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Stochastic Impact of Climate Change on Rice Market for Poverty Control: An Evidence from Bangladesh

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Abstract

This study was undertaken to investigate the stochastic impact of future climate conditions on the rice market and to identify the policy measures for poverty reduction in Bangladesh. Using of supply and demand structure of Bangladesh and secondary data collected from various published and online sources. The study period is divided into two periods where the first period (1977-2010) is taken for the parameter's estimation of reference model and the second period (2011-2030) for comprehensive investigation of stochastic impact. To capture the probabilistic nature of climate variability, a random variable method and the inverse function of the cumulative standard normal distribution were applied. After big set of calibration, a percentile group by 90th and another group by 10th percentiles were set as upper and lower boundary to compare with the calibrated model output. Under stochastic climate impacts, rice yield variations ranged from 0.41 ton/ha to 1.78 ton/ha across the three major rice-growing seasons, clearly indicating the potential effects of climate shocks on future rice production. It undeniably clarifies the stochastic impact of climate shock on rice production in the future. Stochastic shock of climate increases the variation of rice price up to 33% in 2020, which may increase the vulnerable people by 25% through food expenditure increase. Such price instability will elevate food policy concerns through upward pressure on rice prices. Therefore, policymakers and economic policy interventions will play a crucial role in mitigating the stochastic impacts of climate shocks on the rice market.

Keywords: Bangladesh, Climate change, Poverty, Rice Market, Stochastic impact

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Introduction

Bangladesh is located in South Asia between 20°34″ to 26°38″ North latitude and 88°01″ to 92°41″ East longitude, where tropical climatic conditions prevail (HIES, 2022). Rice is the dominant cereal crop and the staple food for approximately 167 million people. Food consumption in Bangladesh has historically been rice-based, making rice the principal source of caloric intake. Consequently, rice represents the most important sub-sector of agriculture, contributing substantially to farm income and generating non-farm employment.

Over the past several decades, Bangladesh has achieved notable progress in rice production, supported by technological advancement, irrigation development, and favorable policy interventions. These efforts enabled steady yield growth and near self-sufficiency in rice (Ganesh et al., 2012). LaFranchi (2015) identified Bangladesh as a global example in the fight against hunger, highlighting its transition from chronic food shortages to a rice-surplus country. According to the Bangladesh Bureau of Statistics (BBS, 2024), in FY 2022–23 Aus rice covered 2,622 thousand acres with a production of 2,901 thousand metric tons. *Aman* rice occupied 14,143 thousand acres producing 15,426 thousand metric tons, while *Boro* rice the highest-producing season covered 11,989 thousand acres with a production of 20,768 thousand metric tons. Rice alone accounts for more than 97% of cultivated area and production among major cereal crops. Compared to FY 2021–22, Aus rice area declined by 8.44%, whereas *Aman* and *Boro* areas increased by 0.082% and 0.78%, respectively (BBS, 2024).

Despite these achievements, rice production in Bangladesh remains highly sensitive to climate change. Climatic factors such as temperature, rainfall, and extreme weather events significantly influence rice yields and production practices. Climate change threatens rice production by altering physiological and morphological characteristics, potentially reducing yields and increasing food insecurity (Nagaraj et al., 2024). Some studies suggest that moderate increases in temperature and rainfall may temporarily enhance rice production. For instance, a 1% increase in maximum temperature is associated with a 1.82% rise in rice production, while a 1% increase in rainfall may raise yields by 0.88% (Hussain, 2024). However, long-term projections indicate that rising temperatures could reduce rice yields by 18%–36% by the end of the century under extreme climate scenarios (Chaudhari and Yadav, 2024). Moreover, irregular rainfall distribution negatively affects rice production across regions (Li et al., 2024).

Bangladesh is increasingly exposed to a daunting challenge of climate because of low-lying topography, a higher level of poverty, an ever-increasing reliance on climate vulnerable sector, in particular agriculture and fisheries, and weak institutional arrangements (Brolley, 2015). Although humid tropical conditions and monsoon rainfall favor agriculture, climate-induced disruptions have already begun to undermine yield stability (Sarker et al., 2012; Siddika, 2013).

Climate projections suggest that mean daily temperatures in Bangladesh may increase by 1.0°C by 2030 and 1.4°C by 2050 (IPCC, 2007a; IPCC, 2007b). Rainfall patterns are becoming increasingly erratic, with shorter rainy seasons despite relatively stable annual averages (UNDP, 2009). With the occurrence of daunting challenges of climate, an uninterrupted agricultural production and assurance of stable price are being threatened and thus the unavoidable matter appears to sustain the global food security to feed millions of hungers. Therefore, all these together become great challenges to the agriculture sector and exhibits the frightening threats on the existence of human beings.

As a strategic commodity, rice plays a critical role in political and economic stability by ensuring adequate and affordable food supplies (FAO, 2014; Nath, 2015). In statistics, Bangladesh is widely recognized as an overpopulated and low-income (USD 958 per capita) country where nearly 31.5% of its people live below the poverty line and are vulnerable to food price hikes (Narayan and Zaman, 2008). Therefore, vulnerability to climate shock, instability of production, and price variation are major features of the food insecurity (Talukder, 2005; Dorosh and Shahabuddin, 2002; Dewan, 2021). For unavoidable present challenges in food sectors, this study is profoundly concerned to assess the magnitude of climatic impact on rice production and search policy directions for poverty reduction in the future (Figure 1).

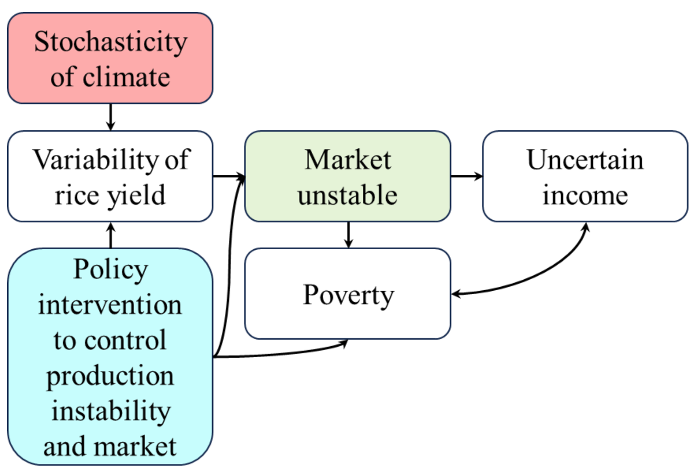

Fig. 1. Conceptual Framework

Methodology

Reference model and estimation method

The basic structure and parameters of the supply demand model were adopted from Salam et al. (2016, 2017). Although both Ordinary Least Squares (OLS) and Two-

Stage Least Squares (2SLS) are commonly used to estimate supply demand systems, the presence of endogenous explanatory variables often necessitates the use of 2SLS to avoid biased estimates (Salam et al., 2016). However, Salam et al. (2016) reported that 2SLS produced several parameters outside reasonable ranges, adversely affecting long-term projections.

As the main objective of this study was to project the impacts of climate pathways on rice supply and demand in Bangladesh, OLS was ultimately adopted to avoid such inconsistencies. Due to data limitations and time-series consistency, parameters were estimated using OLS for the period 1977–2009, supported by a heuristic approach to obtain a suitable model. The adjusted R^2 values ranged from 0.75 to 0.99, indicating strong explanatory power.

