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***Research paper***

# Impact of Climate Dynamics and Agricultural Inputs on Agricultural Greenhouse Gas Emissions in India: An ARDL Cointegration Approach

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## ABSTRACT

In India, where agriculture is both a foundation of the economy and a major source of greenhouse gas (GHG) emissions, rising temperatures due to climate change are accelerating environmental degradation while simultaneously undermining the resilience of the agrarian sector. In this context, the present study examines the long-run relationship between agricultural greenhouse gas emissions, climate variables and agricultural inputs in India. The Autoregressive Distributed Lag (ARDL) model technique is applied to time series data on six key variables from 1990 to 2021. The findings of the ARDL bound F-test confirmed the significant long-run cointegration among variables under consideration. Furthermore, area under paddy crop (0.257) and manure nitrogen content (0.842) exert significant and positive long-run effects on greenhouse gas emissions. Also, maximum temperature (0.341) and rainfall (0.086) positively contribute to the rising of greenhouse gases in the long run. With an adjusted $R^2$ value of 0.947, the ARDL model exhibits strong explanatory power and confirms the impact of climate and agricultural drivers on agricultural emissions in India. These findings highlight the need to consider the climate variables in agricultural GHG mitigation efforts and policy strategies.

***Keywords:*** Greenhouse Gas Emissions, ARDL Cointegration, Climate Variables, Paddy Area, India

India's agricultural economy is crucially intertwined with climate change, food security and environmental sustainability. The need to feed millions of people has led to a shift in India's agricultural production over the past few decades towards a more input-intensive system. Higher fertilizer consumption, paddy farming, intensive irrigation and mismanagement of livestock manure are the major sources of methane, nitrous oxide and carbon dioxide emissions that make Indian agriculture the second largest contributor (14%) to the nation's total GHG emissions (Chachei, 2024). High concentrations of greenhouse gases in the atmosphere expose the climate to variability, especially changing the temperature and rainfall patterns. India's maximum and minimum temperatures rose by 1.44°C and 2.14°C over the last two decades due to climate change (Sathya *et al.,* 2025). These climate variables significantly influence India's agricultural emissions, with rising temperatures and erratic rainfall patterns affecting soil respiration and greenhouse gas emissions. Irregular rainfall events impact water availability and irrigation, influencing soil moisture and anaerobic conditions in paddy ecosystems, thus shaping overall emission outcomes. Elevated temperatures accelerate microbial activity in soil and organic matter, leading to higher emissions of methane ($CH_4$) and nitrous oxide ($N_2O$) from agricultural systems. In this context, rice harvested area and manure management are considered two critical variables, as both are highly sensitive to temperature changes and significantly influence emission dynamics. India devotes around one-third of total cropped area to rice cultivation, making it the single most important crop by area and production (Sindhuja & Malik, 2025), most of which occurs under flooded or irrigated conditions that create anaerobic environments conducive to methane and nitrous oxide generation. Rice harvested area contributed approximately 17.55% to the total agricultural emissions in India (Bhattacharyya *et al.,* 2025). Similarly, India possesses one of the world's largest livestock populations, and its improper manure management results in substantial GHG

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emissions due to enhanced microbial decomposition. Manure from Indian livestock is a major and growing source of methane and nitrous oxide emissions, which have a substantial effect on the rise in global emissions. Although numerous studies have examined India's agricultural GHG emissions, the existing literature remains fragmented in several ways. Research by Patange *et al.* (2024) and Chachei, (2024) focuses on how temperature influences metabolic activities that produce greenhouse gas emissions. Nevertheless, they do not evaluate the long-term effects of climate factors on agricultural GHG emissions and do not analyze these dynamics over time using time-series evidence. Conversely, Ahmed *et al.,* (2023) and Singh *et al.,* (2024) explored the impacts of climate change on Indian agriculture, often prioritizing crop yields, methane emissions, and temperature and rainfall variability, while overlooking how climate variables interact with agricultural practices to shape emissions. As a result, limited attention has been given to the combined effect of agricultural drivers and climate conditions on GHG trajectories. India's agricultural inputs, including area under paddy and manure nitrogen content, show gradual trends interacting with climate variables characterized by long-term shifts and short-term variability, indicating potential cointegration among these factors. Considering their dominant role as emission sources, these variables are incorporated in the present study as key drivers of agricultural GHG emissions. Although agricultural emissions are dominated by non-$CO_2$ gases, particularly methane and nitrous oxide, many previous studies have relied on total $CO_2$ emissions as a proxy for agricultural emissions. Such approach fails to capture the true dynamics of agricultural emissions and their responses to changes in agricultural practices and climatic conditions. Moreover, existing studies on agricultural emissions in India using ARDL have performed with limited focus on climatic factors. Often, climate variables are oversimplified to a single temperature or rainfall measure, neglecting the nuanced effects of maximum and minimum temperatures and failing to account for their time-varying impacts on emissions. This study contributes to the literature by modelling agricultural greenhouse gas emissions in $CO_2$-equivalent terms rather than relying on generic $CO_2$ proxies, disaggregating temperature into maximum and minimum components to capture asymmetric climate sensitivities, and offering one of the first ARDL cointegration-based assessments of the long-run and short-run dynamics between climate variables and agricultural GHG emissions in India. Due to the consistent availability of long-term data, the analysis is conducted at the national level. This is because national-level aggregation fits with global climate policy frameworks like the Paris Agreement and Nationally Determined Contributions (NDCs), where emissions are reported and mitigation strategies are made at the country level. Additionally, aggregated datasets facilitate robust econometric modelling across prolonged timeframes, especially when disaggregated regional data is scarce or inconsistent.

