Assessing The Long- and Short-Run Asymmetrical Effects of Climate Change On Rice Production: Empirical Evidence From India

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Assessing the long- and short-run asymmetrical effects of climate change on rice production: Empirical evidence from India

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Abstract

For a couple of decades, environmental change has arisen as a ubiquitous problem and gained environmentalist's attention across the globe due to its long-term harmful effect on agricultural production, food supply, water supply and livelihoods of rural poor. The primary objective of this study is to explore the asymmetrical dynamic relationship between climate change and production of rice and controlled variables covering 1991-2018 by employing the nonlinear autoregressive distributed lag (NARDL) model and Granger causality approach in India. The NARDL findings demonstrate a significant negative relationship between mean temperature and production of rice in the long run while positively influencing rice production in the short run. Moreover, positive shocks in rainfall and carbon emission have a negative and significant effect on India's rice production in the long and short run. In comparison, negative shock in rainfall has a significant positive impact on rice production in the long and short run. Wald test confirms the asymmetrical relationship between climate change and rice production. The Granger causality test shows feedback effect among mean temperature, decreasing rainfall, increasing carbon emission, and rice production. While no causal relationship between increasing temperature and decreasing carbon emission. Based on our empirical investigations, some critical policy implications emerged. To sustain rice production, improve irrigation infrastructure through increasing public investment and develop climate-resilient seeds varieties to cope with climate change. Along with, at the district level government should provide proper training to farmers regarding the usage of pesticides, proper amount of fertiliser and irrigation systems.

Keywords: Asymmetry, Granger Causality, India, NARDL, Rice Production
1. Introduction

Due to the long-term adverse effect on agricultural productivity, food production, water availability, and rural lives, climate change has garnered environmentalist and policymaker attention across the globe since 1990s (Chavas et al. 2009; Mohorji et al. 2017). Changes in the long-term trends in mean temperature and shifting rainfall patterns, increasing variability, and greater prevalence of extreme events are the facet of climate change. Shifting rainfall patterns may exert a more substantial effect on rice production. However, frequent floods due to heavy rainfall may result in higher rice yield losses under climate change (Wassmann et al. 2009). Climate change results from increasing human activities on the land, including deforestation, land use, urbanisation, increasing population, production and consumption activities to fulfil people's demand for food supply. Climate steadily changes due to global temperature, precipitation, and carbon emission, significantly impacting agricultural productivity and growth (Chandio et al. 2021; Klutse et al. 2021).

Agricultural productivity has decreased due to climate change's main drivers, such as precipitation and warmer temperature (Haile et al. 2017). However, increase in temperature, variation in rainfall, and frequent floods and droughts are mostly faced by the developing nation, situated in the tropical region and relies heavily on the agriculture sector (Janjua et al. 2014). Agriculture and its allied activities are sensitive to climate change, and another hand, it is also contributed to carbon emission (Swaminathan and Kesavan 2012). Climate change is harmful to agriculture production and enhances the vulnerability among small and medium farmers whose livelihoods are mainly dependent on agricultural and allied activities (Zakaria et al. 2020). Climate change's impact may vary from region to region based on geographical location. In the case of a developing nation, climate change deteriorates the performance of the agriculture sector (Abbas 2020; Janjua et al. 2014; Nath and Behera 2011). Likewise, Abbas et al. (2021) revealed that climate change has significantly affected crop production and food security in South Asia in the long. Swaminathan and Kesavan (2012) stated that climate change adversely affected food production. The developing nations are more vulnerable than developed countries due to more extensive dependence on the agriculture sector for livelihood, lack of technological advancement and lack of adaptation policies of climate change on agriculture production (Dogan and Inglesi 2020; Praveen and Sharma 2020; Warsame et al. 2021). However, Chandio et al. (2021) stated that temperature and financial development negatively and positively impact cereal production in Pakistan. While Ahsan et al.
(2020) demonstrated that energy consumption, labour force, cultivated area, and CO$_2$ are the main determinants of agriculture productivity. Likewise, Warsame (2021) explained mean temperature and CO$_2$ has negatively influenced agriculture productivity in Somalia. Similarly, Coulibaly et al. (2020) concluded that temperature and drought are the main factors that negatively affect agriculture productivity. Increasing carbon emission leads to a cascade of impact mechanisms that have harmful and beneficial effects on rice production.

In World, Asian countries produce rice about 90% of the world's total rice production (FAO, 2019). However, India is the first largest exportable country of rice in the world counted 9.8 million tonnes, followed by Thailand (7.5 million tonnes), Vietnam (6.5 million tonnes), Pakistan (4.6 million tonnes) and the USA (3.1 million tonnes). India is the second rice producer in Asia after China, followed by Indonesia, Bangladesh and Vietnam (Figure 1). The Indian agriculture sector is the most sensitive and exposed area to climate change due to its less adaptive capacity to cope with it (Guntukula 2019). Investigating the impact of climate change on agriculture productivity is of immense importance because more than 50% population of India primarily depends on agricultural activities for their livelihoods (Pattanayak and Kumar 2013). Changes in environmental factors such as temperature, precipitation, CO$_2$, and rainfall pattern directly affect agriculture productivity (Res et al. 1998). Increasing carbon emission and global warming created challenges for the countries to cope with it through different strategies and policies (Alharthi et al. 2021). Therefore, it is indispensable to examine the effect of changes in climatic conditions on rice production. More than 60% of the population in India mainly depends on agriculture and its allied sectors (Baig et al. 2020). Trends of rice production and area under crop are shown in Figure 2. Rice output grew from 746.8 (Lakh Tonne) in 1991 to 1164.8 (Lakh tonnes) in 2018. Simultaneously, the cultivated rice area in India has increased from 427 (Lakh Hectare) in 1991 to 442 (Lakh Hectare) in 2018. The area under rice has risen by around 1.5 times, but rice production has increased by more than five times.
Climate change may be the effect of food security by hampering agriculture productivity from one-way and multiple ways. Climate change, on the other hand, has a global impact, and its negative consequences are projected to be more severe in India's agro-ecological zones. Climate models predict the severe impacts of climate change on the agriculture sector (Bahl 2015). Climate change
has significantly affected agricultural productivity and food supply, threatening food security (Moses et al. 2015). Because rice is more vulnerable to fluctuation due to climate change and its associated components, the rising negative effects of climatic change would put pressure on agricultural yield (Bahl 2015). Given rice's vulnerability to environmental change, particularly those connected to temperature increases and extended drought spells, meeting future global rice demand appears to be a difficult undertaking. Temperature-related changes in the duration of the growing season will reduce rice yield and shift farming frameworks away from rice and toward crops with greater temperature optimums (Korres et al. 2017).

This study explores the nonlinear effects of climate change on rice production in India, spanning from 1991 to 2018. Most studies employed crop simulation model (Gupta and Mishra 2019; Kumar 2011; Kumar et al. 2011; Lal et al. 1998; Mishra and Chandra 2016; Mukherjee and Huda 2018), linear econometric models (Baig et al. 2020; Bhanumurthy and Kumar 2018; Birthal et al. 2014; Guntukula 2020; Kumar et al. 2020; Nath and Mandal 2018; Praveen and Sharma 2020; Gupta et al. 2012) and nonlinear model (Mitra 2014; Pal and Mitra 2018) to assess the impact of climate change on India's agriculture production. Several studies examine the effect of climate change on rice yield or production using linear regression analysis. As a result, these studies have produced only linear effects that might lack nonlinear effects. This study adds to the previous literature by addressing the asymmetric impact of climate change on rice production in India rather than sticking to a linear approach.

In this study, we also incorporated other important variables such as rural population, agricultural credit, consumption of fertiliser and cultivated land in the model to examine the impact of these factors on rice production. It is essential to investigate the asymmetrical implications, as it helps to understand whether positive and negative shocks dominate rice production in India. In this manner, this work adopts a more comprehensive understanding. Also, it provides the main factors of rice production for India, which will help formulate economic policies to cope with climate change and enhance rice production in India and other countries with the same agriculture profile.

The remainder of the paper is framed as follows: Section 2 deals with the existing literature. The data and technique are discussed in Section 3. Section 4 presents the empirical findings and comments, while Section 5 concludes with policy implications.
2. Literature Review
Numerous studies have been done on the nexus between climate change and agricultural productivity and growth across the globe. There is growing consensus among environmentalists and researchers that a negative relationship exists between climate change and agricultural productivity in developing nations (Khanal et al. 2018). South Asia is the most susceptible terrain to climate change globally, with the largest population growth, poverty, and insecurity. Climate change such as extreme weather, unexpected rainfall and temperature fluctuations severally affect agriculture production in developing nations (Masud et. Al. 2014; Shabbir et al. 2020). However, it is the primary concern to frame a suitable policy to tackle climate change problems for policymakers, researchers, and government organisations. At the global, regional level, researchers have undertaken numerous studies to assess the impact of climate change on the agriculture sector (Chandio et al. 2020; Praveen and Sharma 2020; Warsame et al. 2021).