In addition, Serial correlation was tested using Durbin–Watson (DW) and h-statistics for equations without and with lagged dependent variables, respectively. DW values between 1.60 and 2.50 suggested no serial correlation, confirming the reliability of the estimates (Table 1). Projections were extended from 2010 to 2030, and the market-clearing price was derived by equating net supply and demand to zero and solving the system using the Gauss–Seidel algorithm (Meyer et al., 2006).

Data Sources and Collection

To implement the supply–demand model, Salam et al. (2016) compiled data from multiple sources. Historical rice area and yield data were obtained from the Bangladesh Bureau of Statistics (BBS, 2024), while farm-gate and retail prices were sourced from World Rice Statistics (FAOSTAT, 2023). Data on rice trade and stock changes were collected from the Food and Agriculture Organization (FAO), and GDP and GDP deflator data were obtained from the World Bank (2017). Information on public procurement, distribution, and prices was taken from the Food Planning and Monitoring Unit (FPMU) Food Database, Ministry of Food and Disaster Management, Bangladesh. Household consumption expenditure data were drawn from the Household Income and Expenditure Survey (HIES, 2010).

Historical climate data (temperature, rainfall, and solar radiation) were collected from the IPCC Data Distribution Centre. Climate projections for 2010–2030 under Representative Concentration Pathways (RCPs) were generated using the MIROC5, General Circulation Model developed by the University of Tokyo, National Institute for Environmental Studies (NIES), and Japan Agency for Marine–Earth Science and Technology (JAMSTEC). Projections of GDP and population under Shared Socio-economic Pathways (SSPs) from the International Institute for Applied Systems Analysis (IIASA) were combined with climate scenarios to assess future food availability and price variability under climate change (MOFA, 2025).

Model Selection Criteria

Durbin–Watson test of serial autocorrelation

Durbin–Watson (DW) statistic is a test measure for first order serial correlation AR (1) which is measured as linear association among successive residuals of the regression model. The hypothesis for Durbin–Watson test statistics can be exhibited such as:

H_0 : = 0, there prevails no first–order serial correlation.

H_A:$\rho \neq 0$, there is First-order serial correlation in the model.

$$u_t = \rho u_{t-1} + \varepsilon_t \quad \text{------------ (1)}$$

where, u_t is regression residual in the period t; u_{t-1} is residual in the preceding period and ρ is the linear association between two residuals. Assuming that the error terms are normally distributed ($u_t, u_{t-1} \sim N(0, \sigma^2)$) and the error terms are stationary. Then the Durbin–Watson statistic can be mathematically noted as below:

$$DW = \frac{\sum_{t=2}^{T}(u_t - u_{t-1})^2}{\sum_{t=2}^{T} u_t^2} \quad \text{------------ (2)}$$

In econometrics, Durbin –Watson test indicates that DW value usually ranges from 0 to 4. If a value is 2, it is supposed that there are no autocorrelation and a value between 0 to <2 indicates that there are positive autocorrelations. Furthermore, a value ranging from 2< to 4 expresses the negative autocorrelation which is very atypical. However, the thumb rule suggests that the test statistics value ranging from 1.5 to 2.5 is generally acceptable (Table 1).

It is assumed that if the regression model includes the lagged dependent variable, conveniently there is a simple alternative approach to DW statistics. This can be defined as h statistics which is formulated from DW statistics as below:

$$h = \left(1 - \frac{DW}{2}\right)\sqrt{\frac{T}{1 - T[se(b_{lag})]}} \quad \text{----------------(3)}$$

where, DW is the usual DWtest, T is the total number of observation and $se(b_{lag})$ is the square of the standard error of the estimated parameter of the lagged dependent variable. The test statistic can be assumed to be standard normal distribution$h \sim N(0,1)$. The test of the null hypothesis of autocorrelation implies that the test value must be compared with a critical value from the standard normal table (Gujarati, 2002).

R² and Adjusted R²

R^2 may be described to measure the fitness of a regression model that could explain the variation in the dependent variable under the assumptions of sample explanatory factors. It can be calculated by the following formula:

$$R^2 = 1 - \frac{ES_{res}}{TS_{tot}} \quad \text{------------------------(4)}$$

where, R^2 is the goodness of fit of regression that indicates the fraction of the dependent variable which could be explained by the incorporated regressors in the model. ES_{res} is the square sum of residual obtained from sum square of a difference between observation of the dependent variable and estimated value from regression. TS_{tot} $(RSres_{exp})$ is the total sum square of residual sum square ES_{res} and explained sum square RS_{exp}.

Table 1 Selection criteria of all estimated model

Function type	Selection criteria of model					
	Yield		Area		Other	
	AdjR²	DW/*h* statistics	AdjR²	DW/*h* statistics	AdjR²	DW/*h* statistics
Aus Modern	0.88	1.77	0.93	2.37		
Aus Local	0.91	2.18	0.99	1.79		
Aman Modern	0.89	1.65	0.99	2.14		
Aman Local	0.86	1.73	0.98	2.28		
Boro Modern	0.93	1.60	0.99	2.50		
Boro local	0.85	1.90	0.98	1.95		
Stock					0.99	2.03
Import					0.60	2.15
Demand					0.75	2.18
Price linkage					0.92	2.08

$AdjR^2$ is adjusted R^2 and DW is Durbin–Watson values

Source: Salam *et al.,*2017

For reasonable explanation power of the model, the R^2 that must be adjusted with the addition of regressors, is commonly denoted as R^{-2} The following notation is for adjusted R^2

$$\overline{R}^2 = 1 - (1 - R^2)\frac{T-1}{T-k} \text{-----------(5)}$$

where, T is the number of observation and k is a number of the coefficient in the model. It is important to note that adjusted R^2 is always slightly smaller than adjusted R^2 (Gujarati, 2002).

Final test criteria

A number of models had been employed in the supply and demand system study. To understand final test statistics easily, it was more convenient to adopt some important models as an example in order to give a general image regarding the fitness of the model with historical observation. The better fit with actual observation meant that there was minimal variance and the model was supposed to perform well in the process of market mechanism analysis (Figure 2-4).

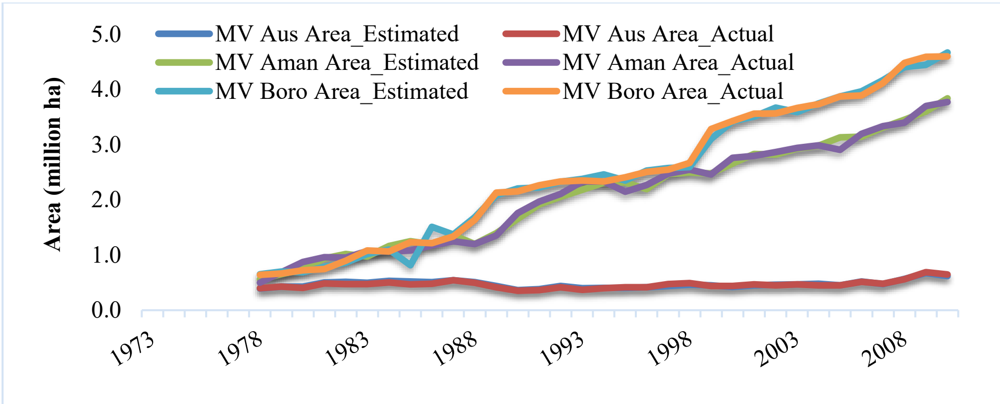

Fig. 2. Final test statistics for Modern Varieties (MV) Area function in three different seasons

