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Time Series Properties of Some Climatic Variables in Dinajpur District

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Abstract: Several direct empirical time series investigations of global climate change and its impact have been studied by several world famous researchers. Some researches regarding local climatic change and its impact have been published but the time series properties of the variables related to national as well as local climate are yet to be able to have proper attention. The presence or absence of unit roots in these time series or inappropriate statistical tools may challenge the validity of the interpretations of their results and implies that cointegration analysis can be used to investigate the relation among variables. This article attempts to deduce time series properties of temperature, rainfall and humidity of Dinajpur district.

Key wards: Global climate, Humidity, Rainfall,Temperature

Introduction

Several direct empirical time series investigations of global climate change and its impact (e.g. Lane *et al*. 1994; Kuo *et al*. 1990; Thomson 1995; Schönwiese 1994; Tol 1994; Lean *et al*. 1995) and some researches regarding local climatic change and its impact (e.g. Karmaker, 1997; Hossain, et al., 2001) have been published but the time series properties of the variables have received little attention with a few notable exceptions in the case of global temperature series (Bloomfield and Nychka 1992; Woodward and Gray 1993).

Classical linear regression techniques may indicate a positive/negative relationship among such climatic series but unable to show any relationship among the climatic variables. However, recent developments in econometrics allow for the analysis of relationships between statistically nonstationary data.

Cointegration techniques (Engle and Granger, 1987; Johansen, 1988) are used by macro-economists to detect and quantify relations among variables such as GDP and aggregate price levels. These non-stationary trending variables may share common long-run stochastic trends.

In this paper, some climatic data (viz., temperature, humidity, and rainfall) are analyzed for the presence of stochastic trends in individual variables and for stochastic trends shared by two or more of these variables.

Objectives of the Study

The aim of this paper is to investigate the time series properties of three climatic variables (temperature, humidity and rainfall) of Dinajpur district of Bangladesh, which is known for wheat production and quality varieties of rice by using these newly available statistically rigorous techniques. The whole study consists of several sections comprising research methodology, data sources and findings of the study.

Time Series Properties

Time series can be characterized in many ways. The study focuses on the presence or absence of stochastic trends in the variables. The reason for this is that, unlike linear deterministic trends, stochastic trends provide a unique "fingerprint" for a variable which we can then look for in other series. A shared stochastic trend is taken as evidence for a causal relation between the series. In the following, review was done for the theory of stochastic trends and tests for stochastic trends, and also the theory of cointegration and discussed its implications.

Deterministic trend

A deterministic trend is a nonrandom function of time. For example, a linear time trend is a linear function of time *t*. In economics and finance, deterministic trends are seldom plausible.

A simple model of a deterministic trend is the following polynomial trend model. Let Y_t be the observed time series generated by

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \cdots + \beta_p t^p + \varepsilon_t \quad \text{................} \quad (2.1)$$

where ε_t is a stationary process. An important special case is the linear time trend model with $p = 1$. If we denote $X_t = (1, t, t^2, \cdots, t^p)$ then we can write (2.1) as a standard regression equation $Y_t = X_t \beta + \varepsilon_t$.

Stochastic trends

If a series is nonstationary but its first difference is stationary the series is said to be integrated of order one or I(1). A process that requires differencing twice to achieve stationarity is referred to as an I(2) process. A process that is stationary without differencing is referred to as an I(0) or "levels stationary" process. For an I(1) process this trend is a simple random walk. An integrated variable shows no particular tendency to return to a mean or deterministic trend and shocks to the variable are "remembered" - those do not die out over time.

An I (2) process (the more general case) can be represented as:

$$Y_t = A_t + \varepsilon_t \text{ …………………..} \quad (2.2)$$

$$A_{t+1} = A_t + \gamma_t + \eta_t \text{ …………..} \quad (2.3)$$

$$\gamma_{t+1} = \gamma_t + \zeta_t \text{ ………………..} \quad (2.4)$$

zero variance then Y_t has a deterministic trend. Though still non-stationary, this variable can be made stationary by the subtraction of a deterministic trend rather than by differencing. This type of I(0) process is known as a "trend stationary" process. If additionally γ_0 = 0, then Y_t is stationary with mean A0. The representation of a stochastic process in (2.2) through (2.4) is used in the structural time series models.

