

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

Imran Ali Baig

AMU: Aligarh Muslim University

Abbas Ali Chandio (✉ aichandio@sicau.edu.cn)

Sichuan Agricultural University <https://orcid.org/0000-0001-8706-9681>

Ilhan Ozturk

Cag University: Cag Universitesi

Pushp Kumar

IIT Bhubaneswar: Indian Institute of Technology Bhubaneswar

Zeeshan Anis Khan

AMU: Aligarh Muslim University

Md. Abdus Salam

AMU: Aligarh Muslim University

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

3 **Imran Ali Baig¹**

4 ¹Department of Economics, Aligarh Muslim University, Aligarh, India
5 Email: ialibaig043@gmail.com

6
7 **Abbas Ali Chandio^{2*}**

8 ²College of Economics, Sichuan Agricultural University, Chengdu, China
9 Email: alichandio@sicau.edu.cn

10
11 **Ilhan Ozturk^{3**}**

12 ³Faculty of Economics and Administrative Sciences, Cag University, 33800 Mersin,
13 Turkey
14 Email: ilhanozturk@cag.edu.tr

15
16 **Pushp Kumar⁴**

17 ⁴Indian Institute of Technology, Bhubaneshwar, India
18 Email: pk27@iitbbs.ac.in

19
20 **Zeeshan Anis Khan¹**

21 ¹Department of Economics, Aligarh Muslim University, Aligarh, India
22 Email: zeeshananiskhan@gmail.com

23
24 **Md. Abdus Salam¹**

25 ¹Department of Economics, Aligarh Muslim University, Aligarh, India
26 Email: salam9@gmail.com

27
28 *Corresponding author: Email addresses: alichandio@sicau.edu.cn (A. A. Chandio)

29 **Corresponding author: Email: ilhanozturk@cag.edu.tr (O. Ilhan)

36 **Abstract**

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

56 **Keywords:** Asymmetry, Granger Causality, India, NARDL, Rice Production

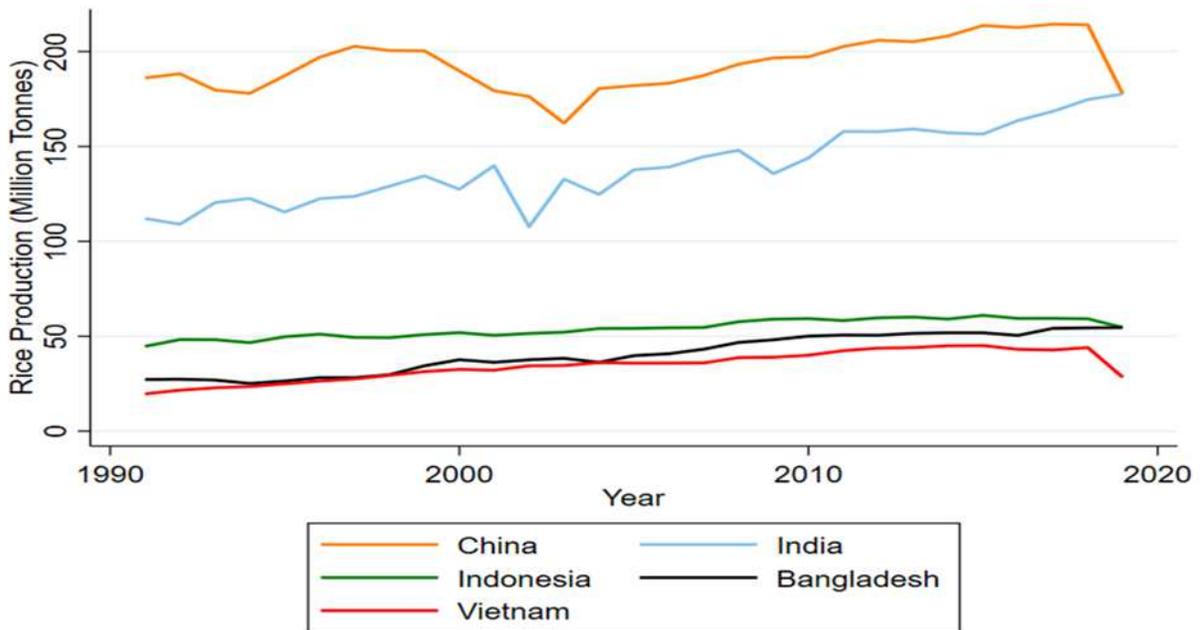
57 **1. Introduction**

58 Due to the long-term adverse effect on agricultural productivity, food production, water
59 availability, and rural lives, climate change has garnered environmentalist and policymaker
60 attention across the globe since 1990s (Chavas et al. 2009; Mohorji et al. 2017). Changes in the
61 long-term trends in mean temperature and shifting rainfall patterns, increasing variability, and
62 greater prevalence of extreme events are the facet of climate change. Shifting rainfall patterns may
63 exert a more substantial effect on rice production. However, frequent floods due to heavy rainfall
64 may result in higher rice yield losses under climate change (Wassmann et al. 2009). Climate
65 change results from increasing human activities on the land, including deforestation, land use,
66 urbanisation, increasing population, production and consumption activities to fulfil people's
67 demand for food supply. Climate steadily changes due to global temperature, precipitation, and
68 carbon emission, significantly impacting agricultural productivity and growth (Chandio et al.
69 2021; Klutse et al. 2021).

70 Agricultural productivity has decreased due to climate change's main drivers, such as precipitation
71 and warmer temperature (Haile et al.2017). However, increase in temperature, variation in rainfall,
72 and frequent floods and droughts are mostly faced by the developing nation, situated in the tropical
73 region and relies heavily on the agriculture sector (Janjua et al. 2014). Agriculture and its allied
74 activities are sensitive to climate change, and another hand, it is also contributed to carbon
75 emission (Swaminathan and Kesavan 2012). Climate change is harmful to agriculture production
76 and enhances the vulnerability among small and medium farmers whose livelihoods are mainly
77 dependent on agricultural and allied activities (Zakaria et al. 2020). climate change's impact may
78 vary from region to region based on geographical location. In the case of a developing nation,
79 climate change deteriorates the performance of the agriculture sector (Abbas 2020; Janjua et
80 al.2014; Nath and Behera 2011). Likewise, Abbas et al. (2021) revealed that climate change has
81 significantly affected crop production and food security in South Asia in the long. Swaminathan
82 and Kesavan (2012) stated that climate change adversely affected food production. The developing
83 nations are more vulnerable than developed countries due to more extensive dependence on the
84 agriculture sector for livelihood, lack of technological advancement and lack of adaptation policies
85 of climate change on agriculture production (Dogan and Inglesi 2020; Praveen and Sharma 2020;
86 Warsame et al. 2021). However, Chandio et al. (2021) stated that temperature and financial
87 development negatively and positively impact cereal production in Pakistan. While Ahsan et al.

