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# CLIMATE CHANGE IMPACT ON RICE PRODUCTIVITY IN BANGLADESH AGRICULTURE: AN ECONOMETRIC ANALYSIS

**Mohammad A. Ashraf**[1]

***Abstract:*** *This paper has two objectives. First it attempts to detect the trend in the present upshots of global warming temperature data. It has been done through the estimation of the long memory fractional parameter, d using simulation technique in the presence of additive outliers, which stand as wild observations generated in the atmosphere due to global warming. Then, the study investigates into the impact of global warming, precipitations and carbon concentration in the air on the particular aspect of rice production in Bangladesh agriculture. The simulation result exhibits a non-trend or a natural cyclical variability that is influenced by a stochastic process in the case of climate change behavior with wild observations (outliers) that produce a contradictory outcome of profound uncertainties against the case of true world temperature systematic data trend. The results of regression analysis show that climate change has a profound impact on rice productivity in Bangladesh agriculture. Overall results of the study indicate that climate change has profound effects on agricultural food production of Bangladesh agriculture.*

***Keywords:*** *climate change, global warming, rice productivity, Bangladesh agriculture JEL codes: Q15*

## 1. Introduction

In recent times, the climate change has been appeared to be a big issue, because global ecological change resulting in rising surface air temperature poses a common threat to all as a ‘highway to extinction’ (IPCC 2007, Rahman 2007, and Toronto Sun, April 1, 2007). In reality, observed data on world temperature over the last century exhibit an unambiguous upswing drift from the second half of the eighteenth century until the present time (Cohn and Lins 2005). The scenarios of higher temperatures documented in the IPCC (2007) suggest that heat waves, droughts, and especially floods, may occur more often, last longer, and inflict greater damage to crops than they do today. Production risks include direct physical plant damage by flooding and water-logging, as well as related problems such as increased pest and pathogen outbreaks, enhanced soil erosion, and threatened groundwater quality from increased pesticide and herbicide runoff. Current state-of-the-art crop models like those used in different assessments do not fully capture yield reductions due to increased climate variability and related disturbances. Once these effects are fully incorporated into the models, it is expected that the projections of future world’s crop yields under climate change could be significantly lower than currently estimated (Cline, 2007).

1. [1]Doctoral Research Scholar in the College of Business at the University Utara Malaysia, and Assistant Professor, School of Business and Economics, United International University

Bangladesh is recognized worldwide as one of the countries most vulnerable to the impacts of climate change (Banerjee, 2007). This is due to its unique geographical location formed by the Eastern Water Basins of the Ganga, the Brahmaputra and the Meghna, dominance of floodplains, low elevation from the sea, high population density, high levels of poverty, and considerable dependence on nature, its resources and services. The country has a history of extreme climatic events claiming millions of lives and destroying past development gains. Variability of rainfall pattern, combined with increased snow melt from the Himalayas and temperature extremes are resulting in crop damage and failure, preventing farmers and those dependents from meaningful earning opportunities.

Rice production constitutes over 90 percent of total foodgrains production in Bangladesh where agriculture contributed about 21 percent in GDP share in 2006-07 (BER, 2007). This evidence indicates that rice production alone constitutes a significant level in overall GDP share of the country. Besides, Bangladesh is the tenth largest rice producing country in the world (Cline, 2007). Hence, rice sector deserves a special account in terms of overall improvements in production and protection from environmental hazards such as soil erosion, droughts, high rainfall and flood, numerous pests and diseases. Failures in doing so involve, therefore, potential risks and the impacts of which may cause substantial costs on lives and resources as well. This study first employs simulation technique involving long memory model to test whether there has been the trend of climatic change particularly of global warming or not and then uses simple regression technique that identifies the impacts of the climate variables such as air temperature, rainfall and concentration of carbon dioxide in the air on rice productivity in the case of Bangladesh agriculture.

