

# Does Climate Change Asymmetrically Affect Rice Productivity In India? New Insight From NARDL Cointegration Approach

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## Research Article

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1 **Does climate change asymmetrically affect rice productivity in India? New**  
2 **Insight from NARDL Cointegration approach**

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14 **Abstract:**

15 This article attempt to answer the question "whether the dynamic relationship between climate change and rice  
16 productivity is symmetrical or asymmetrical" using data from 1990-2017 in India. First, we test the symmetrical and  
17 long-run dynamic relationship using the Autoregressive Distributed Lags (ARDL) model and test the asymmetrical  
18 and cointegration relationship based on Nonlinear Auto-Regressive Distributed Lag (NARDL) technique. The results  
19 of the ARDL model indicates that no symmetrical relationship between the variables in long-run. Whereas outcomes  
20 of the NARDL bound test reveal that there is long-run asymmetrical impact of climate change on rice productivity.  
21 The positive and negative shock of climate change has affected the rice productivity by different magnitude in India.  
22 The Wald statistics confirm asymmetric relationship between rice productivity and climate change in the long-run  
23 while only short-run asymmetrical relationships exist between rainfall and rice productivity in India.

24 Furthermore, dynamic multipliers indicate that negative component of rainfall and temperature has a dominant effect  
25 over the positive component on rice productivity. To the best of the author's knowledge, no studies have been done to  
26 assess both symmetrical and asymmetrical dynamic relationships between climate change and rice productivity using  
27 ARDL and NARDL cointegration approaches in India's context. This study will help frame the environmental policies  
28 and strategy to cope with climate change in India's agriculture productivity.

29 **Key Words:** Rice productivity, Climate Change, Asymmetry, Symmetry, NARDL, India

30 **Introduction**

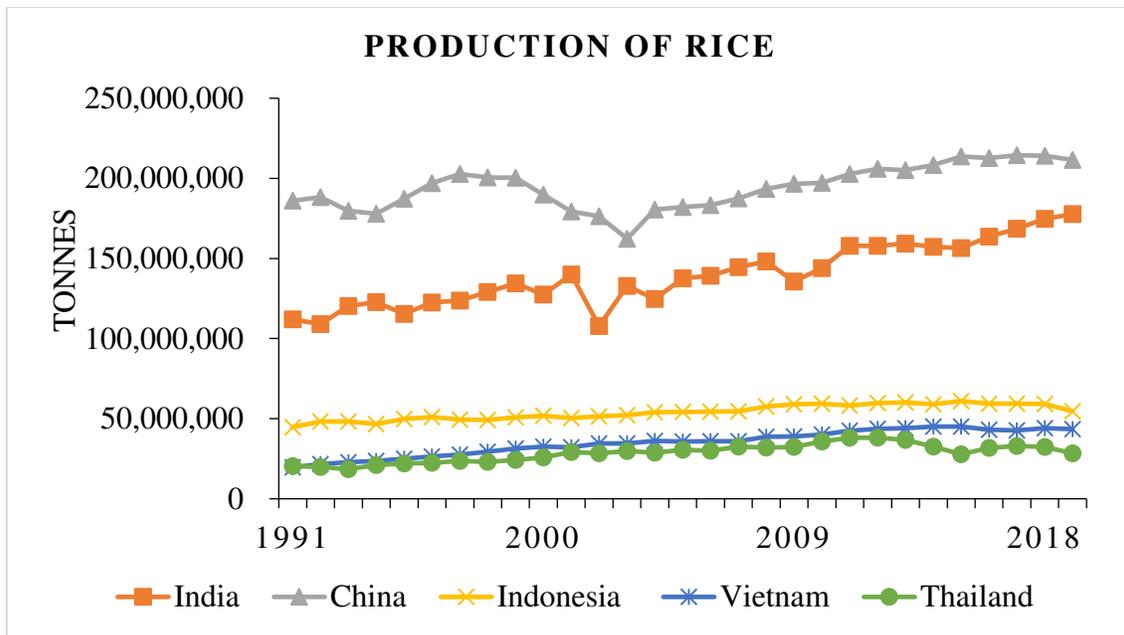
31 Since 1990s climate change has been attracting environmentalist and policymaker's attention across the globe due to  
32 its long-term harmful impact on agricultural productivity, food product, water supply and livelihoods of rural poor  
33 (Artner, 2010; Chavas et al., 2009; Mohorji et al., 2017). Climate change is the results from increasing human activities  
34 on the land, including deforestation, land use, urbanisation, increasing population, production and consumption  
35 activities to fulfil people's demand for food supply. Climate steadily changes due to global temperature, precipitation,  
36 and carbon emission, significantly impacting agricultural productivity and growth (Chandio et al., 2021; Klutse et al.,  
37 2021). Agricultural productivity has been decreasing due to the main driver of climate change such as precipitation  
38 and warmer temperature (Haile et al., 2017). The gradual increase in temperature is due to the increasing carbon  
39 concentration in the atmosphere, mainly caused by high production activities by developed countries. However,  
40 increase in temperature, variation in rainfall and frequent occurrence of floods & droughts are mostly faced by the  
41 developing nation, which is situated in the tropical region and relies heavily on agriculture sector (Janjua et al., 2014).  
42 Agriculture and its allied activities are sensitive of climate change and other hand it is also contributed on carbon  
43 emission (Swaminathan & Kesavan, 2012). Climate change is harmful to agriculture production and enhances the  
44 vulnerability among small and medium farmers whose livelihoods are mainly dependent on agricultural and allied  
45 activities (Zakaria et al., 2020). Impact of climate change may vary from region to region based on the geographical  
46 location. In case of a developed nation, climate change has a positive impact on agriculture productivity while it  
47 deteriorates the performance of agriculture sector in the developing countries (Shujaat Abbas, 2020; Janjua et al.,  
48 2014; P. Nath & Behera, 2011). Likewise, Abbas et al. (2021) revealed that climate change has significantly affected

49 crop production and food security in the long in South Asia. Swaminathan & Kesavan (2012) stated that climate  
50 change adversely affected the food production and also location could be change of main food producing areas.  
51 The developing nations are more vulnerable than developed countries due to more extensive dependence on agriculture  
52 sector for livelihood, lack of technological advancement and lack of adaptation policies of climate change on  
53 agriculture production (Praveen & Sharma, 2020; Warsame, 2021). However, Chandio *et al.*, (2021) stated that the  
54 increase in temperature and financial development, respectively has negative and positive impact on cereal production  
55 in Pakistan. While Ahsan *et al.* (2020) demonstrated that energy consumption, labour force, cultivated area and CO<sub>2</sub>  
56 are the main determinants of agriculture productivity and CO<sub>2</sub> positively impact agriculture productivity. Likewise,  
57 Warsame (2021) explained mean temperature and CO<sub>2</sub> has negatively influenced agriculture productivity in Somalia.  
58 Similarly, Coulibaly *et al.*, (2020) concluded that temperature and drought are the main factors which negatively affect  
59 agriculture productivity. The Indian agriculture sector is the most sensitive and exposed area to climate change due to  
60 less adaptive capacity to cope with it (Guntukula, 2019). Investigating the impact of climate change on agriculture  
61 productivity is of immense importance because more than 50 % population of India primarily depends on agricultural  
62 activities for their livelihoods (Pattanayak & Kumar, 2013). As the changes in environmental factors such as  
63 temperature, precipitation, CO<sub>2</sub> and rainfall pattern directly affect agriculture productivity (Res *et al.*, 1998), it is  
64 indispensable to examine the effect of changes in climatic conditions on agriculture productivity.

65 In India, More than 60 per cent population mainly depends on the agriculture and its allied sectors and Climate change  
66 may be the effect of food security by hampering agriculture productivity are not only from one-way but also from  
67 multiple-ways. However, the impact of climate change is across the globe and its adverse effects are likely to be more  
68 severe under Indian agro-ecological conditions, and climate models predict the severe effect of climate change on the  
69 agriculture sector (Bahl, 2015). Climate change has significantly affected the agricultural productivity and food supply  
70 which will be a threat to food security in the country (Moses *et al.*, 2015). The emerging adverse impacts of climatic  
71 changes will put pressure on crop productivity particularly rice because they are more sensitive to variation due to  
72 climate change and its associated factors (Bahl, 2015). Given the sensitivity of rice to environmental change, especially  
73 those related to temperature increases and extended drought periods, coping with the future worldwide demand for  
74 rice seems a troublesome task. Furthermore, changes in the length of the growing period because of temperature  
75 increments will influence rice yield as well as will move cultivating frameworks from rice towards more appropriate  
76 crops with adequate temperature optima (Korres *et al.*, 2017).

77 India delivers a predominantly remarkable case study for examining how rice may respond to climate change. India  
78 is the first largest exportable country of rice in the World which is counted 9.8 million tonnes followed by Thailand  
79 (7.5 million tonnes), Vietnam (6.5 million tonnes), Pakistan (4.6 million tonnes) and the USA (3.1 million tonnes). In  
80 Asia, India is the second producer after China, followed by Indonesia, Vietnam and Thailand (see Figure 1).

