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An assessment of Climate change and Crop Productivity in India: A Multivariate Cointegration Framework

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Abstract:
This paper assess the dynamic relationship between climate change and productivity of four crops, including wheat, rice, coarse cereal and pulse during the period over 1990-2017 in India. To explore relationship between the underlying variables, we adopt the Autoregressive distributed lag (ARDL) bounds cointegration approach.
The empirical results indicate that long-run relationship between climate change and productivity of underlying crops in India. The outcome reveals that maximum temperature has positive and significant impact on the productivity of underlying crops except for wheat productivity in Indian agriculture. At the same time, minimum temperature has positive and significant impact on the yield of coarse cereal and pulse. Moreover, mean temperature has a significant positive impact on the yield of wheat and coarse cereal, but it has negative impact on rice productivity. In contrast, rainfall has a negative and significant impact on coarse cereal and pulse productivity but positive effect on Wheat productivity. On the contrary, Co2 has a significant positive impact on wheat and pulse productivity in the long run. Thus, empirical evidence indicates that fertiliser and rainfall would adjust any negative shock to agriculture productivity in Indian agriculture.

Keywords: *Climate Change, Agriculture Productivity, Rice, Wheat, Coarse Cereals, Pulse, ARDL, India.*

I. Introduction:

Impact of Climate change on agriculture productivity has attracted the primary concern of researchers across the globe. Climate change is primarily result of human activities, including increasing urbanisation, deforestation, land use, production and consumption phenomena in the country. The gradual increase in temperature is due to the higher in the concentration of carbon emission in the atmosphere, mainly caused by high production activities by developed countries. However, increase in temperature, variation in rainfall and frequent occurrence floods & droughts are mostly faced by the developing nation, which is situated in the tropical region and relies heavily on agriculture sector (Janjua et al., 2014). The agriculture and its allied sector is considered as the most susceptible to climate change. Agriculture production would be encountered by climate change through different ways such as variation in rainfall, increasing temperature, availability of water etc. Variation in climate is primary source of agriculture risk and food system.

Impact of climate change may vary region to region based on the geographical location. In case of a developed nation, climate change has a positive impact on agriculture productivity while it deteriorates the performance of agriculture sector in the developing countries (Abbas, 2020; Janjua et al., 2014; P. K. Nath & Behera, 2011). The climate change has directly affected the agriculture productivity in developing countries through the changes in temperature, variation in rainfall and precipitation. The developing nations are more vulnerable compared to the developed nations due to larger dependence on agriculture sector for livelihood, lack of technological advancement and adverse effect of climate change on agriculture production (Praveen & Sharma, 2020).

The Indian agriculture sector is most sensitive and exposed areas to climate change due to less adaptive capacity to cope with it (Guntukula, 2019). Investigating the impact of climate change on agriculture productivity is of immense importance because more than 50 % population of India primarily depends on agricultural activities for their livelihoods (Pattanayak & Kumar, 2013). As the changes in climatic factors directly affect agriculture productivity, so it is indispensable to examine the effect of changes in climatic conditions on agriculture productivity. However, objectives of this study are to explore the short and long-run dynamic relationship between agriculture productivity (rice, wheat, coarse cereal and Pulse), climate variables (Maximum Temperature, Minimum Temperature, Mean Temperature, Rainfall, Co2 and fertiliser) in India.

The rest of the paper are frame in a such manner in which section 2 discusses the existing literature and distinct types of approaches to measure the impact of climate change on agricultural productivity. Section 3 mentions the data and methodology. Empirical result and discussion are presented in section 4, and in the last section 5 provides the conclusion and policy implication.

II. Literature Review:

Since the last three decades, numerous studies have been done on the major issue of climate change and its impact on agriculture growth and production across the globe. Among previous studies outside of India, Attiaoui & Boufateh (2019) explore the long-run and short-run dynamic relationship between the cereal production and climate variables viz. temperature and rainfall using panel ARDL and granger causality test in Tunisia. The empirical results reveal that due to the shortage of rainfall, climate change negatively affects cereal production, whereas an increase in temperature has positive impact on cereal production in Tunisia.

Chandio *et al.* (2020) explain that Co2 emission has a positive impact on agriculture production in China. In contrast, rainfall and the rising temperature have a significant negative impact on agriculture production in the long run. While in the case of turkey, Chandio *et al*. (2020) state that Co2 emission and temperature has negative but insignificant effect on cereal production. While annual average rainfall has a significant positive impact on cereal production in the short and long run.

Janjua *et al.* (2014) highlight the impact of carbon emission and climate change on the wheat productivity using the ARDL bound testing

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cointegration approach in Pakistan. The empirical evidence indicates that carbon emission has positive impact on wheat productivity. Furthermore, other factors such as precipitation, water and temperature has insignificant impacts. Similarly, Abbas (2020) explores the relationship between climate change and yield of cotton using time series data from 1980 to 2018 in Pakistan. The empirical outcome revels that change in temperature has an insignificant positive impact on cotton production in the short and long run, whereas area and fertiliser have a significant positive impact on yield of cotton in Pakistan.

Rashid *et al*. (2012) examine the long-run relationship between the productivity of three crops of rice and climate change in Bangladesh using the ordinary least square and median regression method. The result indicates that maximum temperature has a significant positive impact on the productivity of Aman and Aus rice but a negative effect on the productivity of Boro rice. While the minimum temperature has positive and significant impact on Boro rice while a negative effect on yield Aman rice.