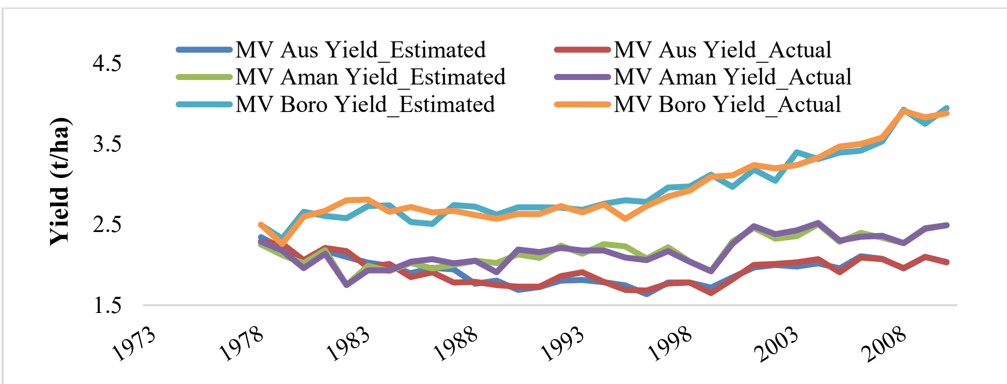

Fig. 3. Final test statistics for Modern Varieties (MV) yield function in three different seasons

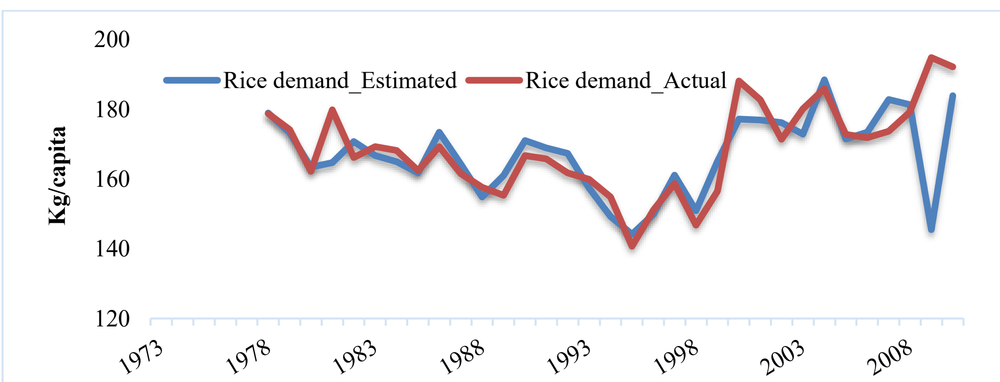

Fig. 4. Final test statistics for rice per capita demand function

Climate Scenarios: Explanation of RCPs

The IPCC developed climate change projections using various climate models to generate Representative Concentration Pathways (RCPs) for use in CMIP5 climate simulations. All RCPs were presumed that Greenhouse Gas (GHG) concentrations to atmosphere continue to be higher in 2100 compared to that in the present days. With unwonted and continued emissions of greenhouse gasses, consequently, the globe would be gradually getting warmer that might be driven to detrimental changes to happen in the climate system (Shiogama et al., 2012). In the IPCC Fifth Assessment Report, RCPs were defined by radiative forcing levels, including RCP2.6, RCP4.5, RCP6.0, and RCP8.5 (Calvin et al., 2023). This study selected two contrasting scenarios: RCP6.0, a medium-mitigation pathway with radiative forcing stabilized at 6.0 W/m² (≈855 ppm CO^c), and RCP8.5, a high-emission pathway reaching 8.5 W/m² (≈1,370 ppm CO_2) by 2100. Both scenarios project high GHG emissions from Asia, making them suitable for assessing climate change impacts on rice production in Bangladesh.

Socioeconomic Scenarios: Explanation of SSPs

IPCC also developed the Shared Socioeconomic Pathways (SSPs) in consistent with RCPs. They had been explained on the basis of challenges to the adaptation and mitigation options (Figure 5) (IPCC, 2007a; IPCC, 2007b).

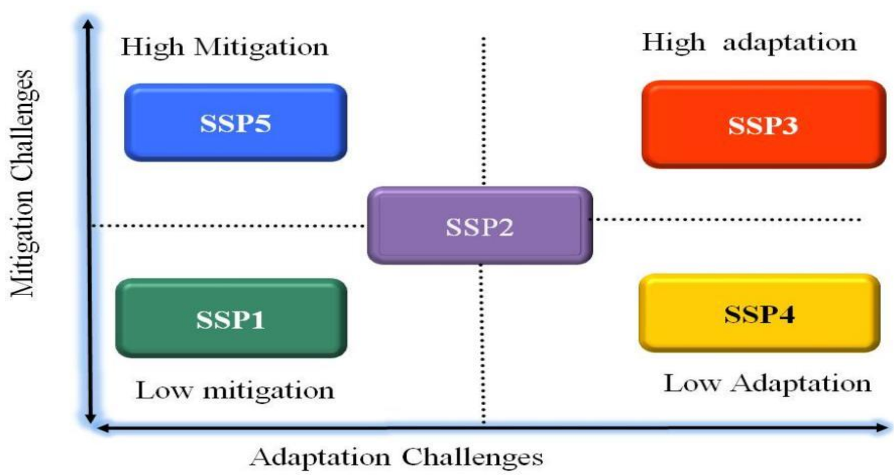

Fig. 5. Mitigation and adaptation challenges for climate changes

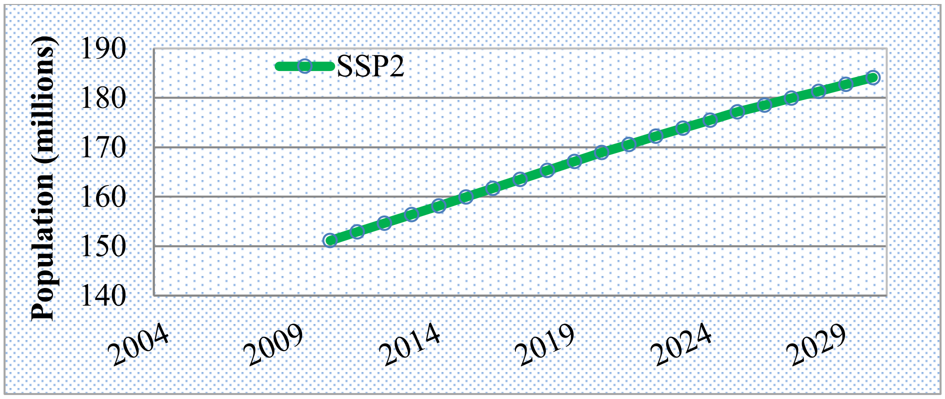

Fig. 6. Forecasted populations in the scenarios of SSP2 and SSP3

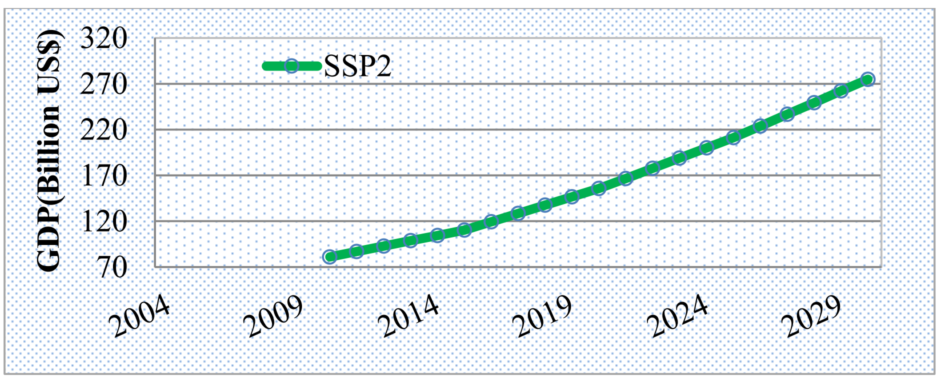

Fig. 7. Forecasted GDP in the scenarios of SSP2 and SSP3

A set of assumptions regarding future demographic trends, economic development, and the degree of global integration underpins the IPCC scenarios, which are designed to assess how climate change may affect the scale of the global economy. GDP projections in the IPCC framework are based on assumptions about regional, national, and sub-national economic structures, sectoral GDP shares (including agriculture), productivity, technological progress, and non-climate policies. These scenarios broadly emphasize the impacts of climate change on agriculture. To ensure consistency with the selected RCPs, SSP2 and SSP3 scenarios developed by the International Institute for Applied Systems Analysis (IIASA) were adopted (Figures 6 and 7). SSP2 represents an intermediate pathway with moderate population and GDP growth, whereas SSP3 reflects high mitigation and adaptation challenges characterized by high population growth, low GDP growth, and regional deglobalization aimed at achieving food security.