## 2. Long Memory Models and Climate Change

In order to get the simulation evidence on global warming as the first objective is specified to see whether there has been any trend of the movement of warming or not, the study employs long memory model. If there is any trend observed, it implies that forecasting and planning are possible. If not, then it implies that there has been climate of uncertainty. Long memory means to rely on past experiences. That is, if something has happened in the past, it is likely to happen again in the future. Statistically, long memory is defined as a series of having a slowly declining correlogram or equivalently an infinite spectrum at zero frequency. In the case of a stationary process with long term autocorrelation function, $\rho(k)$ is said to be a long memory process if $\sum_{k=0}^{\infty}|\rho(k)|$ does not converge (Beran 1994). An intuitive way to such behavior is to say that the process is divergent and has a long memory ((Kallache et al. 2005, Chatfield 1996). In this regard, denoting $\omega$ a particular frequency, Geweke and Porter-Hudak (1983, pp.221) maintained that these are "the models on which the spectral density function is proportional to $\omega^{-r}$, for $1 < r < 2$ for near to the frequency $0$ and the asymptotic decay of the autocorrelation function is proportional to $\tau^{r-1}$. Because the spectral density is unbounded at $\omega = 0$, equivalently, the autocorrelation function is not summable --- these are long memory models."

Seminally, the idea of long memory models appears to have developed its roots in the geophysical sciences in the 1950s. A particular reference in this respect is Hurst (1951). Hurst was motivated to understand the persistence of stream-flow data and the design of reservoirs. This most single reference of Hurst (1951) has broached the question of the effect of very long term autocorrelation in observed time series analysis which later comes to be known as a long memory process applied in econometric studies in the name of Autoregressive Fractionally Integrated Moving Average i.e. $ARFIMA\ (0, d, 0)$), where $d \geq .5$ (Ashraf, 2006). The very slowly decaying autocorrelations demonstrates that the simplest possible model is this $ARFIMA\ (0, d, 0)$ or fractional white noise model. 'Extraordinarily, this very simple, one parameter model accounts for all the dynamics in the conditional mean of the process' (Baillie, 1996). This astounding model of a long memory process has, indeed, attracted the attention of econometricians since around 1980. The pioneering works in this area of econometrics include Taqqu (1975), Granger and Joyeux (1980), Granger (1981), Hosking (1981), Geweke and Porter-Hudak (1983), Baillie and King (1996) and later those have been advanced among many others by Giraitis and Robinson (2003), Robinson and Henry (2003), de Peretti (2007) and Henry (2007).

Despite the fact of its origin in hydrology, long memory models exhibit a particular interest for investigating the possibility of climatic change (see e.g. Baillie, 1996; Seater, 1993; Hipel and McLeod, 1978). Several researchers have demonstrated that there is an upward trend in global temperature readings since the second-half of the nineteenth century (Seater, 1993). In this regard, Baillie (1996, p.7) remarks:

> "An important policy issue concerns whether the higher temperatures are evidence of climatic change and global warming brought on by the manmade emissions of greenhouse gasses or whether the recent observed temperatures are merely part of the regular cyclical variation that is known to occur in world temperature readings."

This observed pattern of climatic change or global warming phenomenon highlights enormous concerns that anthropogenic activities are exhibiting momentous impact on the world climate and results of which raised many important questions over the appropriate government policy. Ironically, designing a policy framework in response to climatic change and global warming is seriously encumbered by ignorance of the problem's quantitative aspects (Seater, 1993). In this respect, long memory model is likely to be very similar approach, which at least can suggest that climatic changes or trends that occur during particularly volatile weather patterns should be interpreted differently than changes during more stable weather regimes.

