UNCERTAINTIES IN GLOBAL WARMING TEMPERATURE-TREND AND THEIR IMPACTS ON AGRICULTURAL PRODUCTION: AN ECONOMETRIC EVALUATION

Ketidakpastian Kecenderungan Pemanasan Global dan Dampaknya terhadap Produksi Pertanian: Suatu Evaluasi Ekonometrik

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ABSTRAK

Makalah ini membahas kecenderungan dampak pemanasan global yang terjadi akhir-akhir ini. Estimasi dilakukan dengan parameter fraksional dari catatan relatif panjang menggunakan tehnik *outlier* aditif sebagai pengamatan bebas yang dihasilkan di atmosfer karena pemanasan global. Selanjutnya penelitian ini mengamati secara empiris dampak pemanasan global terhadap aspek tertentu produksi pertanian global. Berdasarkan simulasi Monte Carlo, proses menghasilkan data diterapkan dimana *outlier* aditif dihasilkan melalui cara *discrete* atau tidak kontinyu. Hasil observasi menunjukkan bahwa *outlier* aditif mempengaruhi bias dan MSE parameter fraksional estimasi. Ukuran *outlier* aditif dalam proses menghasilkan data juga memiliki pengaruh penting terhadap parameter farksional estimasi yang tergantung pada nilai parameter fraksional yang sebenarnya. Hasilnya menunjukkan variabilitas non tren atau siklus alami yang dipengaruhi oleh proses stokastik dalam hal sifat perubahan iklim dengan observasi bebas *(outlier)* yang menghasilkan *outcome* berlawanan dari ketidakpastian yang intensif terhadap tren data temperatur dunia pada kondisi riil. Hasil pengamatan empiris menyimpulkan bahwa pada akhir abad 21 secara meyakinkan pemanasan global akan mempunyai dampak negatif terhadap agregat produksi pertanian global dan dampaknya bisa sangat parah jika manfaat fertilizasi karbon (peningkatan hasil dalam lingkungan yang kaya karbon) tidak tampak, terutama jika kelangkaan air membatasi irigasi. Lagi pula, jika pemasan global tidak berhenti pada tahun 2080, tetapi temperatur global terus meningkat pada abad 22, kegagalan produksi pertanian bisa semakin parah. Studi ini juga menunjukkan bahwa akumulasi pengaruh produksi pertanian kemungkinan lebih serius bagi negara berkembang dengan kerugian terbesar di Afrika, Amerika Latin, dan India.

Kata kunci: *outliers aditif, parameter fraksional, simulasi Monte-Carlo, dampak pemanasan global, pengaruh tren temperatur, ketidakpastian, keberlanjutan, produksi pertanian*

ABSTRACT

This paper primarily 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

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fractional parameter using a simulation technique in the presence of additive outliers which stands as wild observations generated in the atmosphere due to global warming. Then, the study investigates empirically the impact of global warming on the particular aspect of global agricultural production. Based on Monte Carlo simulations, a data generating process is applied where additive outliers are generated in a discrete way. Observed facts reveal that additive outliers affect the bias and the MSE of the estimated fractional parameter. The size of the additive outliers in data generating process has also important effects on the estimated fractional parameter depending on the value of true fractional parameter. The result exhibits a non-trend or a natural cyclical variability 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 data trend. The results of empirical investigations assert that in the late 21st century unabated global warming would have a negative impact on global agricultural production in the aggregate and the impact could be severe if carbon fertilization benefits (enhancements of yields in a carbon-rich environment) do not materialize, especially if water scarcity limits irrigation. In addition, if warming would not halt in the 2080s, but would continue on a path toward still higher global temperatures in the 22nd century, agricultural damage could be more severe. The study also shows that the composition of agricultural effects is likely to be seriously unfavorable to developing countries with the most severe losses in Africa, Latin America and India.