In the final stage of model calibration, RCP and SSP scenarios were jointly incorporated into the supply–demand model to project rice supply, market price variations, and per capita consumption for the period 2010–2030. Additionally, a linear approximation approach was applied to extrapolate the GDP deflator, world rice prices, and exchange rates over the projection period.

Criteria for selection of MIROC5 in the IPCC 5th assessment report

Climate sensitivity (CS), defined as the global mean surface air temperature response to a doubling of atmospheric CO_2, is a key parameter for informing climate adaptation and mitigation policies (Knutti and Hegerl, 2008). Variations in CS across multi-model ensembles arise from differences in model structures and parameterizations (structural uncertainty), as well as from parametric uncertainty. MIROC5 developed a perturbed physics ensemble (PPE) to connect atmosphere–ocean general circulation model (CGCM) to investigate a parametric uncertainty of climate sensitivity (CS) (Murphy et al., 2004).

While earlier PPE studies were valuable, most relied on atmosphere/slab-ocean GCMs with flux corrections, which can introduce biases and climate drift due to top-of-atmosphere (TOA) radiation imbalance. MIROC5 overcame this limitation by developing a CGCM-based PPE without flux corrections, controlling TOA imbalance while perturbing ten atmospheric and surface parameters. The resulting CS range was relatively narrow (2.2–3.2 °C), enabling more reliable climate projections and distinguishing MIROC5 as producing improved climate scenarios (Shiogama et al., 2012).

Method of stochastic impact of climate change

Examining the randomness of climate scenarios is important for policy makers, researchers, and stakeholders (Furuya and Meyer, 2008). Following their stochastic approach to capture climate-induced variability in production and prices, this study developed a modified stochastic method to assess the impacts of climate irregularity. Prior to stochastic analysis, the time-series properties of climate scenarios were examined, as long-term trends can strongly influence results.

Climate data often exhibit both long- and short-term temporal characteristics. Long-term trends were tested using regression analysis between climate variables and time, following the approach discussed by Hennemuth et al. (2013). High goodness-of-fit and significant trend parameters would indicate the presence of a long-term trend. To remove trend effects and ensure stationarity, detrended series were used where necessary, recognizing that time trends are a primary source of non-stationarity. Regression results (Table 2) show generally low R^2 and insignificant trend parameters, except for October temperature, which exhibited a significant trend. This variable was therefore detrended prior to stochastic analysis. Stochastic simulations were then conducted using climate variables derived from General Circulation Model (GCM) scenarios to assess yield and price variability. Simulation outputs were summarized using the 90th and 10th percentiles to define upper and lower bounds (Figures 11–18), with the mean and baseline simulation results also presented.

Table 2 Trend analysis of climate scenarios

Model	Constant	Trend	R^2	F- value	$Pr > F$
Tmp04	28.17*** (66.24)	0.02ns (0.71)	0.03	0.50	0.48
Tmp05	28.48*** (74.07)	0.04 ns (1.24)	0.07	1.54	0.23
Tmp06	29.51*** (65.67)	–0.02 ns (–0.49)	0.01	0.24	0.63
Tmp07	28.72*** (74.61)	–0.01 ns (–0.41)	0.008	0.17	0.69
Tmp10	26.96*** (90.35)	0.06 ** (2.61)	0.26	6.82	0.02
Tmp11_1	24.83*** (71.79)	0.009 ns (0.33)	0.006	0.11	0.74
Rf03	51.11*** (2.57)	0.23 ns (0.15)	0.001	0.02	0.89
Rf04	142.61*** (3.21)	0.41 ns (0.12)	0.0007	0.01	0.91
Rf05	288.18*** (5.63)	–1.86 ns (–0.46)	0.01	0.21	0.65
Rf07	606.96 (4.49)	3.07 ns (0.28)	0.004	0.08	0.77
Rf10	158.24** (3.12)	4.39 ns (1.09)	0.06	1.18	0.29
Rf11_1	25.81* (1.66)	0.58 ns (0.48)	0.01	0.23	0.63
Sr01	332.25*** (32.71)	–0.35 ns (–0.43)	0.0007	0.18	0.67
Sr03	450.92 (33.46)	0.25 ns (0.23)	0.003	0.05	0.81
Sr05	437.85*** (17.86)	0.026 ns (0.13)	0.0009	0.02	0.90
Sr07	322.09*** (16.87)	–0.84 ns (–0.55)	0.016	0.31	0.59
Sr10	376.00*** (24.81)	–0.39 ns (–0.32)	0.005	0.10	075

Values in parenthesis indicate t values. ***, ** and * indicate significant at 1%, 5% and 10%. ns indicates the insignificance, $Rf1....Rf12$ indicate rainfall in January through December, similarly $Tmp1....Tmp12$ and $Sr1....Sr12$ indicate temperature and solar radiation in January through December, respectively.

Based on the results of the trend analysis, stochastic analysis was conducted following two alternative pathways, as illustrated in the flow chart. The choice of pathway depended on whether the trend effect was statistically significant. When significance was confirmed using strict criteria based on t-values and R^2, the left-hand pathway (red arrow) was followed, as explained earlier. If the trend was found to be statistically insignificant, the straight pathway (green arrow) was adopted. In the straight pathway, mean deviation of the climate scenario was first calculated as the difference between the observed scenario values and their corresponding means (Figure 8).

These deviations represent departures of the scenario data from the mean, as illustrated in Figure 9.

$$\text{Average } (\mu_Z) = \frac{1}{n}\sum_{t=1}^{n} Z \text{ -------- (6)}$$

where Z was the variables of climate scenario, n was the number of data of climate variables, and t was the time period. Then, the mean deviation could be calculated in the following way

Mean deviation $d_Z = Z_{it} - \mu_{Zi}$, $t = 1,2,\ldots\ldots\ldots, n$ and $i = 1,2,\ldots\ldots, k$ -------- (7)

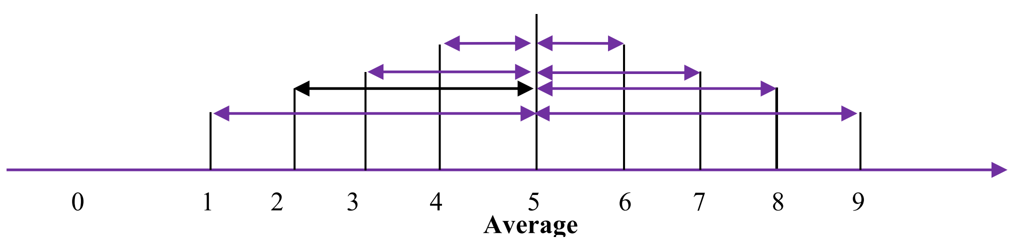

Fig. 9. Distance between average and actual value of forecast climate variables

$$\sigma_{Z_{it}} = \sqrt{\frac{\sum_{t=1}^{n}(Z_{it}-\mu_i)^2}{n-1}} \text{ ------------------------(8)}$$

where, $\sigma_{Z_{it}}$ was the standard deviation of i climate variables.