Numerous studies also has been done in the context of India on climate change and its impact on agriculture growth and food security. Among previous studies, Rao *et al*. (2015) state that minimum temperature has increased at a faster rate than the maximum temperature in wheat-growing areas in India. In the post-anthesis period, the yield of wheat is more sensitive to the minimum temperature in India. From 1980 to 2011, wheat yield declined by 7 % for a 1-degree centigrade rise in minimum temperature. In contrast, Guiteras (2009) explains that major crop yield would harmfully be affected by 4.5 to 9 % due to climate variation from 2010 to 2039 in India. In the same order, in the absence of adaptation productivity of crop would reduce up to 25 %.

Praveen & Sharma (2020) assess the impact of climate variability on agriculture growth for major 15 crops using multiple regression analysis in India. The outcome indicates that insignificant impact of mean temperature and rainfall on the production of linseed, groundnut, arhar, wheat and cotton while two crops namely tea and ragi show positive and significant impact of rainfall and temperature on their productivities in India.

In contrast, Guntukula (2019) assess the impact of climate change on seven major crops in India. The result reveals that rainfall, minimum and maximum temperature has a significant impact on the yield of major crops. However the average maximum temperature has positive impact on food and non-food crops, excluding rice. While minimum temperature has an only positive impact on food crops, but it has a negative association with non-food crops. In comparison, Arora *et al*. (2019) explain that maximum temperature and low rainfall have adversely affected the production of rice and wheat in India. On the other hand side, the increasing temperature has a positive and significant impact on the productivity of commercial crops in India.

Mainly three major methods to analyse the effect of climate change on agriculture productivity. These are (a) crop modelling approach (biophysical) that is also called as a production function approach, (b) Ricardian approach or hedonic approach and (c) econometric approach (Time series and Panel data approach).

Some previous studies including Lal *et al*. (1998); Pathak *et al*. (2003); Gupta *et al*. (2012) and Mukherjee & Huda (2018) use the crop modelling approach. In contrast, Kumar & Parikh (2001); Sanghi & Mendelsohn (2008); Kumar (2011) and Mishra & Chandra (2016) use the Ricardian framework in the context of India.

On the other hand side, Guiteras (2009) ; Kumar *et al*. (2011); Birthal *et al*. (2014); Kumar *et al*. (2015); Singh *et al*. (2017) and Nath & Mandal (2018) use panel data in the context of India. Thus, few studies have been done using time series modelling, including

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Moorthy *et al*. (2012); Bhanumurthy & Kumar (2018) and Pal & Mitra (2018).

To the best of the author's knowledge, this is the first study to investigate the dynamic impact of climate change on yields of four crops viz. wheat, rice, cereal and pulse using the cointegration approach in India. This study highlights the issues of climate change in the perspective of agriculture productivity which gives direction to framing the crops specific environmental policy regarding climate change and the agriculture productivity in India.

III. Data and Methodology:

Data: Time series data spanning from 1991 to 2017, has been collected from various source. Table 1 shows the description and sources of the data of variables viz. yield of food grain crop-wise (rice, wheat, coarse cereal and pulse) as a dependent variable and climate variable are annual average maximum temperature, minimum temperature, mean temperature in Celsius degree, Rainfall, Co2 and fertiliser as explanatory variables.

Table-1: Description of the Variables

Variables	Notations	Description of Variables	Sources
Yield of Food Grain (Crops wise)	R/W/CC/P	Kg/hc	Directorate of Economics & Statistics
Maximum Temperature	MAXTEMP	Degree Celsius (centigrade)	Meteorological Department of India
Minimum Temperature	MINTEMP	Degree Celsius (centigrade)	do
Mean Temperature	MEANTEMP	Degree Celsius (centigrade)	do
Rainfall	Rainfall	Annual Average Rainfall (mm)	do
Co2 emission	Co2	Million Ton	World Bank Indicator
Fertilizer	Fert	Kg/hc	Directorate of Economics & Statistics

Sources: Calculated by Author, Notes: R/W/CC/P indicate Rice/Wheat/Coarse Cereal/Pulse

ARDL Bound Test for Cointegration: This study employs the ARDL bound testing cointegration method to investigate the short and long-run dynamic relationship between variables viz. productivity of food grain crops and climate variables. ARDL cointegration techniques used to overcome those problems arises in the other cointegration models. There are several advantages of ARDL Model compared to other cointegration models such as Engel and Granger (Engel and Granger, 1987) and Johansen & Julius methods (Johansen & Juselius, 1990). Firstly, the ARDL model applicable in any situation either variable is integrated at '0' or '1' level and also at fractionally integrated. Second advantages, it gives the unbiased and efficient result if the sample size is small and finite. A third important advantage of this model in choosing the appropriate number of lags for the empirical analysis.