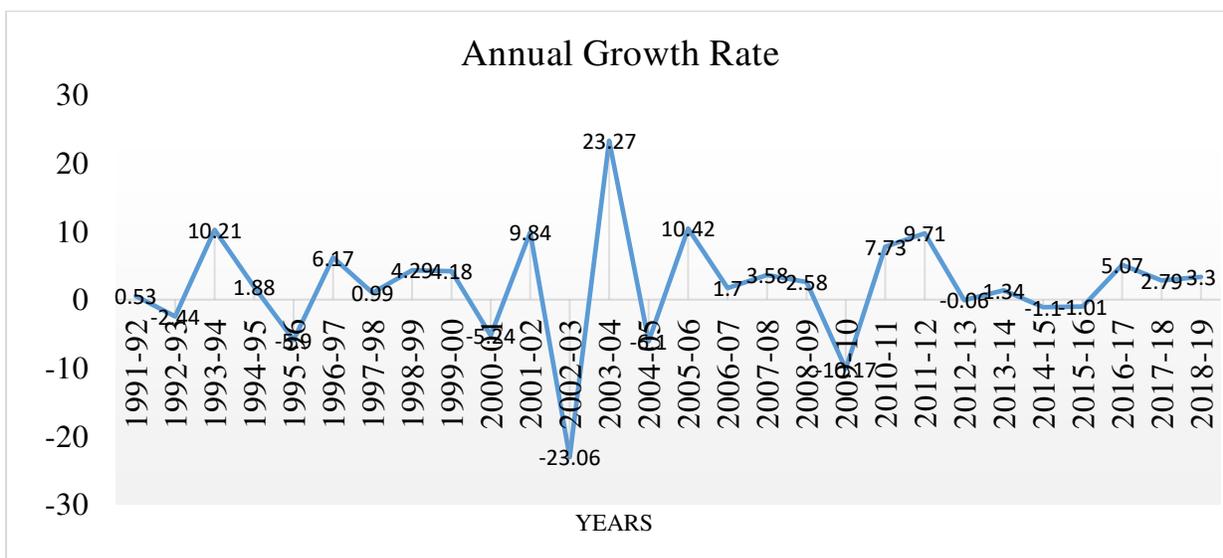
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82  
83 Figure 1: Trend of rice production in Asian countries

84 Sources: FAO 2019

85 Rice is one of India's main crops, which is largely shared area of cultivated land, i.e. 22.89 per cent in India. Apart  
86 from, it is the main staple crop of Asian countries and particularly in India, so the demand has increased from 93.99  
87 million tonnes in 2012-13 to 108.16 in 2020-21 and demand projected in 2029-30 will be 117.56 million tonnes in  
88 India (Directorate of Economics and Statistics, 2019). Increasing rice production is needed to meet the demand for  
89 rice production in India and Asia. It largely depends on climate conditions and mainly grown in the rain-fed areas that  
90 received heavy rainfall in India. Climate and weather play a significant role in influencing rice productivity (Ahsan et  
91 al., 2020). Due to the deficiency of rainfall annual growth rate of rice production has a sharp decline of 10.1 % in  
92 2009-10 in India (see Figure 2).



93  
94 Figure 2: Annual Growth Rate of Rice Production in India

Sources: CMIE Commodities (2019)

95  
96 The annual growth rate of rice has 1.01% in 2015-16, 5.07 % in 2016-17, 2.79% in 2017-18 and 3.3% in 2018-19 in  
97 India. This variation in the growth rate implies that growth depends on the nature of rainfall and temperature, which  
98 is affected due to climate change in the tropics, the most susceptible region of the World. Mostly, rice currently  
99 cultivated in those region where temperature already above optimal for production. However, any further increase in  
100 temperature may be harmful to rice productivity during the sensitive period of the rice crop. Korres et al. (2017) stated  
101 that in future India may be no longer suitable cultivator of rice production. Climate change has disastrous effect on  
102 crop production as well as food security in developing economics (Sarker et al., 2019). Due to the complex interaction  
103 between the yield of crop and climate change, it is the challenging assignment to tackle climate change and its impact  
104 on agricultural productivity. Many previous studies have done by using various climate models over the Indian region  
105 to examine the impact of increasing temperature and changing rainfall patterns during the twenty-first century (Bhatla  
106 et al., 2019). However, this study's main objectives are to explore whether the dynamic relationship is symmetrical  
107 and asymmetrical between rice productivity and climate change in India over the period 1990 to 2017 by using both  
108 ARDL and NARDL approaches.

109 The rest of the paper is framed in the following manner. Section 2 discusses the existing literature and several  
110 approaches to measure the impact of climate change on rice productivity. Section 3 mentions the data and  
111 methodology. Empirical result and discussion are presented in section 4, and in the last section 5 provides the  
112 conclusion and policy implication.

### 113 **Related Literature Review**

114 Numerous studies have been done on the relationship between climate change and agricultural productivity across the  
115 globe, and there is growing consensus among environmentalist and researcher that the negative relationship exists  
116 between the climate change and agriculture productivity in developing nations (Khanal et al., 2018). Among previous  
117 studies conducted by Gupta & Mishra (2019) at India level and Kumar et al. (2020) at states level, i.e. Uttar Pradesh  
118 and Haryana respectively employ the Crop Simulation Model (CSM) and Ricardian regression approach to assess the  
119 nature of the relationship between climate change and rice productivity. Gupta & Mishra (2019) stated that multi-  
120 Global Climate Model indicate that it expected to increase in productivity of rice most of the agro-ecological zones in  
121 Representative Concentration Pathways (RCP) 2.6 but as on moving towards RCP 8.5 through RCP 4.5 and 6.0, the  
122 positive impact on rice yield in RCP 2.6, in major rice-producing zones, is expected to mitigate and lead to the negative  
123 impact by 2080s. Large spatiotemporal variability is expected in most of the zones with enormous variability in arid  
124 and hilly zones. The overall change in spatial rice yield in India taking all used GCM-RCP combinations in  
125 consideration is expected to vary from 1.2% to 8.8%, 0.7% to 12.6% , and -2.9 % to 17.8% due to the expected climate  
126 change in the 2020s, 2050s and 2080s, respectively. Whereas, Guiteras (2009) explained that major crop yield would  
127 harmfully be affected by 4.5 to 9% due to climate variation from 2010 to 2039 in India. In the same order, in the  
128 absence of adaptation productivity, the crop would reduce up to 25%. Kumar et al. (2020) found that any large  
129 deviation in the rainfall harms rice and wheat production in Uttar Pradesh. In contrast, maximum temperature has a  
130 negative impact on rice and wheat in Uttar Pradesh and Haryana. While increasing temperature has a positive effect  
131 on rice production but negatively impact on grain. Abbas & Mayo (2019) reported that maximum temperature has

132 negative impact on rice plant in which decrease number of plants in plantation stage and minimum temperature has  
133 positively affected rice crop at replantation stage during vegetative phase. The rainfall has negative impact on rice  
134 crop during heading and flowering stage. Likewise (Auffhammer et al., 2012) point out that heavy rainfall and drought  
135 have a negative impact on rice yield in the rain fed areas during the 1966-2002 period, and lower rainfall and warmer  
136 night would not occur, then rice yield would increase by 4 per cent in India. In contrast (Rayamajhee et al., 2020)  
137 stated that there is no direct relationship between the rainfall and rice production in Nepal.

138 Attiaoui & Boufateh (2019) and Abbas (2020) find that linear long-run dynamic relationship between climate change  
139 and agriculture productivity. Empirical results reveal that deficiency of rainfall and high temperature respectively has  
140 negatively and positively affected agriculture productivity. Baig et al. (2020) also employ linear dynamic ARDL  
141 model to assess the impact of climate change on yield of major crops including rice, wheat, coarse cereals and pulse  
142 in India. Evidence of outcome indicated a linear long-run association between climate change and yield of the crop.  
143 However, annual mean temperature has a positive impact on the yield of wheat, coarse cereals and pulse except for  
144 rice while rainfall has a positive impact on rice, coarse cereals and pulse except for wheat in India.

145 In contrast, Mitra (2014) and Pal & Mitra (2018) investigated the nonlinear relationship between climate change and  
146 crop productivity in India. Mitra (2014) found no asymmetric relationship between rainfall and food grain in India  
147 and observed that average rainfall has a greater impact on food grain production than below-average rain. In contrast,  
148 Pal & Mitra (2018) explain that coefficient of rainfall has a greater impact on the production of food grain up to 75<sup>th</sup>  
149 quantile and reduce after that in India. While Nsabimana & Habimana (2017) conducted a study in Rwanda's context,  
150 they stated that rainfall has an asymmetric impact on the price of crop in the short and long-run. Moreover, the price  
151 of food crop has gone down in the season of harvest, and after that, it has been increasing. Likewise (Moore et al.,  
152 2017) conducted a study to examine the impact of climate change on agricultural yield and welfare using database  
153 yield to systematically compare results from process-based and empirical studies. He stated that the asymmetric impact  
154 of climate change on welfare and agriculture yield, and showing the substantial probability of large declines in welfare  
155 for warming of 2 °C–3 °C even including the CO<sub>2</sub> fertilization effect.