An alternative representation of a stochastic process is used in a number of widely used tests for the presence of a stochastic trend. This approach approximates the series by an autoregressive process. The first order autoregressive representation is given by:

$$Y_t = \mu + \beta t + \rho Y_{t-1} + \varepsilon_t \text{ ………...} \quad (2.5)$$

where ε_t is a stationary random error process with mean zero, □□is the autoregressive parameter, and t is a deterministic time trend. If □□= *1* and □□= *0* in (2.5) then Y_t is a random walk with drift □. The mean is non-constant over time and the process is nonstationary and integrated of order one. Alternatively, if □□< *1* then the series is either trend stationary if □□□ *0* and levels stationary if □□= *0.* An I (2) process can be modeled by the equation 2.5 through the first differencing of this process.

Effects of stochastic trends

Unit roots or stochastic trends are important in examining the stationarity of a time series. It is important to distinguish stationary processes from unit root processes, for the following reasons:

1. Regressions involving unit root processes may give spurious results.

2. For two or more unit root processes, there may exist linear combinations which are stationary, and these linear combinations may be interpreted as long-run relationships.

3. Tests of parameter restrictions in auto regressions involving unit root processes have in general different null distributions than in the case of stationary processes. In particular, if one would test the null hypothesis $\rho = 1$ in the above AR(1) model using the usual *t*-test, the null distribution involved is non-normal. Therefore, naive application of classical inference may give incorrect results.

Tests for trends (deterministic/stochastic)

To test for the presence of deterministic/stochastic trends, four tests were applied. The Dickey-Fuller (Dickey and Fuller, 1979, 1981) and Phillips-Perron (Phillips and Perron, 1988) tests are the same but use different approaches to deal with serial correlation in the data. For both tests the null hypothesis is that the series contains a stochastic trend. The model for the Dickey Fuller test is:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \text{ …………………} \quad (2.6)$$

where Y_t is the variable under investigation and ε_t is a random error term. The number of lags *p* is chosen using the Akaike Information Criterion (Akaike, 1973). The lagged variables provide a correction for possible serial correlation. The null hypothesis is □□= *0*. The alternative hypothesis is that the process is stationary around the deterministic trend.

The Phillips-Perron test uses the same models as the Dickey-Fuller tests, but rather than using lagged variables, it employs a non-parametric correction (Newey and West, 1987) for serial correlation. The test statistics for both the Dickey Fuller and Phillips Perron tests have the same distributions. Critical levels are reproduced in Hamilton (1994) and Enders (1995).

The Kwiatowski, Phillips, Schmidt, and Shin (1992) test (KPSS) differs from the other tests in that the null hypothesis postulates that the series is stationary, the alternative is the presence of a stochastic trend.

Unit root test by bootstrapping

To test for stochastic trend, The model-based bootstrap for unit root test was considered. To conduct the test assuming the AR(1) model as $y_t = \rho y_{t-1} + \varepsilon_t$ and the test statistic under H_0: $\rho = 1$ is $\tau = \frac{\hat{\rho}-1}{se(\hat{\rho})}$. The bootstrap test can be conducted as follows:

- **Step-I:** Estimate AR (1) model on data *y*; obtain $\hat{\rho}$, standard error of $\hat{\rho}$ and test statistic τ for the hypothesis H_0: $\rho = 1$.
- **Step-II:** Difference the series $e_j = y_j - y_{j-1}$; $j = 2, 3, \ldots, p$.
- **Step-III:** Under the hypothesis that H_0: $\rho = 1$, simulate new time series by generating the bootstrap sample $\varepsilon_2^*, \varepsilon_3^*, \cdots, \varepsilon_n^*$ from ($e_2 - \bar{e}$, $e_3 - \bar{e}$, ..., $e_n - \bar{e}$) and then setting $y_1^* = y_1, y_2^* = y_1^* + \varepsilon_2^*$, and $y_j^* = y_{j-1}^* + \varepsilon_j^*$ for subsequent j.
- **Step-IV:** Estimate AR(1) on data y^* to obtain the test statistic τ^* for the given hypothesis.
- **Step-V:** Repeat Step-III & IV a large number of times.
- **Step-VI:** Compute bootstrap *p*-value: p = prop ($\tau^* > \tau$).