Among previous studies conducted by Gupta and Mishra (2019) at the India level and Kumar et al. (2020) at the states level, i.e., Uttar Pradesh and Haryana respectively employ the Crop Simulation Model (CSM) and Ricardian regression approach to assess the nature of the relationship between climate change and rice productivity. According to Gupta and Mishra (2019), the multi-Global Climate Model predicts an increase in rice productivity in most agro-ecological zones in Representative Concentration Pathways (RCP) 2.6. Guiteras (2009) explained that major crop yield would harmfully be affected by 4.5 to 9% due to climate variation from 2010 to 2039 in India. In the same order, the crop would reduce up to 25% in the absence of adaptation productivity. Kumar et al. (2020) found that any large deviation in the rainfall harms rice and wheat production in Uttar Pradesh.

On the other hand, maximum temperature has a negative impact on rice and wheat in Uttar Pradesh and Haryana. While rising temperatures have a positive effect on rice production, they have a detrimental effect on grain. Abbas and Mayo (2019) reported that maximum temperature harms rice plants. Rice crops at the replantation stage during the vegetative phase have benefited from a decrease in the number of plants in the plantation stage and a lower minimum temperature. During the heading and flowering periods, rain has a deleterious impact on rice crops. Likewise, Auffhammer et al. (2012) point out that heavy rainfall and drought have a negative effect on rice yield in the rain-fed areas during the 1966-2002 period, and lower rainfall and warmer night would
not occur then rice yield would increase by 4 per cent in India. In contrast, Rayamajhee et al. (2020) stated that there is no direct relationship between rainfall and rice production in Nepal. Likewise, Abbas et al. (2021) conducted their study and employed the ARDL cointegration approach to investigate climate factors (CO2, Average temperature and precipitation), technological advancement (consumption of fertiliser used as a proxy variable), and other controlled variables such as the area under cultivated land, improves seed, and agriculture credit on rice production. They stated that average temperature and precipitation positively influenced rice production, while CO2 has a significant and negative impact on rice production in Nepal. Furthermore, agriculture credit and area under cultivated land has a positive effect on rice production.

Pickson et al. (2021) explored the relationship between climate change and rice production using panel data spanning 1998-2017 in Provinces of China. The long-run and short-run effects of climate change on rice production were investigated using pooled mean group methodologies. Rice production has been positively influenced by average rainfall, while rice production has been negatively influenced by average temperature, according to the study. In the long run, rice production has been positively influenced by cultivated area and fertiliser consumption, according to the findings. Furthermore, the causality test revealed that cultivated land and rice production have bidirectional connection.

Similarly, Inayatullah et al. (2021) have investigated the impact of climate change on cereal crops, namely wheat and maise, in the Khyber Pakhtunkhwa (KP) province of Pakistan using panel data from 1986 to 2015. The result indicated that precipitation has a significant and positive impact on wheat and maise yield in the long and short run. In the short run, minimum temperature has a large beneficial effect on maize yield but has no effect on wheat output, according to the estimated results. Maximum temperature, on the other hand, has had a detrimental impact on wheat and maise yields while having a beneficial impact on crop output in the short term.

Attiaoui and Boufateh (2019) and Abbas (2020) find a linear long-run dynamic relationship between climate change and agriculture productivity. Empirical results reveal that deficiency of rainfall and high temperature respectively has negatively and positively affected agriculture productivity. Baig et al. (2020) also employ a linear dynamic ARDL model to assess the impact of climate change on the yield of major crops, including rice, wheat, coarse cereals and pulse in India. Findings showed that temperature positively impacts wheat, coarse grains and pulse except
for rice. At the same time, rainfall has a positive impact on rice, coarse cereals and pulse except for wheat in India. In contrast, Mitra (2014) and Pal and Mitra (2018) investigated the nonlinear relationship between climate change and crop productivity in India. Mitra (2014) found no asymmetric relationship between rainfall and food grain in India and observed that average rainfall has a greater impact on food grain production than below-average rain. In contrast, Pal and Mitra (2018) explain that rainfall has a greater effect on food grain production up to 75th quantile and reduces after that in India. While Nsabimana and Habimana (2017) conducted a study in Rwanda's context, they stated that rainfall has an asymmetric impact on crop prices in the short and long run. Furthermore, the price of food crops has decreased during the harvest season and then increased. Likewise, Moore et al. (2017) used database yield to compare results from process-based and empirical studies in order to comprehensively investigate the influence of climate change on agricultural production and welfare. He claims that the asymmetric impacts of climate change on welfare and agricultural yield show a high possibility of severe welfare losses with warming of 2–3 degrees Celsius, even after accounting for the CO$_2$ fertilisation effect. Fezzi and Bateman (2016) and Kabubo-mariara and Karanja (2007) has observed a nonlinear relationship between climate change and the revenue of agriculture crops. So, it is challenging to cope with it due to the complex asymmetrical association between climate change and agriculture production. Table 1 shows a summary of review of literature.

Table 1. Summary of Review of Literature

| S. No. | Author(s)            | Time       | Country(ies)/State(s) | Model(s) | Results                                                                 |
|-------|----------------------|------------|-----------------------|----------|-------------------------------------------------------------------------|
| 1     | Chandio et al. (2019)| 1968-2014  | Pakistan              | ARDL     | +CO2, Avg. Temperature, Area under cultivation----> +Rice production both in short and long run. +Fertilizers----> +Rice production in long run but -Rice production in short run. |
| 2     | Chandio et al. (2021)| 1980-2016  | Turkey                | ARDL     | +CO2----> -Rice Production both in short & long run. +Temperature, Precipitation, Area harvested of rice----> +Rice |
production both in short and long run. +Domestic Credit --> -Rice production in long run but +Rice Production in short run.

| 3 | Yuliawan et al. (2016) | 1970-2004 | Indonesia | Crop simulation model | +Temperature --> -Rice production. |
|---|-----------------------|------------|-----------|-----------------------|-----------------------------------|
| 4 | Krishnan et al. (2007) | 2001-2003 | Eastern India | ORYZA1 & INFOCROP simulation model | +CO2 --> +Rice yield. +Temperature --> -Rice yield. |
| 5 | Lal et al. (1998) | 1965-1994 | North-West India | CERES rice model | +CO2 --> +Rice yield. Rise in air temperature cancel out the positive effect of +CO2. +Tmin --> -Rice yield. |
| 6 | Chandio et al. (2021) | 1990-2016 | Nepal | ARDL | +CO2 --> -Rice production in long run. +Avg. Temperature, Avg. Precipitation, Cultivated rice area, Fertilizer, Agriculture Credit --> +Rice production in long run. |
| 7 | Warsame et al. (2021) | 1985-2016 | Somalia | ARDL, Granger causality. | +Rainfall --> +Crop production in long run but - Crop production in short run. +Temperature --> -crop production both in short and long run. +Land under cereal --> +Crop productivity in long run. CO2 do not have any significant impact on crop production. |
| 8 | Matthews et al. (1997) | Asia | ORYZA1 & SIMRIW simulation model | +CO2 --> +Rice yield. +Temperature --> -Rice yield. |
|   | Authors                  | Period       | Location          | Model                  | Results                                                                 |
|---|-------------------------|--------------|-------------------|------------------------|----------------------------------------------------------------------|
| 9 | Saseendran et al. (2000)| Kerala       | CERES-Rice V3 Simulation model | +CO₂, Rainfall→+Rice Yield.  
- Rainfall→-Rice yield.  
+Temperature→-Rice yield. |
| 11| Muhammad Nasrullah et al. (2021)| 1973-2018 | South Korea   | ARDL        | +CO₂, Mean Temperature,  
Area under rice→+Rice production both in long & short run.  
+Rainfall→+Rice production both in long & short run.  
+Fertilizer→+Rice production in long run but has no impact in short run. |
| 12| Chandio et al. (2020)   | 1982-2014 | China           | ARDL        | +CO₂, Fertilizer, Land under cereal crops→+Agricultural output both in short & long run.  
+Temperature, Rainfall→-Agricultural output both in short & long run. |
| 13| Siddiqui et al. (2012)  | 1980-2009 | Punjab, Pakistan | Fixed Effect Model [FEM] | +Temperature→+Rice production initially but harmful beyond a certain optimal temperature.  
+Precipitation does not harm rice productivity. |
| 14| Haris et al. (2010)     | 2006-2008 | Bihar            | INFOCROP simulation model | +CO₂→+Rice yield.  
+Temperature→-Rice yield. |
| 15| Kingra et al. (2018)    | 1974-2013 | Punjab, India   | Stepwise Regression | +Tmin, Tmax, Rainfall→-Rice production.  
+Fertilizer, Total cropped area→+Rice production. |
| 16| Sajjad Ali et al. (2017)| 1989-2015 | Pakistan        | FGLS        | +Rainfall, Temperature→-Rice crop yield. |
| 17| Sohail Abbas et al. (2021)| 1979-2018 | Punjab, Pakistan | ARDL & NARDL | Varying effect of temperature and rainfall on rice crop in different region. |
Asymmetric relation between climate and rice production.

|   |       |           |                                                                 |                                                                 |
|---|--------|-----------|----------------------------------------------------------------|----------------------------------------------------------------|
|18 | Hussain et al. (2012) | 1988-2010 | Pakistan | Log linear Cobb-Douglas production function | +Fertilizer, Credit disbursement---+Rice production though statistically insignificant. |
| | | | | | +Area under cultivation---+Rice production. |
|19 | Bashir et al. (2010) | Lahore, Pakistan | Cobb-Douglas production function | +Agriculture credit---+Rice productivity. |
3. Data and Methodology

In this study we explore asymmetrical causal relationship between climate change and rice production in India using times series data from 1991-2018. The data is obtained from different sources including Reserve Bank of India (RBI), World development Indicators (WDI), and the Climate change knowledge portal (CCKP) (Table 2). Figure 3 represents the trend of the variables.

