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ABSTRACT

This study assesses the long-run relationship and short-run dynamics between paddy yields and climate variables, particularly maximum and minimum temperature and rainfall, using time-series data from 1971 to 2014 in Nepal. Applying Autoregressive-Distributed Lag Regression or ARDL bounds testing approach for analysis of co-integration between the variables, we confirm that there is a long-run relationship among the variables. Furthermore, we employ Granger non-causality tests for robustness. The findings reveal that rainfall has substantial effects on the rice yield. Specifically, a positive and significant relationship exists between rice yields and rainfall and that this relationship is unidirectional. Rainfall impacts on rice yield and holding all things constant, a 1 mm increase in rainfall increases rice yields by 0.65 percent. Given the effects of temperature on rice crops and increasing climate change vulnerabilities, agricultural scientists should focus on research and development of temperature tolerant rice varieties in the production of rice yields.

Keywords: climate change, rice production, Nepal, time series analysis, ARDL model

JEL Classification: O13, Q15, Q54

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INTRODUCTION

There is no debate that climate change is real (Hornsey et al. 2016). As it affects people, their livelihoods, and the ecosystem, it presents great development challenges for the global community, in general, and for the poor and natural resource dependent people in developing countries, in particular (Burton, Diringer, and Smith 2006; Khanal 2009). While climate change is a global phenomenon, potential effects are unevenly distributed, both between and within countries (Hunter, Salzman, and Zaelke 1998; O'Brien et al. 2007). The most vulnerable are often the poor, politically disenfranchised and marginalized communities, who are among the first to experience the impacts, and least equipped to diversify their livelihoods (Eriksen, O'Brien, and Rosentrater 2008; Mannke 2011). As a result, low-income populations dependent on subsistence farming will increasingly face severe hardships because they have little flexibility to buffer potentially large shifts in their production bases (FAO 2008; Ribot 2010). Climate stresses will push these populations over an all-too-low threshold into an insecurity and poverty that violates their basic human rights (Moser et al. 2001).

South Asia holds one fourth of the entire world's population (i.e., about 1.89 billion) in a region that is prominently based on agriculture for employment and livelihoods of their people. Here, agriculture employs about 60 percent of its workforce and contributes around 22 percent of its GDP. Nearly 70 percent of South Asian people still live in rural areas and they account for 75 percent of its total poor. Thus, depending on their location, the people of South Asia are very vulnerable to climate change due to geo-climatic conditions, socioeconomic background, population living in this region, and dependence on agriculture and rural sectors for livelihood (Islam, Salma, and Afroz 2009).

As an agricultural commodity, rice is one of the most important food grains and primary staple foods for over half of the world's population (Bachelet and Gay 1993; Swain and Yadav 2009; Dareker and Reddy 2017). Asia alone accounts for about 90 percent of the world's paddy cultivation and production (Rani et al. 2014; Dareker and Reddy 2017). For South Asia in particular, it is the staple food of 158 million Bangladeshi (Chowdhury and Khan 2015), covers one-third of total cultivable land in India (Farook and Kannan 2016), is the second major crop in Pakistan (Rehman et al. 2015), and is the primary staple crop in Bhutan (Katwal et al. 2015), Nepal (Devkota et al. 2018), and Sri Lanka (Thirumarpan 2014).

In Nepal, paddy accounts for the greatest share in farm area (42.2%) and production (51.7%) (MOAC 2017). Rice production contributes the largest proportion of employment, GDP, and raw materials supplied to existing agro-based industries. But these contributions have steadily declined. For instance, the Central Bureau of Statistics of Nepal or CBS noted in 2013 that paddy cultivation area had decreased by more than 129,000 ha, while Bhandari et al. (2017) noted that paddy growing households have decreased from 76 percent in 1996 to 72.3 percent in 2011.

Because of agriculture's direct exposure and reliance on weather conditions (Le 2016), climate is still a key determinant for agricultural productivity and sustainability (Chowdhury and Khan 2015) in many developing countries. Increased temperatures, rainfall fluctuations, and frequent weather extremes (Karn 2014; Le 2016; Devkota et al. 2018) will have beneficial and harmful effects on crops, mainly on crop growth, development, and yield (Amin et al. 2015; Riad and Peter 2017). Also, a change in the climate will affect the distribution and the severity of rice diseases and insect pests (Riad and Peter 2017).

In many regions throughout the world, temperatures and precipitation impact the production potential of major crops (Le 2016; Devkota et al. 2013; Yang et al. 2018). In rice production, modeling studies project country-specific variations in rice production due to climate change in Bangladesh (Sarker et al. 2013), Japan (Matthews et al. 1995), China (Bachelet et al.

1995), India (Mall and Agrawal 2002), Pakistan (Abid et al. 2015), and Nepal (Karn 2014; Adhikari et al. 2017). Reportedly, rice yield declines by 5 to 7 percent with 1°C increase in mean day time temperature (Riad and Peter 2017) and may decline by 10 percent with increase a 1°C in minimum temperature and night time temperature (Farook and Kanna 2016; Riad and Peter 2017).

Very few studies have intensively examined the relationship between climate change and rice production in Nepal. This paper thus aims to undertake a more comprehensive analysis of the impact of climate change, as seen in the effect of temperature and rainfall, on the yield of rice production in Nepal using country-specific historical data for the time period 1971–2014.

RESEARCH METHODOLOGY

Data and Sources

This paper examines the available data of annual observations from Nepal spanning 1971–2014 period. Rice area, production, and yields data were collected from statistical information on Nepalese agriculture from the Ministry of Agriculture and Cooperatives. Other data such as minimum temperature, maximum temperature, and rainfall were obtained from the Department of Hydrology and Meteorology in the Ministry of Energy, Water Resources, and Irrigation. Table 1 provides a summary of basic descriptive statistics of variables utilized in this study. In the base or original form, the mean of rice yield and rainfall is 2,365.50 kg/ha and 1,164.19 mm, respectively. A causal analysis of the standard deviation in Table 1 shows that both variables experienced significant variations during the sample period. Figure 1 represents the rice yields, which fluctuated upward. However, rice production drastically decreased in 1982.