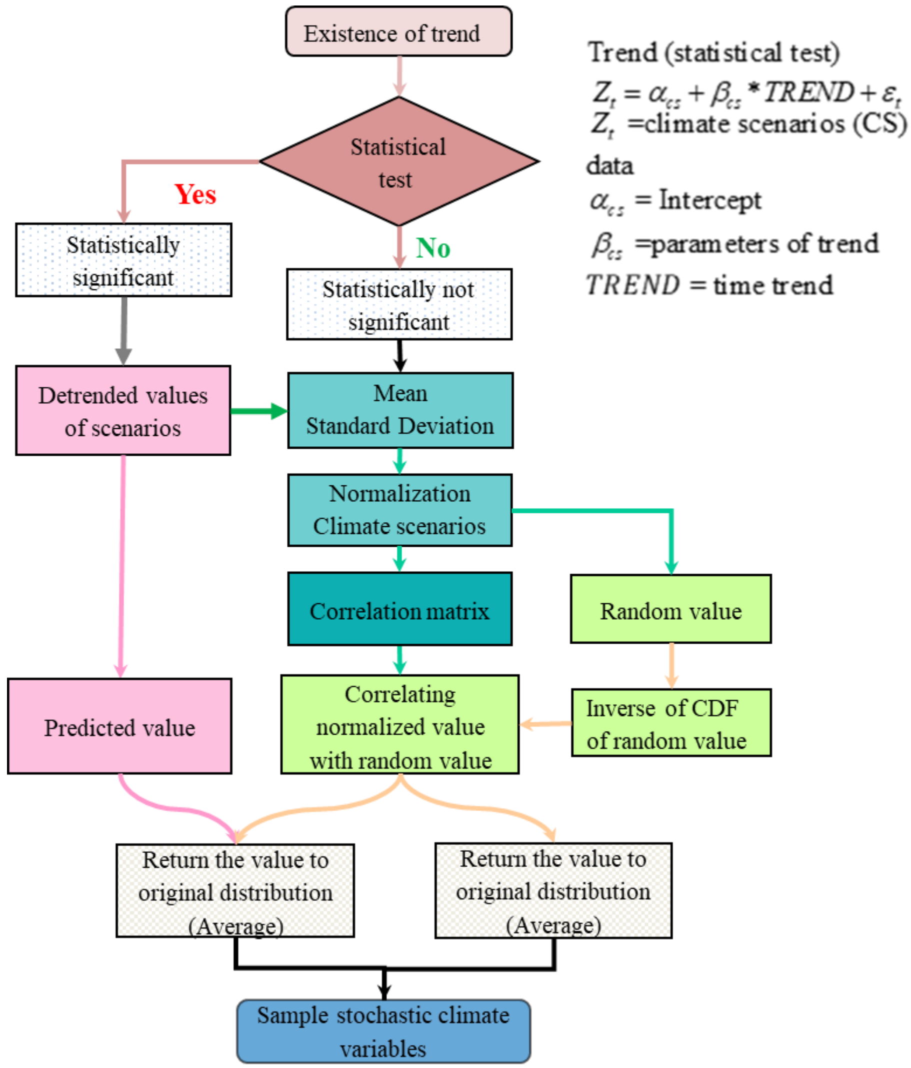

Fig. 8. The correlated stochastic variables of climate scenarios

Standardization of the data

Data of climate scenarios were standardized with mean as 0 and standard deviation as 1 by using the following equations.

$$sz_{it} = d_Z/\sigma_i \text{ ------------------------- (9)}$$

where, sz_{it} was the standardization of climate variables.

In the subsequent, correlation matrix across the standardized climate variables from equation (9) (as for examples such as Temperature, solar radiation, and rainfall) had been computed and employed to obtain a set of correlated random climate variables consistent with the value of actual scenario.

Table 3 Mean and standard deviation of climate scenarios

Variable	Mean	Standard deviation	Min	Max
Tmp04	28.4	0.9	27.7	31.2
Tmp05	28.9	0.8	27.2	30.3
Tmp06	29.3	1.0	25.8	29.2
Tmp07	28.6	0.8	23.9	26.7
Tmp10	27.6	0.7	3.7	175.1
Tmp11_1	24.9	0.7	14.4	359.7
Rf03	53.6	41.9	93.7	469.9
Rf04	147.2	93.4	267.1	1117.6
Rf05	267.7	108.2	49.5	397.2
Rf07	640.7	284.9	1.9	115.2
Rf10	206.6	110.0	293.8	358.4
Rf11_1	32.3	32.8	399.0	501.7
Sr01	328.4	21.5	332.1	537.5
Sr03	453.7	28.4	243.7	384.6
Sr05	440.7	51.5	296.2	415.7
Sr07	312.8	40.4	27.7	31.2
Sr10	371.8	31.9	27.2	30.3

The mathematical formula of correlation:

$$r_{sz} = \left(\frac{\sum z_{it} \sum z_{jt} (sz_{it} - \theta_i)(sz_{jt} - \theta_j)}{S_{sz_{it}} S_{sz_{jt}}}\right) \qquad \text{------(10)}$$

where $S_{sz_{it}} = \sqrt{\frac{\sum_{t=1}^{n}(sz_{it} - \theta_i)^2}{n-1}}$ and $S_{sz_{jt}} = \sqrt{\frac{\sum_{t=1}^{n}(sz_{jt} - \theta_j)^2}{n-1}}$

where, r_{sz} was the correlation score, sz_{it} and sz_{jt} were the standardized climate variables $i = 1,2, \ldots\ldots\ldots, k$ and $j = 1,2, \ldots\ldots\ldots\ldots, k$, $\theta_i = 1/n \sum sz_{it}$ and $\theta_j = 1/n \sum sz_{jt}$ were the average value of standardized climate variables and, $S_{sz_{it}}$ and $S_{sz_{jt}}$ were the standard deviation of standardized climate variables, respectively (Table 3).

The correlation matrix of standardized climate variables could be written as below and the numeric value of correlation matrix was also given in Table 4

$$\begin{array}{c} \\ sz_1 \\ \vdots \\ sz_k \end{array} \begin{array}{c} \begin{array}{ccc} sz_1 & \cdots & sz_k \end{array} \\ \begin{bmatrix} c_1 & \cdots & c_{1k} \\ \vdots & \ddots & \vdots \\ c_{k1} & \cdots & c_{kk} \end{bmatrix} \end{array}$$

where, c was indicted by the correlation coefficient and suffix k was indicated in specific by the number of scenario variables. The inverse function of cumulative standard normal distribution (ICSND), which was applied to create random variables, was defined by$ICSND(RN_i)$.

$$F(n) = \int_{-\infty}^{n} \frac{1}{\sigma_i\sqrt{2\pi}} exp[-\frac{(sz_{it}-\mu_i)^2}{2\sigma_i^2}]dsz_{it}\, , \sigma_i > 0 \quad \text{----------------- (11)}$$

where, $F(n)$ was indicated by cumulative standard normal distribution, exp was indicated by the base of the natural logarithm, and π was indicated by pi (3.14).

