Climate Change Impact on Rice Yield in India – Vector Autoregression Approach

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ABSTRACT

Climate change plays an important role in agricultural production. Agricultural productivity is highly affected by a number of factors including precipitation, temperature. This paper examines the relationship between the yield of two major rice crops (e.g., Kharif and Rabi) and three main climate variables (e.g., maximum temperature, minimum temperature and rainfall). The dynamic relationships among the variables considered for observing the impact of climate change on rice yields are examined based on Vector Autoregression (VAR) model with the use of Granger causality test, impulse response functions and variance decomposition for the data. Maximum and Minimum temperature have significant effects, meanwhile rainfall has negative impact on Kharif rice yield. Adverse effects on Rabi rice yield are observed by maximum temperature and rainfall, whereas minimum temperature affect yield positively. Appropriate adaptive techniques are recommended to overcome this emerging hazard of climate change on rice production.

Keywords: VAR, Granger-causality test, impulse response function, variance decomposition, climate change, rice yield.

1. Introduction

Intergovernmental Panel on Climate Change (IPCC) defines the climate change that the change in climate for the long period of time due to natural and anthropogenic activities. As a result of future increases in atmospheric concentration of greenhouse gases, it is predicted that the annual mean warming about 3ºC in the decade of the 2050s and about 5ºC in the decade of the 2080s over the land regions of Asia (IPCC, 2007). Increase in temperature and changes in precipitation have strong impacts on agriculture with the occurrence and strength of extreme weather events such as floods, droughts, cyclones and heat waves (IPCC, 2007). The vulnerability of climate change on agriculture could affect the food security, trade policy, livelihood activities, etc. It can affect the crop yield positively or negatively and the changes differ largely by region and crop. IPCC states that the developing countries will be more vulnerable to climate change than developed countries. India is considered one of most vulnerable countries, where the agricultural production is being affected by climate change.

IPCC has projected the temperature increase to be between 1.1ºC and 6.4ºC by the end of the 21^{st} century. Temperatures have been increasing in India especially during post monsoon and winter for the last few decades (IPCC, 2007). Rainfall is the most important variable and it has denoted an uneven distribution (Sarkar *et al*. ,2012). It is observed that the increase in extreme rains in north-west India during summer monsoon in recent decades and the number of rainy days in lower along east coast (IPCC, 2007). These unpredictable events produce floods and droughts which affects the crop yield (Adams *et al*., 1998). It is expected that an increase in mean annual temperature will be 3-6ºC and rainfall will increase by 15-40% over India by the end of the 21^{st} century (National Communication Project, 2004).

Rice is the most important food crop of India. It covers about one third of total cultivated area of the country. About 23.3% of gross cropped area of the country is occupied with rice which accounts 43% of the total food grain production and 46% of the total cereal production of the country (Directorate of Rice Development, 2002). Given that approximately 15.7% of India’s GDP is contributed by the agriculture sector and almost 60% of the country’s population for its livelihood depends on this sector (Aggarwal *et al*., 2010). Rice production in India passed the amount of 100 million MT in 2011-2012 accounting for 22.81% of world production in that year.

Rice yield was noticed by International Rice Research Institute to decrease by 10% for every 1ºC increase in growing-season minimum temperature (Peng *et al*., 2004). Lal *et al*. (1998) observed that a 4ºC drop in surface air temperature results 10%

reduction in rice yield, while a 4ºC increase in temperature causes 41% reduction in rice yield. Sinha and Swaminathan (1991) observed that an increase of 2ºC temperature could decrease the rice yield by about 0.75 ton/ha in the high yield areas. For every 1ºC increase in temperature, it would decline the rice yield about 6% (Saseendran *et al*., 2000). Therefore, it is essential need to appraise the possible influences of climate change on rice productivity to assure food security and economic growth.

The influences of climate change on agriculture have been studied on developing countries earlier (Lansigan et al., 2000; Chang, 2002; Gbetibouo and Hassan, 2005;Kurukulasuriya and Ajwad, 2007; Kabubo-Mariara and Karanja, 2007; Haim *et al*., 2008; Sanghi and Mendelsohn, 2008; Deressa and Hassan, 2009; Moula, 2009; and Wang *et al*., 2009). From those studies, it is revealed that the crop yield is more prone to climate change in developing countries. Though the agricultural status of India is most vulnerable to climate change, there are limited empirical investigations of the impact of climate change on crop agriculture (Lal *et al*., 1998; Auffhammer et al., 2011; Krishna Kumar *et al*., 2004; and Aggarwal *et al*., 2010).