Nonetheless, it is recognized that this aggregation may obscure spatial heterogeneity among regions; consequently, the findings should be regarded as macro-level trends rather than region-specific dynamics. The empirical approach of the Autoregressive Distributed Lag (ARDL) framework has been utilized to capture short-run and long-run dynamics among Agricultural emissions and inputs in the presence of climatic variables like temperature and rainfall. This study will shed more light on how agricultural practices and climate conditions interact to affect GHG emissions, which will help India make better management decisions and focus mitigation efforts.

## MATERIALS AND METHODS

### *Data*

The present study is conducted for India using annual time series data on six variables for the period of 32 years from 1990 to 2021. We selected agricultural greenhouse gas emissions as the dependent variable. The independent variables include agricultural inputs, viz. area under paddy crop, manure nitrogen content and climatic factors, viz. maximum temperature, minimum temperature and rainfall. Manure nitrogen content input denotes the quantity of nitrogen discharged by domestic animals and regulated through manure management systems, functioning as an indicator for nitrous oxide emissions arising from manure-associated processes. Six variables were chosen based on two conditions. First, the inclusion of additional variables may reduce the degrees of freedom available for ARDL lag selection, which would compromise the robustness of bounds testing and long-run estimates, given the limited 32 annual observations. Balancing the comprehensiveness of the model with the efficiency of the estimation is necessary for small-sample cointegration analysis. Secondly, and more importantly, the primary objective of this study is to investigate the effects of climate change on agricultural greenhouse gas emissions. In light of this, only two agricultural variables, paddy cultivation area and Manure nitrogen content, were incorporated, as they are the most directly influenced by climatic variations. The study's climate-centered focus and econometric tractability were preserved by excluding other inputs (fertilizer, irrigation, livestock, and energy) due to their less climate-mediated pathways.

The time series data on the above variables were collected from the Climate Watch website of the World Research Institute, FAOSTAT of the Food and Agriculture Organization and the Open Government Data (OGD) platform of India (Table 1).

### *Methodology*

To explore the long-run association and long-term impact of climate and agricultural determinants on sectoral greenhouse gas emissions, we utilized the ARDL cointegration approach developed by Pesaran *et al.,* (2001).

The general equation for the variables under study is as follows:

$$GHG_t = \alpha_0 + \beta_1 RA_t + \beta_2 MN_t + \beta_3 T\max_t + \beta_4 T\min_t + \beta_5 Rain_t + \varepsilon_t \quad ... (1)$$

The ARDL bound test is advantageous over others as it can be applied irrespective of mixed order of integration I(0) or I(1) of the time series variable. The ARDL error correction framework is effective for small sample sizes (n<30), especially when a stable long-run relationship is established via bounds testing (Nkoro & Uko, 2016). The optimal lag length, determined by the Akaike Information Criterion (AIC), reduces overfitting risks by penalizing excessive parameters. By permitting specific lag selection for each

**Table 1:** Variable definitions, logarithmic form, units and data sources

| Variables | Definition | Logarithmic form | Source |
|---|---|---|---|
| GHG | Agricultural greenhouse gas emission (Mt) | lnGHG | Climate Watch(2025) |
| RA | Area under paddy crop (ha) | lnRA | FAOSTAT Database (2025) |
| MN | Manure nitrogen content(Kg) | lnMN | FAOSTAT Database (2025) |
| Tmax | Maximum temperature(°C) | lnTmax | data.gov.in (2025) |
| Tmin | Minimum temperature (°C) | lnTmin | data.gov.in (2025) |
| Rain | Average annual rainfall(mm) | lnRain | data.gov.in (2025) |

variable (e.g., ARDL (p, $q_1$, $q_2$, …)), the ARDL framework generates a parsimonious model that conserves degrees of freedom, which is essential for small sample sizes. Moreover, it reliably estimates short-run dynamics and long-run equilibrium in a single equation without compromising the validity of long-run inferences. Before performing the ARDL bound test we transform the original variable into its natural logarithmic form. This transformation addresses the multicollinearity, heteroscedasticity and time series fluctuations problems in the data, if any.

$$\ln GHG_t = \alpha_0 + \beta_1 \ln RA_t + \beta_2 \ln MN_t + \beta_3 \ln T\max_t + \beta_4 \ln T\min_t + \beta_5 \ln Rain_t + \varepsilon_t \quad \ldots(2)$$