Figure 1. The overall trend of paddy yield in Nepal (1971–2014)

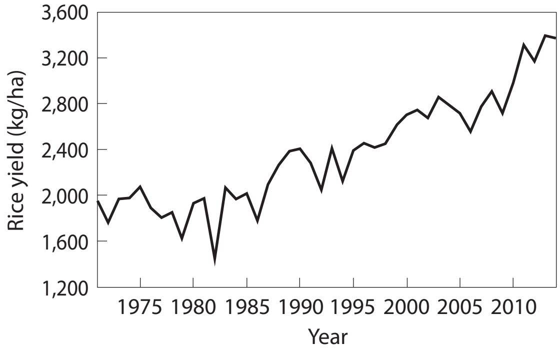

Table 1. Descriptive statistics

Statistics	Riceyield (kg/ha)	T max (°C)	T min (°C)	Rain (mm)	Riceyield	T max	T min	Rain
Mean	2,365.500	21.846	12.642	1,164.189	7.749	3.083	2.536	7.055
Median	2,378.500	22.054	12.603	1,185.050	7.774	3.093	2.534	7.078
Maximum	3,394.000	23.112	14.187	1,361.200	8.130	3.140	2.652	7.216
Minimum	1,449	20.073	11.696	954	7.279	2.999	2.459	6.861
Std. Dev.	481.646	0.821	0.443	111.193	0.203	0.038	0.035	0.097
Skewness	0.382	–0.576	0.652	–0.150	–0.005	–0.630	0.472	–0.301
Kurtosis	2.407	2.287	5.039	2.081	2.338	2.356	4.618	2.132
J.B.	1.712	3.366	10.734	1.712	0.803	3.673	6.435	2.044
Probability	(0.425)	(0.186)	(0.005)	(0.425)	(0.669)	(0.159)	(0.040)	(0.360)

Source: Authors' calculation

Note: The uppercase and lowercase letters refer to the variables in the base and logarithmic form, respectively. The J.B. test indicates the Jarque-Bera normality test.

Econometric Model

Several rice production models have established the level of rainfall and temperature combined with favorable variables, which would result to a significant reduction in rice yield. But one limitation of such models is that they are mostly used in lab-based exercises and applied by agricultural scientists. In fact, results from the use of such rice production models would differ depending on rice varieties, seasonality, and the farm area location. Behavioral socioeconomic studies, however, tend to work with how such effects impact overall GDP, livelihoods of the people, and their poverty level. This study looks at the economics of impact of climate change adaptation on rice farmers based on the selected variables that previous studies used for their analysis.

We examined the possible impact of climate change on rice yield (independent variable), using three climatic variables: maximum and minimum temperature (°C) and rainfall (mm). This study used an average growing season temperature and rainfall to capture the net effect of climate (i.e. temperature and rainfall) on rice yield development, which was used in several previous studies (e.g., Ozkan and Akcaoz 2002; Lobell et al. 2007; Almaraz et al. 2008; Sarker et al. 2012; Farook and Kanan 2016) following this basic model:

$$riceyields = f(t\max, t\min, rain) \quad (1)$$

where *riceyields* is rice production in kg/ha, *t max* is maximum temperature, *t min* is minimum temperature, and *rain* is the average rainfall within the country. To adjust for the ratio, we implement empirical estimations, perform a linear transformation on equation (1) that yields:

$$riceyield_t = \alpha_1 + \beta_1 t\,max_t + \beta_2 t\,min_t + \beta_3 rain_t + \mu_t \quad (2)$$

with the subscript t and μ_t indicating the time period and the Gaussian errors, respectively. Since the lowercase letters in Equation (2) denotes that all variables are in their natural logarithms, β's represent the long-run elasticities to be estimated. This specification also captures the relationship between rice yields, temperatures, and rainfall.

The Autoregressive-Distributed Lag Regression (ARDL) Approach

This study employed the Autoregressive-Distributed Lag Regression (ARDL) approach (Pesaran and Shin 1998; Pesaran et al. 2001) to capture the long-run relationship and the short-run dynamics for rice yield and its determinants on the following grounds. First, the variables *riceyield*, *t max*, *t min*, and *rain* are to be found cointegrated with a mixed order of one and zero-order of integration to be included under a unified framework. This favors the application of the Augmented-Dickey-Fuller (ADF) method to confirm that the tested variables are either (1) or (0).

First, the use of the general-to-specific modeling technique such as optimal lag length selection over a differencing operation will prevent spurious regression and preserves the long-run equilibrium relationship among variables. Second, choosing an appropriate lag structure reduces the problem of serial correlation in the residuals, and provides consistent estimates in the presence of endogenous regressors. Third, the test gives reliable consistency in short-run and long-run coefficient and is valid for a small and finite sample size. Finally, a dynamic unrestricted Error-Correction Model (ECM) is applied to identify the short-run adjustments with long-run equilibrium that can be derived from the ARDL method following a simple linear transformation. Symbolically, the ARDL representation of Equation (2) is expressed as follows:

$$\begin{aligned} \Delta riceyield_t &= \alpha_0 + \beta_0 riceyield_{t-1} + \\ &\beta_1 t\,max_t + \beta_2 t\,min_t + \beta_3 rain_t \\ &+ \sum_{i=1}^{p} \gamma_i \Delta riceyield_{t-i} + \sum_{j=0}^{p} \gamma_j\, \Delta t\,max_{t-j} + \\ &\sum_{k=0}^{p} \gamma_k \Delta t\,min_{t-k} + \sum_{l=0}^{p} \Delta rain_{t-l} + \varepsilon_t \end{aligned} \quad (3)$$

$$\Delta t\max_{t} = \alpha_0 + \beta_0 riceyield_{t-1} + \beta_1 t\max_t + \beta_2 t\min_t + \beta_3 rain_t + \sum_{i=1}^{p}\gamma_i \Delta riceyield_{t-i} + \sum_{j=0}^{p}\gamma_j\, \Delta t\,max_{t-j} + \sum_{k=0}^{p}\gamma_k \Delta t\,min_{t-k} + \sum_{l=0}^{p}\Delta rain_{t-l} + \varepsilon_t \tag{4}$$

$$\Delta t\,min_t = \alpha_0 + \beta_0 riceyield_{t-1} + \beta_1 t\,max_t + \beta_2 t\,min_t + \beta_3 rain_t + \sum_{i=1}^{p}\gamma_i \Delta riceyield_{t-i} + \sum_{j=0}^{p}\gamma_j\, \Delta t\,max_{t-j} + \sum_{k=0}^{p}\gamma_k \Delta t\,min_{t-k} + \sum_{l=0}^{p}\Delta rain_{t-l} + \varepsilon_t \tag{5}$$

$$\Delta rain_t = \alpha_0 + \beta_0 riceyield_{t-1} + \beta_1 t\,max_t + \beta_2 t\,min_t + \beta_3 rain_t + \sum_{i=1}^{p}\gamma_i \Delta riceyield_{t-i} + \sum_{j=0}^{p}\gamma_j\, \Delta t\,max_{t-j} + \sum_{k=0}^{p}\gamma_k \Delta t\,min_{t-k} + \sum_{l=0}^{p}\Delta rain_{t-l} + \varepsilon_t \tag{6}$$

where the terms with the first-difference operator (Δ) represent the error-correction dynamics and the terms with βi correspond to the long-run relationship.