156 Some previous studies (Belloumi, 2008; Fezzi & Bateman, 2016; Kabubo-mariara & Karanja, 2007) has observed  
157 non-linear relationship between climate change and revenue of agriculture crops. So it is a challenging task to cope  
158 with it due to the complex asymmetrical association between climate change and agriculture productivity. In this  
159 manner, the objective of this study is to answer of this question "whether the dynamic relationship between the rice  
160 productivity, and climate change is symmetrical or asymmetrical" in India. To the best of the author's knowledge, no  
161 studies have been done to assess both symmetrical and asymmetrical dynamic relationship between climate change  
162 and rice productivity using the ARDL and the NARDL cointegration approaches in the context of India. This study  
163 contribute in the existing literature in a such a manner, it reveals that climate factors affect the agriculture productivity  
164 in different magnitude, accordingly we need appropriate policy to cope detrimental effect of climate change on  
165 agriculture productivity.

166 Crop modelling, Ricardian and econometric approach, these are three approaches to measure the effect of climate  
167 change on agricultural productivity. Table 1 shows the history of literature in which researchers used above-mentioned  
168 methods to analyse the impact of climate change on agricultural productivity across the globe.

Table 1: History of Previous Studies

<b>Crop Simulation/Modelling Method</b>		
<b>Author Country</b>	<b>Variables</b>	
Gupta & Mishra (2019)	Yield of rice, annual rainfall & temperature	India
(K. S. K. Kumar, 2011)	Yield of crop, rainfall, tractor & area	India
Kumar et al. (2011)	Yield of four major cereals	India
(Lal et al., 1998)	Yield of rice and wheat & climate variables	India
(Mishra & Chandra, 2016)	Agriculture production, temperature and rainfall	Odisha(India)
(Mukherjee & S.Huda, 2018)	Yield of wheat, rainfall & temperature	India
(Auffhammer et al., 2012)	Yield of rice, monsoon and rainfall	India
<b>Linear Econometric Models</b>		
(Shujaat Abbas, 2020)	Cotton Production, Temperature, Area & Fertilizer	Pakistan
(Attiaoui & Boufateh, 2019)	Production, labour, rainfall, & temperature	Tunisia
(Baig et al., 2020)	Yield of major crops, Temperature, rainfall, Co2 & Fertilizer	India
(Bhanumurthy & Kumar, 2018)	Agriculture Output, Temperature, rainfall, GCF & Irrigated Area	India
(Birthal et al., 2014)	Yield of the crop, Temperature rainfall & Irrigation	India
(Guntukula, 2020)	Yield of major crops, Temperature & rainfall	India
Janjua et al. (2014)	Yield of Wheat, Temperature, Precipitation, Area, Fertilizer & Co2	Pakistan
Kumar et al. (2020)	Yield of the crop, Rainfall, tractor, Area, literacy Rate & Forest Area	Haryana & U.P
(A. Kumar et al., 2015)	Yield of Rabi & Kharif Crop, Area, Fertilizer, Tractor, Rainfall & Temperature	India
(H. K. Nath & Mandal, 2018)	Productivity of crop, rainfall, Temperature, Fertilizer and Area Sown	India
(Praveen & Sharma, 2020)	Yield of 15 Crops, mean temperature and rainfall	India
(S. Gupta et al., 2012)	Yield of rice and millets, Temperature, precipitation, irrigation and labour	India
<b>Non Linear Model</b>		
(Mitra, 2014)	Yield of Major crop, Rainfall, fertiliser & Pesticide	India
(Nsabimana & Habimana, 2017)	Yield of crops & rainfall	Rwanda
(Pal & Mitra, 2018)	Agriculture production & rainfall	India

169

**170 Data and Methodology****171 Data**

172 Time series data spanning from 1991 to 2017, has been collected from various sources. Table 2 shows the description  
 173 and sources of the data of variables viz. productivity of rice as a dependent variable, whereas mean temperatures in  
 174 Celsius degree, annual rainfall and area under cultivated land as explanatory variables. Descriptive statistics of  
 175 variables are reported in Table 3, which reveal that all the variables are normally distributed.

Table-2: Description of the variables

Variables	Notations	Description of Variables	Sources
-----------	-----------	--------------------------	---------

Productivity of rice	YR	Kg/hectares	Directorate of Economics & Statistics
Mean Temperature	MTEMP	Degree Celsius (Centigrade)	Meteorological Department of India
Rainfall	RF	Annual average rainfall (mm)	Meteorological Department of India
Area Under Cultivated Land	AUR	Area cultivated land (hc)	Directorate of Economics & Statistics

Sources: Calculated by Authors

Table 3. Descriptive Statistics

Variables	Mean	Median	S.D	Kurtosis	Skewness	J-B(Prob.)
YR	912.63	896.80	118.47	-1.03	0.14	0.511
MTEMP	25.61	25.68	1.72	4.48	-0.31	0.648
RF	1141.49	1133.00	92.37	-0.72	0.05	0.690
AUR	434.18	434.90	10.88	2.43	-0.03	0.83

Sources: Calculated by Authors

176

### 177 **ARDL Bound Cointegration Test**

178 Prior, to check the asymmetric dynamic relationship between climate change and rice productivity, we first employ  
179 linear ARDL bound cointegration technique to analyse the linear dynamic relationship between climate change and  
180 rice productivity. There are some advantages of the ARDL model, the first advantage of this model; it is applicable  
181 in any situation either variable is integrated at '0' or '1' and at fractionally integrated. Second, the empirical results are  
182 unbiased and efficient, even if the sample size is small. A third important advantage of this model in choosing the  
183 appropriate number of lags for the empirical analysis. The dynamic long-run relationship is tested by computing the  
184 general F-statistics or Wald test statistics and comparing them with the two critical bounds values, i.e. lower and upper  
185 bound. If the value of F-statistics greater than the upper bound, means long-run linear relationship exist between the  
186 variables, if the value of F-statistics falls below the lower bound, the null hypothesis is not rejected, means no long-  
187 run association between the variables, and if the value falls within the lower and upper bound, results are inconclusive  
188 (Pesaran.et.al., 2001; Pesaran & Shin, 2002).

### 189 **NARDL Bound Test for Cointegration**

190 Employing recently developed and advanced technique NARDL to assess the asymmetrical and non-linearity impact  
191 of temperature and rainfall on rice productivity. ARDL technique ignored the non-linearity and asymmetrical  
192 relationship among the variables. The ARDL model is expanded to an asymmetric ARDL or NARDL by Shin et al.  
193 (2014) to examine the pattern of dynamic adjustment and asymmetries relationship in the short and long-run between  
194 the variables. To explore the relationship between the variables following model can be specified as:

$$195 \quad Y_t = f(MTEMP_t, Rainfall_t, AUR_t) \quad (1)$$

196 In the above equation,  $Y_t$  indicates the productivity of rice in kilogram per hectare, and MTEMP indicates annual mean  
 197 temperature, average annual rainfall and area under cultivated land. Equation.1 can also be written as:

$$198 \quad Y_t = \alpha_0 + \alpha_1 MTEMP_t + \alpha_2 RAINFALL_t + \alpha_3 AUR_t + \varepsilon_t \quad (2)$$

199 General forms of long-run asymmetry relationship given as follows:

$$200 \quad Y_t = \beta^+ X_t^+ + \beta^- X_t^- + \varepsilon_t \quad (3)$$

201 Where;  $Y_t$  is a  $k \times 1$  vector of rice productivity at time  $t$ ; where  $\beta^+$  and  $\beta^-$  are the associated asymmetric long-run  
 202 parameters. Here  $X_t$  as  $k \times 1$  vector of regressors is decomposed as:

$$203 \quad X_t = X_0 + X_t^+ + X_t^-$$

204 The  $X_t^+$  and  $X_t^-$  are partial sum processes of positive (+) and negative (-) changes in  $X_t$  defined as:

$$205 \quad X_t^+ = \sum_{i=1}^t \Delta X_i^+ ; \quad X_t^- = \sum_{i=1}^t \Delta X_i^- ;$$

$$206 \quad \Delta X_i^+ = \sum_{i=1}^t \max(\Delta X_i, 0) ; \Delta X_i^- = \sum_{i=1}^t \min(\Delta X_i, 0)$$

207 Where;  $\Delta X_i$  is the changes in independent variables ( $X_t$ ) while the superscript '+' and '-' represents the positive and  
 208 negative processes around a threshold of zero, which delineates positive and negative shocks in the explanatory  
 209 variables, this implies that the first differenced series is assumed to be normally distributed with zero means.