Table 2. Description of the Variables

| Variables                  | Abbreviations | Units             | Sources |
|---------------------------|---------------|-------------------|---------|
| Rice Production           | lnPR          | Lakh Tonne (LT)   | RBI     |
| Mean Temperature          | lnAT          | Celsius (°C)      | CCKP    |
| Average Rainfall          | lnRF          | Milli Meter (mm)  | CCKP    |
| Carbon Emission           | lnCO2         | Kiloton(kt)       | WDI     |
| Rural Population          | RP            | % of Total Population | WDI    |
| Agricultural Credit       | lnAC          | Crore (Cr)        | RBI     |
| Consumption of Fertiliser | lnF           | Kilogram/Hectare (Kg/ha) | RBI    |
| Area Under Rice crop     | lnAUR         | Lakh Hectare (Lh) | RBI     |

Note: RBI indicates Reserve Bank of India, CCKP means Climate Change Knowledge Portal and WDI represent World Development Indicators.

This study undertakes rice production (Lakh Tonne) as a dependent variable, mean temperature (°C), average rainfall (mm), carbon emission (kt), rural population (Per cent of the total population), consumption of fertiliser (kg/ha), agriculture credit (Crore) and area under crops (Lakh hectare) used as independents variables. Annual mean temperature, annual average rainfall and carbon emission are the main factors of climate change (Chandio et al. 2020; Kumar et al. 2021; Pickson et al. 2021). Chandio et al. (2021), Pickson et al. (2021) and Warsame et al. (2020) also incorporated agriculture credit, consumption of fertiliser, rural population and area under crops as non-climate factors of agriculture production. All the variables were transformed into logarithmic. Figure 6 shows trends of underlying variables used in this study.
Figure 3. Trends of variables used in this study

NARDL Bound Test for Cointegration

This study employs the recently developed and advanced technique NARDL to investigates the asymmetrical effect of climate change on production of rice. The ARDL technique ignored nonlinearity and the asymmetrical association between the underlying variables. An ARDL model is expanded to an asymmetric ARDL or NARDL by Shin et al. (2014) to assess the pattern of dynamic adjustment and asymmetries relationship in the short and long run between the variables. To explore the relationship between the variables following model can be specified as:

\[
\ln PR_t = f(\ln AT_t, \ln RF_t, \ln CO_{2t}, RP_t, \ln AC_t, \ln F_t, \ln AUR_t)
\]

(1)

We can rewrite equation (1) as follows:
\[ \ln PR_t = \alpha_0 + \alpha_1 \ln AT_t + \alpha_2 \ln RF_t + \alpha_3 \ln CO_{2t} + \alpha_4 RP_t + \alpha_5 \ln AC_t + \alpha_6 \ln F_t + \alpha_7 \ln AUR_t + \varepsilon_t \quad (2) \]

Where \( \ln PR \) is the natural log of rice production, \( \ln AT \) is the natural log mean temperature, \( \ln RF \) is the natural log of average rainfall, \( \ln CO_2 \) is the natural log carbon emission, \( RP \) is rural population, \( \ln AC \) is the natural log of agricultural credit, \( \ln F \) is the natural log of consumption of fertiliser and \( \ln AUR \) indicates natural log of the area under rice crop. Before presenting a full depiction of the NARDL model, General forms of long-run asymmetry relationships are given as follows:

\[ \ln PR_t = \alpha_0 + \alpha_1^+ \ln AT_t^+ + \alpha_2^- \ln AT_t^- + \alpha_3^+ \ln CO_{2t}^+ + \alpha_4^- \ln CO_{2t}^- + \alpha_5^+ \ln RF_t^+ + \alpha_6^- \ln RF_t^- + \alpha_7^+ \ln RP_t^+ + \alpha_8^- \ln RP_t^- + \alpha_9 \ln AC_t + \alpha_{10} \ln F_t + \alpha_{11} \ln AUR_t + \varepsilon_t \quad (3) \]

Where, \( \ln PR_t \) is a \( k \times 1 \) vector of rice production at time \( t \), where, \( \alpha (\alpha_0, \alpha_1^+, \alpha_2^-, \alpha_3^+, \alpha_4^-, \alpha_5^+, \alpha_6^-, \alpha_7^+, \alpha_8^- \) and \( \alpha_{11} \) are the associated asymmetric long-run parameters. Here \( \ln AT_t, \ln RF_t, \ln CO_{2t} \) and \( RP_t \) as \( k \times 1 \) vector of regressors is subdivided as;

\[ \ln AT_t = \ln AT_0 + \ln AT_t^+ + \ln AT_t^- \quad \ln RF_t = \ln RF_0 + \ln RF_t^+ + \ln RF_t^- \quad \ln CO_{2t} = \ln CO_{20} + \ln CO_{2t}^+ + \ln CO_{2t}^- \quad \text{and} \quad \ln RP_t = \ln RP_0 + \ln RP_t^+ + \ln RP_t^- \quad \text{respectively.} \]

Where, \( \ln AT_t^+, \ln AT_t^-; \ln RF_t^+, \ln RF_t^-; \ln CO_{2t}^+, \ln CO_{2t}^- \) and \( \ln RP_t^+, \ln RP_t^- \) are partial sum processes of positive (+) and negative (–) changes in \( \ln AT_t, \ln RF_t, \ln CO_{2t}, \ln RP_t \) respectively. Equation shows partial decomposition of \( \ln AT, \ln RF, \ln CO_2 \) and \( RP \).

\[
\begin{align*}
\ln AT_t^+ &= \sum_{i=1}^{t} \Delta \ln AT_i^+ = \sum_{i=1}^{t} \max(\Delta \ln AT_i, 0) \\
\ln AT_t^- &= \sum_{i=1}^{t} \Delta \ln AT_i^- = \sum_{i=1}^{t} \min(\Delta \ln AT_i, 0) \\
\ln RF_t^+ &= \sum_{i=1}^{t} \Delta \ln RF_i^+ = \sum_{i=1}^{t} \max(\Delta \ln RF_i, 0) \\
\ln RF_t^- &= \sum_{i=1}^{t} \Delta \ln RF_i^- = \sum_{i=1}^{t} \min(\Delta \ln RF_i, 0) \\
\ln CO_{2t}^+ &= \sum_{i=1}^{t} \Delta \ln CO_{2i}^+ = \sum_{i=1}^{t} \max(\Delta \ln CO_{2i}, 0) \\
\ln CO_{2t}^- &= \sum_{i=1}^{t} \Delta \ln CO_{2i}^- = \sum_{i=1}^{t} \min(\Delta \ln CO_{2i}, 0)
\end{align*}
\]
\[
\ln C_{O2}^t = \sum_{i=1}^{t} \Delta \ln C_{O2}^t = \sum_{i=1}^{t} \min(\Delta \ln C_{O2}^t, 0)
\]
(9)

\[
RP^{+}_t = \sum_{i=1}^{t} \Delta RP^{+}_t = \sum_{i=1}^{t} \max(\Delta RP_t, 0)
\]
(10)

\[
RP^{-}_t = \sum_{i=1}^{t} \Delta RP^{-}_t = \sum_{i=1}^{t} \min(\Delta RP_t, 0)
\]
(11)

Shin et al., (2014) prolong ARDL model adopted (Peasaran et al. 2001) by utilising the concept of cumulative positive and negative partials sums. In this manner, the NARDL model proposed by Shin et al. (2014), represent asymmetric error correction form is specified as:

\[
\Delta \ln PR_t = \alpha_0 + \rho \ln PR_{t-1} + \alpha_1^+ \ln AT^+_{t-1} + \alpha_2^- \ln AT^-_{t-1} + \alpha_3^+ \ln RF^+_{t-1} + \alpha_4^+ \ln RF^-_{t-1}
\]

\[
\quad + \alpha_5^+ \ln CO^+_{2,t-1} + \alpha_6^+ \ln CO^-_{2,t-1} + \alpha_7^+ \Delta LP^+_{t-1} + \alpha_8^+ \Delta LP^-_{t-1} + \alpha_9 \ln F_{t-1}
\]

\[
\quad + \alpha_{10} \ln AC_{t-1} + \alpha_{11} \ln AUR_{t-1} + \sum_{i=1}^{p} \beta_i \Delta \ln PR_{t-i} + \sum_{m=1}^{p} (\theta_{1}^+ \Delta \ln AT^+_{t-1})
\]

\[
\quad + \theta_2^- \Delta \ln AT^-_{t-1} + \sum_{m=1}^{p} (\gamma_1^+ \Delta \ln RF^+_{t-1} + \gamma_2^- \Delta \ln RF^-_{t-1}) + \sum_{m=1}^{p} (\varphi_1^+ \Delta \ln CO^+_{2,t-1})
\]

\[
\quad + \theta_2^- \ln CO^-_{2,t-1})
\]

\[
\quad + \sum_{m=1}^{p} (\beta_1^+ \Delta LP^+_{t-1} + \beta_2^- \Delta LP^-_{t-1}) + \sum_{m=1}^{p} \delta_1 \Delta \ln F_{t-1} + \sum_{m=1}^{p} \delta_2 \Delta \ln AC_{t-1}
\]

\[
\quad + \sum_{m=1}^{p} \delta_3 \Delta \ln AUR_{t-1} + \Phi ECT_{(-1)}
\]

\[
+ U_t \]
(12)