Key words : *additive outliers, fractional Parameter, Monte-Carlo simulations, impact of global warming, temperature trend effect, uncertainty, sustainability, agricultural production*

INTRODUCTION

In recent times, issues of climate change and global warming upshot uproars in the media, because global ecological change resulting in rising surface air temperature poses a common threat as a 'highway to extinction' (see e.g. IPCC, 2007; Rahman, 200; 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 upend till the present (Cohn and Lins, 2005), which is consistent with the hypothesis that manmade emissions of greenhouse gasses into the atmosphere should cause average global temperature to rise (Seater, 1993). This behavior of data raises concern whether the trend is genuine. The controversy surrounds mainly on the impact and nature of the information provided by the investigations of scientific communities (Kallache et al., 2005). One school of thought argues that there has been a deterministic trend of world temperature readings, which imply that the consequence of anthropogenic influence is present (Solow, 1987; Bloomfield, 1992; Beran, 1994, Woodward and Gray, 1995; Percival and Walden, 2000; Craigmile et al., 2004). The other school maintains the argument of non-trend or a natural cyclical variability that is influenced by a stochastic

process (Seater, 1993; Jones et al., 1986; Ribsky et al., 2006; Mills, 2007). This result increases contradictions and uncertainties over that issue of climate change and economics of global warming that could have a drastic impact on the sustainability of agricultural food production all over the world.

Overall, uncertainties develop out of three conflicting results of investigations. First, temperature readings for the last century yield trend estimates of about 0.45 degrees Celsius per century, which is consistent with those reported in the scientific literature. The trend is significant statistically, but the 95% confidence interval is substantially wide (0.15, 0.75). Second, the two data sets for the last century produce proximate equal trend estimates, but temporal and geographical patterns seem inconsistent with greenhouse gas emissions as to be the source of the observed trend. Third, a study of the temperature record for the past 15 centuries shows that the recent rise in temperature is nothing unusual. The rise may be a local upswing in a cyclical process that has no overall trend, but that may appear to be a trend when viewed in isolation (Seater, 1993). Similar analogy of the last case is observed when Craigmile et al. (2004) maintain that there is typically little argument about the magnitude of observed trends whether estimated by eye or statistical methods. Moreover, some even express doubts about the existence of a rigorous and consistent definition of trend (Cohn and Lins, 2005). Some others consider the statistical significance or p-value associated with an observed trend as more difficult to assess, because it depends upon subjective assumptions about the underlying stochastic process (von Storch and Zwiers, 1999).

Long memory means to rely on past experiences. That is, if something has happened in the past, it is likely to repeat again in the future. In other words, history repeats itself over and over again. Statistically, 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).

Many applications of this approach have been proposed in the econometric literature. However, while econometricians have been using long memory models since around 1980, they have rutted the mark in physical sciences since at least 1950 with the seminal work of Hurst (1951, 1957). Very often, time series are contaminated due to the presence of aberrant or wild observations, which do not necessarily originate in the true data generating process but in time series modeling. These observations are called outliers (Ashraf, 2006). There are different sorts of outliers. Here, this paper focuses its attention on additive outliers that by definition affect the level of time series but not the disturbance term associated with it.

However, the intent of this paper is to observe the effect of global warming data-trend, treated as additive outliers, on the bias and the MSE of the estimated fractional parameter, which subsequently produce stochastic shocks

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or uncertainties. The study has employed long memory model as proposed by Geweke and Porter-Hudak (1983). The model is used the artificial data generated by Vogelsang (1999) and Perron and Rodriguez (2000) by implementing a Monte Carlo design. If there is any observation that affects the size and the probability of occurrence of the additive outliers as well as the drift parameter in data generating process on the estimated fractional parameter, conclusions could be drawn that the bias, MSE and the size of t-statistic would be influenced which could be used adequately as to be the evidence of affecting the trend stationarity. Thus, the present temperature-trend measures are uncertain, which are in some ways quantifiable and in some ways that are not. These evidence outcome enormous uncertainties that enhance responses to shocks in agricultural food production, which can be drastically reduced in the near future and could cause a catastrophic famine all over the world. In that case a cautious approach of economic policy options for food production is warranted and that is the central theme of this paper.