Aggarwal *et al*. (2010) identified that rice and wheat crops are likely to be affected by the climate change. They have done the simulation analysis using InfoCrop-Wheat and InfoCrop-Rice models in the study area comprising 11 districts in north-west Uttar Pradesh and south-west Uttarakhand. Lal *et al*. (1998) discussed the vulnerability of wheat and rice crops in north-west India by adopting CERES v3. models (crop growth simulation models for wheat and rice). They also revealed that the wheat and rice productivity could be adversely affected by acute water shortage conditions combined with the thermal stress than increased CO_2 concentration in general.

Auffhammer *et al*. (2011) showed that rice yield is affected by the droughts and extreme rainfall in rain-fed areas during 1966-2002 by applying multiple regression. Simulation study that uses the regression based estimates to identify the impacts of changes in monsoon characteristics on rice yield has been also undertaken. Krishna Kumar *et al*. (2004) presented a correlation analysis to identify the crop-climate relationships for India. They showed the significant relationship of rainfall and some of its potential predictors on crop production. The time series data on both climate variables and yields is employed by regression models, which are proficient to assess accurate estimates of the changes in crop yield as a result of changes in climate variables (Almaraz *et al*., 2008; Lobell and Field, 2007; Joshi et al., 2011; and Isik and Devadoss, 2006).

Climate variables such as temperature, precipitation and solar radiation are generally considered to study the climate change and its impact. Peng *et al*. (2004) identified the direct correlation between temperature and solar radiation. To conquer the relationship among the independent variables, this paper considers only temperature and precipitation. Minimum temperature, maximum temperature and rainfall are the three climate variables used as independent variables by considering Almaraz et al. (2008).

There are two major rice crops, Kharif and Rabi, which constitute 100% of total rice production and grow in two different seasons in India. The sowing time of Kharif rice is June or July and it is harvested in November or December. Rabi is sown in November to February and harvested in March to June. However, the sowing and harvesting time slightly vary from state to state according to weather condition and rainfall pattern. In this study, the growing seasons are considered as June to December for Kharif and January-May for Rabi. In the view of the fact that the average growing season climate is able to show the net effects of climate change on crop yields (Lobell and Field, 2007), this study has used an average growing season temperature variable with the total growing season rainfall variable.

Consequently, it is necessary for identifying the relationship between climate variables and crop yields through empirical studies. There are several studies conducted on an international level to study the influence of climate variables on crop production but not on rice yield (Almaraz *et al*., 2008; Ozcan and Akcaoz, 2002). The stationary properties of the time series data have not been determined in those studies. It is a precondition for performing the time series for a period of more than 20 years (Chen *et al*., 2004). The main objective of this article is to examine the relationships between three climate variables and rice yields of Kharif and Rabi in India.

2. Data Sources and Properties

The monthly maximum temperature, minimum temperature and total rainfall data for months January through to December for the period 1974-2011 were obtained from the Indian Meteorological Department (IMD). These monthly data were then transformed as the average of the growing periods for two rice crops: Kharif (June-December) and Rabi (January-May). Therefore, maximum and minimum average temperature and total rainfall are considered as the climate variables for the growing seasons of the respective rice crops for the 1974-2011 periods. Aggregate rice yield data for Kharif and Rabi for the same time period (1974-2011) were collected from Directorate of Rice Development, Patna.

The basic statistics for all of the data are presented in Table 1. The mean value for the Rabi rice yield is higher than the Kharif rice. The highest mean maximum and minimum temperatures are observed for the Kharif rice, while the lowest temperatures were observed for the Rabi rice. In contrast, total rainfall in the Kharif period is approximately eight times higher than the total rainfall in the Rabi period.