In the above equation, \((\alpha_i)\), indicates long-run coefficients, while \((\theta_i), (\gamma_i), (\beta_i), (\delta_i)\) and \((\varphi_i)\) are the short-run coefficients. The NARDL’s estimation method is the same as linear ARDL. The null hypothesis of asymmetrical long-run relationship, \(\rho = \alpha^+ = \alpha^- = 0\) between the variables. Null hypotheses have been tested by computing the general F-statistics \((F_{PSS})\) or t-statistics \((t_{BDM})\) proposed by Banarjee et al. (1998) determined these values by comparing them to the two critical bounds (lower and upper bound), which define a band including all conceivable classifications of the regressors as solely I (0), I (1), or mutually cointegrated. We accept the null
hypothesis if the F-statistics are less than the lower bound value, i.e. I (0). We can infer that there
is no long-run association between the variables. If the F-statistics are in the range I (0) to I (1),
the outcome is inconclusive. If the F-value is greater than the I (1) bound value, the null hypothesis
can be rejected, indicating that variables are long-run cointegrated. \( ECT^{-1} \) is the error correction
term, and is the rate at which the asymmetrical long-run equilibrium relationship is restored
following a disruption.

The long-run \( (\alpha^+ = \alpha^-) \) and short-run \( (\theta_1^+ = \theta_2^-, \theta_1^+ = \theta_2^-, \gamma^+_1 = \gamma^-_1, \beta_1^+ = \beta_2^- ) \) asymmetries
estimates through the Wald test for mean temperature (\( \ln AT \)), average rainfall (\( \ln RF \)), carbon
emission (\( \ln CO_2 \)) and rural population (\( \ln RP \)) variables. Where; \( p \) and \( q \) are representing optimal lags
order of dependent and independent variables, respectively. Akaike and Schwarz information
criteria have been used to find out the optimal lag selection in the model. The long-term
asymmetric coefficients are calculated based on \( L_{mi}^+ = \alpha^+ / \rho \) and \( L_{mi}^- = \alpha^- / \rho \). These long run
coefficients measure the connection between variables in long run equilibrium with respect to
independent variable shocks. By utilising the cumulative dynamic multiplier effect, these long-run
and short-run asymmetry trajectories can be described in the following ways: a unit percentage
change in \( X_t^+ \) and \( X_t^- \) on \( Y_t \) are obtained through the following equation:

\[
\begin{align*}
 m_h^+ &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial \ln AT_t^+} ; \\
 m_h^- &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial \ln AT_t^-} ; \\
 m_h^+ &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial \ln RF_t^+} ; \\
 m_h^- &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial \ln RF_t^-} ; \\
 m_h^+ &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial \ln CO_2_t^+} ; \\
 m_h^- &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial \ln CO_2_t^-} ; \\
 m_h^+ &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial RP_t^+} ; \\
 m_h^- &= \sum_{i=0}^{h} \frac{\partial LPR_{t+i}}{\partial RP_t^-} ;
\end{align*}
\]

Where, if \( h \to \infty \), then \( m_h^+ \to L_{mi}^+ \) and \( m_h^- \to L_{mi}^- \).

The adequacy and stability of the specified NARDL models are also checked with various
diagnostic tests.

4. Results and Discussion

Table 3 reported result of descriptive statistics. We can infer from table 3 the average value of
\( \ln PR, \ln AT, \ln RF, \ln CO_2, \ln AC, \ln F \) and \( \ln AUR \) are \( 2.96, 1.39, 1.94, 6.08, 70.64, 5.25, 2.09 \)
and \( 2.64 \) and the standard deviation are \( 0.06, 0.01, 0.03, 0.19, 2.54, 0.54, 0.13 \) and \( 0.01 \)
respectively. The Jarque Bera test P-value suggests that all variables are normal.

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Table 3: Descriptive Statistics

| Variables | Obs | Mean | Std. Dev. | Min | Max | Skew. | Kurt. | J-B (P) |
|-----------|-----|------|-----------|-----|-----|-------|-------|---------|
| lnPR      | 28  | 2.96 | .06       | 2.86| 3.07| -.01  | 2     | 0.55    |
| lnAT      | 28  | 1.39 | .01       | 1.38| 1.4 | .08   | 3.08  | 0.98    |
| lnRF      | 28  | 1.94 | .03       | 1.86| 2   | -.26  | 2.81  | 0.83    |
| lnCO2     | 28  | 6.08 | .19       | 5.78| 6.39| .12   | 1.69  | 0.35    |
| RP        | 28  | 70.64| 2.54      | 65.97| 74.22| -.29 | 1.83  | 0.37    |
| lnAC      | 28  | 5.25 | .54       | 4.49| 6.11| .12   | 1.59  | 0.30    |
| lnF       | 28  | 2.09 | .13       | 1.87| 2.26| -.21  | 1.64  | 0.30    |
| lnAUR     | 28  | 2.64 | .01       | 2.61| 2.66| -.17  | 2.44  | 0.77    |

Sources: Calculated by the authors

Result of Correlation analysis are reported in Table 4, which indicates that all the variables are positively correlated with production of rice except rural population which are negatively correlated.

Table 4: Matrix of correlations

| Variables | lnPR | lnAT | lnRF | lnCO2 | RP | lnAC | lnF | lnAUR |
|-----------|------|------|------|-------|----|------|-----|-------|
| lnPR      | 1.00 |      |      |       |    |      |     |       |
| lnAT      | 0.45 | 1.00 |      |       |    |      |     |       |
| lnRF      | 0.43 | 0.04 | 1.00 |       |    |      |     |       |
| lnCO2     | 0.92 | 0.60 | 0.27 | 1.00  |    |      |     |       |
| RP        | -0.92| -0.59| -0.25| -0.99 | 1.00|      |     |       |
| lnAC      | 0.74 | 0.56 | 0.35 | 0.85  | -0.83| 1.00|     |       |
| lnF       | 0.89 | 0.65 | 0.34 | 0.96  | -0.94| 0.86| 1.00|     |
| lnAUR     | 0.53 | 0.01 | 0.47 | 0.26  | -0.24| 0.16| 0.32| 1.00 |

Sources: Calculated by the Authors

The next step is to check the stationarity of the underlying variables to guarantee that none of them are integrated at order 2. Because the NARDL model requires that variables be integrated at order 0 or 1 to investigate cointegration among variables, a unit root test must be performed. We used the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests in this order, and the results are shown in Table 5. We can infer from Table 5 that mean temperature, average rainfall, rural population, and land area under rice crop are I (0), while rice production, carbon emission and agriculture credit series are I (1).
Table 5: Unit Root analysis without structural break.

| Variables | I(0) PP | I(0) ADF | I(1) PP | I(1) ADF |
|-----------|---------|----------|---------|----------|
| lnPR      | -2.92   | -1.51    | -40.79*** | -10.27*** |
| lnAT      | -13.18** | -2.52    | -34.06*** | -7.14*** |
| lnRF      | -23.57*** | -3.10**  | -39.88*** | -9.20*** |
| lnCO2     | 0.08    | 0.063    | -23.71*** | -4.589*** |
| RP        | 0.81    | 2.30***  | -0.22    | -2.69*** |
| lnAC      | -4.43   | -1.47    | -118.46*** | -1.34 |
| lnF       | -1.12   | -1.51    | -20.98*** | -4.17*** |
| lnAUR     | -17.09*** | -3.11**  | -33.76*** | -7.95*** |

Sources: Estimated by authors

By neglecting structural breakdowns in the data, common unit root tests such as ADF and PP allow results to be misled. To address this issue, we employ the Zivot and Andrews (1991) test. The results of the Zivot and Andrews (1992) test are shown in Table 6, which reveals that rice output, mean temperature, average rainfall, fertiliser usage, and area under rice crop are integrated at order 0. In contrast, carbon emission, agricultural credit, and rural population are stationary after being first differenced with different structural breaks in the series. Due to the drought in 2002 in India, agricultural productivity had been sharply gone down (Gulati et al. 2013). Hence the structural break has arisen in the data of rice production. Due to the presence of structural breaks in the data, the variables may have nonlinearity. As a result, to check for nonlinearity, we use the BDS independence test, which checks for the presence of linear dependency in the dependent variable in the model.