The bootstrap test is very important from the robustness and diagnostic viewpoint. The test procedures mentioned above are studied rigorously in statistical inference but so far as we know the behavior of these tests based on asymptotic distribution and bootstrap replications is not much reported.

Cointegration

Cointegration analysis can determine whether the stochastic trends uncovered by univariate tests are shared by more than one series. Typically, linear combinations of integrated process also are integrated. The residual from a regression of the two variables will be non-stationary. This violates the classical conditions for a linear regression. Such a regression is known as a spurious regression (Granger and Newbold, 1974). Correlation coefficients and t statistics for the regression are likely to show that there is a significant relation between the variables when no such relation exists.

A further implication of the cointegration concept is that if the variables have different orders of integration they cannot be cointegrated directly.

Sources of Data

The major mean monthly meteorological data of Dinajpur district on temperature, humidity, rainfall are collected from Bangladesh meteorological office. The data were collected for a period of 1948 to 1972 and of 1981 to 2002. But, the data from 1973 to 1980 on these three variables are not available to us. To have this unavailable data on temperature and humidity, the forecasting method was used by choosing the appropriate ARIMA model in each case. The rainfall data are collected from the book "Land resources appraisal of Bangladesh for agricultural development, Report 3, Land resources data base, Volume 1 Climatic data Base (1988). Other missing observations are filled in by the median of available data.

Results and Discussions

Forecasting the Missing Observations

To forecast the missing observation of two climatic variables, humidity and temperature, the study uses suitable ARIMA model. Different possible ARIMA models are investigated for known observations from 1948 to 1970 of each series. Then the Root Mean Square Forecast Error (RMSFE) is determined for each model for the next two years known observations from 1971 to 1972. Since the root mean square forecast error can be used as an average of the forecasts error, the model with the smallest RMSFE is considered as a suitable model for forecasting the missing observations from 1973 to 1980. Hence we selected ARIMA$(1,0,0)(0,1,1)_{12}$ model for humidity (Y_t) and ARIMA$(0,1,1)(0,1,1)_{12}$ model for temperature (X_t) series for the period 1948 to 1970. Estimation results for ARIMA$(1,0,0)(0,1,1)_{12}$ based on 1948 to 1970 humidity series (absolute *t* values are in parentheses) is:

$$(1-0.344958B)\nabla_{12}Y_t = (1-0.7331B^{12})\hat{\varepsilon}_t \qquad (4.1)$$

$$(5.9199) \qquad (20.2838) \qquad \hat{\sigma}_{\varepsilon} = 23.848$$

Next 24 months forecasts from model 4.1 from origin t = 1970:12 and their rough 95% CI are shown in Table-4.1 and in Fig. 4.1 The root mean square forecast error (RMSFE) can be used as an overall measure of accuracy for these 24 forecasts. The RMSEF is defined as

$$RMSFE = \sqrt{\frac{\sum_{t=n+1}^{n+m}(Y_t - f_t)^2}{m}}$$

Here we are considering *m* forecasts (f_t) for periods *n+1* through *n+m*, and m future observed values (Y_t) from time origin t. The RMSFE of the 24 forecasts in Table 4.1 is 3.6068.