## 3. Methodology

This study has two broad objectives: One is to detect the trend of the global temperature and the other is to observe the direct impact of different climatic variables, such as temperature, rainfall and carbon dioxide concentration in the air, on the rice productivity. In so doing, for the first objective, the study uses simulation evidence by using long memory model through estimating the fractional parameter, $d$, in the presence of wild observations of global warming which are termed as additive outliers in the study whether there is any trend or not and for the second objective, a multiple regression analysis has been done incorporating observed meteorological data provided by the Bangladesh Bureau of Statistics (BBS) published in several yearbooks in order to see whether rice productivity is affected or not. In the next section, the study presents underlying models briefly in details.

### 3.1 Theoretical Framework

There are a variety of ways of estimating the fractional parameter $d$. In the present study, the estimation procedure followed the long memory model as proposed by Geweke and Porter-Hudak (1983), which generalized the definitions of fractional Gaussian noise and integrated or fractionally differenced series and showed that the two concepts are equivalent. Here, the procedure is based on estimation in the paradigm of frequency domain. For the model $(1-L)^d x_t = \epsilon_t$ where $\{x_t\}$ is assumed to be a time series process, $d \in (-.5, .5)$ and $\epsilon_t$ is serially uncorrelated, the spectral density of the time series $\{x_t\}$ is:

$$f_2(\omega; d) = \left(\frac{\sigma^2}{2\pi}\right) + \left|1 - e^{-i\omega}\right|^{-2d} = \left(\frac{\sigma^2}{2\pi}\right)\left\{4\sin^2\left(\frac{\omega}{2}\right)\right\}^{-d} \qquad (1)$$

A time series with the spectral density $f_2(\omega; d)$ is called an integrated or fractionally differenced series, which suggests that $\lim_{\omega\to 0}\omega^{2d} f_2(\omega; d) = \left(\frac{\sigma^2}{2\pi}\right)$ and the autocorrelation function for $d \neq 0$ is $\rho_2(\tau; d) = \frac{\Gamma(1-d)\Gamma(\tau+d)}{\Gamma(d)\Gamma(\tau+1-d)}$ which leads to $\lim_{\tau\to\infty}\tau^{1-2d}\rho_2(\tau; d) = \frac{\Gamma(1-d)}{\Gamma(d)}$.

Now consider $(1-L)^d y_t = u_t$, where $u_t$ is a linear and stationary distributed process with the spectral function $f_u(\lambda)$, which is supposed to be finite, bounded away from zero and continuous on the interval $\{-\pi, \pi\}$. Based on this methodology, one has:

$$\log\{f_y(\omega_j)\} = \log\{f_u(0)\} - d\log\left\{4\sin^2\left(\frac{\omega_j}{2}\right)\right\} + \log\left[f_u\left(\frac{(\omega_j)}{f_u(0)}\right)\right] \qquad (2)$$

and $d$ can be estimated from a regression based on the above equation using spectral ordinates $\omega_1, \omega_2, \ldots \omega_m$ from the periodogram of $y_t$ that is $I_y(\omega_j)$:

$$\log\{I_y(\omega_j)\} = a - d\log\left\{4\sin^2\left(\frac{\omega_j}{2}\right)\right\} + v_j, \quad j = 1,\dots,n \qquad (3)$$

where

$$v_j = \log\left[f_u\left(\frac{(\omega_j)}{f_u(0)}\right)\right] \qquad (4)$$

and $v_j$ is supposed to be $i.i.d.$ with zero mean and variance $\pi^2/6$. Thus, the least square estimator of $d$ is asymptotically normal. If the number of ordinates $n$ is chosen such that $n = g(T)$, where $g(T)$ is such that $\lim_{T\to\infty} g(T) = \infty$, $\lim_{T\to\infty}\left\{\frac{g(T)}{T}\right\} = 0$ and $\lim_{T\to\infty}\left\{\frac{\log g(T)^2}{g(T)}\right\} = 0$ then the $OLS$ estimator of $d$ in $(3)$ takes the limiting distribution as follows:

$$\frac{(\hat{d} - d)}{\{var(\hat{d})\}^{\frac{1}{2}}} \sim N(0,1) \qquad (5)$$

When the $OLS$ estimator $d$ is significantly different from zero, the sample of the specific size is fractionally integrated. Here, in this estimation, $n = g(T) = \sqrt{T}$ is used.