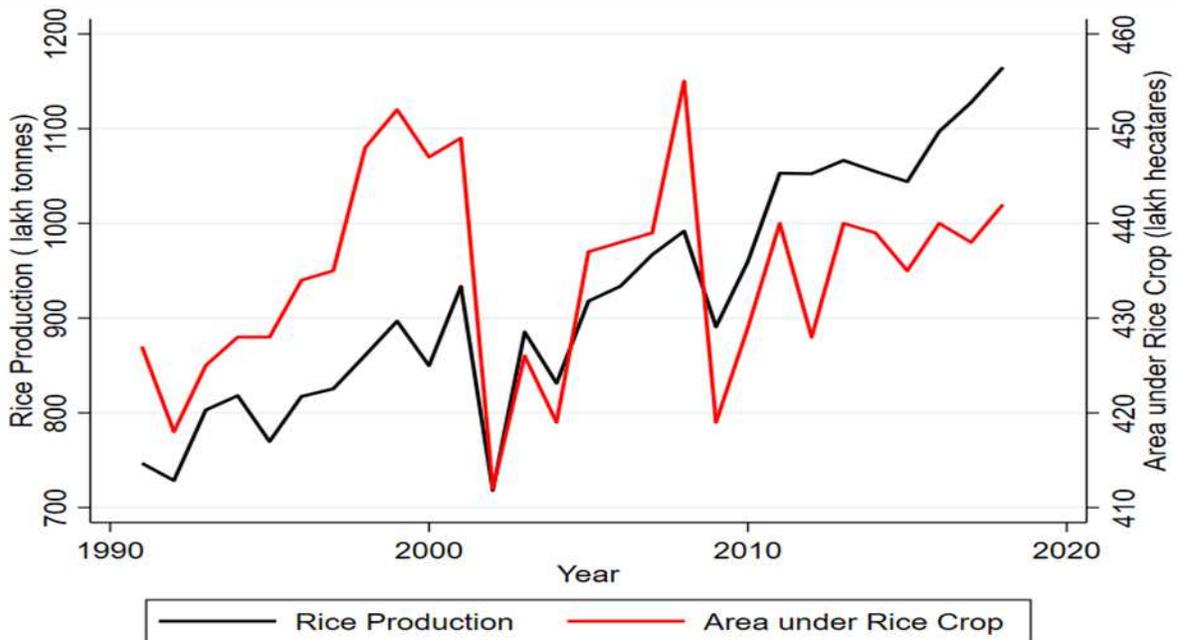
88 (2020) demonstrated that energy consumption, labour force, cultivated area, and CO₂ are the main
89 determinants of agriculture productivity. Likewise, Warsame (2021) explained mean temperature
90 and CO₂ has negatively influenced agriculture productivity in Somalia. Similarly, Coulibaly et al.
91 (2020) concluded that temperature and drought are the main factors that negatively affect
92 agriculture productivity. Increasing carbon emission leads to a cascade of impact mechanisms that
93 have harmful and beneficial effects on rice production.

94 In World, Asian countries produce rice about 90 % of the world's total rice production (FAO, 2019)
95 . However, India is the first largest exportable country of rice in the world counted 9.8 million
96 tonnes, followed by Thailand (7.5 million tonnes), Vietnam (6.5 million tonnes), Pakistan (4.6
97 million tonnes) and the USA (3.1 million tonnes). India is the second rice producer in Asia after
98 China, followed by Indonesia, Bangladesh and Vietnam (Figure 1). The Indian agriculture sector
99 is the most sensitive and exposed area to climate change due to its less adaptive capacity to cope
100 with it (Guntukula 2019). Investigating the impact of climate change on agriculture productivity
101 is of immense importance because more than 50% population of India primarily depends on
102 agricultural activities for their livelihoods (Pattanayak and Kumar 2013). Changes in
103 environmental factors such as temperature, precipitation, CO₂, and rainfall pattern directly affect
104 agriculture productivity (Res et al. 1998). Increasing carbon emission and global warming created
105 challenges for the countries to cope with it through different strategies and policies (Alharthi et al.
106 2021). Therefore, it is indispensable to examine the effect of changes in climatic conditions on rice
107 production. More than 60% of the population in India mainly depends on agriculture and its allied
108 sectors (Baig et al. 2020). Trends of rice production and area under crop are shown in Figure 2.
109 Rice output grew from 746.8 (Lakh Tonne) in 1991 to 1164.8 (Lakh tonnes) in 2018.
110 Simultaneously, the cultivated rice area in India has increased from 427 (Lakh Hectare) in 1991 to
111 442 (Lakh Hectare) in 2018. The area under rice has risen by around 1.5 times, but rice production
112 has increased by more than five times.



113
114

Figure 1. Top Five Asian Rice Producing Countries



115
116

Figure 2. Trends of Rice Production and Area under Rice Crop in India

117 Climate change may be the effect of food security by hampering agriculture productivity from one-
 118 way and multiple ways. Climate change, on the other hand, has a global impact, and its negative
 119 consequences are projected to be more severe in India's agro-ecological zones. Climate models
 120 predict the severe impacts of climate change on the agriculture sector (Bahl 2015). Climate change

121 has significantly affected agricultural productivity and food supply, threatening food security
122 (Moses et al. 2015). Because rice is more vulnerable to fluctuation due to climate change and its
123 associated components, the rising negative effects of climatic change would put pressure on
124 agricultural yield (Bahl 2015). Given rice's vulnerability to environmental change, particularly
125 those connected to temperature increases and extended drought spells, meeting future global rice
126 demand appears to be a difficult undertaking. Temperature-related changes in the duration of the
127 growing season will reduce rice yield and shift farming frameworks away from rice and toward
128 crops with greater temperature optimums (Korres et al. 2017).

129
130 This study explores the nonlinear effects of climate change on rice production in India, spanning
131 from 1991 to 2018. Most studies employed crop simulation model (Gupta and Mishra 2019; Kumar
132 2011; Kumar et al. 2011; Lal et al. 1998; Mishra and Chandra 2016; Mukherjee and Huda 2018),
133 linear econometric models (Baig et al. 2020; Bhanumurthy and Kumar 2018; Birthal et al. 2014;
134 Guntukula 2020; Kumar et al. 2020; Nath and Mandal 2018; Praveen and Sharma 2020; Gupta et
135 al. 2012) and nonlinear model (Mitra 2014; Pal and Mitra 2018) to assess the impact of climate
136 change on India's agriculture production. Several studies examine the effect of climate change on
137 rice yield or production using linear regression analysis. As a result, these studies have produced
138 only linear effects that might lack nonlinear effects. This study adds to the previous literature by
139 addressing the asymmetric impact of climate change on rice production in India rather than
140 sticking to a linear approach.

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

148 The remainder of the paper is framed as follows: Section 2 deals with the existing literature. The
149 data and technique are discussed in Section 3. Section 4 presents the empirical findings and
150 comments, while Section 5 concludes with policy implications.

151

152 **2. Literature Review**

153 Numerous studies have been done on the nexus between climate change and agricultural
154 productivity and growth across the globe. There is growing consensus among environmentalists
155 and researchers that a negative relationship exists between climate change and agriculture
156 productivity in developing nations (Khanal et al. 2018). South Asia is the most susceptible terrain
157 to climate change globally, with the largest population growth, poverty, and insecurity. Climate
158 change such as extreme weather, unexpected rainfall and temperature fluctuations severally affect
159 agriculture production in developing nations (Masud et. Al. 2014; Shabbir et al. 2020). However,
160 it is the primary concern to frame a suitable policy to tackle climate change problems for
161 policymakers, researchers, and government organisations. At the global, regional level, researchers
162 have undertaken numerous studies to assess the impact of climate change on the agriculture sector
163 (Chandio et al. 2020; Praveen and Sharma 2020; Warsame et al.2021).

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

174 On the other hand, maximum temperature has a negative impact on rice and wheat in Uttar Pradesh
175 and Haryana. While rising temperatures have a positive effect on rice production, they have a
176 detrimental effect on grain. Abbas and Mayo (2019) reported that maximum temperature harms
177 rice plants. Rice crops at the replantation stage during the vegetative phase have benefited from a
178 decrease in the number of plants in the plantation stage and a lower minimum temperature. During
179 the heading and flowering periods, rain has a deleterious impact on rice crops. Likewise,
180 Auffhammer et al. (2012) point out that heavy rainfall and drought have a negative effect on rice
181 yield in the rain-fed areas during the 1966-2002 period, and lower rainfall and warmer night would

182 not occur then rice yield would increase by 4 per cent in India. In contrast, Rayamajhee et al.
183 (2020) stated that there is no direct relationship between rainfall and rice production in Nepal.
184 Likewise, Abbas et al. (2021) conducted their study and employed the ARDL cointegration
185 approach to investigate climate factors (CO₂, Average temperature and precipitation),
186 technological advancement (consumption of fertiliser used as a proxy variable), and other
187 controlled variables such as the area under cultivated land, improves seed, and agriculture credit
188 on rice production. They stated that average temperature and precipitation positively influenced
189 rice production, while CO₂ has a significant and negative impact on rice production in Nepal.
190 Furthermore, agriculture credit and area under cultivated land has a positive effect on rice
191 production.