We examine possible cointegration in the system of Equations (3), (4), (5) and (6) by conducting the joint-significance F-test on lagged levels terms $\beta_1 = \beta_2 = \beta_3 = \beta_4$, while the alternative hypothesis states the opposite $H_a: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0$). Then, we reject *H0* if the test statistics exceed their respective upper critical values and conclude that a long-run relationship exists in the system. In contrast, we cannot reject the H0 if the test statistics fall below their respective lower critical values. However, our bounds testing result becomes inconclusive when the F-statistic is observed to be between the lower and upper critical values.

If there is a cointegrating relationship in the system of Equations (3), (4), (5) and (6), our next step is to continue with its corresponding error correction model as shown in equation (3) to investigate the short-run dynamics of respective variables along with short-run adjustment rates toward the long-run. For the purpose of this study, a dynamic error-correction model of Equation (3) was estimated as follows:

$$\Delta riceyield_t = \alpha_0 + \sum_{i-1}^{p}\gamma_i \Delta riceyield_{t-i} + \sum_{j=0}^{p}\gamma_j \Delta t\,max_{t-j} + \sum_{k=0}^{p}\gamma_k \Delta t\,min_{t-k} + \sum_{l=0}^{p}\gamma_l \Delta rain_{t-l} + \lambda ECT_{t-1} + \varepsilon_t \tag{7}$$

where ECT_{t-1} is the one period lagged error-correction term derived from the long-run cointegrating vector. As per Engle and Granger (1987), causality of the cointegrated ECM derives either from ECT (if λ ≠ 0) or from lagged dynamic terms.

Finally, following Pesaran and Pesaran (1997), this study conducts several diagnostic tests to estimate the goodness of fit of the chosen model specification, including the test for serial correlation, functional form, normality, ARCH,[1] and heteroskedasticity. We also look at model stability by examining the plot of the cumulative (CUSUM) and cumulative sum of square (CUSUMSQ) statistics.

Granger Non-causality Test

This study adopted the Toda-Yamamoto (1995) Technique (TY, hereafter) to perform a Granger causality test that is valid irrespective of whether a series is I(0), I(1), or I(2), not-cointegrated or cointegrated with any arbitrary order (Menyah and Wolde-Rufael 2010). Co-integration tests may be sensitive to lag selection and omitted variables and may be biased themselves. The TY technique specifically avoids pre-test bias and some of these problems mentioned. Based on augmented VAR modeling, TY implements a Wald test statistic that produces an asymptotic chi square (χ^2) distribution regardless of the order of integration or the cointegration properties of the variables. The modified Wald test (MWALD) restricts the parameters of the VAR *(k)* where *k*

1 Autoregressive Conditional Heteroscedasticity

is the system's lag length. The basic principle behind the TY method is to arbitrarily augment the correct order, *k*, by the maximum order of integration, say d_{max}.

The following equation system is estimated to undertake the TY version of the Granger non-causality test, for VAR with 2 lags, (k=1 and d_{max}=1):

$$\begin{bmatrix} ln\, rice\, yield_t \\ ln\, t\, max_t \\ ln\, t\, min_t \\ ln\, rain_t \end{bmatrix} = A_0 + A_1 \begin{bmatrix} ln\, rice\, yield_{t-1} \\ ln\, t\, max_{t-1} \\ ln\, t\, min_{t-1} \\ ln\, rain_{t-1} \end{bmatrix} + A_2 \begin{bmatrix} ln\, rice\, yield_{t-2} \\ ln\, t\, max_{t-2} \\ ln\, t\, min_{t-2} \\ ln\, rain_{t-2} \end{bmatrix} + \begin{bmatrix} ^{\varepsilon}ln\, rice\, yield_t \\ ^{\varepsilon}ln\, T\, max_t \\ ^{\varepsilon}ln\, T\, min_t \\ ^{\varepsilon}ln\, rain_t \end{bmatrix} \quad (8)$$

In Equation (8), A1…A2 are four 4 × 3 matrices of coefficients with A0 being the 4 × 1 identity matrix, εs are the disturbance terms with zero mean and constant variance. From Equation (8), the standard modified Wald tests were applied to the first *k* VAR coefficient matrix to determine the direction of Granger causality. The following hypotheses were tested:

$H_{01} = a_{12}^1 = a_{12}^2 = a_{12}^3 = 0,$ meaning that maximum temperature does not Granger cause rice yield;

$H_{02} = a_{21}^1 = a_{21}^2 = a_{21}^3 = 0,$ meaning that rice yield does not Granger cause maximum temperature;

$H_{03} = a_{13}^1 = a_{13}^2 = a_{13}^3 = 0,$ meaning that minimum temperature does not Granger cause rice yield;

$H_{03} = a_{13}^1 = a_{13}^2 = a_{13}^3 = 0,$ meaning that rice yield does not Granger cause minimum temperature; and so on for the other variables.

RESULTS AND DISCUSSION

Unit Root Tests

In this study, the analysis was begun by testing the order of integration for the variables used in the analysis. This step is essential since only I(0) and I(1) order of integration are applicable for bounds testing. Conventional unit root tests were applied, including the augmented Dickey-Fuller (ADF), Phillips-Perron (P-P) and KPSS test. Table 2 reports the results of unit root tests to rule out if any of the selected variables contain an integration order of two or higher. Table 2 reveals that rainfall and minimum temperature is

Table 2. Results of ADF, P-P, and KPSS unit root tests

	ADF	PP	KPSS
Levels			
Lnpyield	0.169(2)	–0.835	0.802***
lntmax	–2.505(3)	–2.095	0.806***
lntmin	–5.691***(0)	–5.653***	0.077
Lnrain	–6.705***(0)	–6.701***	0.097
First differences			
ΔLnpyield	–7.522***(1)	–14.300***	0.217
Δlntmax	–8.260***2(0)	–27.861***	0.500
Δlntmin	–4.821****(1)	–19.002***	0.179
Δlnrain	–7.590***(1)	–22.188***	0.099

Notes: ** and *** represent 5 percent and 10 percent level of significance, respectively.
ADF = Augmented Dickey-Fuller; (P-P) = Phillips-Perron; KPSS = Kwiatkowski–Phillips–Schmidt–Shin

stationary at level I(0). However, rice yields and maximum temperature are non-stationary at that level, but these variables are stationary at their first differences. Thus, we conclude that the variables are of mixed order of integration, i.e., I(0) and I(1).