METHODOLOGY

Theoretical Framework

There are a variety of ways of estimating the parameter d. In the present study, the estimation procedure is followed 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 $(1 - L)^d x_t = \varepsilon_t$, where $\{x_t\}$ is assumed to be a time series process, $d \in (-.5, .5)$ and ε_t is serially uncorrelated, the spectral density of the time series $\{x_t\}$ is:

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

A time series with the spectral density $f_2(\omega; d)$ is called an integrated or fractionally differenced series, which suggests that $\lim_{\omega \to 0} \omega^{2d} f_2(\omega; d) = (\sigma^2/2\pi)$ and the autocorrelation function (for $d \neq 0$) is $\rho_2(\tau; d) = \Gamma(10d)\,\Gamma(\tau + d)\,/\,\Gamma(d)\,\Gamma(\tau + 1 - d)$, which leads to $\lim_{\tau \to \infty} \tau^{1-2d}\,\rho_2(\tau; d) = \Gamma(1 - d)\,/\,\Gamma(d)$.

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

$$\log\{f_y(\omega_j)\} = \log\{f_u(0)\} - d \log\{4\sin^2(\omega_j/2)\} + \log[f_u((\omega_j)/f_u(0)] \quad (2)$$

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 $I_y(\omega_j)$:

$$\log \{I_y(\omega_j)\} = a - d \log \{4\sin^2(\omega_j/2)\} + v_j, \ j = 1\ldots n \qquad (3)$$

where

$$v_j = \log [f_u(\omega_j)/f_u(0)] \qquad (4)$$

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 $\lim_{T\to\infty} g(T) = \infty$, $\lim_{T\to\infty} \{g(T)/T\} = 0$ and $\lim_{T\to\infty} \{(log(T)^2/g(T) = 0$ then the *OLS* estimator of d in (3) takes the limiting distribution as follows:

$$(est\ d - d)/\{var(d)\}^{1/2} \quad \sim N(0,1) \qquad (5)$$

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

Data Sources

For the simulation, the study uses artificial data generated for different sample sizes following specific methods. Based on these data, a Monte Carlo simulation method was carried out in order to estimate the fractional parameter, d. For experimenting on the field evidence, the data are actual county averages collected from the 1982 U.S. Census of Agriculture and the U.S. Bureau of the Census, 1988. These data are used for the agricultural information including values of farm products sold per acre, farm land, building values and market inputs for farms in every county in the United States.

Data about soils are extracted from the National Resource Inventory (NRI) available in the U.S. Department of Agriculture along with the Statistics Canada, 2001. Climatic data are obtained the National Climatic Data Centers. The data include information on precipitation and temperature for each month from 1951 through 1980. The data on developing countries are collected from World Bank farm surveys done in different phases worldwide upend till 1990s. Climatic projections are available in the programs of standardized analysis compiled by the Intergovernmental Panel on Climatic Change (IPCC) in different years.

Method of Analysis

A Monte Carlo simulation method has been used in this study which consists of generating repeated samples of artificial data for some sample size and analyzing the behavior of the relevant statistics (Kennedy, 2003). In this case, the attention is focused on the behavior of the estimates of the fractional parameter. One way to do this is to calculate some characteristics of this

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estimate such as the Mean Square Error (*MSE*) and the bias (e.g. Ashraf, 2001). While the size and power of one statistic is the principal object, the number of rejections of the null hypothesis having found in all the used replications is calculated.

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:

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

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

where, $v_t \sim i.i.d. \ N \ (0,1)$, d is the fractional parameter, $D \ (T_{ao, 1})_t = 1$ if $t = T_{ao, i}$ and 0 otherwise and δ_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 components. 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).

RESULTS AND DISCUSSION

Uncertainties Generated by Global Warming: Simulation Evidence

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 because of the bias and the variances are smaller, probably as a consequence of a better estimation of the fractional parameter in opposition to the case where *d* is close to –1 (Table 1).

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 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). On the other hand, as one can expect, when the true fractional coefficient is close 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 even for higher sample sizes (Table 3 and Table 4).

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

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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).

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). 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 (Table 7).

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

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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

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 *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).

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

The result of simulation discussed above suggests that wild observations of global warming have a significant impact on generating uncertainties in the climate change rather than having any systematic variation of it. In presence of wild observations the estimate of long memory fractional parameter *d* is influenced 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.