However, the adopted random variables were designed to follow uniform distribution such as 0 and 1 where $i = 1 \dots\dots\dots k$ was the number of random variables. Then the random variables were related with the correlation matrix of standardized climate scenarios (Table 4) to produce the correlated uniform standardized climate variables. The following formulas were used to relate between correlation and random value:

$$\left.\begin{array}{l} rz_1 = ICSND(RN_1) \\ rz_2 = c_{12}ICSND(RN_1) + ICSND(RN_2) \\ rz_3 = c_{13}ICSND(RN_1) + c_{23}ICSND(RN_2) + ICSND(RN_3) \\ . \\ rz_k = c_{1k}ICSND(RN_1) + c_{2k}ICSND(RN_2) + \dots\dots\dots\dots + c_{kk}ICSND(RN_k) \end{array}\right\} \text{---(12)}$$

In the following, the correlated standardization of climate variables was added with the corresponding average and standard deviation of scenario variables and repeatedly calibrated. Finally, sample stochastic climate variables were created using the following formula.

$$RZ_i = rz_i * \sigma_i + \mu_i \quad \text{---------------------- (13)}$$

where, RZ_i was the random climate scenarios.

Table 4 Correlation matrix of normalized value of climate scenarios

	Tmp04	Tmp05	Tmp06	Tmp07	Tmp10	Tmp11_1	Rf03	Rf04	Rf05	Rf07	Rf10	Rf11_1	Sr01	Sr03	Sr05	Sr07	Sr10
Tmp04	1																
Tmp05	0.04	1															
Tmp06	-0.27	0.64	1														
Tmp07	0.08	0.45	0.53	1													
Tmp10	0.12	0.60	0.26	0.46	1												

	Tmp04	Tmp05	Tmp06	Tmp07	Tmp10	Tmp11_1	Rf03	Rf04	Rf05	Rf07	Rf10	Rf11_1	Sr01	Sr03	Sr05	Sr07	Sr10
Tmp11_1	0.41	-0.12	-0.34	-0.13	-0.13	1											
Rf03	-0.26	-0.07	-0.12	0.26	0.10	0.15	1										
Rf04	-0.73	0.08	0.34	-0.09	-0.36	-0.38	0.00	1									
Rf05	-0.02	-0.60	-0.48	-0.47	-0.22	0.08	-0.07	-0.10	1								
Rf07	-0.15	-0.15	-0.15	-0.80	-0.29	0.14	-0.32	0.28	0.20	1							
Rf10	0.31	-0.23	-0.03	-0.39	-0.67	0.39	-0.19	0.05	0.07	0.34	1						
Rf11_1	0.18	0.07	0.09	-0.05	0.15	0.07	-0.21	-0.42	0.33	-0.10	0.07	1					
Sr01	0.44	-0.06	0.00	0.16	0.12	0.28	-0.25	-0.59	0.07	-0.15	0.12	0.62	1				
Sr03	0.14	0.20	0.13	-0.22	0.02	0.00	-0.81	0.01	-0.04	0.29	0.18	0.32	0.19	1			
Sr05	0.08	0.68	0.45	0.50	0.38	-0.10	-0.10	0.02	-0.65	-0.40	-0.26	-0.10	0.05	0.01	1		
Sr07	0.31	0.16	0.09	0.74	0.37	0.18	0.37	-0.45	-0.38	-0.80	-0.21	0.06	0.42	-0.31	0.48	1	
Sr10	-0.22	0.42	0.05	0.28	0.73	-0.18	0.42	-0.05	-0.30	-0.18	-0.74	-0.15	-0.1	-0.38	0.40	0.32	1

Several steps for making climate scenarios as stochastic were followed and the process ended up with the simulated stochastic variables of climate which were proposed as stochastic climate scenarios in the market mechanism of supply and demand (Figure 7).

In the final step, these stochastic climate scenarios were incorporated into the supply and demand model to investigate the future impact of climate on supply and market price in the market mechanism (Figure 10).

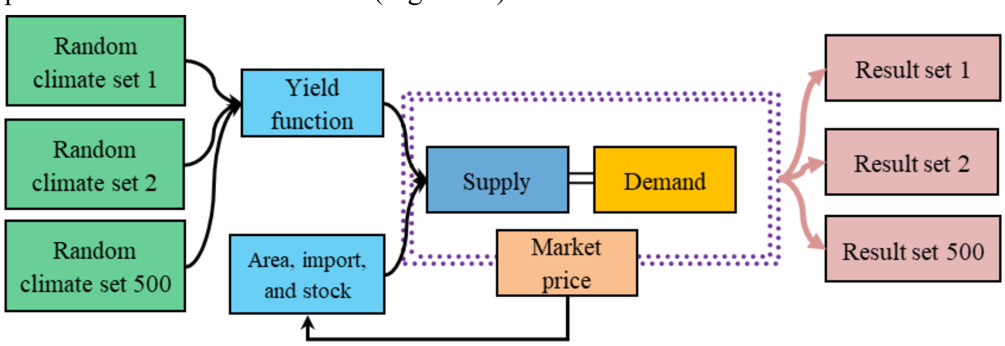

Fig. 10. Simulation diagram of stochastic supply and demand system

Model selection for poverty measure under future climate change

Although price stabilization is often considered inefficient, many developing countries rely on it to reduce food price volatility caused by supply shocks. Stable food prices are essential for poverty reduction, as poverty reflects deprivation, limited purchasing power, and unequal resource distribution (Narayan and Zaman, 2008). In Bangladesh, rice price stabilization is central to food security, where poverty declined to 31.5%, though climate change remains a challenge (World Bank, 2017). Poor households, defined by a minimum intake of 2,100 calories, spend nearly 80% of their income on staple foods; thus, food price spikes reduce real income and worsen food insecurity (Mondal et al., 2010; Ivanic and Martin, 2008).

The poverty gap measure captures the depth of poverty by estimating how far household expenditure falls below the poverty line (Haughton and Khandker, 2009), and is calculated as the poverty gap (PG_i) as follows:

$$PG_i = (PL - E_i) \times I(E_i < PL) \quad \text{------------------- (14)}$$

where, PL was the poverty line and E_i was expenditure or income of ith the individual. $I(.)$ was an indicator function that was equal to 1 if $E_i < PL$ and 0 if poverty line had a zero gap. An $E_i < PL$ would mean that if individual household would live below the poverty line and $E_i > PL$ indicated that individual expenditure exceeded the poverty line which had a zero gap of poverty. Now the poverty index could be expressed:

$$PI = \frac{1}{N}\sum_{i=1}^{N}\frac{PG_i}{PL} \quad \text{---------- (15)}$$

where, PI was the index for poverty gap. This measure represents the proportion of the population living below the poverty line, where a value of zero indicates no poverty and one indicates universal poverty. It explains changes in poverty levels based on household expenditure capacity. In the empirical analysis, average per capita income, income distribution, and the poverty line were assumed to shift over the period 2010–2030. Per capita income scenarios under SSP2 were assumed to follow a log-normal distribution, consistent with the World Bank's poverty estimation approach (World Bank, 2017). The log-normal parameters mean (μ) and standard deviation (σ) were derived from the Household Income and Expenditure Survey 2010.

$$f(E|\mu,\sigma) = \frac{1}{E_i\sigma\sqrt{2\pi}} exp\left\{\frac{-(ln\,E_i-\mu)^2}{2\sigma^2}\right\}; E_i > 0, i = 1,2,\ldots,N \quad \text{------ (16)}$$

where, E_i was the allocation of consumer budget for expenses, mean$\mu = \frac{\sum_{i=1}^{N} ln\,E_i}{N}$, and standard deviation $\sigma = \sqrt{\frac{\sum_{i=1}^{N}(ln\,E_i-\mu)^2}{N}}$, N was the total number of people who belonged to income group of the concerned country.