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

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

207 Attiaoui and Boufateh (2019) and Abbas (2020) find a linear long-run dynamic relationship
208 between climate change and agriculture productivity. Empirical results reveal that deficiency of
209 rainfall and high temperature respectively has negatively and positively affected agriculture
210 productivity. Baig et al. (2020) also employ a linear dynamic ARDL model to assess the impact
211 of climate change on the yield of major crops, including rice, wheat, coarse cereals and pulse in
212 India. Findings showed that temperature positively impacts wheat, coarse grains and pulse except

213 for rice. At the same time, rainfall has a positive impact on rice, coarse cereals and pulse except
 214 for wheat in India. In contrast, Mitra (2014) and Pal and Mitra (2018) investigated the nonlinear
 215 relationship between climate change and crop productivity in India. Mitra (2014) found no
 216 asymmetric relationship between rainfall and food grain in India and observed that average rainfall
 217 has a greater impact on food grain production than below-average rain. In contrast, Pal and Mitra
 218 (2018) explain that rainfall has a greater effect on food grain production up to 75 th quantile and
 219 reduces after that in India. While Nsabimana and Habimana (2017) conducted a study in Rwanda's
 220 context, they stated that rainfall has an asymmetric impact on crop prices in the short and long run.
 221 Furthermore, the price of food crops has decreased during the harvest season and then increased.
 222 Likewise, Moore et al. (2017) used database yield to compare results from process-based and
 223 empirical studies in order to comprehensively investigate the influence of climate change on
 224 agricultural production and welfare. He claims that the asymmetric impacts of climate change on
 225 welfare and agricultural yield show a high possibility of severe welfare losses with warming of 2–
 226 3 degrees Celsius, even after accounting for the CO₂ fertilisation effect. Fezzi and Bateman (2016)
 227 and Kabubo-mariara and Karanja (2007) has observed a nonlinear relationship between climate
 228 change and the revenue of agriculture crops. So, it is challenging to cope with it due to the complex
 229 asymmetrical association between climate change and agriculture production. Table 1 shows a
 230 summary of review of literature.

231

232 **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	+CO ₂ , 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	+CO ₂ --> -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.

9	Saseendran et al. (2000)		Kerala	CERES-Rice V3 Simulation model	+CO ₂ , Rainfall---> +Rice Yield. -Rainfall---> -Rice yield. +Temperature---> -Rice yield.
11	Muhammad Nasrullah et al. (2021)	1973-2018	South Korea	ARDL	+CO ₂ , 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	+CO ₂ , 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	+CO ₂ ---> +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.

234 **3. Data and Methodology**

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

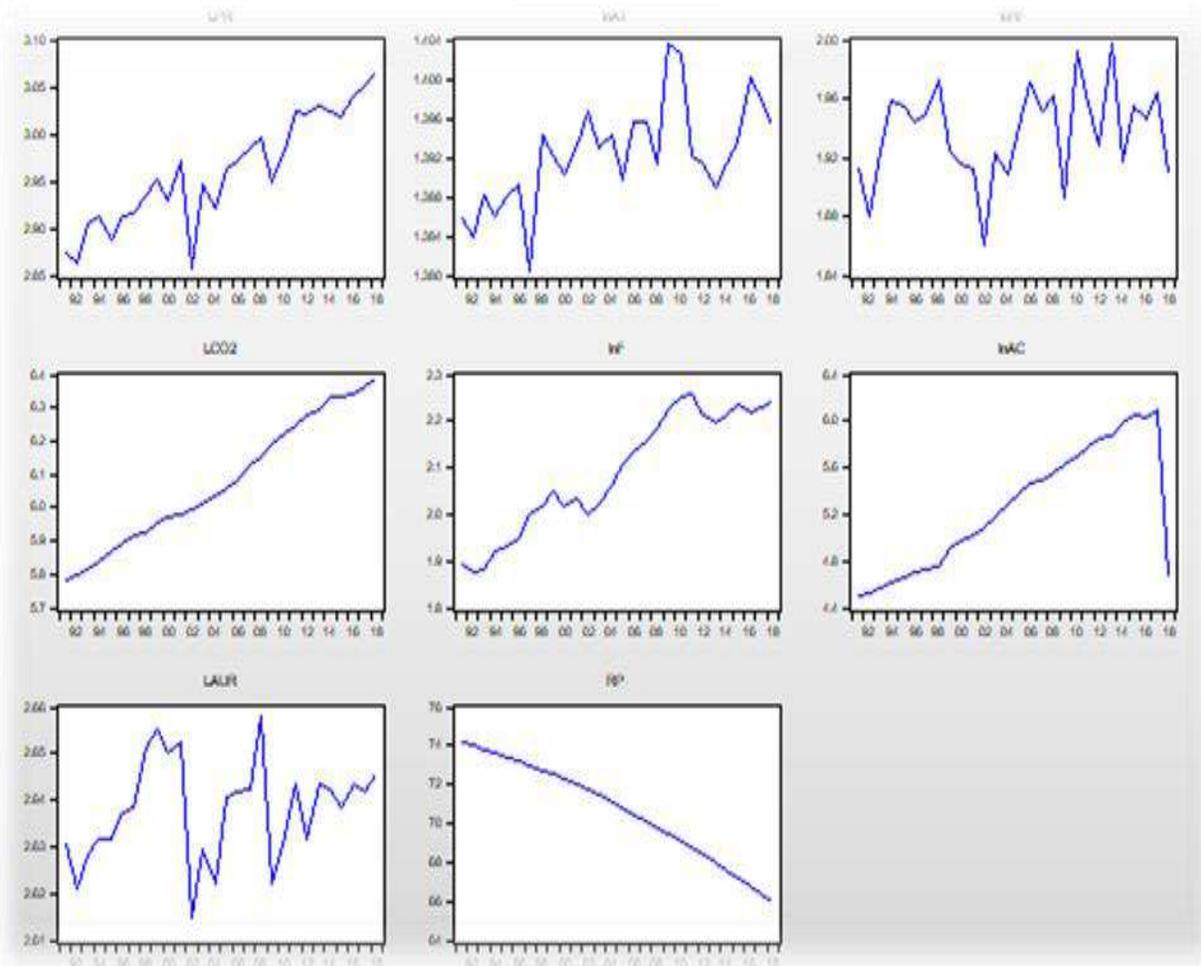
240 **Table 2.** Description of the Variables

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/hc)	RBI
Area Under Rice crop	lnAUR	Lakh Hectare (Lh)	RBI

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

243
244 This study undertakes rice production (Lakh Tonne) as a dependent variable, mean temperature
245 (C), average rainfall (mm), carbon emission (kt), rural population (Per cent of the total population),
246 consumption of fertiliser (kg/ha), agriculture credit (Crore) and area under crops (Lakh hectare)
247 used as independent variables. Annual mean temperature, annual average rainfall and carbon
248 emission are the main factors of climate change (Chandio et al. 2020; Kumar et al. 2021; Pickson
249 et al. 2021). Chandio et al. (2021), Pickson et al. (2021) and Warsame et al. (2020) also
250 incorporated agriculture credit, consumption of fertiliser, rural population and area under crops as
251 non-climate factors of agriculture production. All the variables were transformed into logarithmic.
252 Figure 6 shows trends of underlying variables used in this study.

253
254
255
256



257

258

Figure 3. Trends of variables used in this study

259 **NARDL Bound Test for Cointegration**

260 This study employs the recently developed and advanced technique NARDL to investigate the
 261 asymmetrical effect of climate change on production of rice. The ARDL technique ignored
 262 nonlinearity and the asymmetrical association between the underlying variables. An ARDL model
 263 is expanded to an asymmetric ARDL or NARDL by Shin et al. (2014) to assess the pattern of
 264 dynamic adjustment and asymmetries relationship in the short and long run between the variables.