Climate Change, True Temperature-Trend and Their Impacts on Agricultural Production: Field Evidence

A number of models have been proposed to describe the long memory feature of time series (Wang et al., 2007). Many studies have been carried out on detecting and modeling long memory in various areas such as climate change (e.g. Hussain and Elbergali, 1999; Haslett and Raftery, 1989), economic and financial fields (e.g. Lo, 1991; Meade and Maire, 2003). In climatic research many authors such as Ribsky et al. (2006) used the detrended fluctuation analysis.

As a matter of fact, climate change is a reality in the measured temperature regardless of the selection of a noise model (Bloomfield, 1992). This has led to the accompanying assumptions that also extreme events, such as heavy rains, droughts or floods in Europe in summer 2002 cost 22 billion EUR and in South Asia in summer 2004 claim 1600 casualties and millions of displaced people (Kallache et al., 2005), will increase in frequency and/or magnitude (IPCC, 2001). According to the Statistics Canada Reports, about 1,300 of Canada's glaciers have lost between 25 per cent and 75 per cent of their mass since 1850 and water in the St. Lawrence at Montreal is as much as two meters below its level at the beginning of the 20th century (Paraskevas, 2003). Meaningful global temperature change can be obtained for the past century, despite the fact that the meteorological stations are confined mainly to continental and island locations. The results indicate a global warming of about $0.5^0 - 0.7^0$C in the past century, with warming of similar magnitude in both hemispheres; the northern hemisphere result is similar to that found by several other investigators (Hansen and Lebedeff, 1987). Unfortunately, this observable fact of global warming trend is highly inconsistent with the quantitative information on many things. Data on temperature measurements inferred from tree rings over the past 1,500 years show no trend (Briffa et al., 1990). Nonetheless, a large number of scientific literatures have investigated the historical temperature data in order to determine the magnitude, but still the results are unsatisfactory for policy formulations.

The study of Hansen and Lebedeff (1987) reveals that there is more warming in northern hemisphere and it takes place in the first half of the last century. In the Jones et al. (1986), the warming takes place in the second half of the century but in the southern hemisphere. Neither data set is fully consistent

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with greenhouse gasses being the causal mechanism for the observed warming (Seater, 1993). The study of Briffa et al. (1990) also show that there is no trend behavior found in the tree rings data analysis. Thus, it comes out from the foregoing discussions that, if the temperature process displays no-trend but cyclical behavior as the tree rings, then it will imply that more uncertainty seems substantial, which consequently makes it difficult to quantify the uncertainty as well.

All of these findings imply that the policy formulators encounter massive scale of uncertainty in response to the possibility of climate change or global warming. The most important presage of this article that obtained from the simulation evidence in the presence of extreme observations that global climate displays considerably cyclical variability but evolves slowly. Prima facie, it cannot be expected the climate data to reveal for a long period of time whether any abnormal warming trend is taking place. Consequently, it appears to imply an irreducible component of uncertainty that contains any information based on short term analysis. Therefore, the policy makers will have to formulate decisions about the taxation and regulation of industrial practices such as carbon dioxide emissions without confirmation from the climate data of whether implemented rules are the right things to do. Otherwise, this massive uncertainty will affect the global agricultural sector in terms of sustainable food production for the world population. In the next section, impacts of global warming on agricultural production based on econometric estimates are represented, which are adapted from a recent study of Cline (2007).

'In the list of potential damages from global warming the risk to world agriculture stands out as among the most important' (Cline, 1992). The grounds of importance are of two-fold: first, the aggregate global impacts are on high risk and second, the distribution of likely impacts is skewed across countries because of equity issues. There has, however, been relatively wide consensus that developing countries in general posit to loss more from the effects of global warming on agriculture than the industrial countries, because developing countries incline to have less capability to adjust with the new environment. In addition, agriculture in these countries comprises a much larger proportion of GDP than in industrial countries. Consequently, smaller percentage loss in agricultural production would impose a larger proportionate loss of income in developing countries. Cline (2007) finds that agricultural production in developing countries may fall between 10 and 25 percent, and if global warming progresses unabated India's agricultural capacity, for instance, could fall as much as 40 percent. Thus, policymakers should address this phenomenon now before the world's developing countries are adversely and irreversibly affected. In the following section, a more detailed and systematic estimates are represented in order for affirming the impacts of global warming on agricultural production.