210 Shin, Yu and Greenwood-Nimmo (2014) prolong the ARDL model adopted by the Peasaran et al. (2001) by utilising  
 211 the concept of cumulative positive and negative partials sums. In this manner, the NARDL (p, q) model is given below:

$$212 \quad Y_t = \sum_{i=1}^p \beta_i Y_{t-1} + \sum_{i=1}^q (\gamma_i^+ X_{t-i}^+ + \gamma_i^- X_{t-i}^-) + \varepsilon_t$$

213 Where;  $Y_t$  is  $k \times 1$  is a vector of multiple regressors;  $\beta_i$  is the autoregressive parameter;  $\gamma_i^+$  and  $\gamma_i^-$  are the  
 214 asymmetrically distributed lag parameters while  $\varepsilon_t$  is the error term which is assumed to be normally distributed.  
 215 Following Shin et al. (2014), the modified error correction form is specified as:

$$216 \quad \Delta Y_t = \rho Y_{t-1} + \alpha^+ X_{t-1}^+ + \alpha^- X_{t-1}^- + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{i=1}^q (\gamma_i^+ \Delta X_{t-i}^+ + \gamma_i^- \Delta X_{t-i}^-) + \varepsilon_t$$

$$217 \quad \Delta Y_t = \rho Ect_{t-1} + \sum_{i=1}^p \beta_i Y_{t-1} + \sum_{i=1}^q (\gamma_i^+ \Delta X_{t-i}^+ + \gamma_i^- \Delta X_{t-i}^-) + \varepsilon_t$$

218 In the above equation,  $Ect_{t-1} = Y_t - \beta^+ X_t^+ - \beta^- X_t^-$  is the asymmetrical error correction term and  $\beta_X^+ = -\alpha^+ / \rho$   
 219 and  $\beta_X^- = -\alpha^- / \rho$  is associated with the asymmetric long-run parameters. Estimation procedure of the NARDL is  
 220 same as linear ARDL. The null hypothesis of asymmetrical long-run relationship,  $\rho = \alpha^+ = \alpha^- = 0$  between the  
 221 variables. Null hypotheses have been tested by computing the general F-statistics or Wald test statistics and by  
 222 comparing them with the two critical bounds values (lower and upper bound), that provide a band covering all possible  
 223 classifications of the regressors into purely  $I(0)$ ,  $I(1)$  or mutually cointegrated. The long-run ( $\alpha^+ = \alpha^-$ ) and short-

run ( $\gamma_i^+ = \gamma_i^-$ ) asymmetries estimates through the Wald test. The long-run and short-run asymmetries will also be estimated using the standard Wald test.

These short and long-run asymmetry paths can respectively be presented relying on the cumulative dynamic multiplier effect a unit percentage change in  $X_t^+$  and  $X_t^-$  on  $Y_t$  obtain through the following equation:

$$m_h^+ = \sum_{i=0}^h \frac{\partial Y_{t+i}}{\partial X_t^+}; \quad m_h^- = \sum_{i=0}^h \frac{\partial Y_{t+i}}{\partial X_t^-}; \quad h=0, 1, 2, \dots$$

Noting that,  $h \rightarrow \infty$ ,  $m_h^+ \rightarrow \beta^+$  and  $m_h^- \rightarrow \beta^-$

Thus the NARDL model for underlying variables as follows:

$$\begin{aligned} \Delta \ln Yield_t = & \alpha_0 + \rho \ln Yield_{t-1} + \alpha_1^+ Meantemp_{t-1}^+ + \alpha_1^- Meantemp_{t-1}^- + \alpha_2^+ Rainfall_{t-1}^+ + \alpha_2^- Rainfall_{t-1}^- \\ & + \alpha_3^+ AUR_{t-1}^+ + \alpha_3^- AUR_{t-1}^- + \sum_{i=1}^p \beta_i \Delta Y_{t-i} + \sum_{j=1}^{j=p} (\theta_j^+ \Delta Meantemp_{t-1}^+ + \theta_j^- \Delta Meantemp_{t-1}^-) \\ & + \sum_{j=1}^{j=p} (\gamma_j^+ \Delta Rainfall_{t-1}^+ + \gamma_j^- \Delta Rainfall_{t-1}^-) + \sum_{j=1}^{j=p} (\vartheta_j^+ \Delta AUR_{t-1}^+ + \vartheta_j^- \Delta AUR_{t-1}^-) + \delta ECT_{(-1)} \\ & + U_t \quad (3) \end{aligned}$$

Where; p and q are representing lags order of dependent and independent variables, respectively. Meantemp<sup>+</sup>, Meantemp<sup>-</sup>, Rainfall<sup>+</sup>, Rainfall<sup>-</sup> and AUR<sup>+</sup>, AUR<sup>-</sup> respectively indicate the partial sum of positive (+) and negative (-) changes in the annual mean temperature, annual average rainfall and area under cultivated land. Akaike and Schwarz information criteria have been used to find out the optimal lag selection in the model.  $ECT_{-1}$  is the error correction term, and  $\delta$  is the speed of adjustment in the process to restore equilibrium following a disturbance in the asymmetrical long-run equilibrium relationship. The adequacy and stability of the specified NARDL models are also checked with various Diagnostic tests.

### Empirical Results and Discussions

**Stationarity:** Prior to applying the NARDL, we check the order of integration because NARDL model does not give efficient and appropriate results in case of variables are integrated of order 2. The Dicky-fuller and Philips-Perron unit root tests are employed to check the stationarity of all the variables. The results of the stationarity of underlying variables shown in Table 4.

Table 4. Unit Root Tests

Variables	I(0)		I(1)	
	ADF	PP	ADF	PP
YR	-4.99***	-5.01***	-9.54***	-13.46***
MTEMP	-6.29***	-5.57***	-5.95***	-9.46***
Rainfall	-5.54***	-5.64***	-8.55***	-24.55***
AUR	-4.07***	-3.74***	-7.73***	-7.81***

Source: Calculated by Authors Notes: '\*', '\*\*', and '\*\*\*' denote the 10%, 5%, and 1% level of significance respectively.

248 Table 4 reveals that all the variables are stationary at levels. Results explain that productivity of rice, mean  
 249 temperature, rainfall and area under cultivated land are stationary at 1 % level of significance. None of the variables  
 250 is integrated of order 2 in this study that corroborates NARDL bound testing.

251 The commonly unit root tests such as Augmented and Dicky-Fuller and Phillips and Peron test does not capture the  
 252 break in the series. However, Zivot and Andrews structural break unit root test has been applied to overcome this  
 253 problem. Table 5 present result of a structural break unit root test and indicate that underlying variables are stationarity  
 254 with the different break in the series. Due to the drought in 2002 in India, agricultural productivity had been sharply  
 255 gone down (Gulati et al., 2013). Hence the structural break has arisen in the data of rice productivity. Due to the  
 256 presence of the structural breaks in the data, the variables may have non-linearity. Hence to check non-linearity, we  
 257 employ BDS independence test, as it checks whether there is any presence of linear dependence in the dependent  
 258 variable in the model.

Table 5, Zivot & Andrews (1992) Structural Break Unit root Test

Break-in Intercept and trend Variables	At Level	
	T-statistics	Break
YR	-8.06***	2002
MTEMP	-10.27***	2002
Rainfall	-6.67***	2000
AUR	-7.79***	2008

Source: Calculated by Authors Notes: '\*', '\*\*', and '\*\*\*' denote the 10%, 5%, and 1% level of significance respectively.

259 Table 6 depicts the result of the non-linearity of the underlying variables. At the 1 % level, BDS statistics reject the  
 260 null hypothesis of residual of being independent and identically distributed at all the dimension, which indicates that  
 261 non-linearity in the dependent variable, i.e. rice productivity. Apart from, non-linearity also exists in the area under  
 262 cultivated land, annual mean temperature and annual rainfall.

Table 6; BDS Test for Asymmetry or non-linearity

Variables	Dimensions				
	m=2	m=3	m=4	m=5	m=6
YR	0.07***	0.13***	0.18***	0.18***	0.16***
MTEMP	0.01	0.09**	0.19***	0.25***	0.28***
Rainfall	-0.01	-0.03**	-0.08***	-0.07***	-0.07***
AUR	0.03***	0.08***	0.10***	0.11***	0.09***

Sources: Calculated by Author, \*\*\*,\*\* & \* represent 1 ,5 & 10 % level of Significance

263 After confirming both structural breaks and asymmetry in the time series data, in this order, it is best to use the NARDL  
 264 model to investigate the short and long-run asymmetrical relationship among the variables in this study. But first, we  
 265 check the linear dynamic long-run association through ARDL bound cointegration model. The results are shown in  
 266 Table 7 depicts the result of long-run bound cointegration approach between rice productivity, annual temperature,  
 267 average rainfall and area under cultivated land at the different lags order. F-statistics equal to 2.53, which is less than

268 lower bound value, i.e. 4.29 at the 1% level of significance, which indicates no long-run linear relationships between  
 269 rice productivity and climate change. Thus, linear specification gives the spurious results due to the asymmetry in the  
 270 series or model. Thus we proceed to examine asymmetrical dynamic relationship amongst the variables.