The ARDL equation form of equation (2), which provides a unified framework for testing and estimating cointegration using a single equation, can be represented as,

$$\Delta \ln GHG_t = \alpha_0 + \sum_{I=0}^{p} \beta_I \Delta \ln GHG_{t-i} + \sum_{j=0}^{q1} \gamma_{1j} \Delta \ln RA_{t-j} + \sum_{k=0}^{q2} \gamma_{2k} \Delta \ln MN_{t-k} + \sum_{l=0}^{q3} \gamma_{3l} \Delta \ln T\max_{t-l} + \sum_{m=0}^{q4} \gamma_{4m} \Delta \ln T\min_{t-m} + \sum_{n=0}^{q5} \gamma_{5n} \Delta \ln Rain_{t-n} + \lambda_1 GHG_{t-1} + \lambda_2 RA_{t-1} + \lambda_3 MN_{t-1} + \lambda 4T\max_{t-1} \lambda_5 T\min_{t-1} + \lambda_6 Rain_{t-1} + \varepsilon_t \quad \ldots (3)$$

Where, denotes the intercept, Δ represents the 1st difference *p, $q_1$, $q_2$, $q_3$, $q_4$ and $q_5$* illustrate the order of lags for the dependent and each explanatory variable. represents the long run coefficient, and denotes the error term.

The error correction form of equation 3 is reparametrized as,

$$\Delta \ln GHG_t = \alpha_0 + \sum_{I=0}^{p} \beta_I \Delta \ln GHG_{t-i} + \sum_{j=0}^{q1} \gamma_{1j} \Delta \ln RA_{t-j} + \sum_{k=0}^{q2} \gamma_{2k} \Delta \ln MN_{t-k} + \sum_{l=0}^{q3} \gamma_{3l} \Delta \ln T\max_{t-l} + \sum_{m=0}^{q4} \gamma_{4m} \Delta \ln T\min_{t-m} + \sum_{n=0}^{q5} \gamma_{5n} \Delta \ln Rain_{t-n} + \alpha ECT_{t-1} + \varepsilon_t \quad \ldots (4)$$

Where, denotes the short-run coefficient 'ECT' represents the error correction term. The negative and significant value of 'ECT' less than zero ensure convergence towards equilibrium and stability of the model under consideration.

Before applying the ARDL cointegration approach, the Augmented Dickey-Fuller (ADF) unit root test is used to see if the variables are stationary. This makes sure that none of the series were integrated of order I (2), a prerequisite for the ARDL framework. The ARDL cointegration analysis is performed in two phases following the confirmation of the integration order. In the first step, the Wald or F-bounds test is used to determine whether there is a long-term relationship between the examined and explanatory variables. If the computed F-statistic exceeded the upper bound crucial value, the null hypothesis of no cointegration was rejected; whereas, if the F-statistic is less than the critical lower-bound value, suggesting no long-run association, the null hypothesis is not rejected. Once cointegration is established, the long-run and short-run coefficients are estimated in the second stage using the ARDL and error correction framework using equations 3 and 4. To confirm that the estimated model satisfies the common econometric assumptions, several diagnostic tests are performed to assess the model's robustness and adequacy.

## RESULTS AND DISCUSSION

### *Trend of the variables and correlation*

The trend for the variables spanning from 1990 to 2021 has been presented graphically in Fig. 1. Both agricultural greenhouse gas (GHG) emissions and manure nitrogen content (MN) show a clear upward trajectory, indicating a rapid increase over the period. The area under paddy cultivation also exhibits an overall rising trend, although with substantial fluctuations. Among the climatic variables, maximum and minimum temperatures display a steady increasing pattern, while rainfall remains highly variable around its long-term average. The analysis further shows that all variables, except rainfall, have a positive and significant correlation with GHG emissions. The strongest association is observed for manure nitrogen content, followed by temperature and area under paddy. These strong positive correlations suggest a likely causal link between the explanatory variables and GHG emissions.

**Table 2:** Correlation of GHG emissions with explanatory variables

| Variables | Correlation coefficient |
|---|---|
| | GHG emission |
| Area under paddy crop (RA) | 0.519** |
| Manure nitrogen content(MN) | 0.992** |
| Maximum temperature (Tmax) | 0.703** |
| Minimum temperature (Tmin) | 0.749** |
| Rainfall (Rain) | -0.009 |

'**'level of statistical significance at 1 %

**Table 3:** Variance Inflation Factor (VIF) diagnosis.

| Variable | Coefficient Variance | Centered VIF |
|---|---|---|
| Area under paddy crop (RA) | 0.002649 | 1.519 |
| Manure (MM) | 0.000648 | 3.656 |
| Maximum Temperature (Tmax) | 0.103448 | 5.976 |
| Minimum Temperature (Tmin) | 0.044047 | 4.297 |
| Rainfall | 0.000303 | 1.798 |