Conventional unit root tests have been criticized for their low size and power and presume away any structural breaks in the series as well. As such, the standard unit root tests can fail to test the stationarity of series in the presence of structural break. Zivot and Andrews (1992) (hereafter, ZA) have proposed a unit root testing procedure which, under the alternative hypothesis, allows one to estimate any structural break in the trend function. The order of integration of a series using ZA unit root test was therefore tested to account for structural breaks; results of the test are reported in Table 3.

ZA tests show that rice yields and maximum temperature are integrated of order 1 (i.e., I(1)) at 5 critical level. However, minimum temperature and rainfall shows, in order of integration, stationarity at the level (i.e., I(0)). The structural break in the series of rice yields during 1982 may be explained by huge flooding at the time in the lower belt of Nepal (Teria), which directly affected rice production.

ARDL Bounds Test

As all the selected variables are integrated at I(0) or I(1), bounds testing focuses on the rice yields–maximum temperature–minimum temperature–rainfall linkage for Nepal. It begins by identifying an optimal lag structure, in particular the degrees of freedom retained by restricting the maximum lag length to one before determining the lag structure based on Schwarz Information Criterion (SC). Table 5 presents the results of bounds testing. If all variables are made dependent, the computed F-statistics are 7.03, 7.70, 5.55, and 7.58, respectively, and each equation exceeds the upper critical bound at any conventional level of

Table 3. Zivot-Andrews structural break unit root test

Varible	ZA Test for Level			ZA Test for 1st Difference		
	T-statistic	TB	Outcome	T-statistic	TB	Outcome
lnpaddyP	–4.123	2011	Unit Root	–11.287***	1982	Stationary
lntmax	–3.683	1990	Unit Root	–10.849***	2009	Stationary
lntmin	–7.917***	1981	Stationary	–9.096***	1979	Stationary
lnrain	–6.235***	1995	Unit Root	–12.186***	1991	Stationary

Note: ***, **, * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively.

Table 4. VAR lag order selection criteria

Lag	Log Likelihood	LR Statistic	Final Predictor Error (FPE)	Akaike Information Criterion (AIC)	Schwarz Information Criterion (SC)	Hannan-Quinn Information Criterion (HQ)
0	232.918	NA	1.66E-10	–11.167	–11.000	–11.106
1	298.089	114.447	1.52E-11	–13.565	–12.729*	–13.261*
2##	316.986	29.498*	1.35e-11*	–13.707*	–12.202	–13.159
3	332.174	20.744	1.49E-11	–13.667	–11.494	–12.876

Notes: * indicates lag order selected by the criterion.
** indicates the LR test (each test at 5 percent level).
indicates lag length selection according to SC.

Table 5. Result of ARDL bounds test

Dependent variable	F-stat.	Outcome
$F_{\text{lnPaddy P}}$ (ln *paddyp*| ln *t* max, ln *t* min, ln *rain*	7.029***	Cointegration
$F_{ln\ T\ max}$ ln *t max* | *paddyp*, ln *t* min, ln *rain*	7.701***	Cointegration
$F_{ln\ t\ min}$ (ln *t* min | ln *t* max, ln *paddyp*, ln *rain*	5.552**	Cointegration
$F_{ln\ Rain}$ (ln *rain* | ln *t* max, ln *t* min, ln *paddyp*	7.582***	Cointegration
1 percent significance level	5.17	6.36
5 Percent significance level	4.01	5.07
10 percent significance level	3.47	4.45

Note: *** and ** represent 1 percent and 5 percent level of significance, respectively.

significance. The results suggest that cointegration exists in the rice yields–maximum temperature–minimum temperature–rainfall linkage for Nepal over the sample period 1971–2014.

Long-Run and Short-Run ARDL Estimates

After establishing cointegration in the rice yields–maximum and minimum temperature–rainfall linkage, the results report the long-run and short-run estimates of equation (3) in Table 6 and Table 7, respectively. Table 6 reveals the long-run estimates, which indicate a positive and significant relationship between rice yields and rainfall. The empirical result implies that a 1 percent increase in rainfall increases rice yields by 0.65 percent, holding all things constant. However, starting with the long-run analysis, both the coefficient of maximum and minimum temperatures are negatively associated with rice yields but not statistically significant. Our findings corroborate

Table 6. Long run coefficient using the ARDL approach, (1, 0, 0, 0) selected based on SIC, dependent variable is LnPaddyP

Regressor	Coeff. for time (trend) variable	Std. error	T-Statistic	Prob.
lntmax	–1.264	1.069	–1.182	0.245
lntmin	–0.123	0.491	–0.251	0.803
lnrain	0.648**	0.246	2.639	0.012
C	6.982*	3.694	1.890	0.067

Note: (***) and (***) represent 1 percent and 5 percent level of significance, respectively.

Table 7. Error correction representation of ARDL model (1, 0, 0, 0) selected based on SIC: Dependent variable is Δ ln paddy P

Regressor	Coef. for time (trend) variable	Std. Error	t-Statistic	Prob.
Δ*lntmax*	-0.884	0.765	-1.156	0.255
Δ*lntmin*	-0.086	0.348	-0.248	0.806
Δ*lnrain*	0.453***	0.119	3.798	0.001
ECT_{t-1}	-0.699***	0.145	-4.819	0.000

Note: ***, **, and * represent 1 percent, 5 percent, and 10 percent level of significance, respectively.

Maharjan and Joshi (2013) who also found that in Nepal, rainfall is significantly associated with the paddy production but not maximum and minimum temperatures. On the contrary, (Poudel and Shaw 2016) found that precipitation does not impact on rice yield. However, in the case of Bangladesh, Sarker et al. (2012) found that rainfall has a positive effect on Aus and Aman rice, but an adverse effect on Boro rice.

In the short run analysis (Table 7), only the rainfall sources are statistically significant in determining rice production. On the other hand, a 1 percent increase in rainfall improves rice production by 0.45 percent at 1 percent level of significance. Considering the error correction term, ECT_{t-1}, a negative and statistically significant correction mechanism for the coefficient error implies that deviations from the long-run equilibrium are corrected by nearly 70 percent in each year. As a summary of the short run, rice

Table 8. Diagnostic test of ARDL model

	F-statistic	p-value		F-statistic	p-value
R-squared		0.894	R-bar-squared		0.879
Serial correlation	0.016	0.901	Normality		0.349
ARCH(1)	0.945	0.337	Heteroscedasticity	1.034	0.412
Ramsey RESET	1.226	0.276			

production is not affected by the changes in *t min* in the short run.

