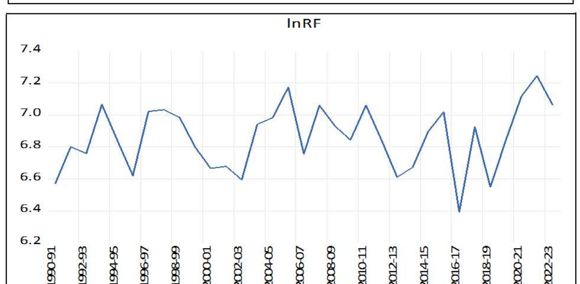

Figure 4

Source: Authors' calculation

Results of Unit Root Test

Table 2 presents the results of the Augmented Dickey-Fuller (ADF) unit root test. The variables RY, RF, and Min-Temp were found to be non-stationary at level but became stationary after first differencing, indicating they are integrated of order one, I(1). On the other hand, Max-Temp was stationary at level, suggesting it is integrated of order zero, I(0). This combination of I(0) and I(1) variables confirms the presence of a mixed order of integration, making the ARDL model suitable for analysing the short-run and long-run relationships among the variables used in this study.

Table 2:Estimated result of ADF unit root test

Variable	Critical Values @		Specifications								
			Constant (1)			Constant +Trend (2)			None (3)		
			Statistics			Statistics			Statistics		
			T-Stat	ADF	Prob	T-Stat	ADF	Prob	T- Stat	ADF	Prob
RY	Level	1%	-3.6537	-3.9118	0.0052	-4.2732	-4.3095	0.0092	-2.6416	0.1171	0.7125
		5%	-2.9571			-3.5577			-1.9520		
		10%	-2.6174			-3.2123			-1.6104		
	First Difference	1%	-3.6616	-7.8764	0.0000	-4.2845	-7.7490	0.0000	-2.6416	-8.0059	0.0000
		5%	-2.9604			-3.5628			-1.9520		
		10%	-2.6191			-3.2152			-1.6104		
RF	Level	1%	-3.6537	-4.0226	0.0040	-4.2732	-4.7603	0.0030	-2.6392	-0.0808	0.6481
		5%	-2.9571			-3.5577			-1.9516		
		10%	-2.6174			-3.2123			-1.6105		
	First Difference	1%	-3.6616	-7.3163	0.0000	-4.2845	-7.2201	0.0000	-2.6416	-7.4391	0.0000
		5%	-2.9604			-3.5628			-1.9520		
		10%	-2.6191			-3.2152			-1.6104		
Min-Temp	Level	1%	-3.6537	-4.0220	0.0040	-4.2732	-6.3079	0.0001	-2.6443	1.4620	0.9611
		5%	-2.9571			-3.5577			-1.9524		
		10%	-2.6174			-3.2123			-1.6102		
	First Difference	1%	-3.6701	-7.8887	0.0000	-4.2967	-7.7557	0.0000	-2.6443	-7.5964	0.0000
		5%	-2.9639			-3.5683			-1.9524		
		10%	-2.6210			-3.2183			-1.6102		
Max-Temp	Level	1%	-3.6616	-5.2912	0.0001	-4.2845	-5.6554	0.0003	-4.2967	7.6897	0.0000
		5%	-2.9604			-3.5628			-3.5683		
		10%	-2.6191			-3.2152			-3.2183		
	First Difference	1%	-3.6701	-7.8046	0.0000	-4.2967	-7.6897	0.0000	-2.6471	-0.2418	0.5900
		5%	-2.9639			-3.5683			-1.9529		
		10%	-2.6210			-3.2183			-1.6100		

Source: Authors' calculation.

Lag selection process

Table 3 reports the lag selection criteria. The Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) results helped determine the optimal number of lags for the models. The results indicate that lag 1 is the optimal lag for the Model.

Table 3: Estimated results of Lag-length criteria

Based on Climate factors and RY						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	126.8273	NA	4.25e-09	-7.92434	-7.73931*	-7.86402
1	149.9255	38.74531*	2.72e-09*	-8.38228*	-7.45713	-8.08071*
2	155.0388	7.25756	5.82e-09	-7.67991	-6.01464	-7.13708

Source: Authors' calculation

ARDL Model and Bounds Tests

Table 4 shows the estimated values of the ARDL bounds test for long-term cointegration. The calculated F-statistic values of the model exceed the upper bound values at significance levels of 1, 2.5, 5, and 10 per cent. As a result, this study concludes that minimum temperature, maximum temperature, and rainfall use have a long-term cointegration connection with Rice Yield (RY).

Table 4: Estimated results of ARDL bounds test

Test statistics	Value	Significance	I(0)	I(1)
F-statistics	4.8568	1 % level	3.65	4.66
K	3	2.5 % level	3.15	4.08
		5 % level	2.79	3.67
		10 % level	2.37	3.2

Source: Authors' calculation

Results of Short-run and Long-run ARDL Model

In the ARDL result presented in Table 5, minimum temperature positively influences rice yield in the short run. A one per cent increase in minimum temperature leads to a 0.62 per cent increase in yield, significant at the 1 per cent level. The lagged maximum temperature is significant at the 5 per cent level, with a coefficient of 4.99, indicating that maximum temperature in the previous period positively affects current rice yield. Rainfall does not show any significant relationship with rice yield.