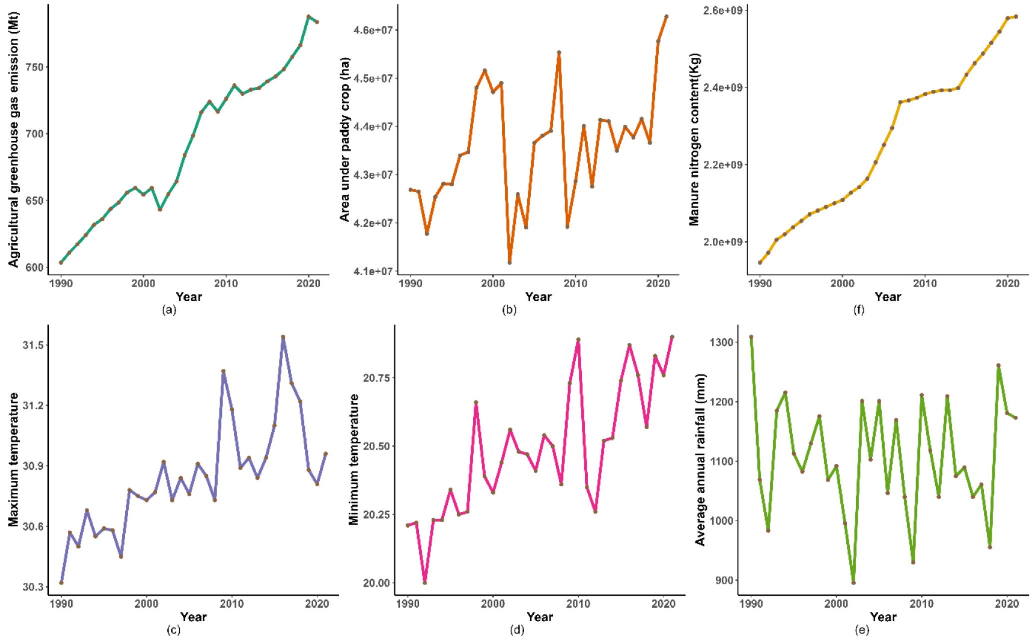


**Fig. 1:** Time series of agricultural GHG emissions, agricultural input and climate variables in India from 1990-2021

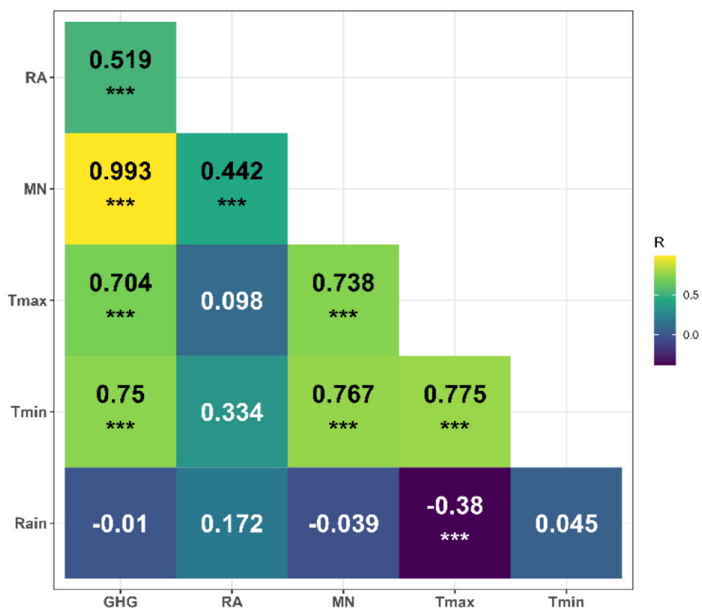


**Fig. 2:** Correlation plot of variables under study

The correlation of explanatory variables with GHG is depicted in Table 2 along with the correlation plot in Fig. 2. From Fig. 2, various explanatory variables reveals significant correlations, particularly between maximum and minimum temperature (r = 0.775) and between manure nitrogen content and both temperature variables (r = 0.738, 0.767). This raises some concerns about multicollinearity. To address this, the Variance Inflation Factor (VIF) was calculated to formally assess the multicollinearity issue, as high correlations among regressors can inflate coefficient variances and destabilize OLS estimates. The VIF results in Table 3 indicated that all centered values (ranging from 1.52 to 5.98) were below the standard threshold of 10, suggesting that multicollinearity is not a significant concern in the estimated model, despite the moderate-to-strong bivariate correlations identified. The observed discrepancy between the correlation matrix and the VIF diagnostics is expected; these metrics evaluate different dimensions of variable relationships. The correlation matrix reflects simple pairwise associations, while the VIF assesses how well each variable can be predicted by all others simultaneously within the model's specification. Given that all VIF values are within acceptable limits, no serious multicollinearity was detected, allowing for the retention of all explanatory variables in the model. Consequently, the estimated ARDL-ECM results are considered robust and largely unaffected by multicollinearity-induced instability.

**Table 4**: Results of ADF unit root test

| Variables | Level | 1st Difference |
|---|---|---|
| | Test | Test |
| GHG | -2.143 | -4.796** |
| RA | -3.162* | - |
| MN | -2.323 | -3.040* |
| Tmax | -1.154 | -4.583** |
| Tmin | -2.341 | -4.105** |
| Rain | -4.660** | - |

'**','*' level of statistical significance at 1%, 5 %

**Table 5**: ARDL Bound F test for cointegration results

| Selected ARDL model (2,2,2,0,0,1) | | AIC: -8.502 | | |
|---|---|---|---|---|
| Test Statistics | Value | Significance | I(0) | I(1) |
| F-Bound Test | Null Hypothesis: No levels relationship | | | |
| F-Statistic | 6.060* | 5% | 2.62 | 3.79 |
| t-Bound Test | Null Hypothesis: No levels relationship | | | |
| t-Statistic | -4.861* | 5% | -2.86 | -4.19 |

'*' level of statistical significance at 5 %

***Unit root test***

The ARDL cointegration assumption is violated if any of the series under consideration has an order of integration I (2). To make sure that none of the variables are integrated of order 2 or higher, the first step is to examine the time series characteristics of the variables. The ADF test is employed to test the stationarity hypothesis for all series under investigation. The results given in Table 4 revealed that GHG, Tmax, Tmin and MN are stationary at first difference I (1) (p-value < 0.05) and RA and Rain are stationary at level I (0) (p-value < 0.05). Since none of the variables are integrated of order 2 or above. Therefore, the existence of the long-run connection can be explored through the ARDL bounds testing approach.