Table 1: Descriptive statistics for the data for 1974-2011 period

Statistics	**Variables**							
	Yield (kg per Hectare)		**Maximum Temperature (ºC)**		**Minimum Temperature (ºC)**		**Rainfall (mm)**	
	Kharif	**Rabi**	**Kharif**	**Rabi**	**Kharif**	**Rabi**	**Kharif**	**Rabi**
Mean	1646.76	2620.82	29.56	28.51	20	17.33	9550.11	1191.55
Std.dev	342.31	427.10	0.30	0.55	0.36	0.49	848.32	230.64
Maximum	2284	3275	30.27	29.76	21	18.30	11119	1920
Minimum	999	1888	28.82	27.65	19.04	16.50	7557	767
Skewness	-0.25	-0.31	0.35	0.61	-0.04	0.28	-0.25	0.65
Kurtosis	-0.92	-1.27	0.25	-0.35	1.46	-0.69	-0.56	1.47

3. Methodology

This study can be employed by the Vector Autoregression modeling to identify the causal relationships between climate variables and rice yield to estimate the possible effects of climate change. VAR models were first developed by Sims (1980) as a better alternative to traditional dynamic simultaneous equation models to examine the dynamic interactions among the interrelated time series data. VAR models are the multivariate extensions of the univariate AR models to the multivariate case and they explain and/or predict the values of a set of variables at any given point in time (Sims, 1980; and Todd, 1984). They are extensively used in forecasting and causality tests (Cooley and Leroy, 1985).

The basic *p*-lag vector auto-regression model has the form

$$Y_t = c + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \varepsilon_t, \qquad t = 1,\ldots,T$$

where $Y_t = (y_{1t}, y_{2t}, \ldots y_{nt})'$ denote an (nx1) vector of time series variables

Γ_i are (nxn) coefficient matrices and

ε_t is an (nx1) unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix $\sum$.

For example, a bivariate VAR model is defined by

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \Gamma_{11}^1 & \Gamma_{12}^1 \\ \Gamma_{21}^1 & \Gamma_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t\text{-}1} \\ y_{2t\text{-}1} \end{pmatrix} + \begin{pmatrix} \Gamma_{11}^2 & \Gamma_{12}^2 \\ \Gamma_{21}^2 & \Gamma_{22}^2 \end{pmatrix} \begin{pmatrix} y_{1t\text{-}2} \\ y_{2t\text{-}2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

where $\operatorname{cov}(\varepsilon_{1t}, \varepsilon_{2s}) = \begin{cases} \sigma_{12}, & t = s \\ 0, & \text{otherwise} \end{cases}$

In lag operator notation, the VAR (*p*) is written as

$$\Gamma(B)Y_t = c + \varepsilon_t \text{ , where } \Gamma(B) = I_n - \Gamma_1 B - \ldots - \Gamma_p B^p \text{ .}$$

All variables are served as endogenous variables, each equation has the same exogenous variables and the lagged exogenous variables. In other words, each endogenous variable is explained by its lagged or past values and the lagged values of all other endogenous variables in the model. An important preliminary step in model building is the selection of the VAR lag order. One way of determining the optimum lag order is to use the minimum information criterion such as Akaike Information, Schwarz criterion or Hannan-Quinn information criterion.

The estimation of the parameters of the VAR model is not difficult, though the structure of the VAR model looks very complex. They can be easily estimated by Ordinary Least Square (OLS) method or Maximum Likelihoods.

3.1 Granger causality test

The supplementary advantage of VAR model is to perform the Granger causality testing to examine the direction of causality among the variables (Granger, 1969). It is a technique for determining whether one time series is useful in forecasting another. If a variable say, *X* is found to be helpful for predicting another variable say, *Y*, then *X* is said to Granger-cause *Y*. To test the null hypothesis that *X* does not Granger-cause *Y*, the test statistic is given by

$$F = \frac{(RSS_R - RSS_{UR})/m}{RSS_{UR}/(n-k)}$$

where RSS_R, restricted residual sum of squares, RSS_{UR}, unrestricted residual sum of squares, *m*, number of lagged X terms, and *k*, number of parameters estimated in the unrestricted regression.

The test statistic follows the F-distribution with *m* and *(n-k)* degrees of freedom.

3.2 Impulse Response Functions and Variance Decompositions

Impulse response functions provided by VAR models are used to know where the impact of change in one variable can be found through all the other variables. They exhibit the current and lagged effects over time of changes in error terms $(\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{kt})$ on the endogenous variables $(y_{1t}, y_{2t}, \ldots, y_{kt})$. When the VAR process of order '*p*' is stable, the error term ε_{1t} has immediate effects and $\varepsilon_{2t}, \varepsilon_{3t}, \ldots, \varepsilon_{kt}$ all have lagged effects on y_{1t}.