265 To explore the relationship between the variables following model can be specified as:

266
$$\ln PR_t = f(\ln AT_t, \ln RF_t, \ln CO_{2t}, RP_t, \ln AC_t, \ln F_t, \ln AUR_t)$$

267 (1)

268 We can rewrite equation (1) as follows:

269 $lnPR_t = \alpha_0 + \alpha_1 lnAT_t + \alpha_2 lnRF_t + \alpha_3 lnCO_{2t} + \alpha_4 RP_t + \alpha_5 lnAC_t + \alpha_6 lnF_t + \alpha_7 lnAUR_t +$
 270 ε_t (2)

271 Where $lnPR$ is the natural log of rice production, $lnAT$ is the natural log mean temperature, $lnRF$
 272 is the natural log of average rainfall, $lnCO_2$ is the natural log carbon emission, RP is rural
 273 population, $lnAC$ is the natural log of agricultural credit, lnF is the natural log of consumption of
 274 fertiliser and $lnAUR$ indicates natural log of the area under rice crop. Before presenting a full
 275 depiction of the NARDL model, General forms of long-run asymmetry relationships are given as
 276 follows:

277 $lnPR_t = \alpha_0 + \alpha_1^+ lnAT_t^+ + \alpha_2^- lnAT_t^- + \alpha_3^+ lnCO_{2t}^+ + \alpha_4^- lnCO_{2t}^- + \alpha_5^+ lnRF_t^+ + \alpha_6^- lnRF_t^- +$
 278 $\alpha_7^+ RP_t^+ + \alpha_8^- RP_t^- + \alpha_9 lnAC_t + \alpha_{10} lnF_t + \alpha_{11} lnAUR_t + \varepsilon_t$
 279 (3)

280 Where, $lnPR_t$ is a $k \times 1$ vector of rice production at time t , where, α ($\alpha_0, \alpha_1^+, \alpha_2^-, \alpha_3^+, \alpha_4^-, \alpha_5^+,$
 281 $\alpha_6^-, \alpha_7^+, \alpha_8^-, \alpha_9, \alpha_{10}$ and α_{11}) are the associated asymmetric long-run parameters. Here $lnAT_t,$
 282 $lnRF_t,$ $lnCO_{2t}$, and RP_t as $k \times 1$ vector of regressors is subdivided as;
 283 $lnAT_t = lnAT_0 + lnAT_t^+ + lnAT_t^-$, $lnRF_t = lnRF_0 + lnRF_t^+ + lnRF_t^-$, $lnCO_{2t} = lnCO_{20} + lnCO_{2t}^+ + lnCO_{2t}^-$
 284 and $RP_t = RP_0 + RP_t^+ + RP_t^-$ respectively.

285 Where, $lnAT_t^+, lnAT_t^-; lnRF_t^+, lnRF_t^-; lnCO_{2t}^+, lnCO_{2t}^-$ and RP_t^+, RP_t^- are partial sum processes
 286 of positive (+) and negative (-) changes in $lnAT_t, lnRF_t, lnCO_{2t}, RP_t$ respectively. Equation shows
 287 partial decomposition of $lnAT, lnRF, lnCO_2$ and RP .

288
 289 $lnAT_t^+ = \sum_{i=1}^t \Delta lnAT_i^+ = \sum_{i=1}^t \max(\Delta lnAT_i, 0)$
 290 (4)

291 $lnAT_t^- = \sum_{i=1}^t \Delta lnAT_i^- = \sum_{i=1}^t \min(\Delta lnAT_i, 0)$
 292 (5)

293 $lnRF_t^+ = \sum_{i=1}^t \Delta lnRF_i^+ = \sum_{i=1}^t \max(\Delta lnRF_i, 0)$
 294 (6)

295 $lnRF_t^- = \sum_{i=1}^t \Delta lnRF_i^- = \sum_{i=1}^t \min(\Delta lnRF_i, 0)$
 296 (7)

297 $lnCO_{2t}^+ = \sum_{i=1}^t \Delta lnCO_{2i}^+ = \sum_{i=1}^t \max(\Delta lnCO_{2i}, 0)$
 298 (8)

$$299 \quad \ln CO_{2t}^- = \sum_{i=1}^t \Delta \ln CO_{2i}^- = \sum_{i=1}^t \min(\Delta \ln CO_{2i}, 0)$$

$$300 \quad (9)$$

$$301 \quad RP_t^+ = \sum_{i=1}^t \Delta RP_i^+ = \sum_{i=1}^t \max(\Delta RP_i, 0)$$

$$302 \quad (10)$$

$$303 \quad RP_t^- = \sum_{i=1}^t \Delta RP_i^- = \sum_{i=1}^t \min(\Delta RP_i, 0)$$

$$304 \quad (11)$$

305

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

$$309 \quad \Delta \ln PR_t = \alpha_0 + \rho \ln PR_{t-1} + \alpha_1^+ \ln AT_{t-1}^+ + \alpha_2^- \ln AT_{t-1}^- + \alpha_3^+ \ln RF_{t-1}^+ + \alpha_4^+ \ln RF_{t-1}^-$$

$$310 \quad + \alpha_5^+ \ln CO_{2,t-1}^+ + \alpha_6^- \ln CO_{2,t-1}^- + \alpha_7^+ RP_{t-1}^+ + \alpha_8^- RP_{t-1}^- + \alpha_9 \ln F_{t-1}$$

$$311 \quad + \alpha_{10} \ln AC_{t-1} + \alpha_{11} \ln AUR_{t-1} + \sum_{i=1}^p \beta_i \Delta \ln PR_{t-i} + \sum_{m=1}^{m=p} (\theta_1^+ \Delta \ln AT_{t-1}^+$$

$$312 \quad + \theta_2^- \Delta \ln AT_{t-1}^-) + \sum_{m=1}^{m=p} (\gamma_1^+ \Delta \ln RF_{t-1}^+ + \gamma_2^- \Delta \ln RF_{t-1}^-) + \sum_{m=1}^{m=p} (\vartheta_1^+ \Delta \ln CO_{2,t-1}^+$$

$$313 \quad + \vartheta_2^- \ln CO_{2,t-1}^-)$$

$$314 \quad + \sum_{m=1}^{m=p} (\beta_1^+ \Delta RP_{t-1}^+ + \beta_2^- RP_{t-1}^-) + \sum_{m=1}^p \delta_1 \Delta \ln F_{t-1} + \sum_{m=1}^p \delta_2 \Delta \ln AC_{t-1}$$

$$315 \quad + \sum_{m=1}^p \delta_3 \Delta \ln AUR_{t-1} + \varphi ECT_{(-1)}$$

$$316 \quad + U_t \quad (12)$$

317 In the above equation, (α_i) , indicates long-run coefficients, while (θ_i) , (γ_i) , (ϑ_i) , (β_i) and (δ_i)
 318 are the short-run coefficients. The NARDL's estimation method is the same as linear ARDL. The
 319 null hypothesis of asymmetrical long-run relationship, $\rho = \alpha^+ = \alpha^- = 0$ between the variables.
 320 Null hypotheses have been tested by computing the general F-statistics (F_{PSS}) or t-statistics
 321 (t_{BDM}) proposed by Banarjee et al. (1998) determined these values by comparing them to the two
 322 critical bounds (lower and upper bound), which define a band including all conceivable
 323 classifications of the regressors as solely I (0), I (1), or mutually cointegrated. We accept the null

324 hypothesis if the F-statistics are less than the lower bound value, i.e. I (0). We can infer that there
 325 is no long-run association between the variables. If the F-statistics are in the range I (0) to I (1),
 326 the outcome is inconclusive. If the F-value is greater than the I (1) bound value, the null hypothesis
 327 can be rejected, indicating that variables are long-run cointegrated. ,ECT-1. is the error correction
 328 term, and is the rate at which the asymmetrical long-run equilibrium relationship is restored
 329 following a disruption.