***Model selection and Bound F test for cointegration***

The study examines the long-run relationship between agriculture, climatic variables and greenhouse gas emissions by using the ARDL approach. In this context, the next step is to identify the best ARDL model for cointegration on the basis of selected optimum lag length. The beauty of the ARDL model is that it can assign different numbers of lags to explanatory variables. As per the suggestion by Pesaran & Shin, (1999) and Hasnul & Masih, (2016), a maximum lag length of two was selected for all the variables and then tested for the AIC values associated with each potential model. The ARDL model selection was conducted in EViews using the Akaike Information Criterion (AIC), where a maximum lag length of 2 was specified for all variables. Given the limited sample size (30 observations), restricting the lag length to 2 is appropriate to avoid over-parameterization while still capturing necessary dynamics. EViews automatically estimated all possible lag combinations and selected the optimal model with the lowest AIC value, as illustrated in the top 20 models graph (Fig. 3).

The ARDL (2,2,2,0,0,1) (AIC:-8.502) model was selected based on the lowest AIC. Further, to determine the presence of cointegration among variables, a bound F-test was performed whose results are shown in Table 5. The results of the bound F-test show that F statistics (6.06) is greater than the upper critical value (3.79), leading to rejection of the null hypothesis of no cointegration at the 5 percent level of significance. The significant F-value confirmed the cointegration and existence of a long-run relationship between GHG and agricultural and climatic variables. In an ARDL bounds framework, the t-test is employed on the coefficient of the lagged dependent variable (error-correction term) to ascertain whether there exists a significant rate of adjustment towards the long-run equilibrium, which aids in substantiating a genuine cointegrating relationship rather than a degenerate instance (Sam *et al.,* 2018). The significant t-test statistic in Table 5 further validated the cointegrating relationship between variables.

***Long run and Short run coefficients***

After confirming a long-term relationship between the variables, we used the normalized levels equation (Equation 3) to find the long-term coefficients. Further, the error correction representation of the ARDL model (Equation 4) was used to find the short-term dynamics and speed of adjustment toward equilibrium. The results of long-run and short-run coefficients for the ARDL model (2, 2, 2, 0, 0, 1) are presented in Table 6.

According to the results in Table 6, the long run equation for selected ARDL model is represented as follows;

$$lnGHG_t = 0.257lnRA_t + 0.842lnMN_t + 0.341lnTmax_t - 0.438lnTmin_t + 0.086lnRain_t + \varepsilon_t$$

The empirical findings reveal that lnRA and lnMN have a positive and significant impact on GHG emissions. A 1 percent increase in lnRA and lnMN leads to a rise of 0.257 percent and 0.842 percent in agricultural GHG emissions, respectively. This highlights the dominant role of agricultural inputs as key drivers of emissions. Climatic variables also contribute to GHG emissions. lnTmax and rainfall lnRain are positively associated with emissions, with a 1 per cent increase in these variables leading to increases of 0.341 percent and 0.086 percent, respectively. In contrast, lnTmin exhibits a significant negative relationship, where a 1 percent increase reduces emissions by 0.438 percent. Overall, the long-run estimates suggest that sustained increases in variables such as Tmax, lnRA, and lnMN use have a strong and persistent effect on agricultural emissions. This implies that continuous growth in both climatic factors and agricultural inputs can significantly amplify GHG emissions over the long term.

The short-run results of the ARDL model include the current and lag effects of change in RA, MM and Rain on GHG. The short-run dynamics indicate that variables with lag structure (q≥1) exert immediate and delayed short-term impacts on emissions. Table 6 indicates that, except Tmax, all explanatory variables exert a strong and statistically significant influence on emissions in the short run. Greenhouse gas (GHG) emissions are also affected by their own lagged values, suggesting that past emissions contribute positively to current emission levels. The input variables lnRA and lnMN influence GHG emissions both in the current period and through their lagged values, but in opposite directions. In the current period, a 1 percent increase in D(lnRA) and D(lnMN) raises