If any covariance stationary VAR (*p*) process has a Wald representation of the form

$$Y_t = \mu + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \ldots$$

where ϕ_s are (nxn) moving average matrices, the impulse responses, φ_{ij}^s, (i,j)th element of ϕ_s are defined by

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial y_{i,t}}{\partial \varepsilon_{j,t-s}} = \varphi_{ij}^s, \qquad i, j = 1, 2, \ldots, n$$

It is only possible if $\mathrm{var}(\varepsilon_t) = \Sigma$ is a diagonal matrix in which ε_t are uncorrelated.

The variance decomposition analysis is typically performed by VAR models, which supplements impulse response function analysis (Ghatak, 1998). It shows that how much the variance of the forecast errors of each variable can be explained by exogenous shocks to the other variables in the VAR.

4. Results and Discussions

As the data set contains more than 20 years of observations, it requires testing of the unit roots for examining stationary of the series (Chen et al., 2004). Augmented Dickey Fuller (ADF) test is incorporated here and the results are presented in Table 2. Table 2 shows that the yields, maximum and minimum temperature for Kharif and Rabi rice are integrated of order one.

Table 2: Results of Augmented Dickey Fuller (ADF) test for determining the stationarity of the time series

Variables	Kharif			Rabi		
	ADF test statistic	p-value	Integration of order	ADF test statistic	p-value	Integration of order
Yield	-7.7342	2.96e-12	I(1)	-7.1416	1.36e-10	I(1)
Max.Temperature	-6.7780	1.3e-09	I(1)	-8.2704	7.93e-14	I(1)
Min.Temperature	-7.1951	9.73e-11	I(1)	-8.4105	3.02e-14	I(1)
Total rainfall	-3.8940	0.0021	I(0)	-4.9202	2.97e-05	I(0)

However, the total rainfall for Kharif and Rabi rice are of I(0), which indicates those data series are stationary in their level form. The variables with I(1) mean that they generally become stationary only after taking their first differences before estimation (Gujarati et al., 2009).

Table 3: Values of the Information Criterion for selecting the order of the VAR model for Kharif and Rabi rice

Lag	Kharif			Rabi		
	AIC	BIC	HQC	AIC	BIC	HQC
1	28.1632*	29.1953*	28.6133*	28.4467*	29.3355*	28.7535*
2	28.1781	29.7630	28.7154	28.6787	30.2785	29.2310
3	28.3065	30.4889	28.9758	28.5546	30.8654	29.3523

Table 3 gives the values of different information criterion for the various lag length of the VAR models to the Kharif and Rabi rice. From the results, the optimal lag order is one for both rice with the values of minimum AIC, BIC and HQC.

4.1 The Results for the Kharif rice

For the Kharif rice, the following VAR(1) model is employed by considering rice yield and climate variables

$$\text{yield}_t = \alpha_0 + \alpha_1 \text{yield}_{t-1} + \alpha_2 \text{maxt}_{t-1} + \alpha_3 \text{mint}_{t-1} + \alpha_4 \text{train}_{t-1} + \varepsilon_{1t}$$

where *yield* is the Kharif rice yield (in kg per hectare), *maxt* is the average maximum temperature (°C) from June to December, *mint* is the average minimum temperature (°C) from June to December, *train* is the total rainfall (mm) from June to December, ε_{1t} is the error term and *t* is the time (i.e., year).

From Table 4, the effects of the climate variables on the Kharif rice yield is obtained that the overall model is statistically significant. The R^2 value indicates that

88% of the variation in the Kharif rice is explained by climate variables. The higher value of F-statistic (59.19) makes collectively all the lagged terms are statistically significant. Granger causality test results from Table 5 suggest that the direction of causality is from *maxt* and *mint* to *yield* since the F-statistic is significant. But there is no causation from *train* to *yield*, since the F value is statistically insignificant.

As shown from Figure 1(a) about impulse response functions for a period of 10 years from *maxt* and *mint* to *yield*, increasing of *maxt* and *mint* in the current period has a positive effect on *yield* in the future and from third period it shows a decreasing trend of positive effect until ninth period. According to the Figure 1(a) about impulse response functions from *train* to *yield*, increasing of *train* in the current period has a negative effect on *yield.* It has positive effect during second period but after third period, it begins to a slow decline.