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

$$Y_t = f(Maxtemp_t, Mintemp_t, Meantemp_t, Rainfall_t, Co2_t, Fert_t) \quad (1)$$

In the above equation Y_t indicates Yields of food grains (Rice, Wheat, Cereal Coarse, pulse) in kilogram per hectare and Maxtemp represents average annual maximum temperature, Mintemp represents minimum temperature, Meantemp indicates mean temperature, Rainfall, Co2, and Fert indicate fertiliser. Equation.1 can also be written as:

$$Y_t = \alpha_0 + \alpha_1 Maxtemp_t + \alpha_2 Mintemp_t + \alpha_3 Meantemp_t + \alpha_4 Rainfall_t + \alpha_5 Co_{2t} + \alpha_6 Fert_t + U_t \quad (2)$$

The ARDL equation used in this study is given below.

$$\begin{aligned}\Delta lnY_t = \alpha_0 &+ \sum_{j=1}^{j=p} \alpha_{1i}\,\Delta\text{lnMaxtemp}_{t-1} + \sum_{j=1}^{j=p} \alpha_{2i}\,\Delta\text{lnMintemp}_{t-1} + \sum_{j=1}^{j=p} \alpha_{3i}\,\Delta\text{lnMeantemp}_{t-1} \\ &+ \sum_{j=1}^{j=p} \alpha_{4i}\,\Delta\text{lnCo2}_{t-1} + \sum_{j=1}^{j=p} \alpha_{5i}\,\Delta ln\text{Fert}_{t-1} + \sum_{j=1}^{j=p} \alpha_{5i}\,\Delta\text{lnRainfall}_{t-1} + \sum_{j=1}^{j=p} \alpha_{5i}\,\Delta lnY_{i(t-1)} \\ &+ \theta_1\text{lnMaxtemp}_{t-1} + \theta_2\text{lnMintemp}_{t-1} + \theta_3\text{lnMeantemp}_{t-1} + \theta_4\text{lnCo2}_{t-1} \\ &+ \theta_5\text{lnFert}_{t-1} + \theta_5\text{lnRainfall}_{t-1} + \theta_7 lnY_{(t-1)} + \delta ECT_{(-1)} + U_t \qquad (3)\end{aligned}$$

In equation (3), Δ shows first difference and coefficients of differenced lagged values ($\alpha_{1i}, \alpha_{2i}\ \alpha_{3i}, \alpha_{4i}, \alpha_{5i}\ \alpha_{6i}\ and\ \alpha_{7i}$) are short-run coefficients, and coefficients of lagged values ($\theta_1, \theta_2, \theta_3, \theta_4, \theta_{5,}\theta_6\ and\ \theta_7$) are long-run coefficients. Akaike and Schwarz information criteria have been used to find out the optimal lag selection in the model. The null hypothesis "there is no cointegration," i.e. H_o: $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = 0$ is checked against the alternatives hypothesis, i.e. H_1:$\theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq \theta_6 \neq \theta_7 \neq 0$. Null hypotheses have been tested by computing the general F-statistics or Wald test statistics and by comparing them with the two critical bounds values (Lower and upper bound), that provide a band covering all possible classifications of the regressors into purely I (0), I (1) or mutually co-integrated. The decision rule is, 1) if the value of F-statistics falls beyond the upper bound, we reject the null hypothesis of no cointegration, 2) if the value of F-statistics falls below the lower bound, the null hypothesis is not rejected, and 3) if the value falls within the lower and upper bound, results are inconclusive (Pesaran.et.al., 2001; Pesaran & Shin, 2002). Rejection of null hypothesis implies that the long-run relationship exists and we proceed towards the Error Correction Term (ECT) which is given in the same equation by (δECT_{-1}), where δ is the speed of adjustment in the process to restore equilibrium following a disturbance in the long-run equilibrium relationship. A negative and significant coefficient of ECT explains how quickly variables return to equilibrium. The adequacy and stability of the specified ARDL models are also checked with various Diagnostic tests.

IV. Empirical Result and Discussion:

Descriptive Statistics:

Descriptive statistics are shown in table 2 that indicates that all variables are approximately normally distributed except pulse, maximum and minimum temperature. Pulse is highly positive skewed followed maximum temperature, Co2 and fertiliser, and others are moderate positive skewed except mean temperature, which is negatively skewed of distribution.

Table 2: Descriptive Statistics

Variables	Rice	Wheat	Coarse Cereals	Pulse	Maxtemp	Mintemp	Meantemp	Rainfall	Co2	Fert
Mean	912.63	765.37	356.76	152.23	30.83	20.56	25.61	1141.49	1202.86	106.53
Median	896.80	727.70	340.70	142.40	30.84	20.54	25.68	1133.00	1022.32	98.91
S.D.	118.47	130.45	58.36	33.58	0.37	0.20	1.72	92.37	518.63	29.66
Kurtosis	-1.03	-0.96	-1.01	2.74	2.44	-0.71	4.48	-0.72	-1.11	-0.12
Skewness	0.14	0.34	0.19	1.58	0.96	0.19	-0.31	0.05	0.57	0.54
J-B(Pro)	0.511	0.448	0.501	0.001	0.026	0.001	0.648	0.690	0.254	0.529

Sources: Calculated by Authors

The result of the correlation analysis is presented in Table 3. The result indicates a weak and moderate association among the explanatory variables except between Co2 and fertiliser.