Result and Discussion

Stochastic Climate Scenarios, 2010–2030

Stochastic simulations using climate variables were conducted to assess yield and price variability. For modern rice varieties, the difference between the 90th and 10th percentiles was 0.41 t/ha in *Aus*, 0.79 t/ha in *Aman*, and 1.78 t/ha in *Boro* seasons, while for local varieties it was 0.48 t/ha, 0.45 t/ha, and 0.99 t/ha, respectively (Figures 11–16). Yield variability was notably higher in *Aman* and *Boro* than in *Aus*.

The percentile difference in total rice production expanded to 7.85 million metric tons, representing 11.0%–10.5% of historical production (Figure 17), indicating high sensitivity to climate variability. Price simulations showed greater fluctuation in retail prices than farm prices, with 90th–10th percentile differences of USD 139.07/ton and USD 63.21/ton, respectively. Both prices increased over time with widening dispersion, posing significant challenges for Bangladesh's rice sector.

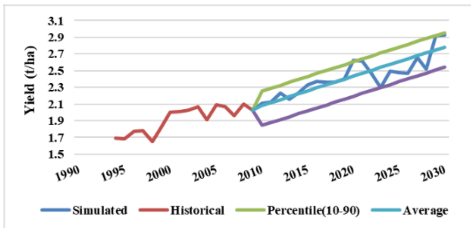

Fig. 11. Yield of modern *Aus* in stochastic state, 2010–2030

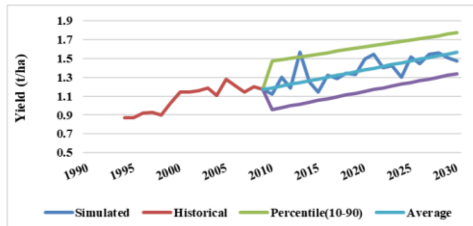

Fig. 12. Yield of local *Aus* under stochastic state, 2010–2030

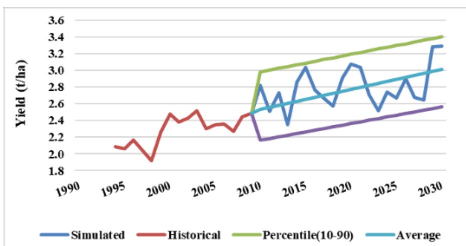

Fig. 13. Yield of modern *Aman* in stochastic state, 2010–2030

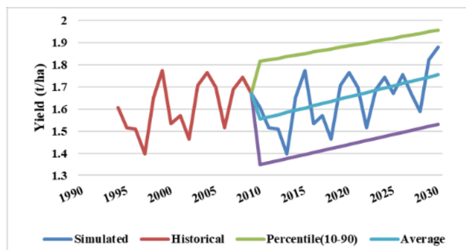

Fig. 14. Yield of local *Aman* in stochastic state, 2010–2030

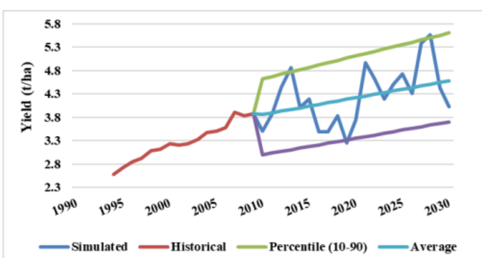

Fig. 15. Yield of modern *Boro* in stochastic state, 2010–2030

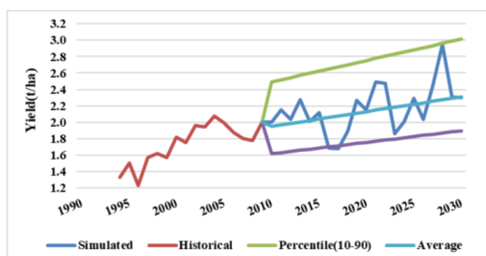

Fig. 16. Yield of local *Boro* in stochastic state in 2010–2030

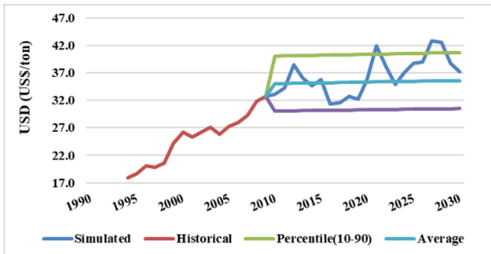

Fig. 17. Rice production in stochastic path in future, 2010–2030

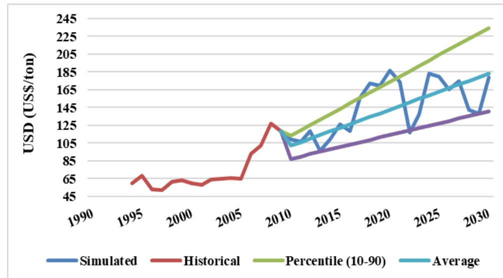

Fig. 18. Farm price variations in stochastic path, 2010–2030

Coefficient of Variation in Stochastic Path, 2010–2030

Table 5 Yield variations in stochastic path in future, 2010–2030

Seasonal yield	Yield variation (%)	
	Historical	Stochastic state
Aus	8.32	11.72
Aman	7.76	11.62
Boro	12.28	17.79

Table 6 Variations of supply and price in stochastic path in future, 2010–2030

Variables	Historical	Stochastic state
Rice Supply	7.1	10.39
Farm price	21.5	25.56
Retail price	27.0	31.77

Table 5 exhibited the coefficient of variation of the seasonal yield of different rice. The variations of supply and market prices could be viewed in Table 6. The simulated results were averaged over 2010 to 2030. The simulated results demonstrated that the variation in yield in all seasons would increase in the stochastic scenario than that in the historical period. In *Aman* and *Boro* season, yield showed a higher fluctuation than that in Aus season and even more than that in *Aman* season. The yield of local varieties in Aus season would fluctuate substantially compared to that in *Aman* and *Boro* season. The yield in *Aman* season would be more sensitive to change in temperature while the erratic rainfall would increase the shock on *Boro* yield. The variation of yield would eventually be transmitted into total national supply and the fluctuation of supply increase by 10.39% point, which is higher than that is 7.1% point in the historical period. Therefore, production fluctuation was found to be substantially higher under stochastic scenario than that in the historical term. Fluctuation of market price (farm and retail price) would be also so susceptible to stochastic analysis than that in the historical period. Furthermore, farm price variation would continue to increase larger and picks up to 25.56% point which is 21.5% point in the historical period. The case of retail price would be peaked up to 31.2% point in the stochastic scenario whereas it is 31.77% point in the historical period (Table 5–6). Therefore, the variation of production and market price would increase in the stochastic scenario and bring more challenges for researchers, policy makers, farmers and market functionaries into the front.