330 The long-run ($\alpha^+ = \alpha^-$) and short-run ($\theta_1^+ = \theta_2^-, \vartheta_1^+ = \vartheta_2^-, \gamma_i^+ = \gamma_i^-, \beta_1^+ = \beta_2^-$) asymmetries
 331 estimates through the Wald test for mean temperature (lnAT), average rainfall (lnRF), carbon
 332 emission(lnCO2) and rural population (RP) variables. Where; p and q are representing optimal lags
 333 order of dependent and independent variables, respectively. Akaike and Schwarz information
 334 criteria have been used to find out the optimal lag selection in the model. The long-term
 335 asymmetric coefficients are calculated based on $L_{mi^+} = \alpha^+ / \rho$ and $L_{mi^-} = \alpha^- / \rho$. These long run
 336 coefficients measure the connection between variables in long run equilibrium with respect to
 337 independent variable shocks. By utilising the cumulative dynamic multiplier effect, these long-run
 338 and short-run asymmetry trajectories can be described in the following ways: a unit percentage
 339 change in X_t^+ and X_t^- on Y_t are obtained through the following equation:

340

$$341 \quad m_h^+ = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial \ln AT_t^+}; \quad m_h^- = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial \ln AT_t^-}; \quad m_h^+ = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial \ln RF_t^+}; \quad m_h^- = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial \ln RF_t^-};$$

$$342 \quad m_h^+ = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial \ln CO2_t^+}; \quad m_h^- = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial \ln CO2_t^-}; \quad m_h^+ = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial RP_t^+}; \quad m_h^- = \sum_{i=0}^h \frac{\partial LPR_{t+i}}{\partial RP_t^-};$$

343 Where, if $h \rightarrow \infty$, then $m_h^+ \rightarrow L_{mi^+}$ and $m_h^- \rightarrow L_{mi^-}$.

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

346 4. Results and Discussion

347 Table 3 reported result of descriptive statistics. We can infer from table 3 the average value of
 348 lnPR, lnAT, lnRF. lnCO₂, RP, lnAC, lnF and lnAUR are 2.96, 1.39, 1.94, 6.08, 70.64, 5.25, 2.09
 349 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
 350 respectively. The Jarque Bera test P-value suggests that all variables are normal.

351

352 **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

353 Sources: Calculated by the authors

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

357 **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

358
 359 The next step is to check the stationarity of the underlying variables to guarantee that none of them
 360 are integrated at order 2. Because the NARDL model requires that variables be integrated at order
 361 0 or 1 to investigate cointegration among variables, a unit root test must be performed. We used
 362 the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests in this order, and the
 363 results are shown in Table 5. We can infer from Table 5 that mean temperature, average rainfall,
 364 rural population, and land area under rice crop are I (0), while rice production, carbon emission
 365 and agriculture credit series are I (1).

366 **Table 5:** Unit Root analysis without structural break.

Variables	I(0)		I(1)	
	PP	ADF	PP	ADF
lnPR	-2.92	-1.51	-40.79***	-10.27***
lnAT	-13.18**	-2.52	-34.06***	-7.14***
lnRF	-23.57***	-.310**	-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***

367 Sources: Estimated by authors

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

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

Variable	I(0)		I(1)	
	Value	Year	Value	Year
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

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

Table 7: BDS Test for non-linearity

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

385
 386 **NARDL Cointegration Results**
 387 Schwarz (1978) information criterion used to choose the optimal lag length of NARDL (p,q). Then
 388 we use general to specific approach by ignoring all insignificant regressors since their inclusion
 389 may produce imprecise estimation results. Table 8 delineates the asymmetric impact of climate
 390 change and other controlled agriculture inputs on rice production. Two operational testings are
 391 used for the existence of an asymmetrical cointegration relationship based on NARDL. We find
 392 that the F-statistics are greater than the critical upper bound value at the 1% level of significance,
 393 confirming the presence of cointegration between mean temperature, average rainfall, carbon
 394 emission, rural population, agricultural credit, fertiliser consumption, the area under rice crop, and
 395 rice production from 1991 to 2018. The Wald test highlights the importance of asymmetry in both
 396 the short and long run, implying that nonlinearity must be considered when researching the
 397 relationship between climate change and rice output. At a 1% level of significance, the t-statistics
 398 support the cointegration among the variables. Shin et al. (2014)'s NARDL F-statistics (FPSS)
 399 confirm asymmetric cointegration among variables. It means that in India, mean temperature,
 400 average rainfall, carbon emissions, agricultural finance, fertiliser usage, rice crop area, and rice
 401 production have a long-term asymmetric relationship.

402

403 **Long and Short-Run Asymmetric Estimates**

404 A positive and negative component in mean temperature has a negative and significant impact on
405 rice production, which represent that any positive and negative shock in mean temperature
406 deteriorates rice production. However, the sign of both coefficients is the same but different in
407 magnitude, which indicates mean temperature has a significant asymmetric impact on rice
408 production. This study is in line with previous studies (Chandio et al. 2020; Haris et al. 2013; Lal
409 et al. 1998; Matthews et al. 1997; Warsame et al. 2021; Yuliawan and Handoko 2016),
410 corroborates the same findings. Chandio et al. (2020), Matthews et al. (1997), and Warsame et al.
411 (2021) explained temperature has an adverse effect on rice production both in the short and long
412 run. For instance, increases (decreases) 1 per cent in temperature reduces rice production by 9.23
413 (10.32) per cent in the long run in India. Several reasons can support this finding; increasing mean
414 temperature is beneficial for rice production initially. However, beyond a certain optimal
415 temperature, further temperature increases become harmful for rice production. Second,
416 temperature rise would make the age of rice shorter and decrease the rice yield (Kumar et al. 2021).
417 Higher temperature increases sea level; consequently, highly productive rice cultivation areas will
418 be more exposed to inundation and salinity intrusion. Moreover, the increased mean temperature
419 has adversely impacted rice production in various parts of South Asia such as India, Bangladesh,
420 Sri Lanka and Pakistan, which results in reduced average yields by 4 per cent (Matthews et al.
421 1997).

422 Table 8 reported the result of the long run and short asymmetrical impact on rice production.
423 Estimated outcomes in the long-run indicate that positive shock in the rainfall has negative and
424 significant effect on rice production at a 1 per cent level in India. The estimated coefficients of
425 positive shock in average rainfall indicate that a 1 per cent rise in average rainfall leads to a
426 decrease of 1.24 per cent of rice production in India. These findings are supported by the previous
427 study (Abbas et al. 2021; Nasrullah et al. 2021), which stated that excess rainfall has negatively
428 influenced rice production in rain-fed areas. Rice production has tremendous pressure due to the
429 high variability of rainfall in rain-fed regions of India (Pal and Mitra 2018). However, heavy
430 rainfall, i.e., the flood-like situation, has adversely affected rice production in India (Pal and Mitra
431 2018). Some previous studies (Abbas et al. 2021; Chandio et al. 2021; Siddiq et al. 2012; Warsame
432 et al. 2021) has contradicted this result and stated that excess rainfall had enhanced rice production

433 in rain-fed areas. In contrast, coefficients of negative shocks in the rainfall have a positive and
434 significant impact on rice production at a 1 per cent level in the long run. This study is in line with
435 (Abbas et al. 2021; Mitra 2014), they found that any negative shock in the rainfall has positively
436 affected rice production in India. Pal and Mitra (2018) stated that scanty rainfall and drought have
437 reduced food grain production in India. We can infer from the estimated result that 1 per cent
438 increases (decreases) in average rainfall has reduced (boosts) rice production by approximately
439 1.24 (2.87) per cent in India.

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

453 Furthermore, positive shock in the rural population has a statistically insignificant impact on rice
454 production with a coefficient of 0.49 in the long run. Interpretively, rice production is growing by
455 0.49 per cent due to a 1 per cent increase in rural population. The coefficients indicate that rice
456 production increases with increase in rural population. Whereas, Negative shock in the rural
457 population has negatively influenced rice production by 0.39 per cent in the long run at a 1 per
458 cent level of significance. This study is in line with previous studies (Kumar et al. 2021; Warsame
459 et al. 2021), who found that the rural population has a negative impact on cereals production. It is
460 because the marginal productivity of agriculture labour is zero due to working surplus labour in
461 the same piece of land (Thirlwall 1994). Agriculture labour productivity has decreased because
462 land can not produce more than its capacity (Kumar et al. 2021).