Table 7. Results of the ARDL Bound Test

<b>Long run Results</b>				
Variables	Coefficient	Std. Error	P-value	
Meantemp	13.53	7.96	0.11	
Rainfall	-0.44	0.18	0.02	
AUR	-0.76	1.09	0.49	
C	624.92	450.25	0.18	
<b>Short Run Results</b>				
Rice	-0.55	0.16	0.00	
Meantemp	3.87	3.75	0.32	
Rainfall	0.05	0.09	0.59	
AUR	4.16	0.53	0.00	
F-Statistic= 2.53		Signif.	I(0)	I(1)
		10%	2.72	3.77
		5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61

Sources: Calculated by Authors

271  
 272 **Results of NARDL Bound Test for Cointegration**  
 273 To choose the maximum lag, we applied the general to a specific technique. Maximum lag of dependent and  
 274 explanatory variables are 2 (p=q=2) choose by the Akaike and Schwarz information criteria. Table 8 shows the results  
 275 of the asymmetrical relationship between the variables.

Table 8: The long results of NARDL ( Productivity of Rice is as dependent variable)

Variables	Coefficient	Std. Error	Prob.	
Meantemp <sup>+</sup>	-8.09	4.52	0.09	
Meantemp <sup>-</sup>	-9.07	7.13	0.22	
Rainfall <sup>+</sup>	0.24	0.11	0.06	
Rainfall <sup>-</sup>	-0.45	0.13	0.00	
AUR <sup>+</sup>	3.72	1.02	0.00	
AUR <sup>-</sup>	3.47	0.62	0.00	
Constant	926.48	136.60	0.00	
Bound Test: F-statistics = 17.68*				
Level of Significance		Critical Bound Values		
		I(0)	I(1)	
10%		2.12	3.23	
5%		2.45	3.61	
2.50%		2.75	3.99	
1%		3.15	4.43	

276 Sources: Calculated by Authors, Notes: (\*) indicates 1 % level of significance  
 277 Table 8 depicts the asymmetrical long-run results, which infers that annual mean temperature, rainfall and area under  
 278 cultivated land are composed of each two possible components, i.e. positive (+) and negative (-). Positive (+) and  
 279 negative (-) component of annual mean temperature has a negative effect on the productivity of rice, but the negative  
 280 component has insignificant in India. Impact of positive and negative shocks of temperature on rice productivity has  
 281 contributed by different magnitude. However, increase 1 degree Celsius in temperature, which leads to a decrease in  
 282 rice productivity by 8.09 unit. Similarly, decrease 1 degree Celsius in temperature has negatively affected rice  
 283 productivity by 9.07 unit. This outcome is in line with Abbas & Mayo (2020), Chandio, Jiang, *et al.* (2020) and  
 284 Swaminathan & Kesavan (2012) and their studies explained that temperature has negatively affected rice productivity.  
 285 Korres *et al.* (2017) revealed that negative relationship between rice yield and increased mean temperature, however  
 286 increased in mean temperature has negatively affected the rice yield. Furthermore, positive rainfall component has a  
 287 positive and significant impact on the rice productivity at the 5 % level of significance and this outcome supported by  
 288 Rashid *et al.* (2012); Baig *et al.* (2020); Chandio, Jiang, *et al.*, (2020) and Chandio, Ozturk, *et al.* (2020) and their  
 289 studies concluded that rainfall has a positive impact on agriculture productivity. Likewise, this result contradicts the  
 290 Arora *et al.* (2012), and Guntukula (2019) and their studies concluded that rainfall has a negative impact on rice  
 291 productivity in India. The negative component of rainfall has negatively affected rice productivity by 0.45 unit in  
 292 India. The negative component has a stronger effect than a positive component of rainfall on rice productivity;  
 293 however, deficiency of rainfall has more harmful to rice productivity because it largely depends on monsoon in India.  
 294 Moreover, positive and negative component of area under cultivated land respectively has positively affected rice  
 295 productivity by 3.72 and 3.47 units. Positive component of area under cultivated land has a larger magnitude than the  
 296 negative component to the rice productivity in India. The value of nonlinear F-statistics is 17.62 which is greater than  
 297 the upper critical bound value (5.06) at the 1 % level of significance which reject the null hypothesis of "no  
 cointegration" clearly indicate that long-run asymmetric relationship exists between the variables.

Table 9: Short-run results of NARDL ( Productivity Rice is as dependent variable)

Variables	Coefficient	Std. Error	Prob.
Y	-0.45	0.12	0.00
Rainfall <sup>+</sup>	0.21	0.09	0.04
Rainfall <sup>-</sup>	0.55	0.15	0.00
AUR <sup>+</sup>	3.72	0.64	0.00
ECT(-1)	-1.21	0.09	0.00

$R^2 = 0.87$ , Adj.  $R^2 = 0.83$  & D-W statistics= 2.21

Sources: Calculated by Authors

298 Table 9 represents the results of the asymmetrical short-run impact on rice productivity. The results infer that the  
 299 positive and negative component of rainfall has a positive impact on rice productivity. This outcome is similar to  
 300 Birthal *et al.* (2014); Rashid *et al.* (2012) and Baig *et al.* (2020) and they concluded that rainfall has a positive impact  
 301 on rice productivity. Similarly, Arora *et al.* (2012) contradicted this outcome and stated that rainfall negatively impacts  
 302 rice productivity in India. Moreover, the positive component of the area under cultivated land has a positive and  
 303 significant impact on rice productivity in the short run. The coefficients of error correction term (ECT) have inferred  
 304

305 that rice productivity has adjusted its equilibrium with speed by 121 % per year in the presence of annual temperature,  
 306 rainfall and area under cultivated land in India.

Table 10: Results of the Wald Test

Explanatory Variables	Long-run Asymmetric		Short-run Asymmetric	
	F-Statistics	P-value	F-Statistics	P-value
Rainfall	7.79	0.01	9.98	0.00
Meantemp	17.19	0.00	-	-
AUR	0.03	0.84	-	-

Sources: Calculated by the Authors

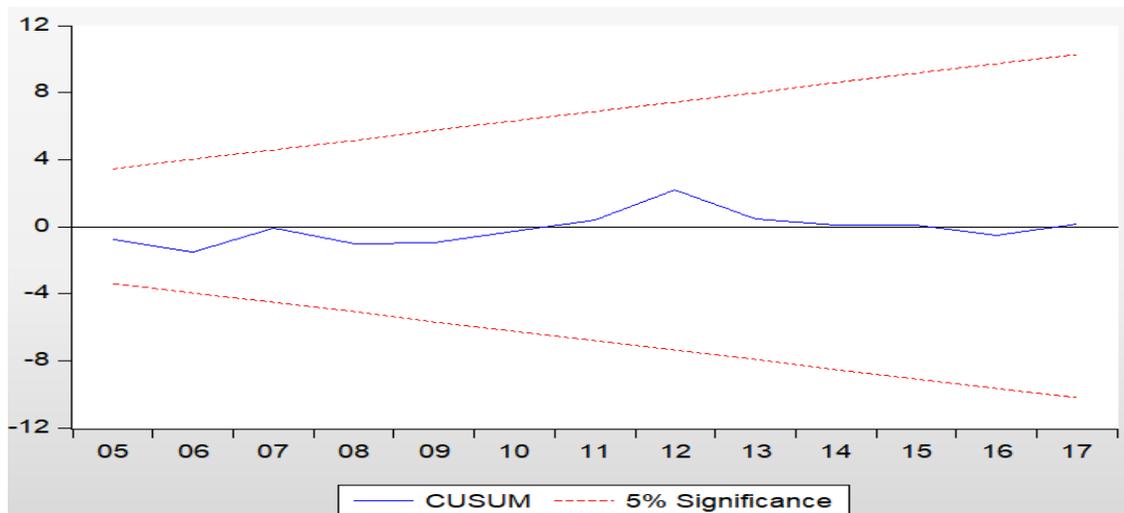
307  
 308 Table 10 depicts the result of short and long-run asymmetry. The P-value of Wald test rejects the null hypothesis of a  
 309 long-run symmetrical relationship between annual mean temperature, rainfall, and rice productivity, which clearly  
 310 indicate that long-run asymmetries in the positive and negative component of annual mean temperature and rainfall  
 311 on rice productivity. Furthermore, the result also infers that there is the asymmetrical association between rice  
 312 productivity and rainfall in the short-run in India. This result is supported by the Nsabimana & Habimana (2017),  
 313 which explained that rainfall has an asymmetric impact on agriculture productivity, and deficiency of rainfall has  
 314 negatively affected agriculture yields and its revenue. Apart from, Mitra (2014) contradicted this result and concluded  
 315 that no asymmetrical relationship between rainfall and food grain production. In contrast, P-value of area under  
 316 cultivated land revealed that there is no asymmetrical relationship between rice productivity and area under cultivated  
 317 land. Table 11 shows various diagnostic results such as heteroscedasticity, serial correlation, normality, and Ramsey  
 318 RESET Test. P-value indicates there is no problem in the model, and data is normally distributed.