Table 6: Result of Structural Breaks Unit Root Test (Zivot & Andrews, 2002)

| Variable | I(0) | I(0) | I(1) | I(1) |
|----------|------|------|------|------|
| lnPR     | -2.41| 2010 | -13.06| 2002 |
| lnAT     | -4.69| 1997 | -7.3  | 1997 |
| lnRF     | -5.43| 2002 | -9.49 | 1996 |
| lnCO2    | -2.3 | 2006 | -4.48 | 1995 |
| RP       | 1.19 | 2003 | -7.27 | 2001 |
| lnAC     | -2.79| 2008 | -5.3  | 2018 |
| lnF      | -3.28| 2011 | -4.97 | 2012 |
| lnAUR    | -5.24| 2001 | -8.04 | 2009 |

Estimated by Author
BDS test for nonlinearity in the residual of the dynamic relationship is performed. The result of
the BDS are reported in Table 7 indicates that all the variables are not identically and independently
distributed (iid) except mean temperature and average rainfall. BDS statistics show the null
hypothesis of residual of being independent and identically residual also is rejected at 1 per cent
level of significance of rice production at all the dimension. After confirming the nonlinearity in
the series, we move towards the estimation of the NARDL model.

| Variables/BDS | Statistics | D=2 | D=3 | D=4 | D=5 | D=6 |
|---------------|------------|-----|-----|-----|-----|-----|
| lnPR          | 0.08***    | 0.14*** | 0.17*** | 0.19*** | 0.19*** |
| lnAT          | 0.034**    | 0.03 | 0.009 | 0.018 | 0.025 |
| lnRF          | -0.03      | -0.02 | -0.01 | 0.00  | -0.02 |
| lnCO2         | 0.18***    | 0.30*** | 0.38*** | 0.42*** | 0.43*** |
| RP            | 0.18***    | 0.29*** | 0.37*** | 0.41*** | 0.42*** |
| lnAC          | 0.16***    | 0.29*** | 0.38*** | 0.43*** | 0.47*** |
| lnF           | 0.16***    | 0.26*** | 0.34*** | 0.39*** | 0.42*** |
| lnAUR         | 0.03       | 0.08*** | 0.11*** | 0.11*** | 0.10** |

Estimated by Author

**NARDL Cointegration Results**

Schwarz (1978) information criterion used to choose the optimal lag length of NARDL (p,q). Then
we use general to specific approach by ignoring all insignificant regressors since their inclusion
may produce imprecise estimation results. Table 8 delineate the asymmetric impact of climate
change and other controlled agriculture inputs on rice production. Two operational testings are
used for the existence of an asymmetrical cointegration relationship based on NARDL. We find
that the F-statistics are greater than the critical upper bound value at the 1% level of significance,
confirming the presence of cointegration between mean temperature, average rainfall, carbon
emission, rural population, agricultural credit, fertiliser consumption, the area under rice crop, and
rice production from 1991 to 2018. The Wald test highlights the importance of asymmetry in both
the short and long run, implying that nonlinearity must be considered when researching the
relationship between climate change and rice output. At a 1% level of significance, the t-statistics
support the cointegration among the variables. Shin et al. (2014)'s NARDL F-statistics (FPSS)
confirm asymmetric cointegration among variables. It means that in India, mean temperature,
average rainfall, carbon emissions, agricultural finance, fertiliser usage, rice crop area, and rice
production have a long-term asymmetric relationship.
Long and Short-Run Asymmetric Estimates

A positive and negative component in mean temperature has a negative and significant impact on rice production, which represent that any positive and negative shock in mean temperature deteriorates rice production. However, the sign of both coefficients is the same but different in magnitude, which indicates mean temperature has a significant asymmetric impact on rice production. This study is in line with previous studies (Chandio et al. 2020; Haris et al. 2013; Lal et al. 1998; Matthews et al. 1997; Warsame et al. 2021; Yuliawan and Handoko 2016), corroborates the same findings. Chandio et al. (2020), Matthews et al. (1997), and Warsame et al. (2021) explained temperature has an adverse effect on rice production both in the short and long run. For instance, increases (decreases) 1 per cent in temperature reduces rice production by 9.23 (10.32) per cent in the long run in India. Several reasons can support this finding; increasing mean temperature is beneficial for rice production initially. However, beyond a certain optimal temperature, further temperature increases become harmful for rice production. Second, temperature rise would make the age of rice shorter and decrease the rice yield (Kumar et al. 2021). Higher temperature increases sea level; consequently, highly productive rice cultivation areas will be more exposed to inundation and salinity intrusion. Moreover, the increased mean temperature has adversely impacted rice production in various parts of South Asia such as India, Bangladesh, Sri Lanka and Pakistan, which results in reduced average yields by 4 per cent (Matthews et al. 1997).

Table 8 reported the result of the long run and short asymmetrical impact on rice production. Estimated outcomes in the long-run indicate that positive shock in the rainfall has negative and significant effect on rice production at a 1 per cent level in India. The estimated coefficients of positive shock in average rainfall indicate that a 1 per cent rise in average rainfall leads to a decrease of 1.24 per cent of rice production in India. These findings are supported by the previous study (Abbas et al. 2021; Nasrullah et al. 2021), which stated that excess rainfall has negatively influenced rice production in rain-fed areas. Rice production has tremendous pressure due to the high variability of rainfall in rain-fed regions of India (Pal and Mitra 2018). However, heavy rainfall, i.e., the flood-like situation, has adversely affected rice production in India (Pal and Mitra 2018). Some previous studies (Abbas et al. 2021; Chandio et al. 2021; Siddiq et al. 2012; Warsame et al. 2021) has contradicted this result and stated that excess rainfall had enhanced rice production.
in rain-fed areas. In contrast, coefficients of negative shocks in the rainfall have a positive and
significant impact on rice production at a 1 per cent level in the long run. This study is in line with
(Abbas et al. 2021; Mitra 2014), they found that any negative shock in the rainfall has positively
affected rice production in India. Pal and Mitra (2018) stated that scanty rainfall and drought have
reduced food grain production in India. We can infer from the estimated result that 1 per cent
increases (decreases) in average rainfall has reduced (boosts) rice production by approximately
1.24 (2.87) per cent in India.

Any positive shock in the carbon emission has negative impact on rice production at the 1 per cent
significance level in India. The estimated outcome indicates a rise in carbon emission in the
atmosphere by 1 per cent, which reduces rice production by 1.95 per cent approximately. This
outcome is in line with Chandio et al. (2021), who found that carbon emissions have negatively
affected rice production in Turkey's short and long run. In contrast, carbon emission negative
shocks have an insignificant positive impact on rice production. The coefficient of the negative
component of carbon emission indicates that it increases rice production by 0.4 per cent when 1
per cent reduce the carbon emission. We can infer from the estimated results that rice production
has been boosted by the reduction of carbon emission in the atmosphere in India. Global warming
results from increasing carbon emissions in the atmosphere, which is critical in reducing crop
production in developing countries (Jan et al. 2021). The positive components have a dominant
effect over negative shock on rice production, which implies that increasing carbon emission has
harmful for rice production in India.

Furthermore, positive shock in the rural population has a statistically insignificant impact on rice
production with a coefficient of 0.49 in the long run. Interpretively, rice production is growing by
0.49 per cent due to a 1 per cent increase in rural population. The coefficients indicate that rice
production increases with increase in rural population. Whereas, Negative shock in the rural
population has negatively influenced rice production by 0.39 per cent in the long run at a 1 per
cent level of significance. This study is in line with previous studies (Kumar et al. 2021; Warsame
et al. 2021), who found that the rural population has a negative impact on cereals production. It is
because the marginal productivity of agriculture labour is zero due to working surplus labour in
the same piece of land (Thirlwall 1994). Agriculture labour productivity has decreased because
land can not produce more than its capacity (Kumar et al. 2021).
Table 8 reported the result of the short-run asymmetrical impact on rice output. The positive and negative shocks in mean temperature have positively influenced rice production in India. Estimated coefficients indicate that a 1 per cent increase and decrease in mean temperature can lead to increases the rice production by 17.23 per cent and 2.60 per cent, respectively, which implies that positive shocks have a more dominant effect than the negative shock on rice production in the short run. Results advocated that rice production has more affected by the increasing temperature rather than decreasing temperature in India. Moreover, rainfall positive shock has a negative and significant effect on rice production at a 1 per cent level of significance. It is found that rice production reduced by 0.74 per cent when 1 per cent increase in positive shock of rainfall. In contrast, coefficients of negative shocks in the rainfall have a positive and significant impact on rice production at a 1 per cent level of significance in the short run. We can infer from the estimated result that 1 per cent decreases in average rainfall have boosted rice production by approximately 0.64 per cent in India. Furthermore, any positive shock in the carbon emission has a negative and significant impact on rice production at the 1 per cent level of significance in India. The estimated outcome indicates a rise in carbon emission in the atmosphere by 1 per cent, which reduces rice production by 6.16 per cent approximately. In comparison, carbon emission negative shocks positively impact rice production at the 1 per cent significance level. The coefficient of the negative component of carbon emission indicates that it increases rice production by 1.69 per cent when there is 1 per cent reduction in the carbon emission. We can infer from the estimated results that rice production has been boosted by reducing carbon emissions in India's atmosphere in the short run. Likewise, the impact of positive shock in the rural population has a negative and insignificant effect on rice production in the short run. Interpretively, a 1 per cent increase in rural population leads to decrease rice production by 0.50 per cent in India. Coefficients indicate that rice production decreases when increasing rural population. In comparison, negative shock in the rural population has positively influenced rice production by 1.82 per cent in the short-run at a 1 per cent level of significance.