463 Table 8 reported the result of the short-run asymmetrical impact on rice output. The positive and
464 negative shocks in mean temperature have positively influenced rice production in India.
465 Estimated coefficients indicate that a 1 per cent increase and decrease in mean temperature can
466 lead to increases the rice production by 17.23 per cent and 2.60 per cent, respectively, which
467 implies that positive shocks have a more dominant effect than the negative shock on rice
468 production in the short run. Results advocated that rice production has more affected by the
469 increasing temperature rather than decreasing temperature in India. Moreover, rainfall positive
470 shock has a negative and significant effect on rice production at a 1 per cent level of significance.
471 It is found that rice production reduced by 0.74 per cent when 1 per cent increase in positive shock
472 of rainfall. In contrast, coefficients of negative shocks in the rainfall have a positive and significant
473 impact on rice production at a 1 per cent level of significance in the short run. We can infer from
474 the estimated result that 1 per cent decreases in average rainfall have boosted rice production by
475 approximately 0.64 per cent in India. Furthermore, any positive shock in the carbon emission has
476 a negative and significant impact on rice production at the 1 per cent level of significance in India.
477 The estimated outcome indicates a rise in carbon emission in the atmosphere by 1 per cent, which
478 reduces rice production by 6.16 per cent approximately. In comparison, carbon emission negative
479 shocks positively impact rice production at the 1 per cent significance level. The coefficient of the
480 negative component of carbon emission indicates that it increases rice production by 1.69 per cent
481 when there is 1 per cent reduction in the carbon emission. We can infer from the estimated results
482 that rice production has been boosted by reducing carbon emissions in India's atmosphere in the
483 short run. Likewise, the impact of positive shock in the rural population has a negative and
484 insignificant effect on rice production in the short run. Interpretively, a 1 per cent increase in rural
485 population leads to decrease rice production by 0.50 per cent in India. Coefficients indicate that
486 rice production decreases when increasing rural population. In comparison, negative shock in the
487 rural population has positively influenced rice production by 1.82 per cent in the short-run at a 1
488 per cent level of significance.

489 Moving on to other controlled variables such as fertiliser consumption (InF), agricultural credit
490 (InAC), and area under crops on rice production (InAUR), these are three core elements of rice
491 production (Chandio et al. 2021). Our findings show that a 1 per cent increase in fertiliser
492 consumption, agricultural credit and area under crop enhance rice production by 0.70 per cent,
493 0.04 per cent and 2.34 per cent, respectively, in India. These findings are consistent with previous

494 studies (Chandio et al. 2021; Chandio et al. 2020; Janjua et al. 2014; Nasrullah et al. 2021;
495 Omoregie et al. 2018; Zakaria et al. 2020). In the context of India, agricultural credit plays a
496 significant role to boost agriculture production and farm income (Mohan 2006). Chandio et al.
497 (2021) found that agriculture credit has a positive and significant impact on rice production in
498 Nepal. Baig et al. (2020) state that fertiliser positively influenced rice production in India. Due to
499 might be the reason that fertiliser enhances soil fertility and nutrition, which create a considerable
500 positive impact on rice production (Janjua et al. 2014). Chandio et al. (2021) stated that the area
501 under crop positively impacts rice production in Turkey. The area under rice has the largest share
502 in India, which positively contribute to rice production. The negative and significant ECT value
503 shows that all the variables move towards long-run stability at a medium annual speed of
504 adjustment of 70.97 per cent.
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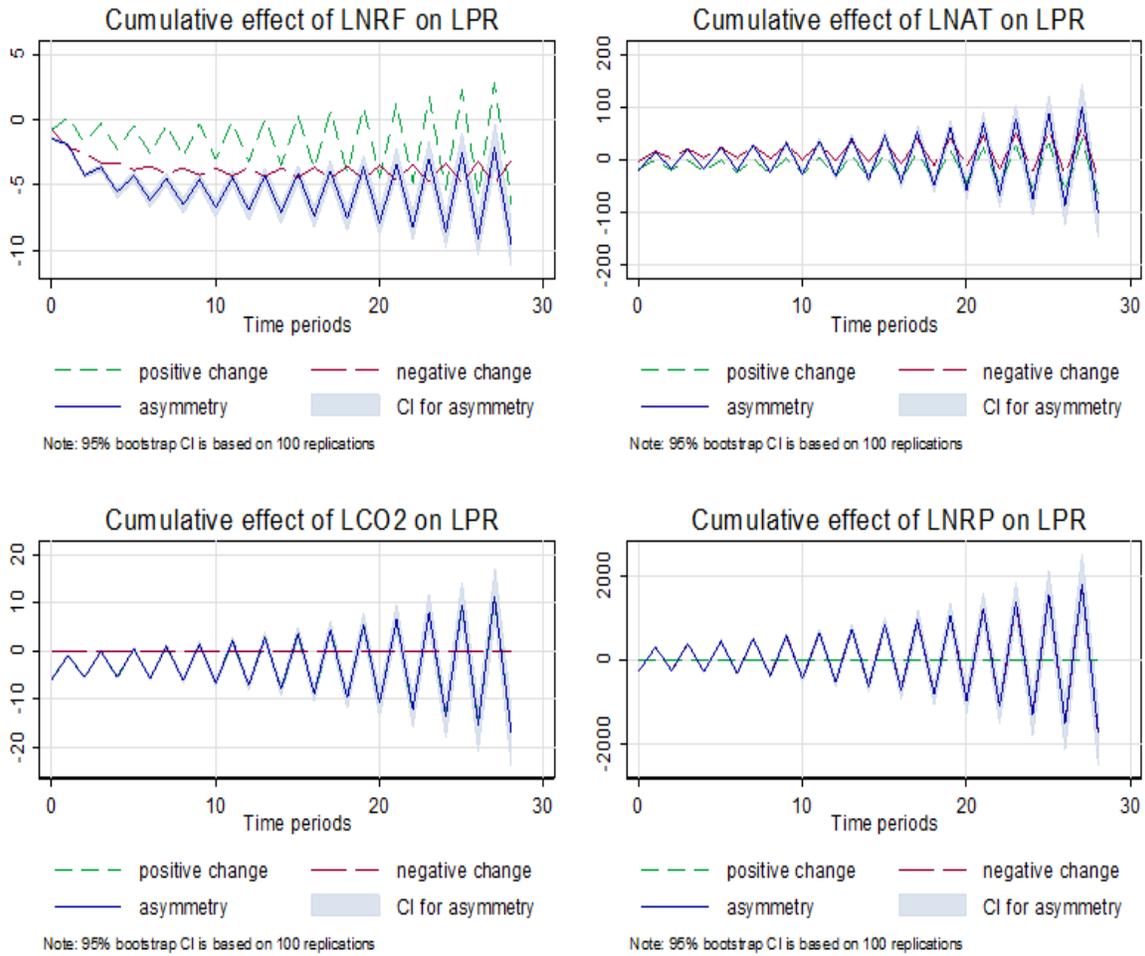
Table 8. Cointegration Result (Dependent Variable: LNPR)

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
lnCO ₂ ⁺	-1.956***	0.93	0.002
lnCO ₂ ⁻	0.421	0.004	0.581
RP ⁺	0.492	0.3	0.172
RP ⁻	-0.396***	0.139	0.001
ΔlnPR	-0.727***	0.042	0.003
ΔlnAT ⁺	17.23***	0.661	0.001
ΔlnAT ⁻	2.610**	0.447	0.028
ΔlnAT ⁻ (-1)	-4.75***	0.43	0.008
ΔlnRF ⁺	-0.745***	0.052	0.006
ΔlnRF ⁺ (-1)	1.114***	0.585	0.003
ΔlnRF ⁻	0.647***	0.052	0.007
ΔlnRF ⁻ (-1)	-0.523**	0.063	0.014
ΔlnCO ₂ ⁺	-6.163***	0.301	0.002
ΔlnCO ₂ ⁻	1.690	0.165	0.091
ΔRP ⁺	-0.504	0.30	0.142
ΔRP ⁻	1.827***	0.084	0.002