### 3.2 The Simulation Design

In order to achieve its first objective, the study involves the Monte Carlo experiment. A Monte Carlo experiment consists of generating repeated samples of artificial data (according to some characteristic or properties) for some sample size and then analyzing the behavior of the relevant statistics. In this case, for example, the behavior of the estimates of the fractional parameter is under investigation. One way to do this is to calculate some characteristics of this estimate such as the Mean Square Error $(MSE)$ and the bias. When the size and power of one statistic is the principal object, it is calculated the number of rejections of the null hypothesis found in all the replications used.

The same data generating process is followed as that of considered in Vogelsang (1999) and Perron and Rodriguez (2000). It involves the case where additive outliers are fixed. The process could be defined as follows:

$$y_t = n_t + \sum_{i=1}^{m} \delta_i D((T_{a0,i}))_t + u_t \qquad (6)$$

$$(1 - L)^d u_t = v_t \qquad (7)$$

where, $v_t \sim i.i.d.N(0,1)$, $d$ is the fractional parameter, $D((T_{a0,i}))_t = 1$ if $t = T_{a0,i}$ and $0$ otherwise and $\delta_i$ is the size of the additive outliers. Four sizes of additive outliers are considered (that is m = 4 in expression (6)), along with two different assumptions about their values. In the first case, $\delta_i = 0$ $(\,for\; i = 1,2,3,4)$. This case illustrates that no outliers, no size distortions and no bias are observed in the estimates. In the second case, $\delta_1 = 10, \delta_2 = 5, \delta_3 = 2, \delta_4 = 2.$ This case indicates that the effects of additive outliers of "large" size are present. The second specification is close to that used by Perron and Rodriguez (2000). The goal is to see the effects of large additive outliers. The variable $n_t$ represents the deterministic component. In the experiment, it considers only the case where a constant is included in the regressions; that is, $n_t = \mu$. In the simulations of the expression (6), it, without loss of generality, includes the case where $\mu = 0$. The sample sizes considered in the study are $T = 50, 100, 200, and\ 500$ . These sample sizes are fairly common as in any empirical work. The number of replications considered for each set of parameters is 1000 and a seed of 12345 is used. The number of simulations used is similar to those of used in the literature of Lima de Pedro (2001).

### 3.3 The Multiple Regression Model

In order to investigate the impacts of climate change on the agricultural production such as in the case of rice in Bangladesh, the study formulates the following multiple regression model which incorporates the observed data on rice production, temperature and rainfall collected from Bangladesh. The model also includes the square variables of temperature and rainfall variables to see any extreme impacts on rice productivity as Cline (2007) did. Thus, the model is:

$$Y_t = \alpha + \beta_1 T_t + \beta_2 T_t^2 + \beta_3 R_t + \beta_4 R_t^2 + \beta_5 C_t + U_t \qquad (8)$$

where,

$Y_t$ = Productivity of rice (metric tons per hectare);

$T_t$ = Annual average temperature in Bangladesh (in Celsius);

$R_t$ = Annual average rainfall in Bangladesh (mm - millimeter);

$C_t$= Carbon dioxide concentration in the air of Bangladesh (ppm - part per million);

$U_t$= Disturbance term; and

$\alpha, \beta_1, \beta_2, \beta_3, \beta_4\ \beta_5$ = Parameters to be estimated.

## 4. Results and Discussions

### 4.1. Simulation Results

First, results are considered for the case where outliers are generated in a simple additive manner. Tables 1- 4 present the results for the case where there are no additive outliers. In terms of the bias and the *MSE,* there are no significant variations for all of the fractional parameter values ascribed. The *MSE* is observed to be different for the two extreme values of *d*. In fact, when *d* is close to unity, the *MSE* is smaller. This is so, because the bias and the variances are smaller, which happens probably as a consequence of a better estimation of the fractional parameter in opposition to the case where *d* is close to –1. This result implies that in absence of outliers uncertainties in the climate are in small magnitude, which indicates that the climatic variations are not following any trend as well.