Policy scope for poverty reduction

The estimated parameters and poverty head count ratio (31.5%) (World Bank, 2017) in the base year 2010 had been placed into the inverse of cumulative log–normal distribution and then, the representative poverty line was computed. The calculated poverty line was regarded as base poverty line for 2010. The poverty line for every year in the study period was shifted in a parallel way from base poverty line according to income per capita under the SSP2 scenario. To find out the poverty line for the entire period of 2010–2030, the new poverty line as well as probability density function (PDF) for income per capita of the SSP2 scenarios must have been calculated. An average 18.7% of total population in Bangladesh were upper poverty line (HIES, 2022). They were also regarded greatly vulnerable to expenditure increase which would be triggered by rice price hikes in the course of future climate change. In figure 21, the parallel poverty line and probability density function for 2020 were considered for the interpretation of price hike effect. The log normal distribution curve could be referred to by the probability density function of the per capita income of the SSP2. Moreover, the data from HIES, 2010 estimated that 20% of total expenditure was made for rice consumption (Table 7) by the marginalized group. On the other hand, compared with an approximated average of market price, the market price hikes of rice would be peaked up at 33% in 2020 and the possible impact could be attributed to stochastic climate shocks (Figure 19). The new poverty line was calculated with respect to the increase in rice expenditure by a 33% of price hikes. If 33% of rice expenditure increased, the poverty line would be shifted to the right–hand side. The price hikes would tremendously increase the number of vulnerable people by 25% who could not be able to spend adequate food budget compared to the average poverty line (21%) (Figure 20).

Table 7 Monthly budget allocations for consumers' items by the marginalized group

Expenses items	Expenditure (USD/month) -HIES 2010
Non–rice food expenditure	60.0
Rice expenditure	22.8
Fuel expenditure	8.0
House rent expenditure	8.5

Expenses items	Expenditure (USD/month) -HIES 2010
Education expenditure	5.0
Miscellaneous expenditure	24.4
Total expenditure	116.9

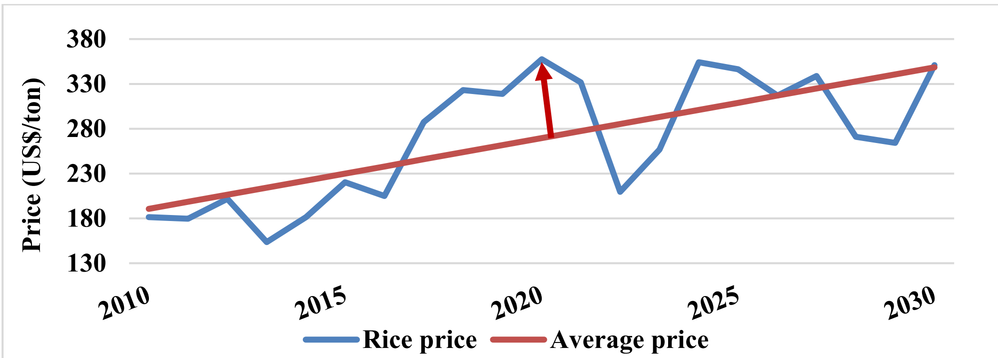

Fig. 19. Market price hikes from the assumed average rice price

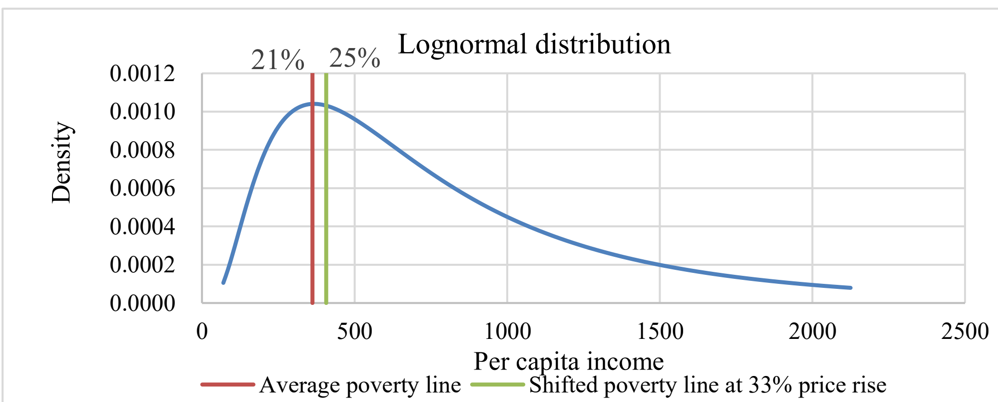

Fig. 20. Impact of variation of rice price on poverty line and food expenditure

Due to price hike which was possibly induced by climate, household expenditure on food stuff would also increase. The increasing expenditure was found to have an enormous effect on poverty. The results further concluded that the variation of rice price would increase the vulnerability of households in Bangladesh because the rice was the main source of daily food stuff and also nutrition. Therefore, price hikes had a tremendous concern for policy maker in the future.

Many researchers concluded in the same notions that the poor and marginalized households were greatly vulnerable to adverse erosion of real purchasing power and thereby enlarging the number of households below the poverty line in Bangladesh (Raihan, 2013; Ivanic and Martin, 2008). The policies, which could be intervened by governments, included the increasing food production, lowering food prices, and providing more reliable access to poor households. All of these interventions that were being executed come at a cost. There was a gradual return to basic market forces as the food crisis and market price would recede. Historically, these market forces would have pushed food prices to lower, even if investments in productivity-enhancing research, food policies and infrastructure development would become unprofitable. Without these investments, growth in supply likely would fall behind the growth in demand, and a dreadful stage would be happened to induce price hikes, which causes lower access to food, more especially for the marginalized section of the nation.

Conclusion

This study had been conducted based on the supply and demand structure of Bangladesh. Secondary data were used in this manuscript from different published and online sources. Then random variable method and inverse function of cumulative standard normal distribution (ICSND) have been applied to generate a big set of climate variables. To observe the behavior of yield and market prices under stochastic nature of climate, the comprehensive calibration was accomplished with the produced sets of stochastic climate data over the period of 2011-2030. After completion of 500 sets of simulated results, a 90 percentile and a 10 percentile had been calculated. The linear approximated value of 90 percentile and 10 percentile was adopted. The difference between 90th and 10th percentile ranged from 0.41 t/ha to 1.78 t/ha among three different rice growing season. It unambiguously appeared that rice yield will be shocked by stochastic nature of climate change in future. The unpredicted spread of climatic shock over the period of 2011-2030 put the rice sector in Bangladesh into a tremendous challenge. Therefore, the stochastic shock of climate on rice market is so sensitive to policy makers and economic measures.

Stochastic shock of climate leads the market price hikes of rice peaked up at 33% in 2020. The negative effect of such shock increased the vulnerable people by 25% compared to the average poverty line (21%). Price hikes lead to increase the food expenditure enormously. The variation of rice price would increase the vulnerability of households in Bangladesh since daily dish of food stuff and major source of calorie comes from rice. Therefore, stochastic shock of climate will be transmitted into concern of food policy through price hike. Since this research utilized partial equilibrium supply and demand model, it is a great limitation to avoid the comprehensive relation with other sectors. It provides further scope to extend the research ideas under different equilibrium approaches.

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Competing interests

This research received financial support as scholarship in Doctoral course (PhD) from Ministry of Education, Culture, Sports, Science and Technology of Japan and administrative support from Bangladesh Rice Research Institute. However, this is MAS fundamental research work in PhD. We honestly declared that there is no any competing interest.

Conflict of interest: There is no conflict of interest.

Author's Contribution

MAS developed the concept and model; accomplished all parts of the manuscript and wrote this manuscript. The author read and approved the final manuscript. Dr. Shintaro Kobayashi provided support to develop and design the research methodology of this manuscript and MMH contributed to improve the calibration and write-up of the manuscript.

Data availability statement

All raw data can be accessed from the corresponding author on reasonable request.

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