Table 11: Results of Diagnostic Tests

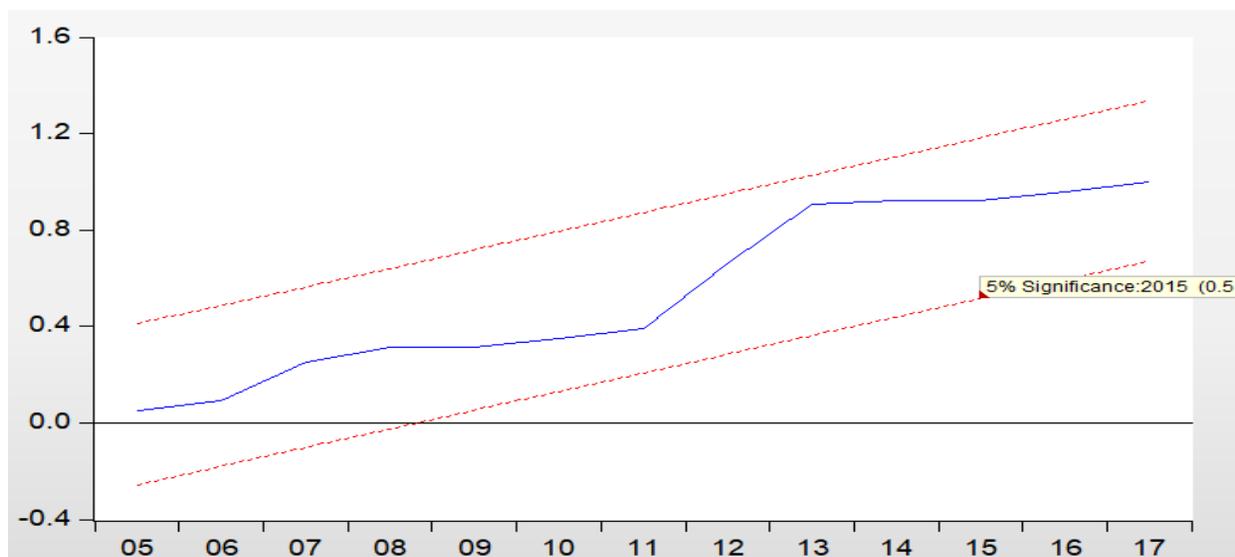
Diagnostic Test	Statistics	P-value
LM Test	0.36	0.70
Heteroskedasticity Test	0.87	0.58
Jarque-Bera Test	0.82	0.66
Ramsey RESET Test	0.54	0.47

Sources: Calculated by the Authors

319  
 320 The figure, 3 indicates the result of CUSUM and CUSUMQ to assess the stability of parameters at the 5 % level of  
 321 significance. The blue line shows the estimated line, which is lies within the two critical red lines which indicate that  
 322 parameters are stable in this model at the 5 % level of significance.



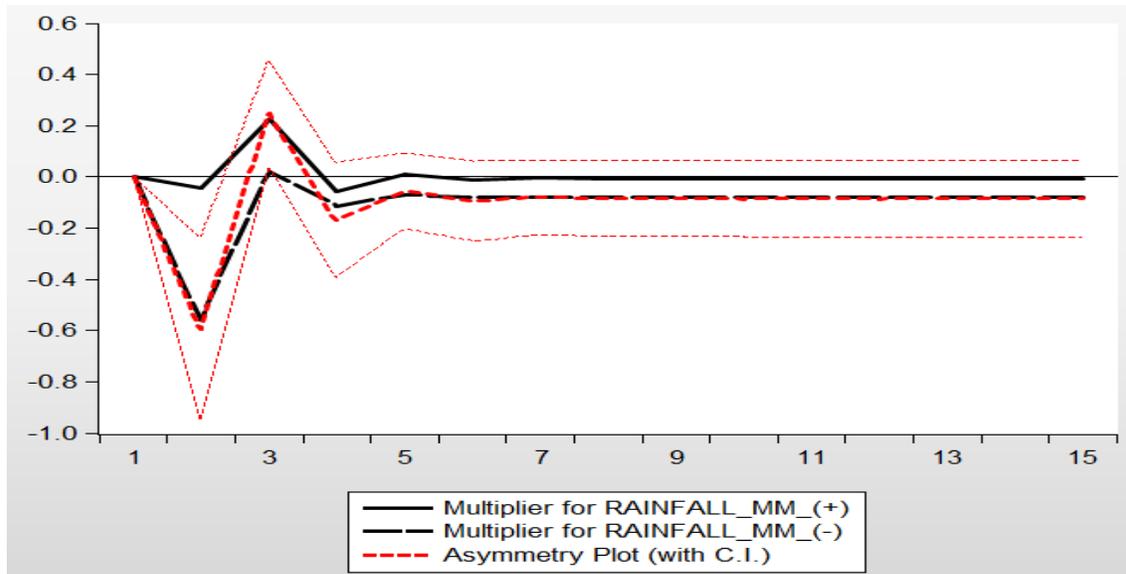
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Figure 3: CUSUM and CUSUMQ square

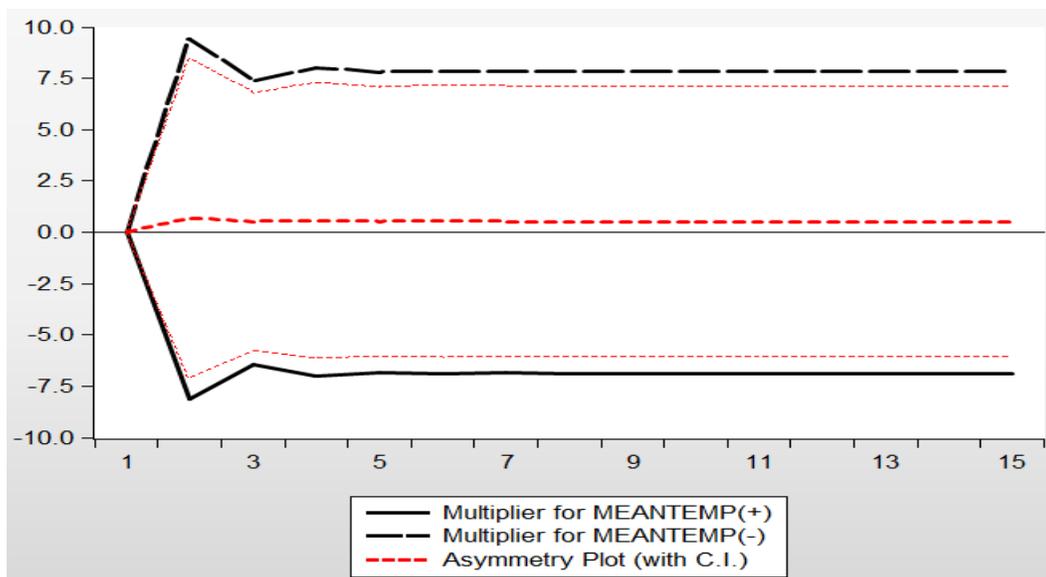
327  
328 Figure 4 (a, b & c), depict the cumulative adjustment pattern of the rice productivity to a unitary negative (-) and  
329 positive (+) component in annual rainfall, temperature and area under cultivated land. The negative (Black Dashed  
330 line) and positive (Continuous Blackline) line respectively measure cumulative adjustment of climate variables spread  
331 to negative and positive shocks at the given forecast horizon. The dark dotted red line is the asymmetry curve reflects  
332 the difference between the positive and negative shock of a dynamic multiplier of each independent variables. This  
333 asymmetry curve lies between line upper and lowers dotted two red lines in order to provide the measures of  
334 asymmetry at a given horizon at the 95 % level of significance.



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Figure 4 (a): Result of Dynamic Multiplier Graph

Figure 4 (a) indicates that the Positive and negative component of annual rainfall has a positive and negative shock in rice productivity, respectively. The negative component has a dominant shock over the positive component of rainfall in rice productivity.



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Figure 4 (b): Result of Dynamic Multiplier Graph

While, Figure 4 (b), infer that long-run asymmetry in the rice productivity due to changes of positive and negative shock in mean temperature, the negative component has dominant shocks over the positive component on the rice productivity.