The estimated ARDL model also requires diagnostic testing for robustness. Table 8 reveals that there is no serial correlation, which means we can reject the null hypothesis at 5 percent level of significance as p-value is greater than 0.05.

Similarly, normality of residual and heteroskedasticity cannot be rejected in favor of the alternative hypothesis. Additionally, the goodness of fit of the specification (R^2=0.94 and Adjusted R^2 = 0.92) is very close to unity that is favored in econometric analysis. The stability test is the last identification related to the goodness of the model fit. For this purpose, we conduct CUSUM and CUSUMQ tests. As seen in Figure 2, the estimated parameters are unstable over time since the plot of CUSUM and CUSUMQ test statistics fall out within the boundaries, implying some instability in the rice yield function. However, the plot of CUMUMQ is returned toward the critical boundaries, the deviation is only transitory.

Toda-Yamamoto Granger Causality Test

To establish the order of integration of the series (d_{max}) and the optimum lag length (k), the next step is to conduct Granger non-causality test by augmenting the VAR (k) by the maximum order of integration of the series, d_{max}. As the emphasis of the study was more on the relationship between rice yields and rainfall, discussion will focus on results about these variables.

Table 9 presents the results of the TY (hereafter) Granger non-causality tests revealing an interesting outcome—there is a unidirectional causality running from rainfall to rice yields. However, maximum temperature and minimum temperature do not "cause" rice yield, which is consistent with the results from the log-run test presented in Table 6. This result reveals that there is a causal relationship between the climate variables and rice yield in the Nepal case. These results are also in line with a result for India (Farook and Kanan 2016), which concluded causal relationship between the climate variables

Figure 2. Plots of cumulative sum of recursive residual and cumulative sum of squares of recursive residuals

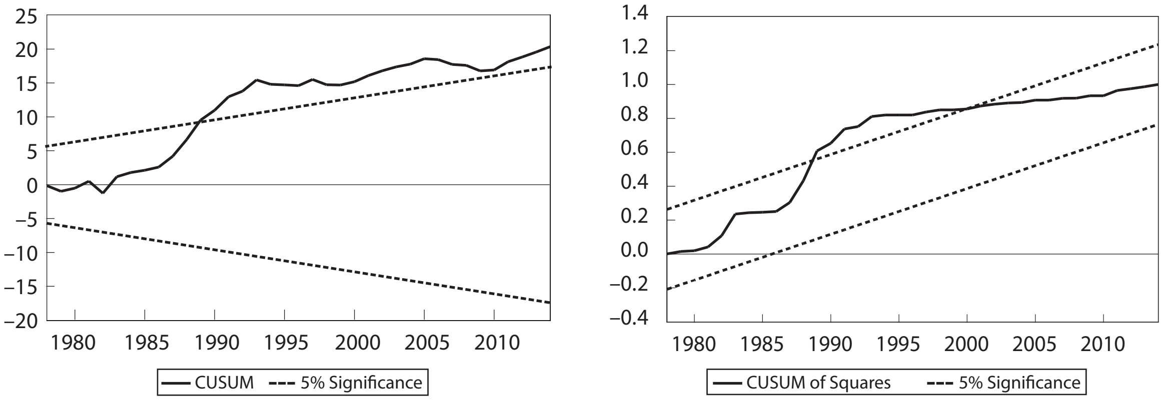

Table 9. Toda-Yamamoto Granger causality

Effect	Cause			
	lnpyield	lnTmax	lnTmin	lnrain
lnpyield	–	0.207	0.159	6.128**
lntmax	12.129***	–	0.366	4.946*
lntmin	8.412**	1.186**	–	2.909
Lnrain	0.459	1.248	3.263	–

Note: ***, **, and * represent 1 percent, 5 percent, and 10 percent level of significance, respectively.

and Rabi rice yields. The same study, however, concludes that rainfall does not "cause" Kharafi rice yield.

Generalized Impulse Response Function and Variance Decompositions

A way to test the long-run Granger causality relationship among the series is employed via the TY process. The results of the tests, however, do not consider how variables generally respond to innovations in other variables. In order to investigate how a shock may affect one variable from another variable, and how long the impact of innovations in all variables in the system on rice yield give useful insight in the short-run, this study uses generalized impulse response and generalized variance decompositions (Koop et al.1996; Pesaran and Shin 1998), which overcome the orthogonality problem in traditional out-of-sample Granger Causality tests. Hence, the study estimates a VAR[2] system in levels. The generalized impulse responses of maximum temperature, minimum temperature, and rainfall to one standard deviation innovations in rice yield are visualized in Figure 3.[3]

A shock in one of the rainfall variables has a positive and significant initial impact on rice yield. Nonetheless, although initial impact is significant, it decreases under the horizons after around two years. It implies that global warming is the main issue to consider in the variation of rainfall. On the other hand, maximum and minimum temperatures are negative and insignificant in their initial impact. Hence, this result seems to have a more robust base on ARDL long-run and Granger Causality test results with the Nepal status quo previously discussed.

Karn (2014) found, however, that in a positive relationship between rice yield–minimum temperature, rice yield increases up to a critical threshold of 29.9°C. When maximum temperature goes beyond this threshold, rice yield declines.

Table 10 encapsulates the generalized variance decompositions. The initial impact of rice yield on forecast error variance of maximum temperature is approximately 3 percent in shorter horizons and more than 34 percent in the longer horizons—higher than any other variable in the system. In all horizons, the impact of maximum temperature on rice yield is the highest. However, rainfall almost remains the same in all horizons. The results based on the rice yield equation indicate that maximum temperature accounts for more than other variables. These results support the previously reported causal relationship between maximum temperature, rainfall, and rice yield. Overall, these results are robust to findings of impulse response functions.

Implications of the Study

As paddy contributes highest in terms of production, consumption, and demand of the people of Nepal, it has received special focus in national planning documents along with major plans and policies (Bhandari et al. 2017). To encourage farmers toward paddy production and growth, the government of Nepal has introduced several policies, such as the Agricultural Perspectives Plan (1995); National Agriculture Policy (2004); National Seed Vision (2013–2015); Special Agriculture Production Program (since 2012); Agriculture Mechanization Policy (2014); and Agriculture Development Strategy (2015–2035) (Devkota et al. 2018). In pursuit

2 The estimated VAR(2) system is as below: $Y_t = ay\, \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \varepsilon_{yt}$ where $Y_t = f\,(riceyield_t, tmax_t, tmin_t\; rain_t)$, α_y are (4x1) coefficient matrices, and ε_{yt} indicates white noise residuals.