Table 6 gives the variance decomposition values of rice yield for both categories. During the changes of *yield,* its own affect is 100% in first period and then gradually declines to 67.42%. The volatility of *yield* from 0% to 19.72% fluctuations can be explained by *maxt*; 0% ~ 0.37% and 0% ~ 12.49% fluctuations can be explained by *mint* and *train* respectively. All the above results imply a higher contribution of maximum temperature and minimum temperature to the Kharif rice yield. Although total rainfall during Kharif period is insignificant, it is negatively associated with the rice yield.

4.2 The results for the Rabi rice

On the basis of the distribution of the Rabi rice yield, the following VAR model of order one is used.

$$\text{yield}_t = \beta_0 + \beta_1 \text{yield}_{t-1} + \beta_2 \text{maxt}_{t-1} + \beta_3 \text{mint}_{t-1} + \beta_4 \text{train}_{t-1} + \varepsilon_{2t}$$

where *yield* is the Rabi rice yield (in kg per hectare), *maxt* is the average maximum temperature (ºC) from January to May, *mint* is the average minimum temperature (ºC) from January to May, *train* is the total rainfall (mm) from January to May, ε_{2t} is the error term and *t* is the time (i.e., year).

Table 4: The Estimated Vector Autoregression models of Kharif and Rabi rice

Vector autoregression estimates based on 1 lag
Sample (adjusted): 1974-2011
Included observations: 37 after adjustments
Standard errors in ( ) and *t*-statistics in [ ]

	Kharif				Rabi			
	yield	***maxt***	***mint***	***train***	***yield***	***maxt***	***mint***	***train***
***yield* (-1)**	0.865585	0.00045	0.00051	-0.51266	0.85061	0.00075	0.00063	0.22587
	(0.07503)	(0.00016)	(0.00018)	(0.53429)	(0.09225)	(0.00024)	(0.00021)	(0.12637)
	[11.54]	[2.7630]	[2.795]	[-0.9595]	[9.220]	[3.076]	[2.925]	[1.787]
***maxt* (-1)**	15.7418	0.12698	-0.08049	-821.088	-6.80272	-0.04122	-0.16232	-68.0752
	(123.849)	(0.27063)	(0.30405)	(881.0881)	(109.684)	(0.29052)	(0.25541)	(150.250)
	[0.1271]	[0.4692]	[-0.2647]	[-0.9311]	[-0.06202]	[-0.1419]	[-0.6355]	[-0.4531]
***mint* (-1)**	99.4669	0.00184	0.16652	625.770	121.960	0.18136	0.26450	-29.3737
	(90.7924)	(0.19840)	(0.22290)	(646.496)	(127.243)	(0.33702)	(0.29630)	(174.302)
	[1.096]	[0.00929]	[0.7471]	[0.9695]	[0.9585]	[0.5381]	[0.8927]	[-0.1685]
***train* (-1)**	-0.08160	0.00002	0.00003	-0.21743	-0.35644	-0.00022	0.00003	-0.11854
	(0.03010)	(0.00007)	(0.00007)	(0.21436)	(0.13538)	(0.00036)	(0.00032)	(0.18545)
	[-2.711]	[0.3374]	[0.4148]	[-1.014]	[-2.633]	[-0.6034]	[0.1008]	[-0.6392]
constant	-1420.48	24.8329	17.9376	24224.6	-1068.01	24.8573	15.7200	3199.69
	(2872.40)	(6.27664)	(7.05181)	(20453.2)	(1806.24)	(4.78415)	(4.20595)	(2474.27)
	[-0.4945]	[3.956]	[2.544]	[1.184]	[-0.5913]	[5.196]	[3.738]	[1.293]
R-squared	0.88094	0.32165	0.33966	0.08966	0.84908	0.40570	0.39215	0.09408
Adj. R-squared	0.86605	0.23685	0.25712	-0.02414	0.83022	0.33141	0.31617	0.01916
Sum squared residuals	464902	2.21986	2.80202	23571874	936287.2	6.56848	5.07672	1756908
S.E of regression	120.5329	0.26339	0.29591	858.2663	171.0525	0.45306	0.39831	234.3147
F-statistic	59.19055	3.79323	4.11498	0.78791	45.00816	5.46121	5.16116	0.83084
p-value	2.46e-14	0.01236	0.00841	0.54161	1.06e-12	0.00181	0.00253	0.51556
Mean dependent	1664.270	29.57270	20.01881	9572.946	2640.514	28.52385	17.35129	1196.081
S.D. dependent	329.3355	0.301497	0.34332	848.0930	415.1257	0.55409	0.48166	232.1022
Durbin-Watson	2.35829	2.03892	2.31300	1.81426	2.74018	1.95711	2.01075	1.91826
Log likelihood	-503.57919				-505.22514			
Determinant of cov. matrix	7794964.5				8520272.4			
AIC	28.3016				28.3905			
BIC	29.1723				29.2613			
HQC	28.6086				28.6975			