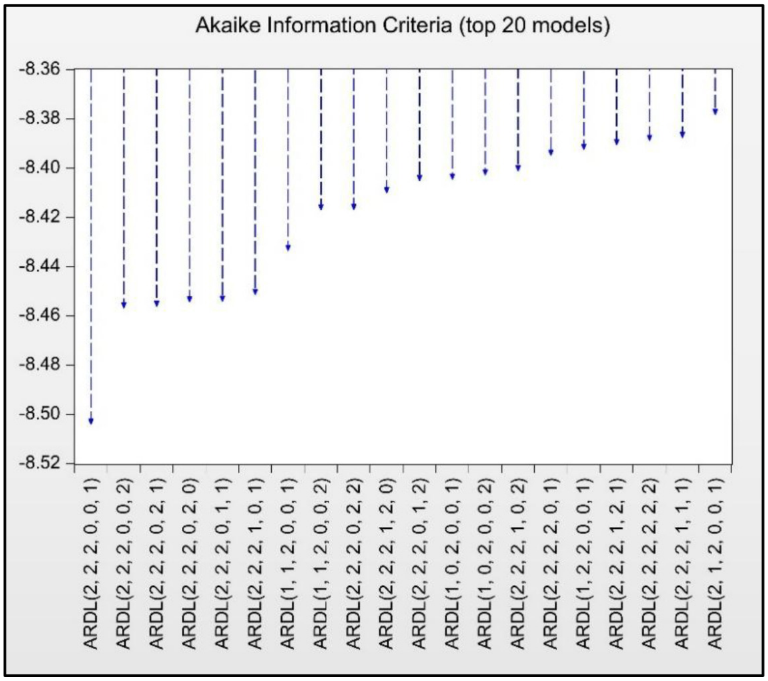


**Fig. 3:** ARDL Model Selection Graph

GHG emissions by 0.2301 percent and 0.734 percent, respectively. In contrast, their lagged effects are negative: a 1 percent increase in D(lnRA(-1)) and D(lnMN(-1)) leads to a reduction in emissions by 0.117 percent and 0.784 percent, respectively. Rainfall also exhibits an immediate effect on agricultural emissions, with a 1 percent increase in current rainfall (D(lnRain)) resulting in a 0.050 percent rise in GHG emissions. These findings highlight both immediate and lagged effects, underscoring the dynamic interactions between climate variables, agricultural practices and emissions. Although maximum and minimum temperatures do not explicitly appear in the short-run equation due to zero lag ($q = 0$), their short-run impacts are captured contemporaneously through the conditional error correction framework in the ECM output. The positive coefficient of Tmax suggests that a 1 per cent increase leads to a rise in GHG emissions by 0.303 percent as an immediate response, likely due to enhanced microbial activity in soil and water, which accelerates the release of gases such as $CH_4$ and $N_2O$. Conversely, the negative and significant coefficient of Tmin needs to be interpreted carefully, as the result shows 1% increase in Tmin reduces GHG emissions by 0.389% in the short run. The negative and significant error correction term (ECT) with CointEq(-1) coefficient is -0.887 indicates a strong cointegrating relationship among greenhouse gas emissions, agricultural drivers, and climate dynamics. This demonstrates a rapid adjustment speed of approximately 88.7%, meaning the system will automatically self-correct and recover to its long-term equilibrium following any short-term shocks. The Rsquared value of 96% and adjusted Rsquared of 94.7% indicate that the ECM explains most of the variation in the dependent variable, suggesting a very good overall fit.

***Model diagnostics***

To determine the robustness of the selected ARDL model, several diagnostic tests have been performed and results are given in Table 7.

The non-significant value of the Breusch-Pagan-Godfrey test (p-value=0.344) confirms homoscedasticity, while the Breusch-Godfrey Serial Correlation LM Test (p-value=0.312) shows no evidence of serial correlation, suggesting that the model's dynamic structure is appropriate. Additionally, the Ramsey RESET test (p-value=0.85) indicates that the chosen ARDL specification is correctly formulated, with no functional-form misspecification or omitted relevant nonlinearities. The Jarque-Bera normality test (p value=0.476) confirmed that residuals are normally distributed, validating the use of standard inferential statistics.

Further, to assess the stability of the model, we performed the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests on the residuals to track the changes in model parameters over period of time whose graphs are depicted in the Fig. 4. The red dashed lines in the figures represent the plotted trajectories for the CUSUM and CUSUMSQ statistics, which consistently stay strictly within the 5% critical boundaries. The lack of coefficient instability is confirmed because the plots never cross these critical bounds. This indicates that the estimated ARDL model's short-run and long-run parameters remain highly stable throughout the sample period, which ensures the model's robustness and reliability for making statistical conclusions. Taken together, these results demonstrate that the ARDL model satisfies the fundamental classical assumptions; therefore, its coefficients and hypothesis tests can be understood with a high level of confidence.

***Effect of climatic and agricultural variables on Agricultural greenhouse gas emissions***

In the present study the long-run results reveal that climatic

**Table 6**: Long run and short run coefficients of ARDL model

| Cointegrating equation | CointEq1 | Selected Model: ARDL(2,2,2,0,0,1) | |
|---|---|---|---|
| Long run Coefficients | Coefficient | Std. error | t-Statistics |
| lnRA | 0.257** | 0.055 | 4.640 |
| lnMN | 0.842** | 0.015 | 53.88 |
| lnTmax | 0.341· | 0.164 | 2.080 |
| lnTmin | -0.438** | 0.134 | -3.256 |
| lnRain | 0.086 | 0.024 | 3.452 |
| ECM Regression | | | |
| Short run Coefficients | Coefficient | Std. error | t-Statistics |
| constant | -14.714** | 2.144 | -6.860 |
| D(lnGHG(-1)) | 0.364** | 0.130 | 2.797 |
| D(lnRA) | 0.230** | 0.019 | 11.527 |
| D(lnRA(-1)) | -0.117** | 0.043 | -2.70 |
| D(lnMN) | 0.734** | 0.091 | 8.057 |
| D(lnMN(-1)) | -0.784** | 0.159 | -4.910 |
| D(lnRain) | 0.050** | 0.008 | 5.870 |
| Tmax | 0.303· | 0.161 | 1.876 |
| Tmin | -0.389** | 0.139 | -2.787 |
| CointEq(-1) | -0.887** | 0.129 | -6.860 |
| R-squared | 0.960 | | |
| Adj.R-squared | 0.947 | | |