Table 3: Result of Correlation Analysis

Variables	MAXTEMP	MINTEMP	MEANTEMP	Rainfall	Co2	Fertiliser
MAXTEMP	1.00					
MINTEMP	-0.05	1.00				
MEANTEMP	0.07	0.15	1.00			
Rainfall	-0.31***	0.24	-0.03	1.00		
Co2	0.54*	0.22	0.13	-0.38*	1.00	
Fertlizer	0.47*	0.15	0.16		0.90*	1.00

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

Unit Root Test: Phillips-Perron and Augmented Dicky fuller test are used to check the stationarity of the variable. Because the ARDL model gives a spurious result at integration of order 2. The result of the stationarity of underlying variables shown in table 4.

Table 4 reveals that all the variables are stationary at levels except wheat, pulse and Co2; these variables are stationary after first difference. Results explain that rice, wheat, Coarse Cereal, pulse Mean temperature, rainfall is stationary at 1 % level of significance. While foodgrain, Co2, Maximum temperature and minimum temperature are stationary at 5 % and 10 % level of significance respectively. None of the variables is integrated of order 2 in this study that corroborates ARDL bound testing. In this order, it is best to use the ARDL model to investigate the short and long-run relationship among the variables in this study.

Table 4: Unit Root Test

	I(0)		I(1)	
Variables	ADF	PP	ADF	PP
Rice	-4.99*	-5.01*	-9.54*	-13.46*

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Wheat	-2.18	-2.92	-7.14*	-7.14*
Coarse Cereal	-5.47*	-5.47*	-6.45*	-20.42*
Pulse	-1.81	-1.71	-6.58*	-7.89*
Maxtemp	-3.54***	-3.49***	-8.01*	-8.30*
Mintemp	-4.53***	-3.41***	-2.25	-6.86*
Meantemp	-6.29*	-5.57*	-5.95*	-9.46*
Rainfall	-5.54*	-5.64*	-8.55*	-24.55*
Co2	-1.9	-2.92	-1.26	-5.10*
Fertiliser	-4.30**	-4.30**	-7.63*	-17.23*

Source: Calculated by Authors, Notes: Asterisks '*s' indicate the same as in Table 2.

Autoregressive Distributed Lag (ARDL) Bound Testing of Cointegration: Table 5 represents the results of the ARDL bound test of each crop of underlying variables. F-statistics and selected model of each corresponding dependent variables are also shown in Table 5. The appropriate lags of the crop-wise specific ARDL model are chosen by the Akaike information and Schwarz information criteria.

Table 5, Result of ARDL bound test (Part-A)

Dependent Variable	Slected Model	F-statistics
Rice	ARDL (1, 1, 2, 0, 0, 0, 2)	10.32*
Wheat	ARDL (2, 2, 1, 2, 1, 0, 2)	6.27*
Coarse Cereals	ARDL(2,2,2,1,2,2,0)	15.23*
Pulse	ARDL (1, 0, 2, 0, 2, 2, 2)	5.73*

PART -B

Level of Significance		Critical Bound Values	
		I (0)	I (1)
10%	→	1.99	2.94
5%	→	2.27	3.28
2.50%	→	2.55	3.61
1%	→	2.88	3.99

Sources: Calculated by Author

Notes: Table 5, divided into two parts i.e. upper and lower. Upper part showed F-statistics of each model crop wise and lower part represent critical bound value at different level of significance. F-statistics of each model comparing to the critical bound value i.e. I (0) or I (1) at different level of significance. The (*) marks shows 1 % level of significance

Rice: Table 5 presents the results of the ARDL Bounds Testing Framework. Firstly, we elaborate the result of ARDL bound test in which rice is dependent variable and maximum temperature, minimum temperature, mean temperature, annual average rainfall, Co2 and fertiliser are used as explanatory variables. Akaike and Schwarz information criteria are used to choose the appropriate lags of each specific models. Table 5 represent F- Statistics is 10.32 is greater than critical upper bound (Narayan, 2005) rejecting the null hypothesis which indicates there is a long-run relationship between the underlying variables, viz. yield of rice and climate change variables (maximum temperature, minimum temperature, mean temperature, rainfall, Co2 and fertiliser) at 1 % level of significance.

Table 6 presents the dynamic result of the error correction model. The value of the coefficient of ECT is negative and significant at 1 % level. We can infer from the result that the value of ECT necessitates that change in yield of rice from shorter to longer span of time is corrected by almost 96 % in each year. Evidence shows that any negative shock to rice productivity would be adjusted by the fertiliser in the short run.

The results shown in table 6, reveal that impact of climate variable viz. an annual average of maximum temperature, minimum temperature, mean temperature, rainfall, Co2 and fertiliser on crop productivity of rice. The empirical results indicate that maximum temperature has positive and significant impact on rice productivity in the long run, this result supported by Guntukula (2019) and Singh & Sharma (2018) who explained that maximum temperature has significant positive impact on the yield of rice in Indian agriculture. Whereas, another study conducted by Arora *et al*. (2019) contradict this result and explained that maximum temperature had negatively affected the productivity of rice in the Indian context.

Furthermore, the result also indicated that there is no significant impact of minimum temperature on yield of rice in the short as well as long run. In contrast, mean temperature has a short-run negative impact on rice productivity at 1 % level of significance. The outcome of this study is similar to Mahmood *et al.* (2012), Amin *et al*. (2015) and Chandio.*et.al*. (2020) and these studies concluded that mean temperature has a significant and negative impact on rice productivity.