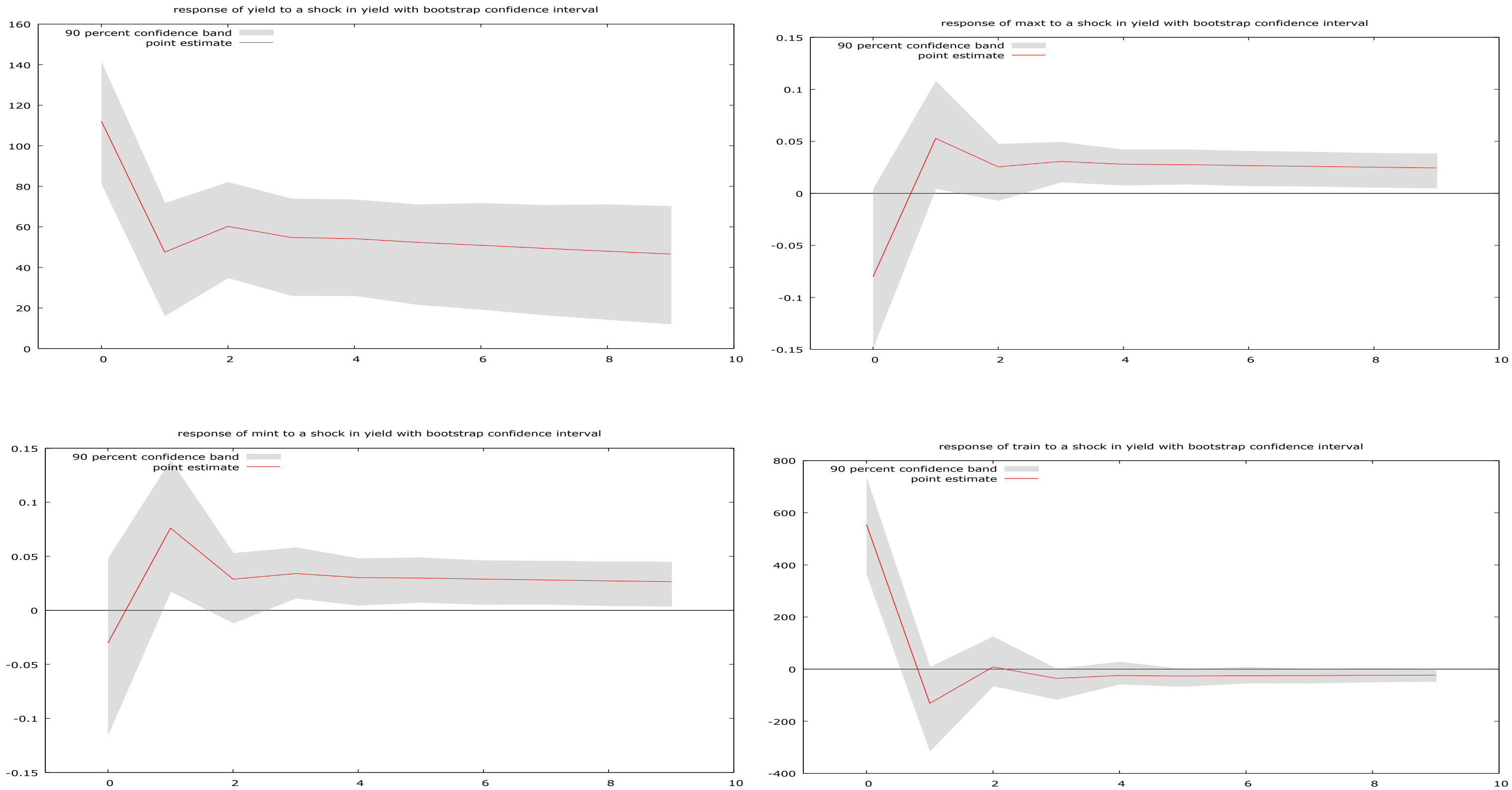
Table 5: Results of Granger causality test