**Table 1: Bias, MSE and t-statistic with no additive outliers and sample size 50**

| Parameter $d$ | Bias | MSE | Size of t-statistic $H_0: d = 0$ | Size of t-statistic $H_0: d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.18 | 0.20 | 0.61 | 0.96 |
| -0.72 | 0.09 | 0.17 | 0.46 | 0.95 |
| -0.48 | 0.05 | 0.16 | 0.30 | 0.92 |
| -0.24 | 0.03 | 0.16 | 0.16 | 0.85 |
| 0.00 | 0.02 | 0.16 | 0.10 | 0.75 |
| 0.24 | 0.02 | 0.16 | 0.20 | 0.56 |
| 0.48 | 0.03 | 0.16 | 0.38 | 0.35 |
| 0.72 | 0.05 | 0.15 | 0.60 | 0.17 |
| 0.96 | 0.02 | 0.13 | 0.82 | 0.11 |

When the true parameter $d = 0$, the exact size is closer to the nominal size when sample size increases that is the result actually expected. When the true fractional coefficient is closer to –1, the null hypothesis is strongly rejected that the fractional coefficient is equal to zero.

**Table 2: Bias, MSE and t-statistic with no additive outliers and sample size 100**

| Parameter $d$ | Bias | MSE | Size of t-statistic $H_0: d = 0$ | Size of t-statistic $H_0: d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.21 | 0.14 | 0.74 | 1.00 |
| -0.72 | 0.09 | 0.10 | 0.62 | 1.00 |
| -0.48 | 0.02 | 0.09 | 0.40 | 0.99 |
| -0.24 | 0.01 | 0.09 | 0.20 | 0.97 |
| 0.00 | 0.01 | 0.09 | 0.08 | 0.90 |
| 0.24 | 0.01 | 0.09 | 0.19 | 0.73 |
| 0.48 | 0.02 | 0.09 | 0.46 | 0.46 |
| 0.72 | 0.03 | 0.09 | 0.76 | 0.20 |
| 0.96 | 0.02 | 0.07 | 0.92 | 0.09 |

On the other hand, it is observed that when the true fractional coefficient is closer to unity, it is very difficult to reject the null hypothesis that the coefficient is different from one. This is also true for very large sample sizes such as $T = 500$. It is consistent with the results of even for higher sample sizes.

**Table 3: Bias, MSE and t-statistic with no additive outliers and sample size 200**

| Parameter *d* | Bias | MSE | Size of t-statistic $H_0$: $d = 0$ | Size of t-statistic $H_0$: $d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.20 | 0.13 | 0.86 | 1.00 |
| -0.72 | 0.07 | 0.06 | 0.80 | 1.00 |
| -0.48 | 0.02 | 0.05 | 0.56 | 1.00 |
| -0.24 | 0.00 | 0.05 | 0.22 | 1.00 |
| 0.00 | 0.00 | 0.05 | 0.06 | 0.98 |
| 0.24 | 0.00 | 0.05 | 0.27 | 0.90 |
| 0.48 | 0.01 | 0.05 | 0.62 | 0.64 |
| 0.72 | 0.03 | 0.06 | 0.89 | 0.24 |
| 0.96 | 0.01 | 0.05 | 0.97 | 0.07 |