Moreover, the result indicates that coefficient of rainfall has a significant positive impact on rice productivity in the long run which is similar to the Rashid *et al.* (2012) who explain that impact of rainfall has a positive impact on the yield of rice in case of Bangladesh. Whereas this result contradicts in the case of India by Arora *et al.* (2019), who explained that rainfall has negatively affected the productivity of rice.

The outcome also shows that of Co2 has a positive impact on rice productivity but insignificant in the long run that is similar to the Janjua *et al.* (2013) who explain that Co2 does not play a significant role to affecting the rice productivity. Furthermore, fertiliser has shown short and long-run positive significant impact on the productivity of rice in Indian agriculture. The finding of this study supported by Chandio *et al.* (2020), Chandio *et al.* (2018), Rahman *et al.* (2018) & Janjua *et al.* (2013) explained that fertiliser plays an important role in enhancing soil fertility and nutrition, which create a considerable positive impact on rice production.

Wheat: Result of ARDL bound test are shown in Table 5. Here, we elaborate the result of ARDL bound test in which yield of wheat is dependent variable and explanatory variables are same for all dependent variables which are mentioned above. Table represent F- Statistics 6.27 is greater than the critical upper

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bound value "I (1)" rejecting the null hypothesis. It can be inferred that there is a significant long-run relationship among the variables at 1 % level of significance.

Table 6 present the dynamic result of the error correction model. The coefficient of ECT is negative and significant at 1 % level. Evidenced showed that any negative shock to wheat productivity would be adjusted by the fertiliser in the short run. This result is similar to the Janjua *et al.* (2013), who explained negative shock would be adjusted by the fertiliser and area.

Table 6 represents the result of the short and long-run impact of climate change on yield of wheat. The outcome of regression reveals that maximum temperature has shown significant negative impact in short as well as in the long run. This finding contradicts by Guntukula (2019) and who explained that maximum and minimum temperature has an insignificant negative impact on wheat productivity in Indian agriculture. Moreover, mean temperature has shown a positive statistically significant impact on the yield of wheat in the short-run and long-run at 1 % level (Table 6).

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Table 6, Result of ARDL bound co-integration model.

	Independent Variables														
Dependent Var.	MAXTEMP		MINTEMP		MEANTEMP		Rainfall		Co2		Fertiliser			Residual Diagnostic	
	SR	LR	SR	LR	SR	LR	SR	LR	SR	LR	SR	LR	Ect		
Rice	33.40	95.50**	-46.76	78.90	-132.90*	-6.00		0.48*		0.02	1.52*	3.14**	-0.96*	R2	0.94
ARDL(1,1,2,0,0,0,2)														Prob.(F)	0.000
Wheat	-60.24*	-109**	-13.11*	65.06	7.15(-1)*	12.14*	0.016	0.19		0.22**	-0.99*	0.95	-1.06*	R2	0.98
ARDL(2,2,1,2,1,0,2)														Prob. (F)	0.000
Corase Cerealse	103.01*	139.2*	-27.18**	135*	6.53*	0.28	0.23*	-0.12*	0.78*	0.03		-1.01**	-1.24*	R2	0.99
ARDL(2,2,2,1,2,2,0)														Prob. (F)	0.000
Pulse		27.2***	47.12*	130.49*		0.49	0.05*	-0.1***	0.23*	0.06**	-0.63*	-1.06**	-0.89*	R2	0.98
ARDL(1,0,2,0,2,2,2)														Prob. (F)	0.000

Sources: Calculated by the Author

Notes: SR, LR and Ect indicate short-run, long-run and error correction term respectivelyAsterisks '*s' indicate the same as in Table 2.

Table 7, Result of Diagnostic test of each specific ARDL Model

Dependent Variables	Specific ARDL Model	LM test (Prob.)	White Test (Prob.)	J-B Test (Prob)
Rice	ARDL (1, 1, 2, 0, 0, 0, 2)	0.69	0.88	0.36
Wheat	ARDL (2, 2, 1, 2, 1, 0, 2)	0.18	0.23	0.49
Coarse Cereal	ARDL (2, 2, 2, 1, 2, 2, 0)	0.66	0.82	0.99
Pulse	ARDL (1, 0, 2, 0, 2, 2, 2)	0.15	0.69	0.89

Sources: Calculated by Author

While CO_2 has shown only positive statistically significant impact in the long run at 5 % level. But the impact of rainfall has positive but insignificant that supported by the Guntukula (2019) and Praveen & Sharma (2019). Apart from, coefficients of fertiliser indicated that positive statistically significant impact on the yield of wheat, which is similar to the Singh & Sharma. (2018) in Indian agriculture.

Coarse Cereal: Table 5, indicates the result of ARDL bound test in which yield of coarse cereal is dependent variable and explanatory variables are the same for all dependent variables. Table 5 represents that F-statistics, i.e. 15.23, is larger than the critical upper bound value, which indicates that long-run relationship between the yield of coarse cereal and climate variables.

Result of error correction model present in Table 6, indicates that coefficient of ECT is negative and significant at 1 % level. From the result, we can infer that any negative shock to coarse cereal productivity will be adjusted by the temperature and rainfall in the short run. The table 6, reveals that coefficient of maximum temperature had shown a statistically significant positive impact on the yield of coarse cereal in short as well as in the long run at 1 % level of significance. Moreover, the minimum temperature has also a positive impact on the yield on coarse cereal at 5 % level of significance. In contrast, the only average of annual temperature shown positive impact in the long run at 1 % level of significance.