In order to show the potential effect of global warming on agriculture, two principal sets of models such as Ricardian and crop models are widely used (Cline 2007). In so doing, specific agricultural impact models are reviewed beginning with the estimates of Mendelsohn and Schlesinger (1999). Then, crop model estimates by Rosenzweig and Iglesias (2006) is examined. The Cross-section or Ricardian agricultural impact function identified by Mendelsohn and Schlesinger (1999) is

$$v = (r). (g). (x) [-475.5 + 223.2T - 7.87T^2 + 0.063P - 0.000026P^2 +$$

$$480 \ ln(c/350)] \tag{8}$$

where r is the interest rate and g is a factor for the growth rate of agricultural output, set at 0.03 and 1.02 respectively. In the cross-section function the value in brackets is the capital value of land per hectare, multiplying it by the interest rate   yield estimated rental equivalent opportunity cost of land per hectare, v in dollars in dollars per hectare. In principle, this amount should be significantly smaller than the output value per hectare in the following reduced-form equation (9), because it is only the land factor share of output rather than the total. The impact of global warming through the 2080s is obtained using this equation to estimate the difference between agricultural productivity using the base period (1961-90) and future period (2070-99) climate estimates of this study.

A reduced-form agronomic crop model's summary results are derived as follows:

$$y = (2.16) [-308 + 53.7 \ T - 2.3 \ T^2 + 0.22 \ P + 36.5 \ ln \ (c/350)] \tag{9}$$

where y is annual agricultural output in 1990 dollars per hectare of agricultural land, T is average annual temperature in degrees Celsius, P is average annual precipitation in millimeters, and c is atmospheric concentration of carbon dioxide ppm (parts per million). Note that in the base period, carbon concentration 350 ppm, so that the final term becomes 36.5 times the natural logarithm of unity, which is zero, so the carbon fertilization (carbon-rich environment) term drops out when examining the present influence of climate on agriculture. The following figure 1 shows curves corresponding to zero output and output of $200 per hectare on the basis of equation (9). Both curves show the optimal temperature at 11.7° C (Figure 1).

Figure 1 shows curves corresponding to zero output (q=0) and output of $200 ($q$=200) per hectare of land on the basis of equation (9). Both curves show the optimal temperature at 11.7^{0}C. At this temperature, output is $200 per hectare at daily precipitation of about 2.5 mm. With zero precipitation, output is zero even at this optimal temperature. At higher temperature, more precipitation is required to keep productive potential positive.

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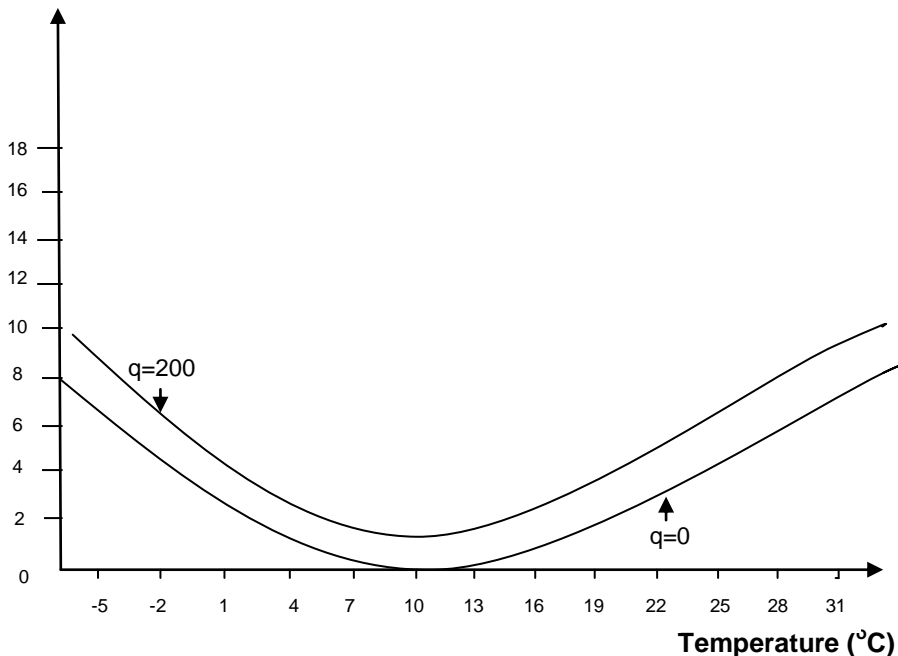
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Precipitation (mm per day)