Table 4.1. Twenty four forecasts from model 1 from time origin t=1970:12

Month	95% lower limit	Forecasted value	95% upper limit	Observed value	Error
Jan-71	64.3024	72.3634	80.4243	76	3.6365
Feb-71	53.8815	62.4085	70.9356	63	0.5914
Mar-71	44.4151	52.9960	61.5768	53	0.0040
Apr-71	45.4374	54.0247	62.6119	59	4.9753
May-71	59.0981	67.6861	76.2741	74	6.3138
Jun-71	74.3075	82.8956	91.4837	83	0.1043
Jul-71	78.1811	86.7692	95.3574	86	-0.76927
Aug-71	77.2594	85.8475	94.4356	86	0.1524
Sep-71	76.0959	84.6840	93.2721	85	0.3159
Oct-71	71.6041	80.1922	88.7803	81	0.8077
Nov-71	66.3756	74.9637	83.5519	77	2.0362
Dec-71	66.6636	75.2517	83.8398	74	-1.2517
Jan-72	64.2866	73.1401	81.9936	75	1.8598
Feb-72	53.7919	62.6765	71.5610	70	7.3234
Mar-72	44.2001	53.0884	61.9766	55	1.9115
Apr-72	45.1678	54.0565	62.9452	59	4.9434
May-72	58.8083	67.6971	76.5858	74	6.3028
Jun-72	74.0107	82.8994	91.7882	76	-6.89945
Jul-72	77.8818	86.7705	95.6593	83	-3.7705
Aug-72	76.9592	85.8479	94.7367	82	-3.8479
Sep-72	75.7954	84.6841	93.5729	82	-2.6841
Oct-72	71.3035	80.1923	89.0810	79	-1.1923
Nov-72	66.0750	74.9637	83.8525	78	3.0362
Dec-72	66.3630	75.2517	84.1404	78	2.7482
RMSFE					3.6068

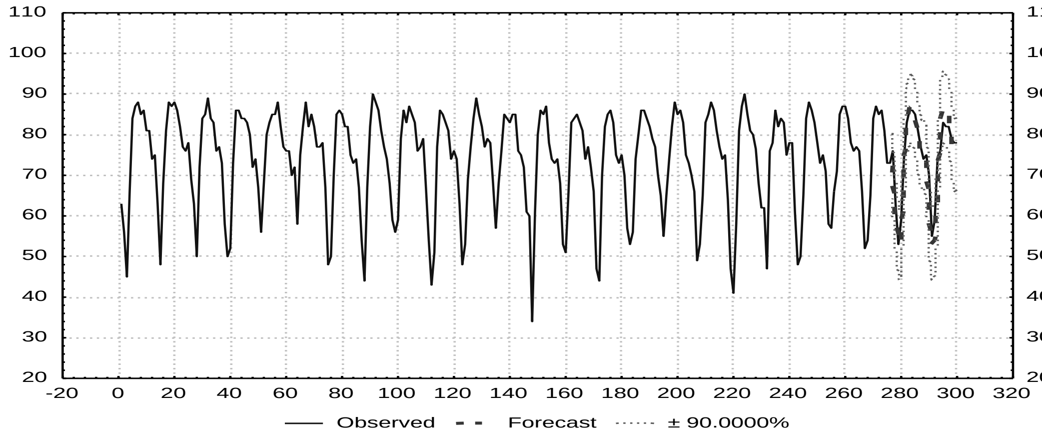

Fig. 4.1. Forecasts 24 observations from model (4.1) from time origin t=1970:12

Estimated ARIMA (1,0,0) (0,1,1) $_{12}$ model for temperature series based on 1948 to 1970 realizations (absolute *t* values are in parentheses) is:

$$\nabla\nabla_{12}X_t = (1-0.8326B)(1-0.7544B^{12})\hat{\varepsilon}_t \qquad (4.2)$$

(18.7185) (19.4392) $\hat{\sigma}_{\varepsilon} = 1.0163$

Table 4. 2 and in Fig. 4.2 are used to show the next 24 months forecasts from origin t = 1970:12 and their rough 95% CI from model 4.1. The RMSFE is 0.9075.