3 For simplicity, the responses of some variables are omitted, which are available from the author upon request.

Figure 3. Generalized impulse responses of *t max, t min, and rain* to rice yield

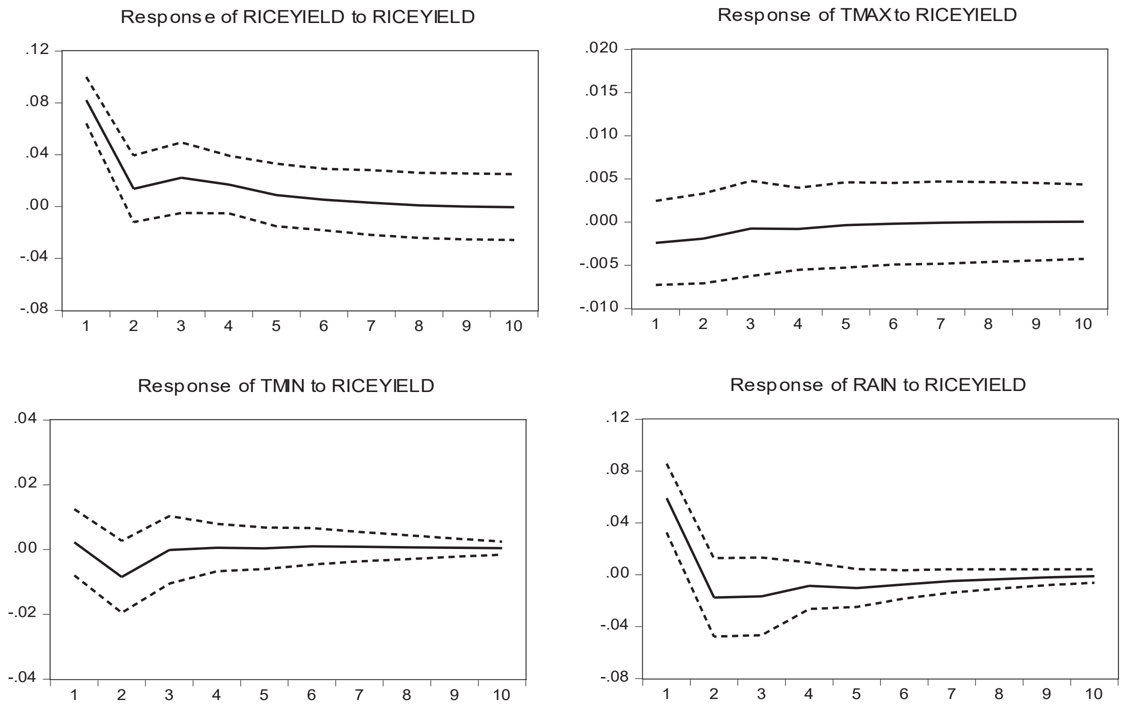

Table 10: Forecast error variance decomposition for rice yield

Period	S.E.	Rice Yield	t max	t min	rain
1	0.082	100.000	0.000	0.000	0.000
2	0.085	96.355	2.498	0.038	1.110
3	0.098	77.984	6.619	14.488	0.909
4	0.103	72.802	8.381	17.925	0.892
5	0.111	63.201	14.994	21.024	0.781
6	0.117	57.074	18.423	23.799	0.704
7	0.123	51.499	23.505	24.361	0.634
8	0.129	47.364	27.291	24.739	0.607
9	0.134	43.877	31.077	24.456	0.590
10	0.138	41.120	34.177	24.099	0.604

of food security, it has also introduced important programs and guidelines such as the Mega Rice Production Program, and the Fine and Aromatic Rice Production Promotion Program and Prime Minister Agriculture Modernization Program (PMAMP). Under the PMAMP, the government of Nepal envisions a commercial agriculture with specialized production center development (also known as pocket areas). Under this scheme, blocks will be developed based on their commercial feasibility, 24 blocks of 100 ha each, 5 zones covering 500 ha each, and 1 super zone covering 1,000 ha. The project aims to make the country self-reliant in rice in three years. Under this project, the super zone for rice is being implemented in Jhapa District (Bhandari et al. 2017). Also, there are more than five dozens of food grain-related periodic projects launched by the government of Nepal in the different time periods with the principal aim of strengthening research and extension for the development of the agricultural sector.

To implement the government's plan and policies, several government and international governmental organizations such as the Nepal Agricultural Research Center or NARC, Local Initiatives for Biodiversity, Research and Developments or LI-BIRD, Forum for Rural Welfare and Agricultural Reform for Development or FORWARD, and the International Rice Research Institute or IRRI have been involved in paddy production in Nepal. At the educational level, the Institution of Agriculture and Animal Sciences and the Agriculture Forest University are providing academic research, experimental areas, and other teaching-learning support to the students (Devkota et al. 2018).

In 2018, the paddy super zone and paddy blocks have been established in Jhapa and the rice zone program has been implemented in Kapilavastu under PMAMP. The main aim of declaring such zones is to increase the production and productivity of rice by supporting necessary technology, inputs, mechanization, processing, and marketing. Unfortunately, paddy production in Jhapa district's paddy super zone and paddy blocks failed to meet expectations of many due to low soil quality, floods, and irregular rain (Rajbanshi 2018). It requires further actions from the government to recoup the huge expenditures incurred.

Despite all the efforts, the result has not been as planned. Moreover, the recent phenomenon of the stagnant or even declining yields, land degradation, and environmental pollution has raised concern regarding the long-term sustainability of increasing productivity (Joshi 2017). In light of all these, the results of this research could help explain why climate anomalies restrict rice production in Nepal. These results will be a primary input for those institutions planning and developing policies for Nepalese rice production and sustainability.

CONCLUSION AND RECOMMENDATION

The study finds a positive rice yield–rainfall nexus both in the short-run and the long-run. These results are consistent with the view that the technique and composition effects capture long term adjustment, such that rainfall does cause paddy productivity in the long-term.

On the other hand, the findings suggest a negative but statistically insignificant relationship between both minimum and maximum temperatures with rice yields. This study notes that the current average maximum temperature for the decade of 1999 to 2008 is already 30.8°C. Thus, it is expected that rice yields are already being negatively affected by increases in the daily maximum temperature.

Research on sustainable agricultural development shows the avenues to explore the long-term relationship between climate change and cereal production in a mountainous economy. Rice grows in a very wide climatic area where the cultivation conditions greatly vary. Moreover, higher yield, better grain quality, and stronger stress resistance are important goals of grain production everywhere. Adaptation strategies for increasing rice productivity in future environments will have to integrate these rice characteristics into one ultimate target. Improving rice quality without sacrificing high yield and pest resistance could be a major challenge for scientists. The above recommendation should be helpful as policy input to Agriculture Development Strategy 2015–2035, and the PMAMP being implemented in Nepal.