In the short-run, the coefficient of CO_2 emissions is positive, which is significant at 1 % level. This finding supports by Janjua *et al.* (2014), they explained that CO_2 has a positive impact on the production of wheat. Findings of this study contradict by the Alam (2013) and Amponsah *et al.* (2015), they explain that carbon emission has a negative impact on the productivity of coarse cereal.

The result infers that short-run and long-run coefficients of rainfall shown a positive and negative impact on the yield of coarse cereal at 1 % level of significance, respectively. This finding supports by previous empirical research such as Janjua *et al.* (2014); Zaied and Cheikh (2015) and Chandio *et al*. (2020), who explains that rainfall has a positive and significant impact on the agriculture productivity. Furthermore, the estimated long-run coefficient of fertiliser is significantly positive at 5 % level. The increase fertiliser leads to the yield of Coarse Cereal.

Pulse: Table 5 infers that result of ARDL bound test in which yield of the pulse is dependent variable and explanatory variables are the same for all dependent variables. Table 5 shows that the value of F- Statistics, i.e. 5.73 is greater than critical upper bound values at 1 % level of significance that is evidence of a long-run relationship among the variables.

Result of dynamic error correction model is present in Table 6. The coefficient of ECT is negative and significant at 1 % level. We can infer from the result that the value of ECT necessitates that change in pulse productivity from short to the long span of time is corrected by almost 89 % in each year. Evidenced shows that any negative shock to rice productivity will be adjusted by the rainfall and fertiliser in the short run.

Table 6 present the result of the short and long-run impact of climate change on pulse yield. The coefficient of maximum temperature indicates positive impact on the yield of the pulse with the 10 % level of significance in the long run. These findings supported by Guntukula (2019), Arora *et al.* (2019) and Kumar & Upadhayay (2019) they explained that maximum temperature positively affected yield of the pulse. While the impact of minimum temperature also shown a positive impact on pulse yield in short as well long run at 1 % level of significance. These findings are similar to the previous study such as Guntukula (2019)

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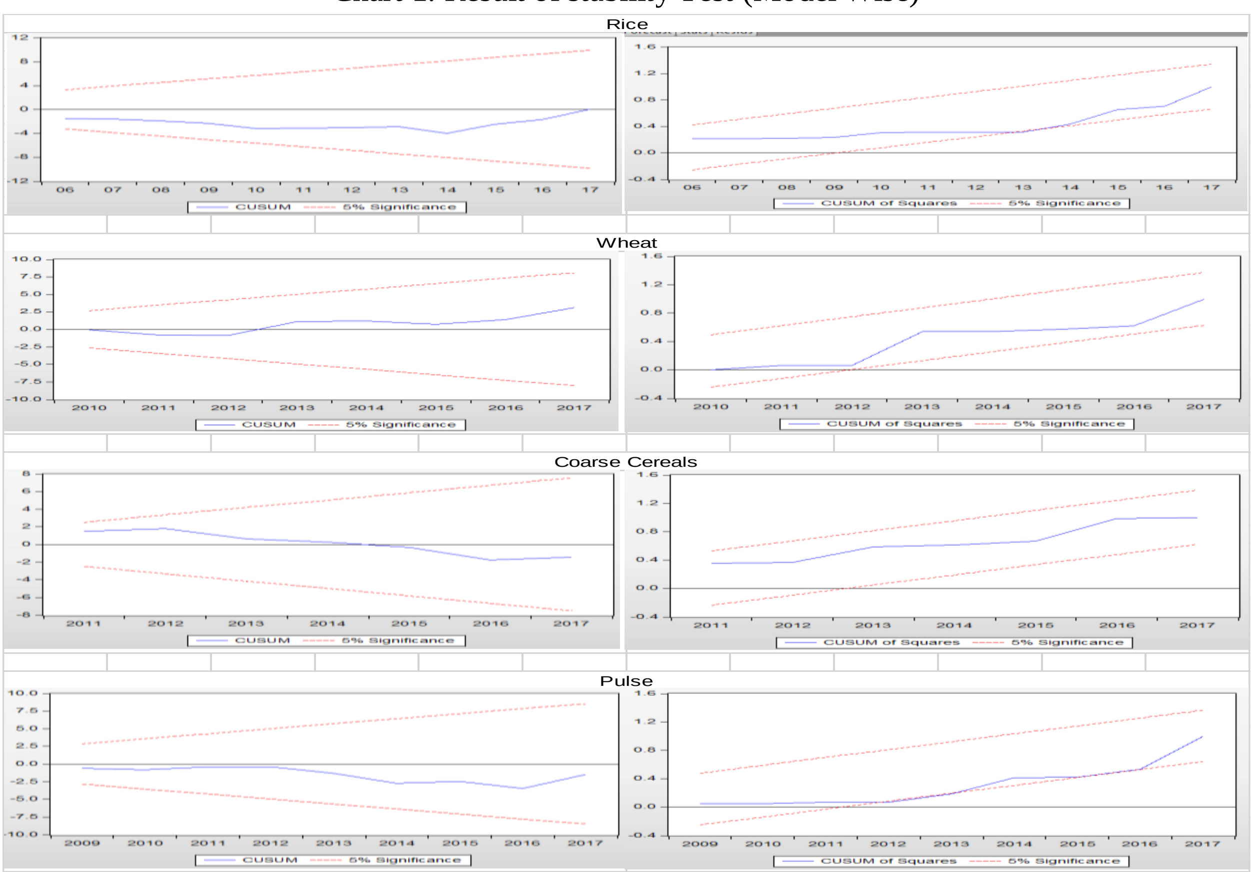
and Kumar & Upadhayay (2019) they explained that minimum temperature has a positive impact on pulse yield and also contradict by other findings Arora *et al*. (2019) they explained that minimum temperature has a negative role in the productivity of pulse in Indian agriculture. Moreover, the annual mean temperature has shown an insignificant positive impact on the productivity of pulse. Result also shows that there is a positive impact of Co2 on the pulse yield in short as well as in the long run at 1 % and 10 % level of significance respectively. Furthermore, the fertiliser has shown that statistically significant positive impact on the productivity of pulse at 1 % and 5 % level of significance in the short and long run in Indian agriculture, respectively.