Figure 1. Iso-production curves for the Mendelsohn-Schlesinger reduced-form function (Adapted from Mendelsohn and Schlesinger, 1999)

For industrial countries (e.g. the United States), Mendlelsohn and Neumann (1999) as well as Mendelsohn and Nordhaus (1999) use cross-section models in order to provide the Ricardian estimates. For developing countries of Asia, Africa and Latin America, Cline (2007) provides estimates based on the following model structure:

$$z = \Sigma_i \left[\alpha_i\, T_i + \beta_i\, T_i^2 + \gamma_i\, P_i + \delta_i\, P_i^2 \right] + K \tag{10}$$

where z is the measure of agricultural productivity (net revenue per hectare for Africa, natural logarithm of net revenue per hectare for Asia (India) and land value per hectare for the Latin American studies), T is average temperature, P is average monthly precipitation, i refers to the season and K is a composite variable that reflects the regression constant. The impact of global warming through the 2080s is obtained using this equation to estimate the difference between agricultural productivity using the base period (1961-1990) and future period (2070-2099) climate estimates of this study.

In principle, the reduced-form model of Mendelsohn and Schlesinger (1999) takes account of the potential for adaptation. The specific observation of Adams et al. (1999) on the aspect of possibilities of adaptation is that "adaptation could potentially offset roughly half of the negative impacts of a moderate climate change. However, this evidence suggests adjustment possibilities are smaller for larger temperature change." (p. 32)

The crop-model results of Rosenzweig et al. (1993) provide a query-based database that shows estimates of the impact of prospective global warming, under alternative climatic scenarios and using climate projections for general circulation models (GCMs), on four major crops: wheat, rice, maize and soybeans. The underlying research was developed in the 1990s, by a team of agricultural scientists from 18 countries, who estimated compatible crop models at 125 agricultural sites using consistent climate change scenarios. The process-based dynamic crop growth models incorporate the effects of change in temperature, precipitation, and solar radiation; the effect of carbon fertilization from carbon dioxide; and crop management, particularly with respect to timing of planting and extent of fertilization and irrigation. The estimates are used for three levels of adaptations.

The two basic frameworks discussed earlier in above discussion (Ricardian statistical model, on the one hand, and crop models on the other) provide the basis for identifying a set of estimates that synthesize the alternative model results in showing the impact of global warming on overall agricultural outputs. Table 9 presents several alternative aggregations to show such agricultural impact by major regions of developing and industrialized countries. Besides, it provides overall weighted results using population weights to examine how the implications differ from global averages by agricultural productions. In the table, it is evident that with carbon fertilization, output-weighted agricultural potential rise for industrial countries by a synthesized estimate of 7.7 percent, whereas for developing countries defined as excluding developing Europe it falls by 9.1 percent. The table also shows that in the synthesized estimate (with carbon fertilization) output potential falls by about 17 percent in Africa excluding North Africa, by 7 percent in Asia, 9 percent in the Middle East and North Africa and 13 percent in Latin America. In contrast for developing Europe, it was by 4 percent (Table 9).

These results indicate that Africa (excluding Egypt and other North Africa) and Latin America are the developing regions most vulnerable to global warming. This finding is consistent with the IPCC (1996) pattern noted in the survey above. Asia on average is less vulnerable, but this masks the divergence between more favorable results for China in particular and more unfavorable results for India (Mendlesohn et al., 1994) , reflecting in part the differences in their latitudes. Table 9 also provides the global impact weighting by population rather than outputs. In this case, output potential falls by a weighted average of 18 percent without carbon fertilization and by about 6 percent with carbon

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fertilization. The greater decline in output potential weighting by population reflects the predominance of more severe adverse effects in developing countries in contrast to milder losses or even gains in industrial countries.