Limitation of the Study and Further Avenues

Other than temperature and rainfall, other rice production-related variables such as land area and production-related variables that have been established by previous studies as significant explanatory variables of rice yield can be included in further econometric analysis. Furthermore, the extension would vary depending on other variables like soil type, soil quality, farm management, and scale/area of operation. Including such variables can clearly isolate the effects of each of these variables on rice yield and determine the specific elasticities with the maximum and minimum temperatures and rainfall. While acquiring data for such variables is challenging in the Nepalese context, such study would be novel in terms of being the first of its kind for a mountainous country like Nepal.

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REFERENCES

Abid, M.E.A., J. Scheffran, U.A. Schneider, and M. Ashfaq. 2015. "Farmers' Perceptions of and Adaptation Strategies to Climate Change and Their Determinants: The Case of Punjab Province, Pakistan." *Earth System Dynamics 6*(1): 225–243. https://doi.org/10.5194/esd-6-225-2015

Adhikari, V.R., N. Devkota, and R.K. Phulyal. 2017. "Impact of Climate Variation in Paddy Production in Nepal." *International Journal of Economics Prospective 11*(3): 1084–1092.

Almaraz, J.J., F. Mabood, X. Zhou, E.G. Gregorich, and D.L. Smith. 2008. "Climate Change, Weather Variability and Corn Yield at a Higher Latitude Locale: Southwestern Quebec." *Climatic Change* 88(2): 187–197.

Amin, M.R., J. Zhang, and M. Yang. 2015. "Effects of Climate Change on the Yield and Cropping Area of Major Food Crops: A Case of Bangladesh." *Sustainability* 7(1): 898–915.

Bachelet, D., and C.A. Gay. 1993. "The Impacts of Climate Change on Rice Yield: A Comparison of Four Model Performances." *Ecological Modelling* 65(1–2): 71–93. https://doi.org/10.1016/0304-3800(93)90127-E

Bachelet, D., J. Kern, and M. Tölg. 1995. "Balancing the Rice Carbon Budget in China Using Spatially-Distributed Data. *Ecological Modelling* 79(1-3): 167–177. https://doi.org/10.1016/0304-3800(94)00031-C

Bhandari, D.R., P.K. Sanjel, and S. Adhikari. "2017 Policy Review of Paddy Production in Nepal." In ed. M.N. Paudel, et al., *Rice Science and Technology in Nepal,* 719–736. Crop Development Directorate (CDD), Hariharbhawan and Agronomy Society of Nepal (ASoN), Khumaltar.

Burton, I., E. Diringer, and J Smith. 2006. *Adaptation to climate change: International policy options.* Arlington, VA: Pew Center on Global Climate Change.

CBS (Central Bureau of Statistics). 2013. *National Sample Census of Agriculture Nepal 2011/12*. Kathmandu: Central Bureau of Statistics.

Chowdhury, I.U.A., and M.A.E. Khan. 2015. "The Impact of Climate Change on Rice Yield in Bangladesh: A Time Series Analysis." *Russian Journal of Agricultural and Socio-Economic Sciences* 40(4): 12–28.

Clarke, J., and S.A. Mirza. 2006. "A Comparison of Some Common Methods of Detecting Granger Noncausality." *Journal of Statistical Computation and Simulation* 76(3): 207–231. https://doi.org/10.1080/10629360500107741

Darekar, A., and A. Reddy. 2017. "Forecasting of Common Paddy Prices in India." *Journal of Rice Research* 10(1): 1–75. DOI: 10.2139/ssrn.3064080

Devkota, K.P., A.M. Manschadi, M. Devkota, et al. 2013. "Simulating the Impact of Climate Change on Rice Phenology and Grain Yield in Irrigated Drylands of Central Asia." *Journal of Applied Meteorology and Climatology*, *52*(9): 2033–2050.

Devkota, N., R.K. Phuyal, and D.L. Shrestha. 2018. "Perception, Determinants and Barriers for the Adoption of Climate Change Adaptation Options among Nepalese Rice Farmers." *Agricultural Sciences* 9(3): 272–298. DOI: 10.4236/as.2018.93021

Engle, R.F., and C.W. Granger. 1987. "Co-integration and Error Correction: Representation, Estimation, and Testing." *Econometrica* 55(2): 251–276. DOI: 10.2307/1913236

Eriksen, S., K. O 'Brien, and L. Rosentrater. 2008. *Climate Change in Eastern and Southern Africa: Impacts, Vulnerability and Adaptation* (GECHS Report No. 2). Norway: Global Environmental Change and Human Security, University of Oslo, Norway.

Farook, A.J., and K.S. Kannan. 2016. "Climate Change Impact on Rice Yield in India–Vector Autoregression Approach." *Sri Lankan Journal of Applied Statistics* 16(3): 161–178. DOI: 10.4038/sljastats.v16i3.7830

FAO (Food and Agriculture Organization). 2008. *Climate Change and Food Security: A Framework Document*. Rome, Italy: FAO.

Hornsey, M.J., E.A. Harris, P.G. Bain, and K.S. Fielding. 2016. "Meta-analyses of the Determinants and Outcomes of Belief in Climate Change." *Nature Climate Change* 6(6): 622–626.

Hunter, D., J. Salzman, and D. Zaelke. 1998. *International Environmental Law and Policy*. New York: Foundation Press.

Islam, A.K.M.N., S. Salma, and Afroz. 2009. "Climate Change and South Asia: What Makes the Region Most Vulnerable?" *MPRA Paper* 21875. University Library of Munich, Germany. https://mpra.ub.uni-muenchen.de/21875/

Joshi, G. R. 2017. Challenges and opportunities for enhancing rice production in Nepal. In *Rice Science and Technology in Nepal* edited by M. N. Paudel, D. R. Bhandari, M. P. Khanal, B. K. Joshi, P. Acharya and K. S. Ghimire. Read, pp. 719–736. Lalitpur: Crop Development Directorate. Retrieved from http://www.doacrop.gov.np/downloadfile/Rice_science_and_technology_1512106674.pdf

Karn, P.K. 2014. "The Impact of Climate Change on Rice Production in Nepal." *Working Paper* No. 85-14. South Asian Network for Development and Environmental Economics (SANDEE). Kathmandu, Nepal.