Moving on to other controlled variables such as fertiliser consumption (lnF), agricultural credit (lnAC), and area under crops on rice production (lnAUR), these are three core elements of rice production (Chandio et al. 2021). Our findings show that a 1 per cent increase in fertiliser consumption, agricultural credit and area under crop enhance rice production by 0.70 per cent, 0.04 per cent and 2.34 per cent, respectively, in India. These findings are consistent with previous
studies (Chandio et al. 2021; Chandio et al. 2020; Janjua et al. 2014; Nasrullah et al. 2021; Omorogie et al. 2018; Zakaria et al. 2020). In the context of India, agricultural credit plays a significant role to boost agriculture production and farm income (Mohan 2006). Chandio et al. (2021) found that agriculture credit has a positive and significant impact on rice production in Nepal. Baig et al. (2020) state that fertiliser positively influenced rice production in India. Due to might be the reason that fertiliser enhances soil fertility and nutrition, which create a considerable positive impact on rice production (Janjua et al. 2014). Chandio et al. (2021) stated that the area under crop positively impacts rice production in Turkey. The area under rice has the largest share in India, which positively contribute to rice production. The negative and significant ECT value shows that all the variables move towards long-run stability at a medium annual speed of adjustment of 70.97 per cent.

Table 8. Cointegration Result (Dependent Variable: LNPR)

| Variables | Coefficient | Std. Error | Prob. |
|-----------|-------------|------------|-------|
| Constant  | 7.096***    | 0.412      | 0.003 |
| lnPR      | -0.686**    | 0.08       | 0.014 |
| lnAT+     | -9.231***   | 0.392      | 0.002 |
| lnAT-     | -10.32***   | 0.64       | 0.004 |
| lnRF+     | -1.247***   | 0.089      | 0.005 |
| lnRF-     | 2.870***    | 0.158      | 0.003 |
| lnCO2+    | -1.956***   | 0.93       | 0.002 |
| lnCO2-    | 0.421       | 0.004      | 0.581 |
| RP+       | 0.492       | 0.3        | 0.172 |
| RP-       | -0.396***   | 0.139      | 0.001 |
| ∆lnPR     | -0.727***   | 0.042      | 0.003 |
| ∆lnAT+    | 17.23***    | 0.661      | 0.001 |
| ∆lnAT-    | 2.610**     | 0.447      | 0.028 |
| ∆lnAT-(-1)| -4.75***    | 0.43       | 0.008 |
| ∆lnRF+    | -0.745***   | 0.052      | 0.006 |
| ∆lnRF-(-1)| 1.114***    | 0.585      | 0.003 |
| ∆lnRF-    | 0.647***    | 0.052      | 0.007 |
| ∆lnRF(-1) | -0.523**    | 0.063      | 0.014 |
| ∆lnCO2+   | -6.163***   | 0.301      | 0.002 |
| ∆lnCO2-   | 1.690       | 0.165      | 0.091 |
| ∆RP+      | -0.504      | 0.30       | 0.142 |
| ∆RP-      | 1.827***    | 0.084      | 0.002 |
ÀRP (-1) -0.642** 0.092 0.02
lnF 0.709*** 0.043 0.004
lnAC 0.0458*** 0.002 0.004
lnAUR 2.349*** 0.166 0.005
ECT(-1) -0.7097***
R-squared 0.99
Adj-R^2 0.98

|                |        |        |        |
|----------------|--------|--------|--------|
| L_{lnAT}^+     | -13.64*** | L_{lnAT}^- | *      |
| L_{lnRF}^+     | -1.81**  | L_{lnRF}^- | -4.18*** |
| L_{lnCO2}^+    | -2.85*** | L_{lnCO2}^- | *      |
| L_{RP}^+       | 0.001*** | L_{RP}^-    | 0.57*** |

|                |        |        |        |
|----------------|--------|--------|--------|
| W_{LR, lnAT}  | 3.925*** | W_{SR, lnAT} | *      |
| W_{LR, lnRF}  | 53.33*** | W_{SR, lnRF} | 8.95*** |
| W_{LR, lnCO2} | 57.81*** | W_{SR, lnCO2} | 329.4** |
| W_{LR, RP}    | 58.59*** | W_{SR, RP}   | 575.5** |
| F_{PSS}        | *      |        |        |
| T_{BDM}        | -8.47*** |        |        |

Sources: Calculated by authors. *** p<0.01, ** p<0.05, * p<0.1

Finally, we performed several dynamic adjustments, the results of which are given in Figure 4, which depicts the cumulative dynamic multipliers. These multipliers depict the pattern of rice production adjustment toward its new long-term equilibrium as a result of a negative or positive unitary shock in rainfall, mean temperature, carbon emissions, and rural population, respectively. The dynamic multipliers are computed using the AIC's best-fit NARDL model. A particular prediction horizon's rice production adjustment to positive (green line) and negative (red line) shocks is captured by the positive and negative curves. As seen in the graph, the asymmetric curve (dashed red line) represents the difference between the dynamic multipliers for positive and negative shocks, respectively. There is a 95 percent confidence interval between the lower and upper bands (dotted red lines) of this curve.
Figure 4 confirms a negative association between rainfall and rice output. A negative shock in rainfall outperforms a positive shock over the horizon. There is also a large asymmetric reaction to rainfall shocks. As with mean temperature, rice production is negatively correlated. This confirms the results in Table 8 that a negative shock in mean temperature dominates a positive shock in the long term. Furthermore, positive carbon emission shocks must outweigh beneficial effects on rice production for there to be a negative correlation. However, a negative shock in rural areas outweighs a positive one. Table 9 displays the results of different diagnostic tests used to assess the model's reliability (normality, autocorrelation, heteroscedasticity, and Ramsey RESET model). The NARDL model does not suffer from any diagnostic problem. CUSUM and
CUSUMQ tests were used to assess model stability. In Fig. 5 (A & B), the predicted line is within the crucial values at the 5% level of significance, indicating the model is highly stable.

Table 9. Result of Diagnostic Test

| Diagnostic Test | Statistics | P-Value |
|-----------------|------------|---------|
| Jarque-Bera     | 2.08       | 0.35    |
| Auto Correlation| 8.03       | 0.7     |
| BPG Test        | 0.21       | 0.64    |
| Ramsey Reset    | 0.87       | 0.81    |

Notes: BPG indicates Breusch/Pagan heteroskedasticity test

Fig. 5 (A) Stability Model (CUSUM)
Granger Causality Results

Asymmetrical causality between dependent and independent variables are reported in Table 10. We observed a bidirectional impact between a negative shock in rainfall and rice production. In contrast, one-way causality running from positive shock in rainfall to rice production. In addition, we found bi-direction asymmetrical causality among mean temperature and rice production. Furthermore, a two-way causal relationship exists between carbon emission (Positive and negative shock) and rice production. Similarly, we found bidirectional asymmetrical causality running among the rural population and rice production. However, bidirectional impact between fertiliser consumption and rice production while one-way causal nexus between area under crop and rice production. Meanwhile, no causal relation runs from agricultural credit to rice production. It implies that positive and negative shocks in mean temperature, carbon emission, and rural population will influence rice production and vice-versa. This work is in line with Chandio et al. (2021), who stated that average rainfall, consumption of fertiliser and agriculture credit has positively influenced production of rice in Nepal. This study contradicts Warsame et al. (2021), who argued that there is no causal relationship between average rainfall, mean temperature carbon emission and cereals crop production in Somalia. While negative shock in rainfall, fertiliser consumption and area under crop has granger causes rice production and vice versa. Moreover, one-way causality flows from rainfall positive shock towards the area under crop to rice production. Furthermore, unidirectional causality also running from rice production to increasing carbon emission and agricultural credit, which indicates that increasing rice production will increase carbon emission and agricultural credit. In contrast, there is no asymmetrical causality running from average rainfall positive shock, a negative shock in carbon emissions, and a positive shock in agricultural credit to rice production. It indicates that increasing rainfall, decreasing carbon emissions, and increasing agricultural credit has no significant impact on rice production. Similarly, two-way causality exists between variables such as LnRF⁺ => LnRF⁻, LnRF⁺ => lnAT⁺, LnRF⁻ => lCO₂⁺, LnRF⁺ => lCO₂⁻, LnRF⁻ => lnAT⁻, LnRF⁺ => lCO₂⁺, LnRF⁻ => lnAT⁻, LnRF⁺ => lnF, LnRF⁻ => lnAC, and LnRF⁻ => LAUR. While unidirectional causality running from postive and negative shock in rural population, agricultural credit to increasing rainfall. Furthermore, two-way directional causality
running between $\ln AT^+ \leftrightarrow \ln AT^-$, $\ln AT^+ \leftrightarrow \ln CO_2^+$, $\ln AT^+ \leftrightarrow \ln RP^-$, $\ln AT^+ \leftrightarrow \ln AC$, $\ln AT^- \leftrightarrow \ln LAUR$, $\ln AT^- \leftrightarrow \ln CO_2^+$, $\ln AT^- \leftrightarrow \ln CO_2^-$, and $\ln AT^- \leftrightarrow \ln LAUR$. This findings is consistent with (Warsame et al. 2021), who stated that area under crop has positively influenced mean temperature in the atmosphere. Likewise, one-way causality running from increasing and decreasing temperature to increasing rural population, which indicates that increasing and decreasing temperature will positively influenced rural population. Furthermore, there is also evidence that decreasing temperature ($\ln AT^-$) will increase fertilizer consumption ($\ln F$) and agricultural credit ($\ln AC$).