'**', '*', '·' level of statistical significance at 1%, 5 %, 10%

factors and agricultural inputs play a significant role in determining GHG emissions. The positive significant relationship of maximum temperature (Tmax) in long run on agricultural GHG emissions (Table 6) indicated that the rising temperatures increase greenhouse gas emissions in agriculture by boosting microbial activity and soil respiration, resulting in higher carbon dioxide release. Our results are supported by the study of Gao *et al.,* (2022), who reported that rising temperatures contribute to increased agricultural greenhouse gas (GHG) emissions by enhancing soil microbial activity, which accelerates the breakdown of organic matter and releases more $CO_2$ and $NO_2$. Warmer weather affects agricultural operations, leading to increased fertilizer use and more frequent irrigation, which increase methane and $N_2O$ emissions, especially on rice and nitrogen-intensive farms. Additionally, extended heat and dry weather encourage crop residue burning, a substantial source of agricultural GHGs in India. Therefore, even while temperature rise isn't the main cause, it greatly increases burning activities, soil processes, and management techniques, which results in a major indirect increase in agricultural GHG emissions. The ARDL analysis shows a significant negative long-run relationship (-0.438) between minimum temperature and agricultural greenhouse gas emissions. While this result appears counter-intuitive since warmer nights typically enhance soil microbial respiration, it must be interpreted within the context of a multivariate time-series model. Analysis of the time-series data for minimum temperatures indicates a clear upward trajectory throughout the study duration, whereas the increase in maximum temperatures has been relatively slight, as evidenced by the positive yet less robust coefficient for lnTmax (0.341, $p = 0.052$). This asymmetric warming pattern, where nighttime (minimum) temperature increases faster than daytime (maximum) temperature results in a progressive narrowing of the diurnal temperature range, a phenomenon widely documented in climate literature. Because the model controls for maximum temperature (Tmax), a rise in Tmin effectively represents a narrowing of the Diurnal Temperature Range (DTR). Previous research indicates that a smaller DTR often correlates with reduced GHG emissions, as regions experiencing warmer nights frequently adopt different land-use patterns, agricultural technologies, and structural frameworks (Vinnarasi *et al.,* 2017). Experimental research on cereal crops demonstrates that narrowing diurnal temperature amplitude increases night time respiration relative to growth, changing the plant's carbon balance (Mohammed & Tarpley, 2009; Peng *et al.,* 2004). In rice-centric agricultural systems, DTR results in decreased biomass production, reduced tillering rates, and less residual organic matter, all of which limit the supply of methanogenic substrates in flooded paddy soils. The identified inverse relationship between minimum temperature and agricultural greenhouse gas emissions in this study aligns with a productivity mechanism mediated by diurnal temperature range, in which elevated nighttime temperatures hinder crop biomass and consequently the biological substrate for methane and related emissions, rather than indicating a direct inhibition of the emission processes (Saud *et al.,* 2022). Consequently, the negative coefficient of Tmin in the present study implies that structural and technological adaptations in India's agricultural sector may have successfully offset the biological emission increases that would otherwise result from warmer night time temperatures. The positive and significant long run value of Rain (0.086) in this study indicated that rainfall variation is a critical factor influencing agricultural GHG emissions. Increased rainfall enhances greenhouse gas emissions in agriculture by affecting soil moisture and microbial activity. It promotes nitrification and denitrification, leading to higher nitrous oxide ($N_2O$) emissions, especially in anaerobic conditions. A study conducted by Li *et al.,* (2024) supported our results. Increased rainfall generally enhances $N_2O$ and $CO_2$ emissions, with $CH_4$ responses depending on soil and management context. The strong positive long-run effect of paddy harvested area (0.257) drives agricultural greenhouse gas emissions rapidly through the emission of methane in flooded paddy fields. Due to the development of flooded, anaerobic soils that promote the production of methane ($CH_4$), the expansion of paddy cultivation dramatically increases greenhouse gas emissions. When rice fields are submerged, oxygen is reduced, which encourages methanogenesis and increases methane emissions as the area and

**Table 7:** Diagnostic and stability test

| Diagnostic test | coefficient | Degree of freedom | p-Value |
|---|---|---|---|
| Heteroskedasticity Test: Breusch-Pagan-Godfrey | 1.221 | F(12,17) | 0.344 |
| Breusch-Godfrey Serial Correlation LM Test: | 1.257 | F(2,15) | 0.3127 |
| Ramsey RESET Test | 0.191 | 16 | 0.850 |
| Jarque-Bera Normality Test | 1.484 | | 0.476 |