**Table 4: Bias, MSE and t-statistic with no additive outliers and sample size 500**

| Parameter *d* | Bias | MSE | Size of t-statistic $H_0$: $d = 0$ | Size of t-statistic $H_0$: $d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.24 | 0.12 | 1.00 | 1.00 |
| -0.72 | 0.09 | 0.04 | 1.00 | 1.00 |
| -0.48 | 0.03 | 0.03 | 1.00 | 1.00 |
| -0.24 | 0.01 | 0.03 | 1.00 | 1.00 |
| 0.00 | 0.01 | 0.03 | 0.05 | 1.00 |
| 0.24 | 0.01 | 0.16 | 1.00 | 1.00 |
| 0.48 | 0.02 | 0.03 | 1.00 | 1.00 |
| 0.72 | 0.04 | 0.03 | 1.00 | 1.00 |
| 0.96 | 0.01 | 0.03 | 1.00 | 0.09 |

Tables 5 - 8 present the results for the case when there are some large and small additive outliers. For the sample sizes $T$= 50, 100, and 200, the exact size for the null hypothesis that $d = 0$ is closest to zero when the true fractional parameter is closer to –1. The reverse is true when the true fractional parameter is closer to unity. The opposite case arises when the true exact size of the null hypothesis that the fractional parameter is equal to unity. However, no size distortion is observed when we use $T = 500$, a sample size that is, unfortunately, not frequently available in macroeconomic applications.

**Table 5: Bias, MSE and t-statistic with large /small additive outliers and sample size 50**

| Parameter $d$ | Bias | MSE | Size of t-statistic $H_0$: $d = 0$ | Size of t-statistic $H_0$: $d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.86 | 0.76 | 0.03 | 0.95 |
| -0.72 | 0.61 | 0.41 | 0.04 | 0.95 |
| -0.48 | 0.37 | 0.18 | 0.04 | 0.93 |
| -0.24 | 0.13 | 0.08 | 0.06 | 0.92 |
| 0.00 | -0.09 | 0.11 | 0.07 | 0.86 |
| 0.24 | -0.23 | 0.18 | 0.08 | 0.77 |
| 0.48 | -0.27 | 0.19 | 0.13 | 0.58 |
| 0.72 | -0.24 | 0.19 | 0.35 | 0.34 |
| 0.96 | -0.19 | 0.16 | 0.63 | 0.15 |

The results with respect to the bias and the *MSE* are also related to the behavior of the true fractional parameter. In fact, when this parameter is closer to –1, bias and *MSE* appear to increase. The reverse is true when $d > 0$ but less than unity. For this sample size, the bias is important when $d < 0$. Although bias and *MSE* are smaller for $T = 500$, the exact size of the t-statistic of the null hypothesis that d = 1 is higher compared to other sample sizes.

**Table 6: Bias, MSE and t-statistic with large /small additive outliers and sample size 100**

| Parameter $d$ | Bias | MSE | Size of t-statistic $H_0$: $d = 0$ | Size of t-statistic $H_0$: $d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.82 | 0.68 | 0.05 | 0.99 |
| -0.72 | 0.57 | 0.34 | 0.06 | 0.99 |
| -0.48 | 0.32 | 0.13 | 0.07 | 0.98 |
| -0.24 | 0.07 | 0.05 | 0.10 | 0.98 |
| 0.00 | -0.11 | 0.08 | 0.09 | 0.96 |
| 0.24 | -0.18 | 0.11 | 0.08 | 0.88 |
| 0.48 | -0.17 | 0.11 | 0.26 | 0.68 |
| 0.72 | -0.12 | 0.11 | 0.63 | 0.33 |
| 0.96 | -0.08 | 0.08 | 0.87 | 0.12 |

**Table 7: Bias, MSE and t-statistic with large /small additive outliers and sample size 200**

| Parameter *d* | Bias | MSE | Size of t-statistic $H_0$: $d = 0$ | Size of t-statistic $H_0$: $d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.93 | 0.88 | 0.01 | 1.00 |
| -0.72 | 0.67 | 0.46 | 0.02 | 1.00 |
| -0.48 | 0.40 | 0.18 | 0.03 | 0.99 |
| -0.24 | 0.14 | 0.06 | 0.07 | 0.99 |
| 0.00 | -0.01 | 0.05 | 0.07 | 0.98 |
| 0.24 | -0.05 | 0.06 | 0.19 | 0.92 |
| 0.48 | -0.03 | 0.06 | 0.56 | 0.69 |
| 0.72 | 0.00 | 0.06 | 0.87 | 0.28 |
| 0.96 | 0.00 | 0.05 | 0.97 | 0.07 |