$\Delta RP^- (-1)$	-0.642**	0.092	0.02
$\ln F$	0.709***	0.043	0.004
$\ln AC$	0.0458***	0.002	0.004
$\ln AUR$	2.349***	0.166	0.005
$ECT(-1)$	-0.7097***		
R-squared	0.99		
Adj-R ²	0.98		
<hr/>			15.05**
$L_{\ln AT^+}$	-13.64***	$L_{\ln AT^-}$	*
$L_{\ln RF^+}$	-1.81**	$L_{\ln RF^-}$	-4.18***
			0.002**
$L_{\ln CO2^+}$	-2.85***	$L_{\ln CO2^-}$	*
L_{RP^+}	0.001***	L_{RP^-}	0.57***
<hr/>			153.5**
$W_{LR, \ln AT}$	3.925***	$W_{SR, \ln AT}$	*
$W_{LR, \ln RF}$	53.33***	$W_{SR, \ln RF}$	8.95***
			329.4**
$W_{LR, \ln CO2}$	57.81***	$W_{SR, \ln CO2}$	*
			575.5**
$W_{LR, RP}$	58.59***	$W_{SR, RP}$	*
		288.00**	
F_{PSS}		*	
T_{BDM}		-8.47***	

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

506
507 Finally, we performed several dynamic adjustments, the results of which are given in Figure 4,
508 which depicts the cumulative dynamic multipliers. These multipliers depict the pattern of rice
509 production adjustment toward its new long-term equilibrium as a result of a negative or positive
510 unitary shock in rainfall, mean temperature, carbon emissions, and rural population, respectively.
511 The dynamic multipliers are computed using the AIC's best-fit NARDL model. A particular
512 prediction horizon's rice production adjustment to positive (green line) and negative (red line)
513 shocks is captured by the positive and negative curves. As seen in the graph, the asymmetric curve
514 (dashed red line) represents the difference between the dynamic multipliers for positive and
515 negative shocks, respectively. There is a 95 percent confidence interval between the lower and
516 upper bands (dotted red lines) of this curve.



517

518

Figure 4: Dynamic Multiplier Adjustment Graph

519

520 Figure 4 confirms a negative association between rainfall and rice output. A negative shock in
 521 rainfall outperforms a positive shock over the horizon. There is also a large asymmetric reaction
 522 to rainfall shocks. As with mean temperature, rice production is negatively correlated. This
 523 confirms the results in Table 8 that a negative shock in mean temperature dominates a positive
 524 shock in the long term. Furthermore, positive carbon emission shocks must outweigh beneficial
 525 effects on rice production for there to be a negative correlation. However, a negative shock in rural
 526 areas outweighs a positive one. Table 9 displays the results of different diagnostic tests used to
 527 assess the model's reliability (normality, autocorrelation, heteroscedasticity, and Ramsey RESET
 528 model). The NARDL model does not suffer from any diagnostic problem. CUSUM and

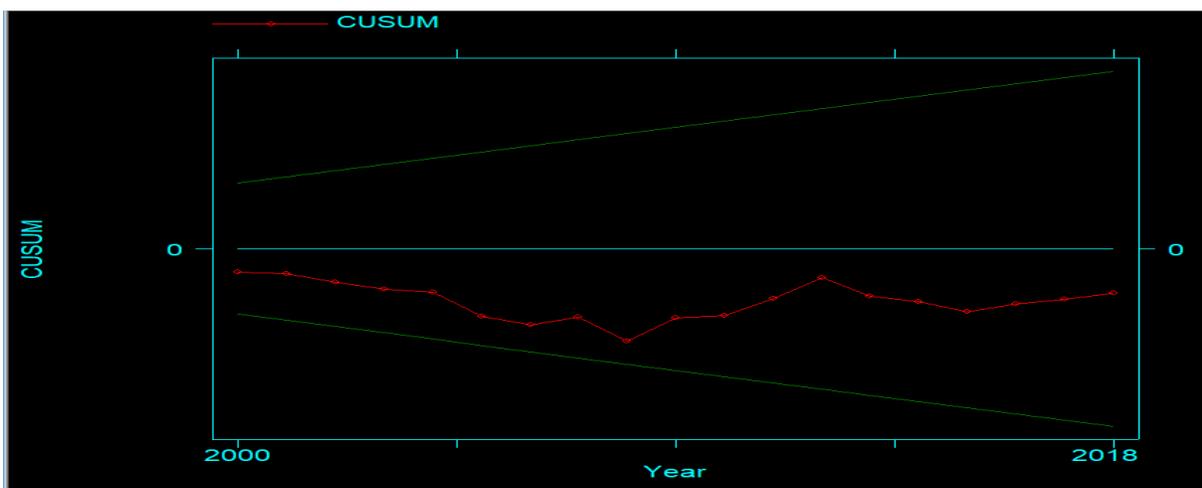
529 CUSUMQ tests were used to assess model stability. In Fig. 5 (A & B), the predicted line is within
 530 the crucial values at the 5% level of significance, indicating the model is highly stable.

531

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

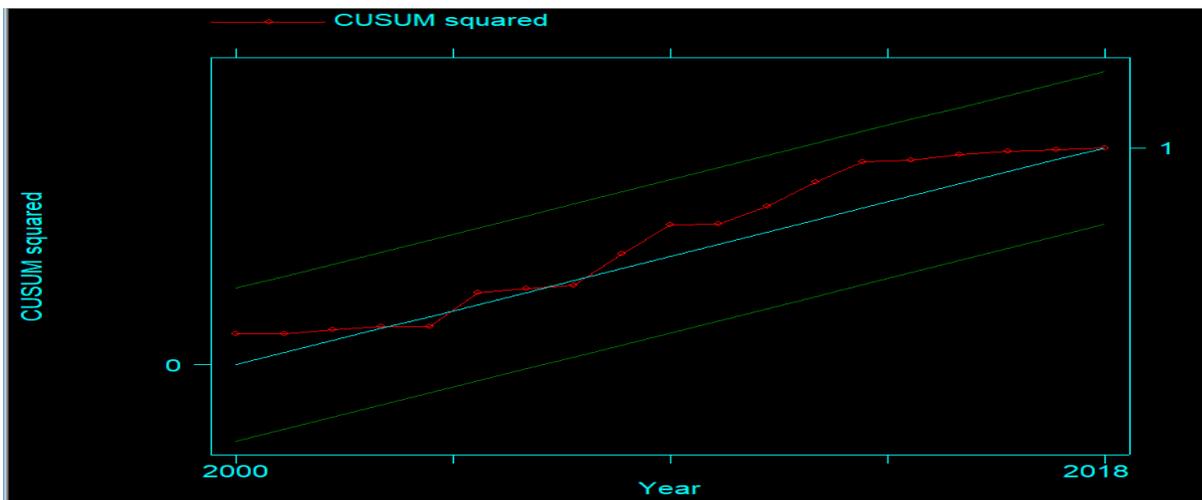


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Fig. 5 (A) Stability Model (CUSUM)

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Fig. 5 (B) Stability Model (CUSUMSQ)

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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 $\text{LnRF}^+ \Leftrightarrow \text{LnRF}^-$, $\text{LnRF}^+ \Leftrightarrow \text{LnAT}^+$, $\text{LnRF}^+ \Leftrightarrow \text{ICO2}^+$, $\text{LnRF}^+ \Leftrightarrow \text{ICO2}^-$, $\text{LnRF}^- \Leftrightarrow \text{LnAT}^+$, $\text{LnRF}^- \Leftrightarrow \text{ICO2}^+$, $\text{LnRF}^- \Leftrightarrow \text{ICO2}^-$, $\text{LnRF}^- \Leftrightarrow \text{RP}^+$, $\text{LnRF}^- \Leftrightarrow \text{RP}^-$, $\text{LnRF}^- \Leftrightarrow \text{LnF}$, $\text{LnRF}^- \Leftrightarrow \text{LnAC}$, and $\text{LnRF}^- \Leftrightarrow \text{LAUR}$. While unidirectional causality running from positive and negative shock in rural population, agricultural credit to increasing rainfall. Furthermore, two-way directional causality

567 running between $\ln AT^+ \Leftrightarrow \ln AT^-$, $\ln AT^+ \Leftrightarrow \ln CO_2^+$, $\ln AT^+ \Leftrightarrow \ln RP^-$, $\ln AT^+ \Leftrightarrow \ln AC$,
568 $\ln AT^+ \Leftrightarrow \ln LAUR$, $\ln AT^- \Leftrightarrow \ln CO_2^+$, $\ln AT^- \Leftrightarrow \ln CO_2^-$, and $\ln AT^- \Leftrightarrow \ln LAUR$. This findings is
569 consistent with (Warsame et al. 2021), who stated that area under crop has positively influenced
570 mean temperature in the atmosphere. Likewise, one-way causality running from increasing and
571 decreasing temperature to increasing rural population, which indicates that increasing and
572 decreasing temperature will positively influenced rural population. Furthermore, there is also
573 evidence that decreasing temperature ($\ln AT^-$) will increase fertilizer consumption ($\ln F$) and
574 agricultural credit ($\ln AC$).