Katwal, T.B., S. Dorji, R. Dorji, et al. 2015. "Community Perspectives on the On-farm Diversity of Six Major Cereals and Climate Change in Bhutan." *Agriculture* 5(1): 2–16. https://doi.org/10.3390/agriculture5010002

Khanal, R.C. 2009. "Climate change and organic agriculture." *Journal of Agriculture and Environment* 10: 116–127. DOI: 10.3126/aej.v10i0.2136

Koop, G., M.H. Pesaran, and S.M. Potter. 1996. "Impulse Response Analysis in Nonlinear Multivariate Models." *Journal of Econometrics* 74(1): 119–147. https://doi.org/10.1016/0304-4076(95)01753-4

Le, T.T.H. 2016. "Effects of Climate Change on Rice Yield and Rice Market in Vietnam." *Journal of Agricultural and Applied Economics* 48(4): 366–382.

Lobell, D.B., and C.B. Field. 2007. "Global Scale Climate-Crop Yield Relationships and the Impacts of Recent Warming." *Environmental Research Letters* 2: 1–7.

Maharjan, K.L., and N.P. Joshi. 2013. "Effect of Climate Variables on Yield of Major Food-Crops in Nepal: A Time-Series Analysis." In *Climate Change, Agriculture and Rural Livelihoods in Developing Countries,* 127–137. Springer, Tokyo. https://doi.org/10.1007/978-4-431-54343-5_9

Mall, R.K., and P.K. Aggarwal. 2002. "Climate Change and Rice Yields in Diverse Agro-Environments of India. I. Evaluation of Impact Assessment Models." *Climatic Change* 52(3): 315–330.

Mannke, F. 2011. "Key Themes in Local Adaptation to Climate Change: Results from Mapping Community- Based Initiatives in Africa. In W.L. Filho (ed.), *Experiences of Climate Change Adaptation in Africa. Climate Change Management*. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-22315-0_2

Matthews, R.B., T. Horie, M.J. Kropff, et al. 1995. "A Regional Evaluation of the Effect of Future Climate Change on Rice Production in Asia." In *Modeling the Impact of Climate Change on Rice Production in Asia,* 95–139. CAB International, UK.

Menyah, K., and Y. Wolde-Rufael. 2010. "Energy Consumption, Pollutant Emissions and Economic Growth in South Africa." *Energy Economics* 32(6): 1374–1382. https://doi.org/10.1016/j.eneco.2010.08.002

Ministry of Agriculture and Cooperatives (MOAC). 2017. *Statistical Information on Nepalese Agriculture: 20015/16*. Agri-Business Promotion and Statistics Division, Ministry of Agriculture and Cooperatives, Kathmandu, Nepal.

Moser, C., A. Norton, T. Conway, C. Ferguson, and P. Vizard. 2001. *To Claim our Rights: Livelihood Security, Human Rights and Sustainable Development*. London: Overseas Development Institute.

O'Brien, K. L., S. Eriksen, L. P. Nygaard, and A. Schjolden. 2007. "Why Different Interpretations of Vulnerability Matter in Climate Change Discourses." *Climate Policy* 7(1): 73–88.

Ozkan, B., and H. Akcaoz. 2002. "Impacts of Climate Factors on Yields for Selected Crops in Southern Turkey." *Mitigation and Adaptation Strategies for Global Change* 7: 367–380.

Pesaran, H.H., and Y. Shin. 1998. "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58(1): 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0

Pesaran, M.H., and B. Pesaran. 1997. *Working with Microfit 4.0: Interactive Econometric Analysis*. Oxford University Press.

Pesaran, M.H., Y. Shin, and R.J. Smith. 2001. "Bounds Testing Approaches to the Analysis of Level Relationships." *Journal of Applied Economics* 16(3): 289–326. https://doi.org/10.1002/jae.616

Poudel, S., and R. Shaw. 2016. The Relationships Between Climate Variability and Crop Yield in a Mountainous Environment: A Case Study in Lamjung District, Nepal. *Climate 4*(1):13. https://doi.org/10.3390/cli4010013

Rajbanshi, H. 2018. "Jhapa's Paddy Super Zone Output less than Steller." *The Kathmandu Post*, 4 January 2018. https://kathmandupost.com/money/2018/01/04/jhapas-paddy-super-zone-output-less-than-stellar

Rani, V.U., and G.P. Reddy, Y.E. Prasad, and A.A. Reddy. 2014. "Competitiveness of Major Crops in Post-WTO Period in Andhra Pradesh." *Indian Journal of Agricultural Economics* 69(1): 126–141. DOI: 10.2139/ssrn.2666940

Rehman, A., L. Jingdong, B. Shahzad, A.A. Chandio, I. Hussain, G. Nabi, and M.S. Iqbal. 2015. "Economic Perspectives of Major Field Crops of Pakistan: An Empirical Study." *Pacific Science Review B: Humanities and Social Sciences* 1(3): 145–158. https://doi.org/10.1016/j.psrb.2016.09.002

Riad, N., and D. Peter. 2017. "The Impact of Climate Change and Climate Variability on The Agricultural Sector in Nickerie District." *Journal of Agriculture and Environmental Sciences* 6(1): 51–65. DOI: 10.15640/jaes.v6n1a6

Ribot, J. 2010. "Vulnerability Does Not Fall from the Sky: Toward Multiscale, Pro-poor Climate Policy." In R. Mearns and A. Norton (eds.) *Social Dimensions of Climate Change: Equity and Vulnerability in a Warming World*. Washington, DC: The World Bank.

Sarker, M.A.R., K. Alam, and J. Gow. 2013. "Assessing the Determinants of Rice Farmers' Adaptation Strategies to Climate Change in Bangladesh." *International Journal of Climate Change Strategies and Management* 5(4): 382–403.

______. 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

Swain, D.K., and A. Yadav. 2009. "Simulating the Impact of Climate Change on Rice Yield Using CERES-Rice Model." *Journal of Environmental Informatics* 13(2): 104–110.

Thirumarpan, K. 2014. "Determinants of Household Food Security of Paddy Farmers in Bat-ticaloa District, Sri Lanka." *Tropical Agricultural Research and Extension* 17(3–4): 135–142. http://doi.org/10.4038/tare.v17i3-4.5317

Toda, H.Y., and T. Yamamoto. 1995. "Statistical Inference in Vector Autoregressions with Possibly Integrated Processes." *Journal of Econometrics* 66(1–2): 225–250. https://doi.org/10.1016/0304-4076(94)01616-8

Yang, M., R. Zuo, L. Wang, and X. Chen. 2018. "Simulation of Land Surface Climate Over China with RegCM4. 5: Verification and Analysis." *Advances in Meteorology* 2018 Article ID 7960908. https://doi.org/10.1155/2018/7960908

Zivot, E., and D.W.K. Andrews. 1992. "Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis." *Journal of Business & Economic Statistics* 10(3): 251–270. DOI: 10.2307/139154