Moreover, at 1 per cent significance level asymmetrical causality between decreasing carbon emission and increasing rural population which indicates reducing carbon emission leads to the increase in rural population. Apart from, one-way directional causality running from increasing rural population to increasing carbon emission means that increasing population leads to decrease environmental quality in the atmosphere. Population increase in rural areas leads to increase deforestation, which play a key role to deteriorate environmental quality. Researchers stated that the rising population is a dominant cause of environmental degradation (Abbas et al. 2021).

However, evidence shows that causality runs from increasing and decreasing carbon emissions towards fertiliser consumption and agricultural credit at the 1 per cent level of significance. The outcome indicates that increasing and decreasing carbon emissions has influenced fertiliser consumption. The causal relationship between agricultural credit and decreasing carbon emission demonstrates that unidirectional causality running from agricultural credit towards decreasing carbon emission at 5 levels of significance, which indicates that increasing agricultural credit leads to increase environmental quality in the atmosphere. Asymmetrical causality exists between increasing carbon emission and area under crop, which suggests that increasing carbon emission leads to the increasing area under crop and vice-versa. Unidirectional asymmetrical causality also running from decreasing carbon emission towards the area under crop at the 1 level of significance.

**Table 10: Result of Granger Causality Test**

|                      | F-Statsics | Prob. | Result  |
|----------------------|------------|-------|---------|
| $\ln RF^+ \neq > \ln PR$ | 5.306      | 0.070 | Rejected |
| $\ln PR \neq > \ln RF^+$     | 2.465      | 0.292 | Accepted |
| Variable1 | Operator | Variable2 | p-value | Decision |
|-----------|----------|-----------|---------|----------|
| lnRF      | ≠ >      | lnPR      | 151.900 | 0.000    | Rejected |
| lnPR      | ≠ >      | lnRF      | 11.316  | 0.003    | Rejected |
| lnAT⁺      | ≠ >      | lnPR      | 47.324  | 0.000    | Rejected |
| lnPR      | ≠ >      | lnAT⁺      | 25.970  | 0.000    | Rejected |
| lnAT⁻      | ≠ >      | lnPR      | 8.623   | 0.013    | Rejected |
| lnPR      | ≠ >      | lnAT⁻      | 59.598  | 0.000    | Rejected |
| lnCO₂⁺      | ≠ >      | lnPR      | 23.220  | 0.000    | Rejected |
| lnPR      | ≠ >      | lnCO₂⁺      | 82.799  | 0.000    | Rejected |
| lnCO₂⁻      | ≠ >      | lnPR      | 45.560  | 0.310    | Accepted |
| lnPR      | ≠ >      | lnCO₂⁻      | 92.540  | 0.000    | Rejected |
| RP⁺      | ≠ >      | lnPR      | 20.475  | 0.000    | Rejected |
| lnPR      | ≠ >      | RP⁺      | 27.425  | 0.000    | Rejected |
| RP⁻      | ≠ >      | lnPR      | 17.238  | 0.000    | Rejected |
| lnPR      | ≠ >      | RP⁻      | 45.742  | 0.000    | Rejected |
| lnF      | ≠ >      | lnPR      | 25.882  | 0.000    | Rejected |
| lnPR      | ≠ >      | lnF      | 27.880  | 0.000    | Rejected |
| lnAC      | ≠ >      | lnPR      | 3.286   | 0.193    | Accepted |
| lnPR      | ≠ >      | lnAC      | 11.394  | 0.003    | Rejected |
| lnAUR      | ≠ >      | lnPR      | 162.650 | 0.000    | Rejected |
| lnPR      | ≠ >      | lnAUR      | 0.484   | 0.785    | Accepted |
| lnRF⁺      | ≠ >      | lnRF⁻      | 118.850 | 0.000    | Rejected |
| lnRF⁻      | ≠ >      | lnRF⁺      | 67.221  | 0.000    | Rejected |
| lnRF⁺      | ≠ >      | lnAT⁺      | 112.700 | 0.000    | Rejected |
| lnAT⁺      | ≠ >      | lnRF⁺      | 206.620 | 0.000    | Rejected |
| lnRF⁻      | ≠ >      | lnAT⁺      | 105.550 | 0.000    | Rejected |
| lnAT⁺      | ≠ >      | lnRF⁻      | 155.480 | 0.000    | Rejected |
| lnRF⁺      | ≠ >      | lnCO₂⁺      | 44.896  | 0.000    | Rejected |
|    |    |    |    |    |
|----|----|----|----|----|
| lnCO2⁺ ≠ > lnRF⁺ | 21.851 | 0.000 | Rejected |
| LnRF⁻ ≠ > lnCO2⁺ | 239.350 | 0.000 | Rejected |
| lnCO2⁺ ≠ > lnRF⁻ | 23.968 | 0.000 | Rejected |
| lnRF⁺ ≠ > lnCO2⁻ | 34.568 | 0.000 | Rejected |
| lnCO2⁻ ≠ > lnRF⁺ | 15.456 | 0.000 | Rejected |
| lnRF⁻ ≠ > lnCO2⁻ | 18.547 | 0.000 | Rejected |
| lnCO2⁻ ≠ > lnRF⁻ | 24.411 | 0.000 | Rejected |
| lnRF⁺ ≠ > RP⁺ | 36.487 | 0.000 | Rejected |
| RP⁺ ≠ > lnRF⁺ | 10.254 | 0.140 | Accepted |
| lnRF⁺ ≠ > RP⁻ | 79.799 | 0.000 | Rejected |
| RP⁻ ≠ > lnRF⁺ | 3.126 | 0.450 | Accepted |
| lnRF⁻ ≠ > RP⁺ | 41.124 | 0.000 | Rejected |
| RP⁺ ≠ > lnRF⁻ | 16.245 | 0.033 | Rejected |
| lnRF⁻ ≠ > RP⁻ | 31.100 | 0.000 | Rejected |
| RP⁻ ≠ > lnRF⁻ | 6.849 | 0.033 | Rejected |
| lnRF⁺ ≠ > lnF | 50.609 | 0.000 | Rejected |
| lnF ≠ > lnRF⁺ | 10.561 | 0.005 | Rejected |
| lnRF⁻ ≠ > lnF | 144.400 | 0.000 | Rejected |
| lnF ≠ > lnRF⁻ | 5.009 | 0.082 | Rejected |
| lnRF⁺ ≠ > lnAC | 13.220 | 0.001 | Rejected |
| lnAC ≠ > lnRF⁺ | 0.845 | 0.655 | Accepted |
| lnRF⁻ ≠ > lnAC | 112.530 | 0.000 | Rejected |
| lnAC ≠ > lnRF⁻ | 34.865 | 0.000 | Rejected |
| lnRF⁺ ≠ > lnAUR | 105.860 | 0.000 | Rejected |
| lnAUR ≠ > lnRF⁺ | 17.338 | 0.000 | Rejected |
| lnRF⁻ ≠ > lnAUR | 31.726 | 0.000 | Rejected |
| lnAUR ≠ > lnRF⁻ | 29.127 | 0.000 | Rejected |
| Variable 1 | Relation | Variable 2 | t-value | p-value | Status  |
|-----------|----------|------------|---------|---------|---------|
| lnAT⁺      | ≠ >      | lnAT⁻      | 157.740 | 0.000   | Rejected |
| lnAT⁻      | ≠ >      | lnAT⁺      | 38.469  | 0.000   | Rejected |
| lnAT⁺      | ≠ >      | lnCO₂⁺     | 51.393  | 0.000   | Rejected |
| lnCO₂⁺     | ≠ >      | lnAT⁺      | 17.843  | 0.000   | Rejected |
| lnAT⁺      | ≠ >      | lnCO₂⁻     | 25.452  | 0.124   | Accepted |
| lnCO₂⁻     | ≠ >      | lnAT⁺      | 12.687  | 0.541   | Accepted |
| lnAT⁻      | ≠ >      | lnCO₂⁺     | 22.442  | 0.000   | Rejected |
| lnCO₂⁺     | ≠ >      | lnAT⁻      | 19.493  | 0.000   | Rejected |
| lnAT⁻      | ≠ >      | lnCO₂⁻     | 31.258  | 0.009   | Rejected |
| lnCO₂⁻     | ≠ >      | lnAT⁻      | 29.874  | 0.000   | Rejected |
| lnAT⁺      | ≠ >      | RP⁺        | 51.487  | 0.145   | Accepted |
| RP⁺        | ≠ >      | lnAT⁺      | 34.897  | 0.001   | Rejected |
| lnAT⁺      | ≠ >      | RP⁻        | 93.946  | 0.000   | Rejected |
| RP⁻        | ≠ >      | lnAT⁺      | 22.796  | 0.000   | Rejected |
| lnAT⁻      | ≠ >      | RP⁺        | 23.478  | 0.005   | Rejected |
| RP⁺        | ≠ >      | lnAT⁻      | 14.369  | 0.451   | Accepted |
| lnAT⁺      | ≠ >      | lnF        | 100.800 | 0.000   | Rejected |
| lnF        | ≠ >      | lnAT⁺      | 1.907   | 0.385   | Accepted |
| lnAT⁻      | ≠ >      | lnF        | 12.921  | 0.002   | Rejected |
| lnF        | ≠ >      | lnAT⁻      | 0.923   | 0.630   | Accepted |
| lnAT⁺      | ≠ >      | lnAC       | 65.634  | 0.000   | Rejected |
| lnAC       | ≠ >      | lnAT⁺      | 5.367   | 0.068   | Rejected |
| LnAT⁻      | ≠ >      | lnAC       | 5.818   | 0.055   | Rejected |
| lnAC       | ≠ >      | lnAT⁻      | 1.430   | 0.489   | Accepted |
| lnAT⁺      | ≠ >      | lnAUR      | 251.070 | 0.000   | Rejected |
| lnAUR      | ≠ >      | lnAT⁺      | 103.650 | 0.000   | Rejected |
| lnAT⁻      | ≠ >      | lnAUR      | 26.626  | 0.000   | Rejected |
| Condition 1 | Condition 2 | p-value | Outcome |
|-------------|-------------|---------|---------|
| \( \ln \text{AUR} \) ≠ > \( \ln \text{AT} \) | 174.970 | 0.000 | Rejected |
| \( \ln \text{CO}_2^+ \) ≠ > \( \ln \text{CO}_2^- \) | 87.925 | 0.000 | Rejected |
| \( \ln \text{CO}_2^- \) ≠ > \( \ln \text{CO}_2^+ \) | 60.874 | 0.001 | Rejected |
| \( \ln \text{CO}_2^+ \) ≠ > \( \text{RP}^+ \) | 12.547 | 0.124 | Accepted |
| \( \text{RP}^+ \) ≠ > \( \ln \text{CO}_2^+ \) | 24.571 | 0.002 | Rejected |
| \( \ln \text{CO}_2^- \) ≠ > \( \text{RP}^+ \) | 92.478 | 0.004 | Rejected |
| \( \text{RP}^+ \) ≠ > \( \ln \text{CO}_2^- \) | 34.142 | 0.110 | Accepted |
| \( \ln \text{CO}_2^+ \) ≠ > \( \ln \text{F} \) | 25.990 | 0.000 | Rejected |
| \( \ln \text{F} \) ≠ > \( \ln \text{CO}_2^+ \) | 2.456 | 0.293 | Accepted |
| \( \ln \text{CO}_2^- \) ≠ > \( \ln \text{F} \) | 15.412 | 0.003 | Rejected |
| \( \ln \text{F} \) ≠ > \( \ln \text{CO}_2^- \) | 43.258 | 0.150 | Accepted |
| \( \ln \text{CO}_2^+ \) ≠ > \( \ln \text{AC} \) | 22.286 | 0.000 | Rejected |
| \( \ln \text{AC} \) ≠ > \( \ln \text{CO}_2^+ \) | 2.841 | 0.242 | Accepted |
| \( \ln \text{CO}_2^- \) ≠ > \( \ln \text{AC} \) | 75.142 | 0.145 | Accepted |
| \( \ln \text{AC} \) ≠ > \( \ln \text{CO}_2^- \) | 25.197 | 0.051 | Rejected |
| \( \ln \text{CO}_2^+ \) ≠ > \( \ln \text{AUR} \) | 7.234 | 0.027 | Rejected |
| \( \ln \text{AUR} \) ≠ > \( \ln \text{CO}_2^+ \) | 159.890 | 0.000 | Rejected |
| \( \ln \text{CO}_2^- \) ≠ > \( \ln \text{AUR} \) | 14.589 | 0.156 | Accepted |
| \( \ln \text{AUR} \) ≠ > \( \ln \text{CO}_2^- \) | 102.741 | 0.187 | Accepted |
| \( \text{RP}^+ \) ≠ > \( \text{RP}^- \) | 99.457 | 0.007 | Rejected |
| \( \text{RP}^- \) ≠ > \( \text{RP}^+ \) | 24.175 | 0.001 | Rejected |
| \( \text{RP}^+ \) ≠ > \( \ln \text{F} \) | 12.871 | 0.000 | Rejected |
| \( \ln \text{F} \) ≠ > \( \text{RP}^+ \) | 48.545 | 0.841 | Accepted |
| \( \text{RP}^- \) ≠ > \( \ln \text{F} \) | 21.506 | 0.000 | Rejected |
| \( \ln \text{F} \) ≠ > \( \text{RP}^- \) | 6.664 | 0.036 | Rejected |
| \( \text{RP}^+ \) ≠ > \( \ln \text{AC} \) | 56.471 | 0.090 | Rejected |
| \( \ln \text{AC} \) ≠ > \( \text{RP}^+ \) | 102.587 | 0.005 | Rejected |
RP' $\not\Rightarrow$ lnAC $12.421$ $0.002$ Rejected
lnAC $\not\Rightarrow$ RP' $19.815$ $0.000$ Rejected
RP* $\not\Rightarrow$ lnAUR $21.457$ $0.142$ Accepted
lnAUR $\not\Rightarrow$ RP* $8.547$ $0.751$ Accepted
RP' $\not\Rightarrow$ lnAUR $0.031$ $0.985$ Accepted
lnAUR $\not\Rightarrow$ RP' $84.564$ $0.000$ Rejected
lnF $\not\Rightarrow$ lnAC $7.670$ $0.022$ Rejected
lnAC $\not\Rightarrow$ lnF $6.376$ $0.041$ Rejected
lnF $\not\Rightarrow$ lnAUR $10.500$ $0.005$ Rejected
lnAUR $\not\Rightarrow$ lnF $81.095$ $0.000$ Rejected
lnAC $\not\Rightarrow$ lnAUR $18.191$ $0.000$ Rejected
lnAUR $\not\Rightarrow$ lnAC $75.941$ $0.000$ Rejected