In the long run, rainfall is showing a negative relationship and the minimum temperature is showing a positive effect on the rice yield, but both are significant at the 10 per cent level, which indicates a weak long-run relationship. The error correction term of -0.618 confirms the presence of a long-run relationship. This implies that approximately 61.8 per cent of the disequilibrium from the previous year is corrected in the current year, indicating a moderately fast speed of adjustment toward equilibrium. The adjusted R-squared value of 0.4943 indicates that approximately 49.43 per cent of the variation in the rice yield is explained by the climate factors used in the model.

This finding was similar to the findings of Dumrul and Kilicaslan (2017), Akram (2012), and Brown et al. (2010), which showed a mixed response to climate factors. Most of the studies, including those by Kelkar et al. (2020), Kumar et al. (2011), Geethalakshmi et al. (2011), and Kumar and Parikh (2001), indicate a negative relationship between rainfall and temperature on agricultural GDP or crop yield.

Table 5: Estimated results of ARDL models

Dependent variable = Rice Yield			
Short-run		Long-run	
Variable	Coefficient	Variable	Coefficient
Constant	-14.617 (-1.179)	Constant	-23.628 (-0.974)
lnRY(-1)	0.381** (2.098)	lnRF	-0.006* (-0.024)
lnRF	-0.003 (0.024)	lnMax-Tem	7.948 (1.171)
lnMin-Tem	0.619*** (0.863)	lnMin-Tem	1.001* (0.884)
lnMax-Tem	-0.069 (-0.03)		
lnMax-Tem(-1)	4.986** (2.414)		
ECT	-0.618*** (-5.293)		
R-squared	0.510678		
Adjusted R-squared	0.494367		
Observation	33		

Source: Authors' calculation

*Note: ***, **,and *are statistically significant at 1%, 5%, and 10% levels, respectively. Values in the parentheses are t-statistics.*

Results of Diagnostic Test

Table 6 gives the residual diagnostic test results of the model. The residual diagnostics table tests the robustness and reliability of the ARDL models by checking key assumptions like heteroskedasticity, serial correlation, and normality of residuals.

Table 6: Estimated results of the residual diagnostic test

ARDL Model Based on Climate Factors and RY		
Tests	F-Statistics	Probabilities
Heteroskedasticity ARCH	0.280250	0.6009
Godfrey Serial Correlation LM	0.952600	0.4018
Jarque-Bera Normality	0.947402	0.622693

Source: Authors' calculation

The ARCH test was used to evaluate whether the residuals exhibit constant variance or homoscedasticity across the variables. The P-values of the model were greater than 0.05, indicating no significant heteroskedasticity and supporting the assumption of homoscedasticity. The Godfrey Serial Correlation LM test was employed to check

Results of Stability Tests

The stability of the parameters in ARDL model specifications was evaluated using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests.

CUSUM and CUSUMSQ help ensure that the estimated coefficient remains consistent and reliable throughout the period. In the model, CUSUM and CUSUMSQ statistically fall within the critical limits of 5 % significance, represented in Figures 5 and 6 simultaneously. All the models' CUSUM and CUSUMSQ results confirm that the estimated coefficient variables are stable throughout the study period.

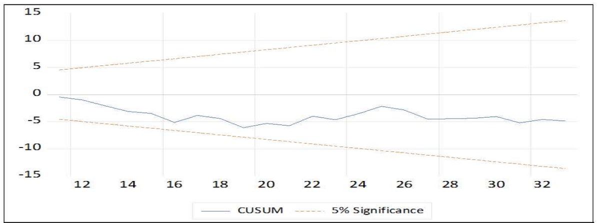

Figure 5. Plot of CUSUM test

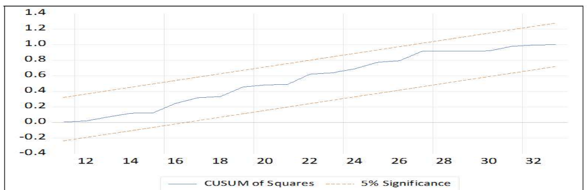

Figure 6. Plot of CUSUMSQ test

V. SUMMARY AND CONCLUSION

This study examined the impact of climate change factors on Tamil Nadu's Rice Yield from 1990-91 to 2022-23. In this study, minimum temperature, maximum temperature, and rainfall were used as the independent variables to identify the impact of climate change on the agriculture sector. The effect of climate factors on the Rice Yield in Tamil Nadu was examined with the help of the Autoregressive Distributed Lag (ARDL) model. ARDL bound tests indicate that the values of the F-statistics of the models were above the critical value, implying a long-run relationship between the variables.

In the short run, minimum and lagged maximum temperaturesshow a positive relation with rice yield at a 1 per cent and 5 per cent level. In the long run, rainfall shows a negative relationship, and minimum temperature shows a positive relationship at a 10 per cent level. The bound test confirms the long run relation, and the error correction term implies that approximately 61.8 per cent of the disequilibrium from the previous year is corrected in the current year.

These results emphasise the critical role of climate factors on Rice Yield in Tamil Nadu. These empirical findings provide valuable insights for policymakers to mitigate the effects of high climate variability and to create necessary facilities to enhance agricultural growth and development.

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