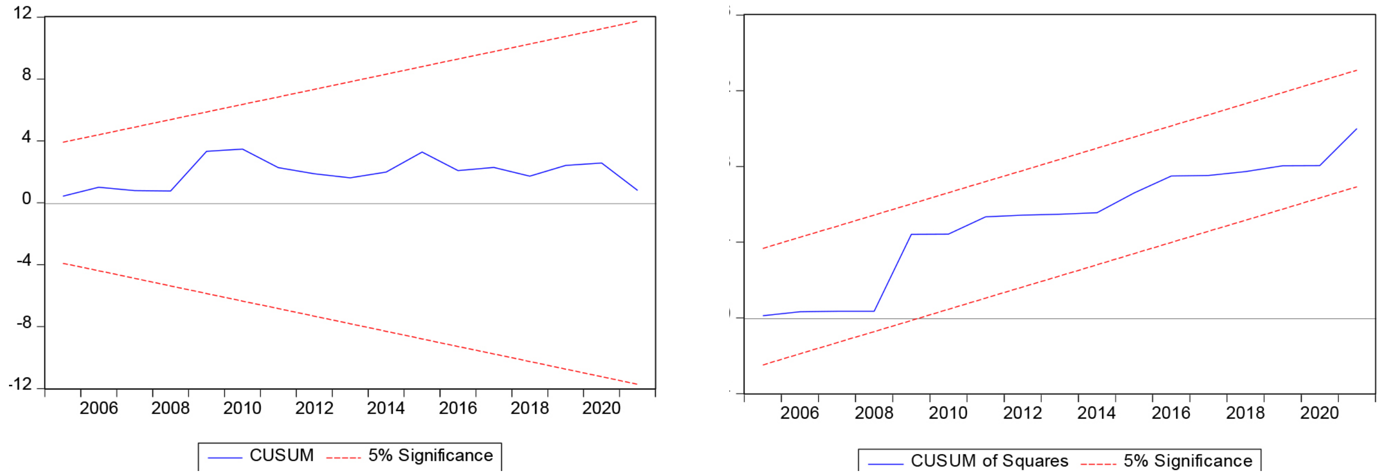


**Fig. 4**: (a) Cumulative Sum and (b) Cumulative Sum of Square plots for stability of the model

populations of methanogenic microorganisms increase. Anaerobic conditions, increased nitrogen cycling, and residue management techniques all contribute to an increase in GHG emissions when rice cultivation area is expanded. Gupta *et al.,* (2021) found that due to the heavy chemical fertilizer inputs and flooded conditions characteristic of these systems, increasing the area under paddy agriculture in India immediately raises greenhouse gas emissions, especially methane. The highly significant and positive long-run coefficient of lnMN (0.842) suggested that manure nitrogen content has the strongest positive impact on agricultural emissions over the long period of time. This is the largest contributor, indicating that improper manure handling significantly enhances methane and nitrous oxide emissions in Indian agriculture. According to the study of Shakoor *et al.,* (2020) to increase soil fertility and organic matter, it is common practice to apply animal manure to agricultural soils. However, this approach frequently results in higher emissions of greenhouse gases, primarily carbon dioxide ($CO_2$), nitrous oxide ($N_2O$), and methane ($CH_4$). Anaerobic decomposition is the main process that produces methane during storage, and the amount of methane released varies depending on the climate and management system (Pant, 2009). Furthermore, the application of manure to agricultural soils affects the dynamics of soil nitrogen and produces $N_2O$ emissions; livestock waste also contributes to emissions of ammonia ($NH_3$).

## CONCLUSIONS

Using rigorous econometric tools involving the ARDL model, this study adds to the body of literature by offering a context-specific investigation into the long-run causal relationship between agricultural drivers, climate variables, and agricultural greenhouse gas emissions in India. The study concluded that climate variables and agricultural inputs are the key long-run drivers of agricultural greenhouse gas emissions in India. Rising maximum temperature and increased rainfall stimulate biological processes that contribute to faster emission rates. Even though the ARDL framework showed a negative long-term association between minimum temperature and GHG emissions, more research is necessary to fully comprehend the underlying amplification processes and management strategies that influence this relationship. Selected agricultural factors, the area under paddy cultivation and manure nitrogen content, were the most significant long-term sources of non-$CO_2$ emissions. The study has limitations in spite of these revelations. First, while the ARDL framework is specifically recognized for providing robust and efficient estimates in small sample sizes, the study's timeframe (1990-2021) remains a primary constraint that may restrict a comprehensive understanding of very long-term environmental patterns. The limited number of annual observations nonetheless constrains the degrees of freedom available for lag selection and limits the power of certain diagnostic tests. Secondly, the reliance on national-level aggregated data serves as a significant limitation, as it masks spatial heterogeneity and regional disparities across a country's diverse agricultural landscape. Factors such as climate variability, soil types, and localized crop preferences are obscured by national averages, resulting in generalized findings that may lack the granular nuance required to design region-specific mitigation strategies or identify localized emission "hotspots" To better understand emission trends and create focused policy interventions appropriate for the nation's many agricultural ecosystems, region-specific research is recommended.

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***Author's certificate:*** We state to declare that the present manuscript entitled "Impact of climate dynamics, agricultural input on agricultural greenhouse gas emissions in India: An ARDL cointegration approach" is the original manuscript. The manuscript or its part is not under consideration for publication elsewhere and the same has been approved by all co-authors.

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