$\not\Rightarrow$ indicates that there is no causality running from x to y,

5. Conclusion and Policy Implications

In India, the rice crop has a crucial role in agricultural growth and food security. Rice is a staple food for India's people; more than 50 per cent population consumed rice crops once a day. Rice crop has widely grown, followed by the wheat, coarse cereals and pulse in India. This study's primary purpose is to investigate the asymmetrical relationship and granger causality between climate change and rice production through nonlinear ARDL using time series data spanning from 1991-2018 in India. The outcomes confirm the presence of asymmetric relationships among selected variables in the short and long run.

The findings reveal that increasing and decreasing temperature influenced rice production adversely in the long run while positively affected in the short run by different magnitude. However, excess rainfall has adversely affected rice production, while a decrease in rainfall has no evidence of an adverse effect on rice production in the long and short run. Furthermore, in the long and short run, increased carbon emission levels in the atmosphere had impeded rice production. In contrast, decrease carbon emissions had no adverse impact on rice production. In the long and short run, positive shock in the rural population has positively affected rice
production, while negative shock has adversely affected rice production. The estimated outcome indicates that other controlled variables such as fertiliser consumption, agricultural credit, and area under crop have positively affected rice production in India.

The result from asymmetrical causality divulges a feedback effect between negative shock rainfall and rice production. At the same time, a one-way direction causal relationship runs from positive shock in rainfall towards rice production. Furthermore, there is a two-way directional causal relationship between a positive and negative shock in mean temperature and rice production. At the same time, there is no causal relationship between mean temperature and decreasing carbon emission. Moreover, there is a feedback effect between increasing carbon emission and rice production, while a one-way causal relationship runs from rice production to decreasing carbon emission. However, we observed the two-way directional causal relationship among a positive and negative shock in rural population and rice production. Likewise, a two-way causal relationship runs between fertiliser consumption and rice production, while a one-way causal relationship runs from rice production to agricultural credit and from the area under crop to rice production.

Based on our empirical investigations, some key policy implications emerged. Specifically, the government should promote mechanisms of research and development to meet the demand of the population. In this regard, the new fertilisers are required to produce and provided at a subsidised rate to the farmers. To sustain rice production, improve irrigation infrastructure through increasing public investment and develope climate-resilient seeds varieties to cope with or adapt to climate change. Along with, at the district level government should provide proper training to farmers regarding the usage of pesticides, a proper amount of fertiliser and irrigation systems. This study was conducted at the national level and undertaken only on rice production, which cannot explain the main influence of climate change or unlike the agro-environment region. However, to tackle regional disparities and season wise production (Rabi or Kharif) into consideration, should perform area-specific and season-specific research for better insight.

**Authors’ contributions**

**Imran Ali Baig**: Conceptualization, Data curation, Formal analysis, Writing – original draft  
**Abbas Ali Chandio**: Supervision  
**Ilhan Ozturk**: Editing and Validation, Supervision  
**Pushp Kumar**: Methodology, Investigation, Formal analysis  
**Zeeshan Anis Khan and Md. Abdus Salam**: Review, Editing and made suggestions
Data availability
Data will be made available upon request

Conflict of interest
We do not have any conflict of interest.

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Not applicable

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Not applicable

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Not applicable

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