Under the given condition of the case of *d* is close to unity, this behavior is similar to the power problems observed for most of unit root tests in the econometric literature. Finally, some issues that pertain to all sample sizes need to be mentioned here. First, when Table 2 is compared with Table 1, it observes the direct effects of additive outliers against a case where no aberrant observations exist. The evidence with respect to higher bias and higher *MSE* is also obvious. Moreover, it can be readily observed that there are size distortions for the t-statistic of the null hypothesis that $d = 0$.

**Table 8: Bias, MSE and t-statistic with large /small additive outliers and sample size 500**

| Parameter *d* | Bias | MSE | Size of t-statistic $H_0$: $d = 0$ | Size of t-statistic $H_0$: $d = 1$ |
|---|---|---|---|---|
| -0.96 | 0.91 | 0.84 | 1.00 | 1.00 |
| -0.72 | 0.65 | 0.43 | 1.00 | 1.00 |
| -0.48 | 0.36 | 0.14 | 1.00 | 1.00 |
| -0.24 | 0.09 | 0.03 | 0.96 | 1.00 |
| 0.00 | -0.01 | 0.03 | 0.05 | 1.00 |
| 0.24 | -0.01 | 0.03 | 0.98 | 1.00 |
| 0.48 | 0.01 | 0.03 | 1.00 | 1.00 |
| 0.72 | 0.03 | 0.03 | 1.00 | 1.00 |
| 0.96 | 0.01 | 0.03 | 1.00 | 0.63 |

As mentioned earlier, one of the motives of this paper is to analyze the effects of additive outliers treated as wild observations of temperature present in the climate on the behavior of the estimated value of the fractional parameter. With this end in view, an extensive set of simulation has been done employing additive outliers. The principal criteria for analyzing the behavior of the estimated parameter are the bias, the *MSE* and the exact size of the t-statistics of the estimated fractional parameter.

When there are additive outliers which are generated according to the pre-specified data generating process, the exact size of the t-statistic of the null hypothesis that d=0 goes to zero. This fact is more pertinent particularly when the true fractional parameter is negative. The opposite situation occurs or the t-statistic of the null hypothesis that d=1 when the true fractional parameter is positive. In the case of the bias and the *MSE*, t-statistics are more affected by the size of the fractional parameter. Comparison between a situation in which there exists additive outliers to a situation in which these kinds of observations do not exist, showed that they have important effects on the estimation of the fractional parameter and on the estimation of the t-statistic for verifying the null hypothesis that d=1 or d=0. Overall, is has been observed that clear size distortions and the bias and the *MSE* are higher or clearly different with respect to the case where these kinds of observations do not exist. This outcome implies that wild or aberrant observations of global warming present in the climate are effectively changing the environment and this change is not being happened with a systematic variation or trend. Rather, it is active in the change process that is creating more and more uncertainties in natural environment which is truly a cumbersome phenomenon that cannot be predicted systematically earlier.

The simulation evidence of the present investigation is in line with the studies those show uncertainties in the climate change rather than any systematic variation. In presence of aberrant observation the estimate of long memory fractional parameter *d* is influenced which is proved through the test statistic of the bias, the MSE and also the size of t-statistic. When the wild observation of world temperature data is construed as the abnormal temperature record, a shock is appeared to exist in the climate system. This shock leads to a cyclical variation rather than a trend. Thus, ultimately, the findings of this research are producing more uncertainties rather than helping to resolve the conflicting situation and easing policy formulation for the policy makers.