Null Hypothesis	Kharif			Rabi		
	F-statistic	p-value	conclusion	F-statistic	p-value	conclusion
maxt does not Granger-cause *yield*	7.6357	0.0094	Reject	9.4601	0.0043	Reject
mint does not Granger-cause *yield*	7.8122	0.0087	Reject	8.5540	0.0063	Reject
train does not Granger-cause *yield*	0.92066	0.3445	Do not reject	3.1947	0.0834	Reject*

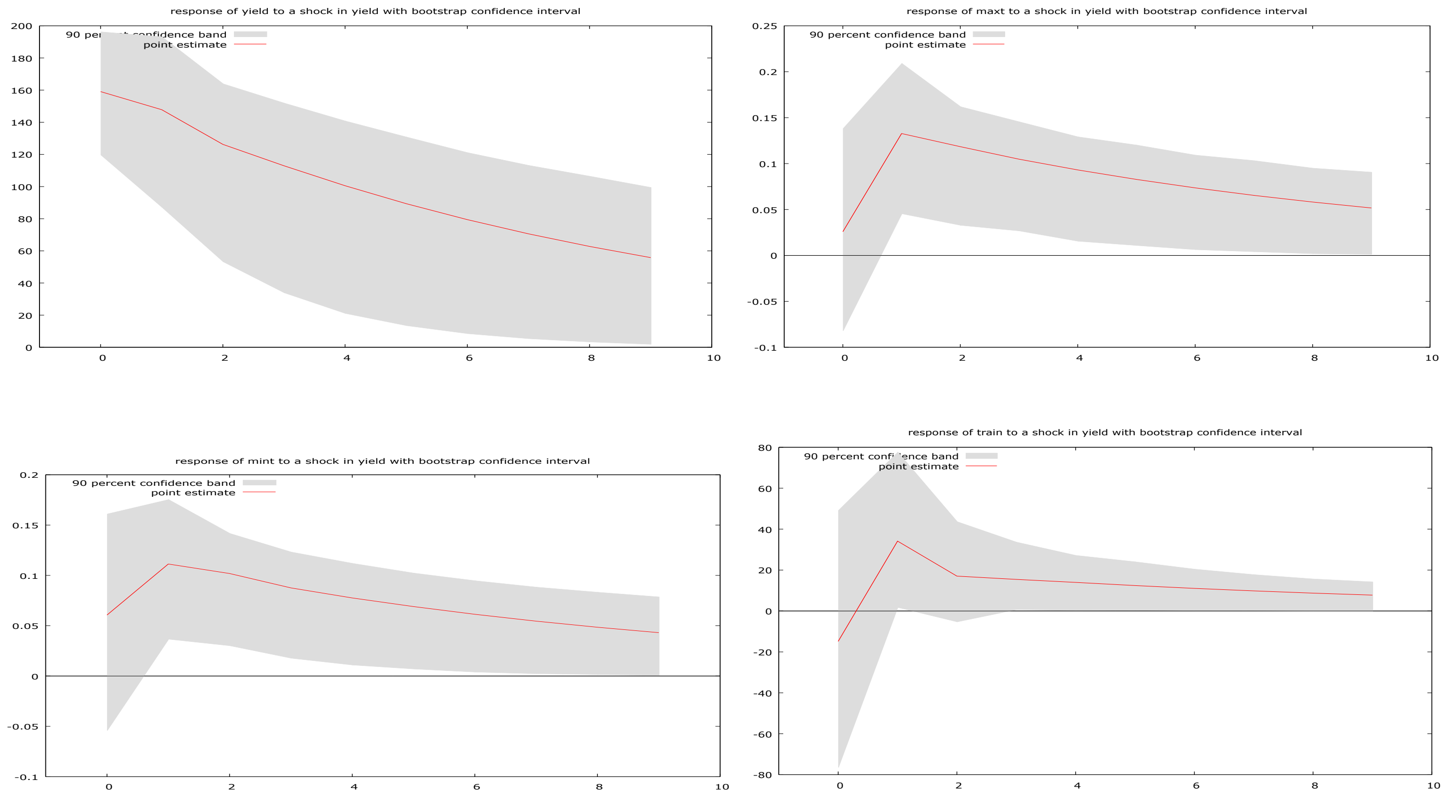
* Reject at 10% level of significance

The contribution of climate variables to the Rabi rice is presented in Table 4. It is observed that the F-statistic value associated with p-value ensures the significance of the model. Moreover, 85% of the variation in Rabi rice yield is explained by the climate variables, which represents the important role of climate for Rabi rice cultivation.

The results from Table 5 indicate that there is causal relationship between climate variables and Rabi rice yield. The null hypothesis in each case assumes that *maxt, mint* and *train* does not 'Granger-cause' the *yield.* Since the F-statistic is statistically significant, the direction of causality from *maxt, mint* and *train* to *yield* is observed. It is necessary to observe that the impulse response functions of *maxt, mint* and *train* to Rabi rice yield. Figure 1(b) traces out the responses of *maxt, mint* and *train.* According to the figure about impulse response functions from climate variables to *yield,* increasing of *maxt, mint* and *train* in the current period has a positive effect on *yield* in the future and shows a decreasing trend of positive effect until the tenth period.



a) Responses of *yield*, *maxt*, *mint* and *train* to Kharif rice yield



b) Responses of *yield*, *maxt*, *mint* and *train* to Rabi rice yield

Figure 1: Impulse Response Functions of climate variables on rice yield

Table 6: Forecast Error Variance Decompositions for rice yield

Period	Kharif					Rabi				
	S.E	*yield*	*maxt*	*mint*	*train*	S.E	*yield*	*maxt*	*mint*	*train*
1	112.09	100.00	0.00	0.00	0.00	159.08	100.00	0.00	0.00	0.00