The estimates result of the diagnostic test of each specific ARDL model (Crop wise) described in Table 7. P-Value indicated that each specific model has passed of all the diagnostic tests such as series auto-correlation, heteroscedasticity and normality.

To check the stability of each specific ARDL model used a cumulative sum of recursive residuals (CUSUM) and cumulative sum square of recursive residuals (CUSUMSQ) suggested by the Brown *et al.* (1975). Chart 1, are the plots of CUSUM and CUSUMSQ of each ARDL model (Crop wise) lines are within critical boundaries at 5 % level of significance over time and confirmed that each model is stable in this study.

Chart 1: Result of stability Test (Model Wise)



V. Conclusion and policy implication:

This paper examines the dynamic relationship among climate change and yield of four crops, including rice, wheat, coarse cereal and pulse during the period over 1990-2017 in India. To explore the relationship between the underlying variables; we adopt the ARDL bounds cointegration approach. The empirical result of each ARDL model indicates that a long-run relationship exists between climate change and the yield of crops in India.

The empirical results of each ARDL model indicate that a long-run relationship exists between climate change and yield of underlying crops in India. The outcome reveals that maximum temperature has a positive and significant impact on the productivity of underlying crops except wheat in the long run. At the same time, minimum temperature has a positive and significant impact on the productivity of coarse cereal and pulse. Moreover, mean temperature has a significant positive impact on the yield of wheat and coarse cereal, but it has a negative impact on rice productivity. In contrast, rainfall has a negative and significant impact on coarse cereal and pulse productivity but positive effect on wheat productivity. Whereas Co2 has a significant positive impact on wheat and pulse productivity in the long run. Thus empirical evidence indicates that fertiliser and rainfall would adjust any negative shock to agriculture productivity in Indian agriculture.

The aftereffects of this study may be vital for strategy and policymakers to adopt environmental policies and modern technology with respect to precise climate estimating, and precautionary and direct actions are additionally expected to create and support an improved water system framework. In a nutshell, crop-specific research should be conducted to highlight environmental issues and also the Government should take an initiate to cope with the harmful effects of climate change on the productivity of agriculture. However, the Government provide the fertilisers at the subsidised rate to avoid the problem of food insecurity of food grain in future due to adverse shock by climate change.

References

1. Abbas, S. (2020). Climate change and cotton production : an empirical investigation of Pakistan. Environmental Science and Pollution Research, 1998.
2. Arora, P., Devi, R., & Chaudhry, S. (2019). Impact of Climate Change on the Production of Major Food and Commercial Crops in India: A Five Decadal Study. International Journal of Environment and Climate Change, September, 477–485. https://doi.org/10.9734/ijecc/2019/v9i930133
3. Attiaoui, I., & Boufateh, T. (2019). Impacts of climate change on cereal farming in Tunisia : a panel ARDL – PMG approach. Environmental Science and Pollution Research, 26(January 2011), 13334–13345.
4. Bhanumurthy, K. ., & Kumar, L. (2018). Climate Change and Agriculture in India: Studying Long-Term Patterns in Temperature , Rainfall and Agriculture Ouput. Management and Economics Research Journal, 4(S2), 156–173.
5. Birthal, P. S., Khan, T., Negi, D. S., & Agarwal, S. (2014). Impact of Climate Change on Yields of Major Food Crops in India : Implications for Food Security. 27(2), 145–155. https://doi.org/10.5958/0974-0279.2014.00019.6
6. Chandio, A. A., Jiang, Y., Rehman, A., & Rauf, A. (2020). Short and long-run impacts of climate change on agriculture: an empirical evidence from China. International Journal of Climate Change Strategies and Management, 12(2), 201–221. https://doi.org/10.1108/IJCCSM-05-2019-0026
7. Chandio, A. A., Ozturk, I., Akram, W., Ahmad, F., & Mirani, A. . (2020). Empirical

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ISSN: 0193-4120 Page No. 3438 - 3452

analysis of climate change factors affecting cereal yield : evidence from Turkey. Environmental Science and Pollution Research, 27, 11944–11957.