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

582 However, evidence shows that causality runs from increasing and decreasing carbon emissions
583 towards fertiliser consumption and agricultural credit at the 1 per cent level of significance. The
584 outcome indicates that increasing and decreasing carbon emissions has influenced fertiliser
585 consumption. The causal relationship between agricultural credit and decreasing carbon emission
586 demonstrates that unidirectional causality running from agricultural credit towards decreasing
587 carbon emission at 5 levels of significance, which indicates that increasing agricultural credit leads
588 to increase environmental quality in the atmosphere. Asymmetrical causality exists between
589 increasing carbon emission and area under crop, which suggests that increasing carbon emission
590 leads to the increasing area under crop and vice-versa. Unidirectional asymmetrical causality also
591 running from decreasing carbon emission towards the area under crop at the 1 level of significance.
592

Table 10 :Result of Granger Causality Test

			F-Statistics	Prob.	Result
$\ln RF^+$	$\neq >$	$\ln PR$	5.306	0.070	Rejected
$\ln PR$	$\neq >$	$\ln RF^+$	2.465	0.292	Accepted

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

lnAT ⁺	≠ >	lnAT ⁻	157.740	0.000	Rejected
lnAT ⁻	≠ >	lnAT ⁺	38.469	0.000	Rejected
lnAT ⁺	≠ >	lnCO ₂ ⁺	51.393	0.000	Rejected
lnCO ₂ ⁺	≠ >	lnAT ⁺	17.843	0.000	Rejected
lnAT ⁺	≠ >	lnCO ₂ ⁻	25.452	0.124	Accepted
lnCO ₂ ⁻	≠ >	lnAT ⁺	12.687	0.541	Accepted
lnAT ⁻	≠ >	lnCO ₂ ⁺	22.442	0.000	Rejected
lnCO ₂ ⁺	≠ >	lnAT ⁻	19.493	0.000	Rejected
lnAT ⁻	≠ >	lnCO ₂ ⁻	31.258	0.009	Rejected
lnCO ₂ ⁻	≠ >	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

lnAUR	≠ >	lnAT ⁻	174.970	0.000	Rejected
lnCO2 ⁺	≠ >	lnCO2 ⁻	87.925	0.000	Rejected
lnCO2 ⁻	≠ >	lnCO2 ⁺	60.874	0.001	Rejected
lnCO2 ⁺	≠ >	RP ⁺	12.547	0.124	Accepted
RP ⁺	≠ >	lnCO2 ⁺	24.571	0.002	Rejected
lnCO2 ⁻	≠ >	RP ⁺	92.478	0.004	Rejected
RP ⁺	≠ >	lnCO2 ⁻	34.142	0.110	Accepted
lnCO2 ⁺	≠ >	lnF	25.990	0.000	Rejected
lnF	≠ >	lnCO2 ⁺	2.456	0.293	Accepted
lnCO2 ⁻	≠ >	lnF	15.412	0.003	Rejected
lnF	≠ >	lnCO2 ⁻	43.258	0.150	Accepted
lnCO2 ⁺	≠ >	lnAC	22.286	0.000	Rejected
lnAC	≠ >	lnCO2 ⁺	2.841	0.242	Accepted
lnCO2 ⁻	≠ >	lnAC	75.142	0.145	Accepted
lnAC	≠ >	lnCO2 ⁻	25.197	0.051	Rejected
lnCO2 ⁺	≠ >	lnAUR	7.234	0.027	Rejected
lnAUR	≠ >	lnCO2 ⁺	159.890	0.000	Rejected
lnCO2 ⁻	≠ >	lnAUR	14.589	0.156	Accepted
lnAUR	≠ >	lnCO2 ⁻	102.741	0.187	Accepted
RP ⁺	≠ >	RP ⁻	99.457	0.007	Rejected
RP ⁻	≠ >	RP ⁺	24.175	0.001	Rejected
RP ⁺	≠ >	lnF	12.871	0.000	Rejected
lnF	≠ >	RP ⁺	48.545	0.841	Accepted
RP ⁻	≠ >	lnF	21.506	0.000	Rejected
lnF	≠ >	RP ⁻	6.664	0.036	Rejected
RP ⁺	≠ >	lnAC	56.471	0.090	Rejected
lnAC	≠ >	RP ⁺	102.587	0.005	Rejected

RP ⁻	≠ >	lnAC	12.421	0.002	Rejected
lnAC	≠ >	RP ⁻	19.815	0.000	Rejected
RP ⁺	≠ >	lnAUR	21.457	0.142	Accepted
lnAUR	≠ >	RP ⁺	8.547	0.751	Accepted
RP ⁻	≠ >	lnAUR	0.031	0.985	Accepted
lnAUR	≠ >	RP ⁻	84.564	0.000	Rejected
lnF	≠ >	lnAC	7.670	0.022	Rejected
lnAC	≠ >	lnF	6.376	0.041	Rejected
lnF	≠ >	lnAUR	10.500	0.005	Rejected
lnAUR	≠ >	lnF	81.095	0.000	Rejected
lnAC	≠ >	lnAUR	18.191	0.000	Rejected
lnAUR	≠ >	lnAC	75.941	0.000	Rejected

≠ > indicates that there is no causality running from x to y,

593

594 **5. Conclusion and Policy Implications**

595 In India, the rice crop has a crucial role in agricultural growth and food security. Rice is a staple
596 food for India's people; more than 50 per cent population consumed rice crops once a day. Rice
597 crop has widely grown, followed by the wheat, coarse cereals and pulse in India. This study's
598 primary purpose is to investigate the asymmetrical relationship and granger causality between
599 climate change and rice production through nonlinear ARDL using time series data spanning from
600 1991-2018 in India. The outcomes confirm the presence of asymmetric relationships among
601 selected variables in the short and long run.

602 The findings reveal that increasing and decreasing temperature influenced rice production
603 adversely in the long run while positively affected in the short run by different magnitude.
604 However, excess rainfall has adversely affected rice production, while a decrease in rainfall has
605 no evidence of an adverse effect on rice production in the long and short run. Furthermore, in the
606 long and short run, increased carbon emission levels in the atmosphere had impeded rice
607 production. In contrast, decrease carbon emissions had no adverse impact on rice production. In
608 the long and short run, positive shock in the rural population has positively affected rice

609 production, while negative shock has adversely affected rice production. The estimated outcome
610 indicates that other controlled variables such as fertiliser consumption, agricultural credit, and area
611 under crop have positively affected rice production in India.

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

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

634 **Authors' contributions**

635 **Imran Ali Baig:** Conceptualization, Data curation, Formal analysis, Writing – original draft

636 **Abbas Ali Chandio:** Supervision

637 **Ilhan Ozturk:** Editing and Validation, Supervision

638 **Pushp Kumar:** Methodology, Investigation, Formal analysis

639 **Zeeshan Anis Khan and Md. Abdus Salam:** Review, Editing and made suggestions

640 **Data availability**

641 Data will be made available upon request

642 **Conflict of interest**

643 We do not have any conflict of interest.

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648 **Consent to Participate**

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650 **Consent to Publish**

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