Table 9. Impact by Major Regions: Developing and Industrial Countries

Country/Region	Base Output (Billions of 2003 dollars)	Population (Million)	Changes in Agricultural Output Potential Synthesized Estimates (percent)	
			Without Carbon Fertilization	With Carbon Fertilization
Developing Countries	**838**	**5,202**	**-19.7**	**-7.7**
Excluding Europe	745	4,807	-21.0	-9.1
Africa	73	660	-27.5	-16.6
Nigeria	15	136	-18.5	-6.3
South Africa	6	46	-33.4	-23.4
Asia	500	3,362	-19.3	-7.2
China	213	1,288	-7.2	6.8
India	132	1,064	-38.8	-28.8
Indonesia	35	215	-17.9	-5.6
Mid-East North Africa	61	280	-21.2	-9.4
Algeria	7	32	-36.0	-26.4
Egypt	13	68	11.3	28.0
Iran	15	66	-28.9	-18.2
Latin Amerika	11.1	506	-24.3	-12.9
Argentina	14	37	-11.1	2.2
Brazil	30	177	-16.9	-4.4
Mexico	25	102	-35.4	-25.7
Europe	93	395	-9.4	4.1
Poland	5	38	-4.7	9.5
Russia	22	143	-7.7	6.2
Turkey	27	71	-16.2	-3.6
Industrial Countries	**338**	**846**	**-6.3**	**7.7**
Australia	13	20	-26.6	-15.6
Canada	17	32	-2.2	12.5
Germany	17	83	-2.9	11.7
United Kingdom	13	59	-3.9	10.5
United States	99	291	-5.9	8.2
World	**1,176**	**6,049**	**-15.9**	**-3.2**
Population weighted			**-18.2**	**-6.0**

Source : Cline (2007).

CONCLUSIONS AND RECOMMENDATIONS

Broadly, this paper has two goals --- one is to observe the simulation evidence of global warming and another is to collate that simulation evidence to the available field evidence in order to show the impacts of global warming on world agricultural food production. With these ends in view, the paper first investigates the simulation process to see the nature of the impact of global warming, which is treated here in the simulation process as additive outliers (i.e. wild observations of global warming temperature-readings), on the estimated value of the fractional difference parameter, d and their subsequent impacts on the sustainability of overall global agricultural food production. 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 (wild observations of temperature) are observed to affect the bias and the *MSE*. 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. Having applied this result to the case of global warming, it 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 stochastic uncertainty.

The paper then investigates the field evidence. From the field evidence, the paper reaches two more fundamental conclusions. The first is that in the late 21st century unabated global warming would have at least a modest negative impact on global agricultural production in the aggregate and the impact could be severe if carbon fertilization benefits (enhancements of yields in a carbon-rich environment) do not materialize, especially if water scarcity limits irrigation. In addition, if warming would not halt in the 2080s, but would continue on a path toward still higher global temperatures in the 22nd century, agricultural damage could be more severe. And the second conclusion is that the composition of agricultural effects is likely to be seriously unfavorable to developing countries with the most severe losses in Africa, Latin America and India.

The results of this study strongly suggest that the global warming would turn malignant for agriculture globally and that the damages would be the most severe in the developing countries if not the proper measures of mitigating this global problem are formulated. Besides, it would turn to be a serious mistake to downplay the risks of future agricultural losses from global warming on grounds that technological advancement, for instance, will offset any negative climatic damages. Hence, the Kyoto Protocol as one of the principal initiatives to date against global warming is recommended as a policy measure in order to have a more positive position on global warming abatement for long term interests of developing and developed countries equitably.

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Last but not least, in the long list of potential damages from global warming, the risk to world agriculture stands out as among the most important (Cline, 1992). In the development of international policy, it is particularly momentous for policymakers to share the sense of not only the aggregate global impacts, but also the distribution of similar effects across countries, for reasons of equity.

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