2	134.57	81.86	8.26	0.40	9.48	232.68	87.10	3.86	0.02	9.02
3	154.12	77.70	12.06	0.35	9.89	274.42	83.78	6.25	0.16	9.81
4	170.01	74.23	14.54	0.36	10.86	302.97	82.63	7.05	0.25	10.07
5	183.84	72.17	16.14	0.36	11.34	323.75	82.00	7.47	0.30	10.22
6	195.97	70.65	17.28	0.36	11.71	339.28	81.60	7.75	0.33	10.32
7	206.76	69.53	18.12	0.36	11.98	351.07	81.33	7.93	0.36	10.38
8	216.44	68.67	18.78	0.36	12.19	360.11	81.14	8.05	0.37	10.43
9	225.18	67.98	19.30	0.37	12.36	367.10	81.00	8.15	0.38	10.46
10	233.13	67.42	19.72	0.37	12.49	372.53	80.91	8.22	0.39	10.49

From variance decomposition values of Rabi rice yield which are shown in Table 6, 100% ~ 80.91% fluctuations can be explained by their own *yield* fluctuations; 0% ~ 8.22%, 0% ~ 0.39% and 0% ~ 10.49% fluctuations can be explained by the volatility of *maxt*, *mint* and *train* respectively. The above results show that all the climate variables are statistically significant for Rabi rice yield. However, the effects of maximum temperature and total rainfall are negative, whereas minimum temperature has a positive influence on Rabi rice yield.

Conclusions

This paper analyzed the impact of climate change on rice yield using aggregate-level time series data. Three climate variables have significant effects on the rice yield of Kharif and Rabi crops. For the Kharif rice yield, average maximum temperature and average minimum temperature are statistically significant. Moreover, total rainfall is perceived to adversely affect the Kharif rice yield, despite this effect is not significant. For the Rabi rice yield, all three climate variables were statistically significant. However, the direction of the effects is not identical. Average maximum temperature and total rainfall have negative effects on yield, whereas average minimum temperature affect yield positively. Given these influences of climate factors on the rice yield, it is recommended the adaptive techniques to overcome this situation.

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