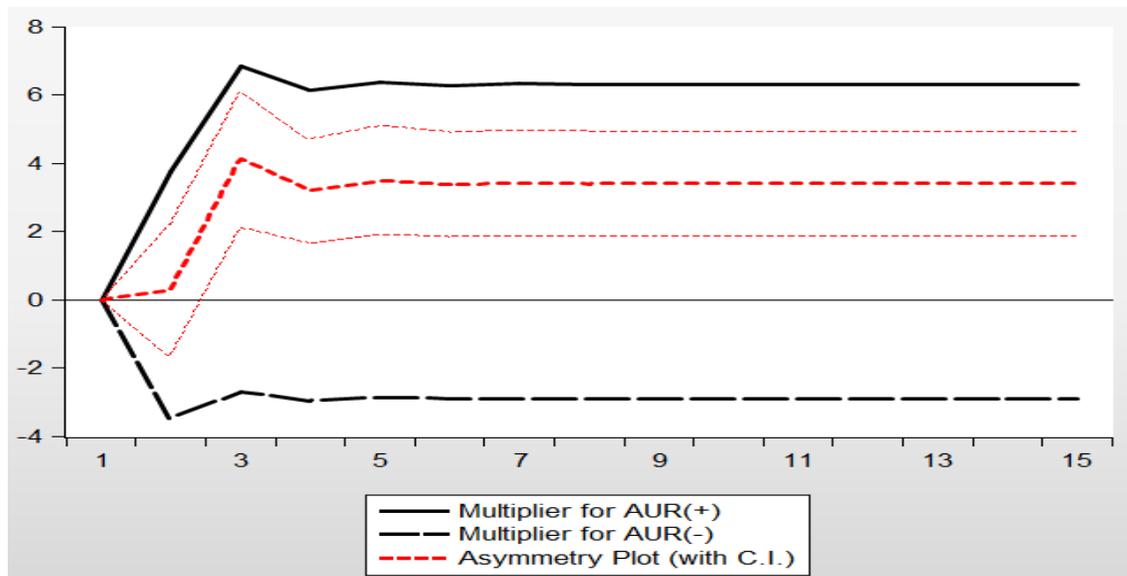


Figure 4 (C): Result of Dynamic Multiplier Graph

Furthermore, Figure 4 (c) revealed that positive component of area under cultivated land has dominant shock over the negative shock on the rice productivity in India.

### Concluding Remarks and Policy Implications

This paper examines whether the dynamic relationship is symmetrical and asymmetrical between climate change and rice productivity using linear ARDL and NARDL cointegration approach during 1990-2017 in India. NARDL techniques developed by Shin et al. (2014), which is the extension model of linear ARDL, captures the asymmetries relationship between the variables both in the long and short-run and provides an efficient and flexible approach that transmission of positive and negative shocks in each explanatory variables to the rice productivity.

The empirical outcome of ARDL infers that the absence of a linear dynamic relationship between climate change and rice productivity in India. Whereas, NARDL result indicates a significant long-run and dynamic asymmetric relationship between climate change and rice productivity in India. The positive and negative shock of climate change has affected the rice productivity by different magnitude in India. However, the linear ARDL model has not appropriate to effectively measure the asymmetries impact of climate change on rice productivity in the short and long-run and might lead to misspecified and biased results. In particular, asymmetric long-run result, positive (+) and negative (-) annual mean temperature component negatively affect rice productivity in India. In contrast, positive and negative component of rainfall respectively has a positive and negative impact on rice productivity. Moreover, the short-run positive and negative component of rainfall has a significant positive impact on rice productivity. Similarly, the positive component of the area under cultivated land has a positive impact on India's rice productivity.

This study's outcomes may be vital for planning and strategy for policymakers to adopt appropriate environmental policies and modern technology regarding precise climate forecasting, and precautionary and direct actions are also expected to create and support an improved water system framework. In a nutshell, crop-specific research should be conducted to highlight environmental problems. The Government should also take the initiative to cope with climate change's harmful effects on agriculture's productivity. The Government should provide better irrigation facilities such

374 as water canal, tube wells, and government can subsidise the electricity to cope with deficiency of rainfall, enhancing  
375 rice production in India. To cope with climate change, the Government should set-up a team of two or three people to  
376 give guidance and proper knowledge regarding the different aspects of climate change phenomenon at the block level  
377 in India.

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# Figures

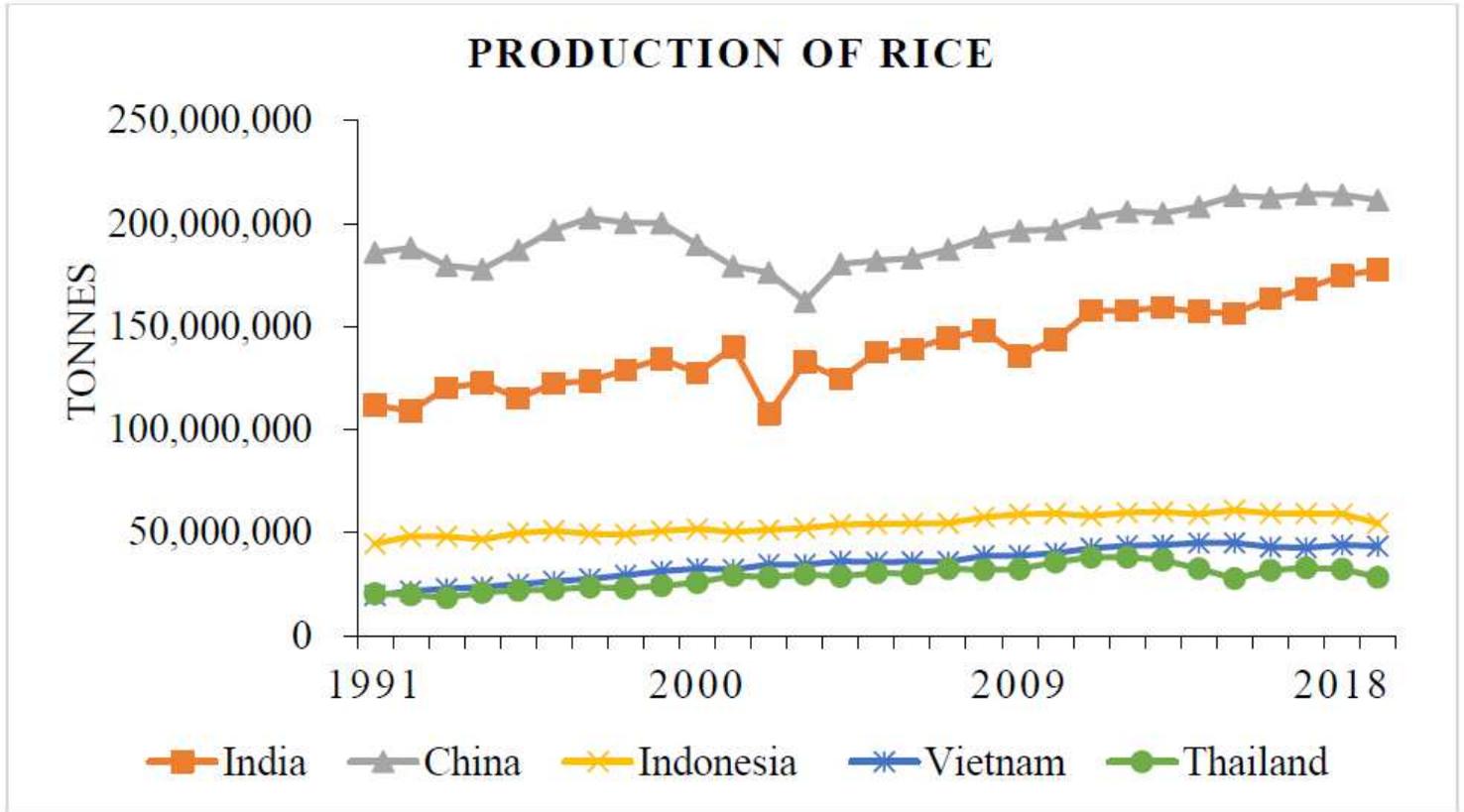


Figure 1

Trend of rice production in Asian countries 83 Sources: FAO 2019



Figure 2

Annual Growth Rate of Rice Production in India Sources: CMIE Commodities (2019)