### 4.2. Regression Results

The regression results (Table 9) are based on the sample size of 38 years' annual data starting from 1971 to 2008. The analysis has been done with the SPSS 18.0 version in order to have accurate results. The results indicate that out of five independent variables only three variables are statistically significant at .01 level. Both coefficients of rainfall i.e. R and $R^2$ are observed to be negatively related to the productivity of rice. This evidence has amply been supported by excessive precipitations and floods since the liberation of Bangladesh in 1971. Bangladesh witnessed catastrophic contemporaneous heavy rains and floods almost in every year, which has profound negative impacts on the productivity level of rice in Bangladesh.

**Table 9: Impacts of Climate Change on Rice Productivity in Bangladesh Agriculture**

| Variables | Coefficients | Standard Error | t-Statistics |
|---|---|---|---|
| Constant | -0.326 | 25.36 | -0.013 |
| T | -0.59 | 1.76 | -0.336 |
| $T^2$ | 0.011 | 0.031 | 0.358 |
| R | -0.0055 | 0.002 | 2.727** |
| $R^2$ | -0.0000014 | 0 | 2.62** |
| C | 0.011024 | 0.003 | 3.2** |
| $R^2$ | 0.40 | | |
| Adj. $R^2$ | 0.30 | | |
| F | 4.128** | | |
| N | 38 | | |

**p<.01

Carbon concentration is observed to be highly significant and positively related to the productivity of rice. Carbon dioxide is used by the plants for manufacturing foods through photosynthesis. Although excess carbon dioxide is blamed to act as a catalytic agent for lurching up the atmospheric temperature, plenty carbon dioxide may be helpful to plant kingdom to produce adequate foods and to their healthy physical growth. In spite of the fact that the presence of excess carbon dioxide in air is undesirable, but it may be helpful for the plants that is evident in this study.

Temperature has been observed here to have no significant relationship with rice productivity, but it has a negative influence on the productivity of rice in Bangladesh. This outcome is consistent with the general assumption that global warming is detrimental to agricultural production. High temperature is liable for accelerating high evaporation as well as for making catastrophic drought. Due to this problem, rivers are becoming dry which has a devastating effect on overall crop production especially in dry season. For this reason, the areas of desert have been increasing all over the world. Based on the evidence, it can easily be concluded that high temperature is affecting the overall productivity of rice in Bangladesh. Hence, clearly there has been a catastrophic impact of climate change on the rice productivity of Bangladesh agriculture which is deadly for densely populated country of Bangladesh.

## 5. Conclusion

This paper has two goals. The first goal is to observe the simulation evidence of global warming and the second goal is to observe the regression results in order to show the impacts of global warming, precipitations and carbon dioxide concentration in the air on rice productivity particularly in Bangladesh agriculture. With these ends in view, the study first investigates the simulation process to see the nature of the impact of global warming, which is treated here in the simulation as additive outliers (i.e. wild observations of global warming), on the estimated value of the fractional difference parameter, *d*. The principal criteria for analyzing the behavior of the estimated parameter are the bias, the *MSE* and the exact size of t-statistic of the estimated fractional parameter. Overall, additive outliers or wild observations of global warming are observed to affect the bias and the *MSE* and the size of t-statistics. Besides, the size of the additive outliers and a drift parameter has also important effects on the estimated value of *d*, depending on the true value of *d*. This result implies that there has been a momentary shock process involved rather than a systematic trend in the atmospheric change. This outcome appears to be grim and lead to conclude that in the contradictory climatic condition it produces no more than a complex process of momentous stochastic uncertainty.

The regression results show that rainfalls and carbon precipitations in the air have statistically highly significant impact on the productivity of rice. Especially, rainfalls have negative impacts on rice production. The temperature variable is not observed statistically significant, but the negative coefficient of global warming implies that there has been a negative relationship between the global warming observations and the rice productivity of Bangladesh agriculture.

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