8. Guiteras, R. (2009). The Impact of Climate Change on Indian Agriculture (Issue September).
9. Guntukula, R. (2019). Assessing the impact of climate change on Indian agriculture : Evidence from major crop yields. Journal of Public Affairs, October, 1–7. https://doi.org/10.1002/pa.2040
10. Gupta, S., Sen, P., & Srinivasan, S. (2012). Impact of Climate Change on the Indian Economy : Evidence from Foodgrain Yields (Issue 218).
11. Janjua, P. ., Samad, G., & Khan, N. (2014). Climate Change and Wheat Production in Pakistan : An Autoregressive Distributed Lag Approach. NJAS - Wageningen Journal of Life Sciences, 68, 13–19. https://doi.org/10.1016/j.njas.2013.11.002
12. Johansen, S., & Juselius, K. (1990). Maximum Likelihood Estimation and Inference on Cointegration — With Applications To the Demand for Money. Oxford Bulletin of Economics and Statistics, 52(2), 169–210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x
13. Kumar, A., Sharma, P., & Joshi, S. (2015). Effects of Climatic Factors on Agricultural Productivity in India : A State-wise Panel Data Analysis. International Journal of Basic and Life Sciences, 3(1), 48–67.
14. Kumar, K., & Parikh, J. (2001). Indian Agriculture and climate sensitivity. Global Environmental Change, 11(2)(July), 147–154. https://doi.org/10.1016/S0959-3780(01)00004-8
15. Kumar, K. S. K. (2011). Climate sensitivity of Indian agriculture : do spatial effects matter ? Cambridge Journal of Regions, Economy and Society, 4(March), 221–235. https://doi.org/10.1093/cjres/rsr004
16. Kumar, S. N., Aggarwal, P. K., Rani, S., Jain, S., Saxena, R., & Chauhan, N. (2011). Impact of climate change on crop productivity in Western Ghats , coastal and northeastern regions of India. Current Science, 101(3), 332–341.
17. Lal, M., Rathore, L. ., & Anapalli, S. . (1998). Vulnerability of rice and wheat yields in NW India to future changes in climate. Agricultural and Forest Meteorology, 89(February), 101–114. https://doi.org/10.1016/S0168-1923(97)00064-6
18. Mishra, D., & Chandra, N. (2016). Impact of climate change on agricultural production of Odisha (India): a Ricardian analysis. Regional Environmental Change, 16, 575–584. https://doi.org/10.1007/s10113-015-0774-5
19. Moorthy, A., Buermann, W., & Rajagopal, D. (2012). The Impact of Climate Change on Crop Yields in India from 1961 to 2010 (Vol. 28).
20. Mukherjee, A., & S.Huda, A. . (2018). Assessment of climate variability and trend on wheat productivity in West Bengal , India : crop growth simulation approach. Climate Change, 147, 235–252.
21. Nath, H. K., & Mandal, R. (2018). Heterogeneous Climatic Impacts on Agricultural Production : Evidence from Rice Yield in Assam , India. Asian Journal of Agriculture and Development, 15 No.1, 23–42.
22. Nath, P. K., & Behera, B. (2011). A critical review of impact of and adaptation to climate change in developed and developing economies. Environment, Development and Sustainability, 13, 141–162. https://doi.org/10.1007/s10668-010-9253-9

23. Pal, D., & Mitra, S. K. (2018). Asymmetric impact of rainfall on India ' s food grain production : evidence from quantile autoregressive distributed lag model. Theoretical Applied Climatology, 131, 69–76. https://doi.org/10.1007/s00704-016-1942-3
24. Pathak, H., Ladha, J. K., Aggarwal, P. K., Peng, S., Das, S., & Singh, Y. (2003). Trends of climatic potential and on-farm yields of rice and wheat in the Indo-Gangetic Plains. Field Crop Research, 80, 223–234.
25. Pattanayak, A., & Kumar, K. S. K. (2013). Weather Sensitivity of Rice Yield : Evidence from India (Issue September).
26. Pesaran.et.al. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. 16(3), 289–326. https://doi.org/10.1002/jae.616
27. Pesaran, M. H., & Shin, Y. (2002). LONG-RUN STRUCTURAL MODELLING. 4938(2002).
28. Praveen, B., & Sharma, P. (2020). Climate Change and its impacts on Indian agriculture: An Econometric analysis. Journal of Public Affairs, 20(1). https://doi.org/10.1002/pa.1972
29. Rao, B. B., Chowdary, P. S., Sandeep, V. M., Pramod, V. P., & Rao, V. U. M. (2015). Agricultural and Forest Meteorology Spatial analysis of the sensitivity of wheat yields to temperature in India. Agricultural and Forest Meteorology, 200, 192–202. https://doi.org/10.1016/j.agrformet.2014.09.023
30. Rashid, A., Alam, K., & Gow, J. (2012). Exploring the relationship between climate change and rice yield in Bangladesh : An analysis of time series data. Agricultural Systems, 112, 11–16. https://doi.org/10.1016/j.agsy.2012.06.004
31. Sanghi, A., & Mendelsohn, R. (2008). The impacts of global warming on farmers in Brazil and India. Global Environmental Change, 18, 655–665. https://doi.org/10.1016/j.gloenvcha.2008.06.008
32. Singh, A. K., Narayanan, K. G. S., & Sharma, P. (2017). Effect of climatic factors on cash crop farming in India: An application of Cobb-Douglas production function model. International Journal of Agricultural Resources, Governance and Ecology, 13(2), 175–210. https://doi.org/10.1504/IJARGE.2017.086452