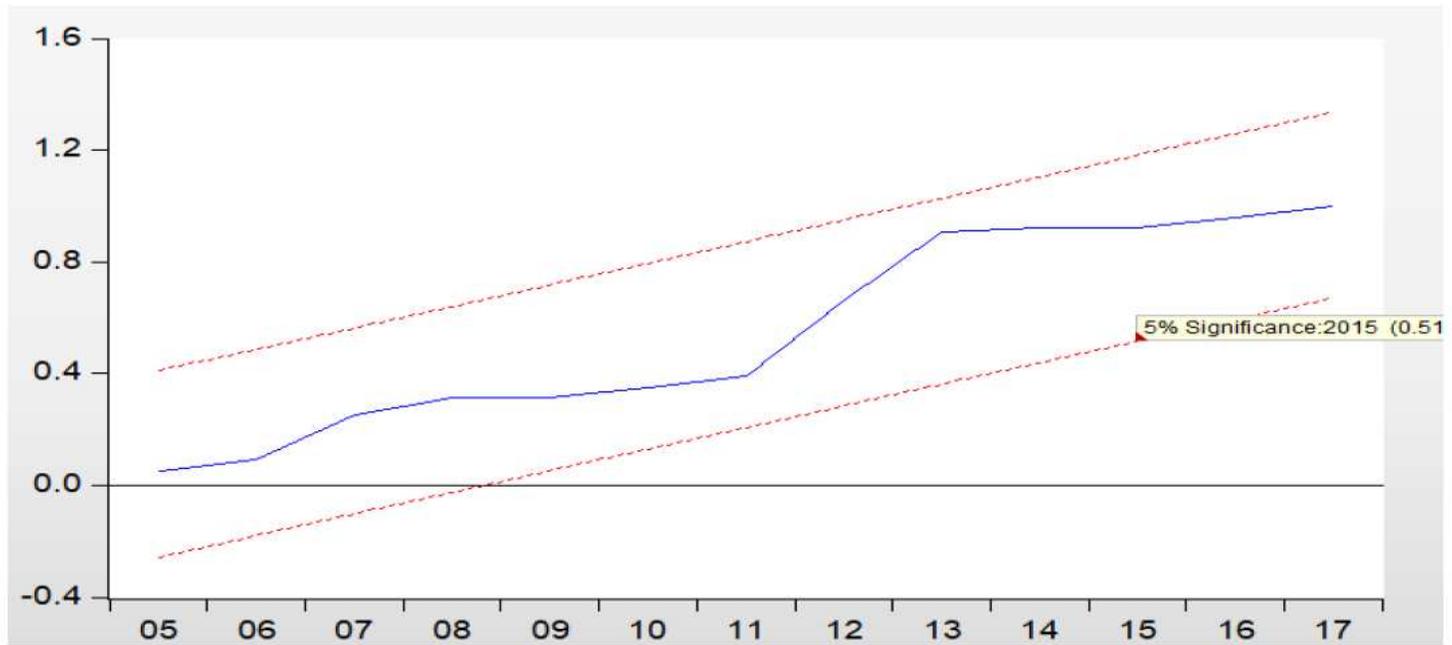
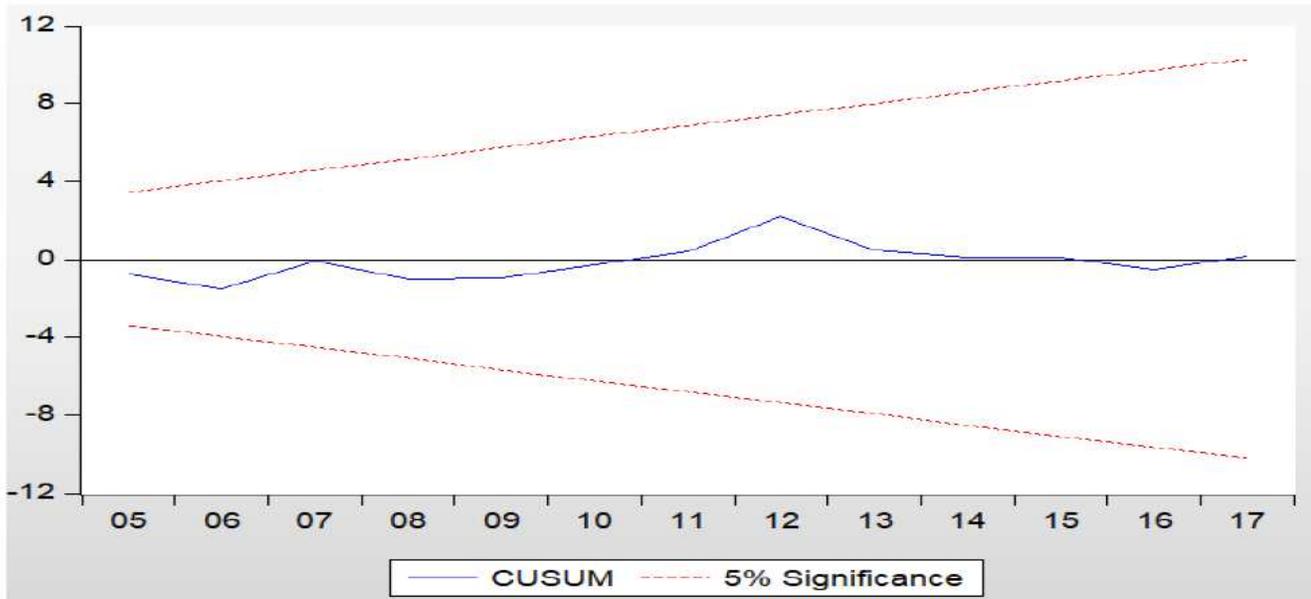
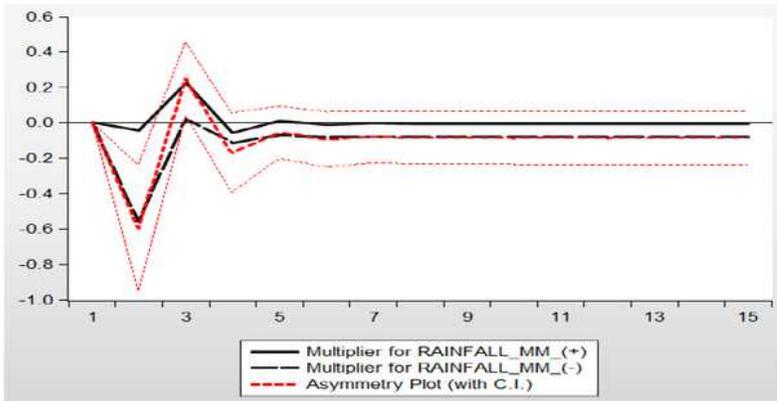
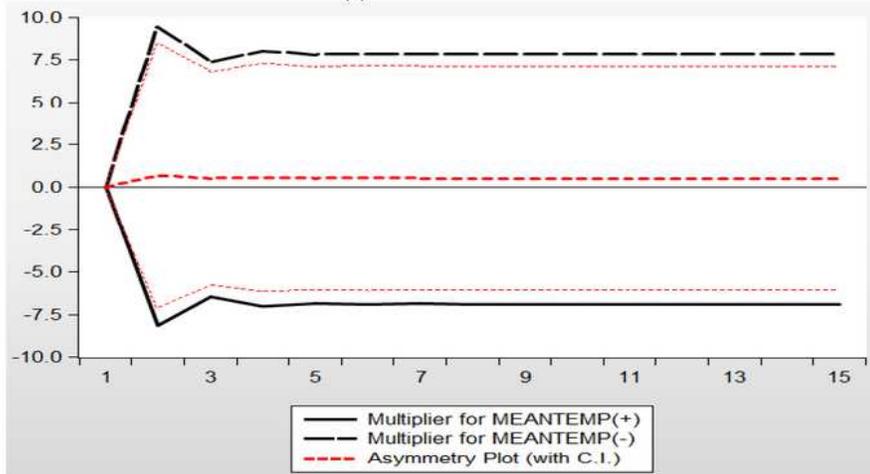


Figure 3

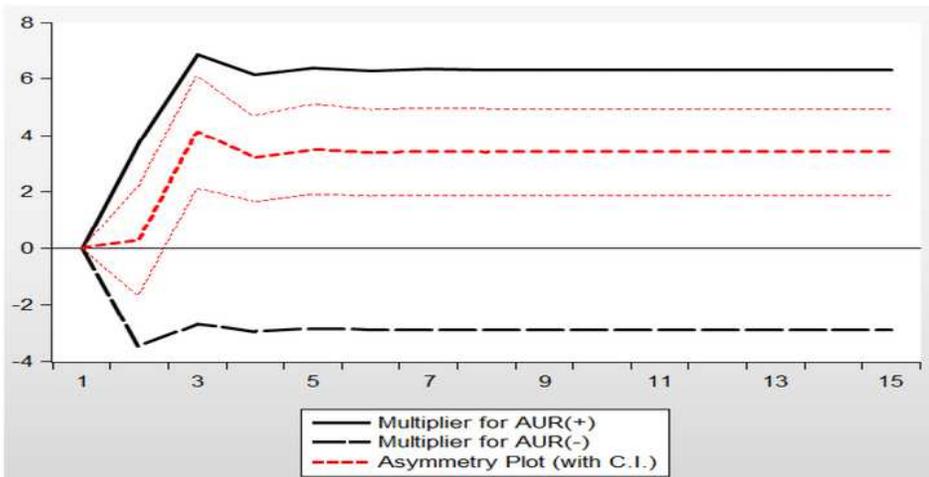
CUSUM and CUSUMQ square



(a)



(b)



(c)

**Figure 4**

(a): Result of Dynamic Multiplier Graph (b): Result of Dynamic Multiplier Graph (C): Result of Dynamic Multiplier Graph