Table 4.2 Twenty four forecasts from model 4.2 from time origin t =1970:12

Month	95% lower limit	Forecasted Value	95% upper limit	Observed Value	Error
Jan-71	14.6724	16.3079	17.9433	16.2	-0.1079
Feb-71	17.4977	19.2243	20.9508	18.5	-0.7243
Mar-71	23.3639	25.1005	26.8372	23.5	-1.6005
Apr-71	27.7258	29.4636	31.2014	28.2	-1.2636
May-71	28.1863	29.9242	31.6622	28.5	-1.4242
Jun-71	27.1008	28.8388	30.5767	29	0.1611
Jul-71	26.7753	28.5133	30.2512	28.6	0.0866
Aug-71	26.8686	28.6065	30.3445	27.8	-0.8065
Sep-71	26.5942	28.3322	30.0702	27.8	-0.5322
Oct-71	24.7104	26.4483	28.1863	26.4	-0.0483
Nov-71	20.1105	21.8485	23.5864	21.4	-0.4485
Dec-71	16.0209	17.7588	19.4968	18	0.2411
Jan-72	14.6100	16.3955	18.1809	17.8	1.4044
Feb-72	17.4631	19.2539	21.0447	17.4	-1.8539
Mar-72	23.3192	25.1106	26.9020	26.1	0.9893
Apr-72	27.6755	29.4670	31.2585	28.2	-1.2670
May-72	28.1339	29.9254	31.7169	28.5	-1.4254
Jun-72	27.0477	28.8392	30.6306	29.8	0.9608
Jul-72	26.7219	28.5134	30.3049	29.2	0.6865
Aug-72	26.8151	28.6066	30.3980	29.0	0.3933
Sep-72	26.5407	28.3322	30.1237	28.5	0.1677
Oct-72	24.6569	26.4484	28.2398	26.8	0.3516
Nov-72	20.0570	21.8485	23.6399	22.1	0.2514
Dec-72	15.9674	17.7588	19.5503	17.6	-0.1588
RMSFE					0.9075

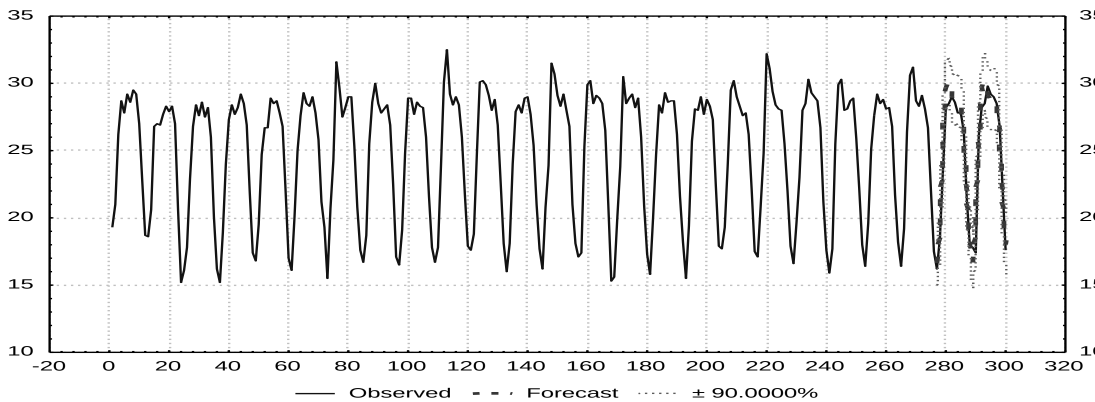

Fig 4.2. Forecasts 24 observations from model 4.2 from time origin t=1970:12

Since the RMSFE for the above two models appeared smallest than all other possible models, we finally select those model for forecasting the unavailable values for two series. Estimation results for final ARIMA models based on realizations (1948-1972), by which we forecast the realizations from 1973 to 1980 of humidity (Y_t) and temperature (X_t) series are given below:

$$(1-0.34466B)\nabla_{12}Y_t = (1-0.7328B^{12})\hat{\varepsilon}_t$$

(6.1771) (20.6221) $\hat{\sigma}_\varepsilon = 22.680$

$$\nabla\nabla_{12}X_t = (1-0.8295B)(1-0.7607B^{12})\hat{\varepsilon}_t$$

(18.7289) (20.4427) $\hat{\sigma}_\varepsilon = 1.001$

Results of Investigation of Time Series Patterns

Exploratory data analysis

The study considers three climatic monthly average series: humidity, rainfall and temperature of Dinajpur district over the period 1948 to 2002. There exists a great diversity and complexity in these climatic series. Time series plot, autocorrelation function (ACF) and boxplots of these monthly average series are given below:

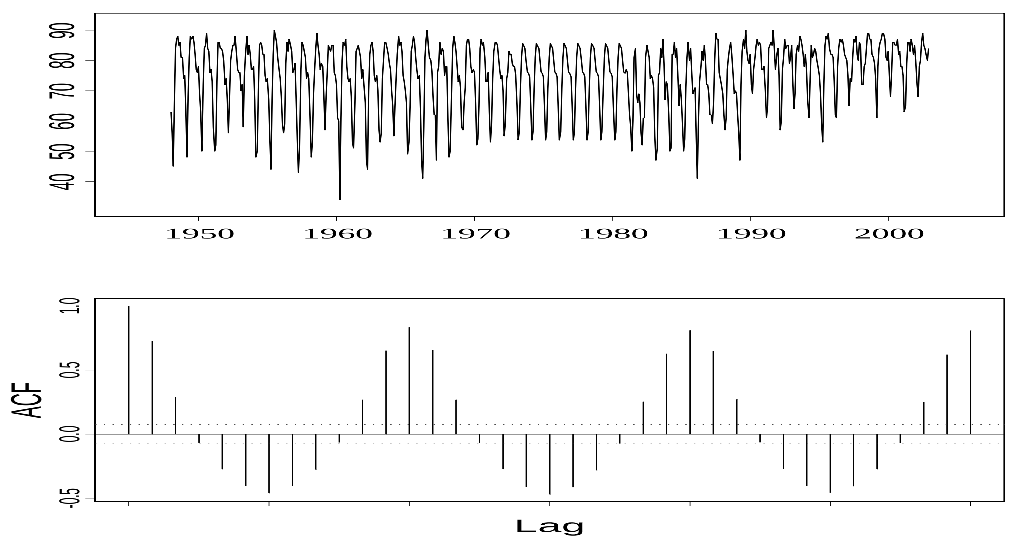

Fig 5.1. Time series plot and SACF of Humidity for 1948:1 – 2002:12

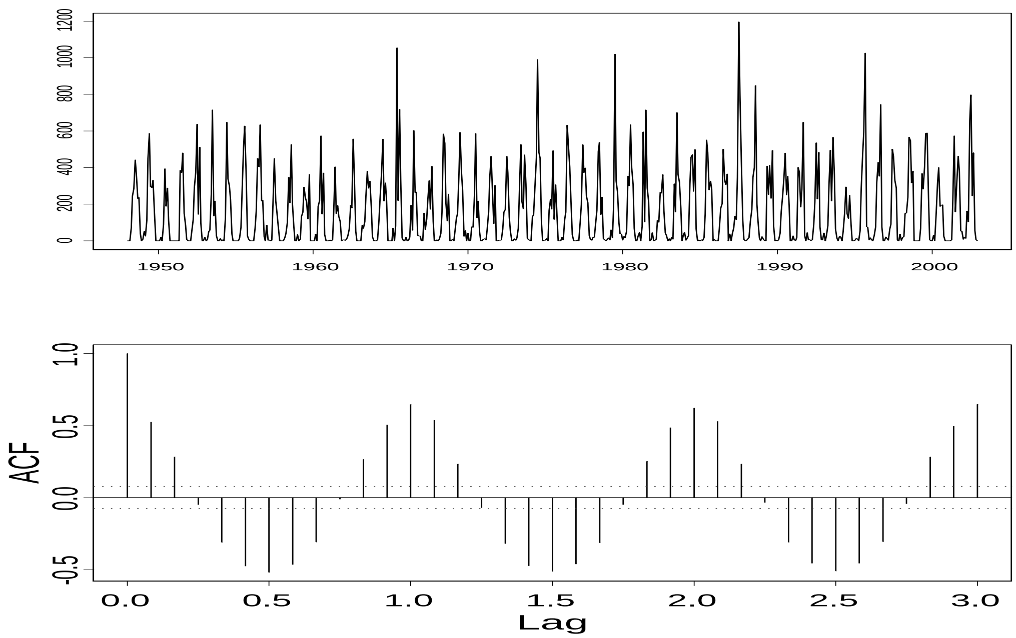

Fig-5.2. Time series plot and SACF of Rainfall for 1948:1 – 2002:12

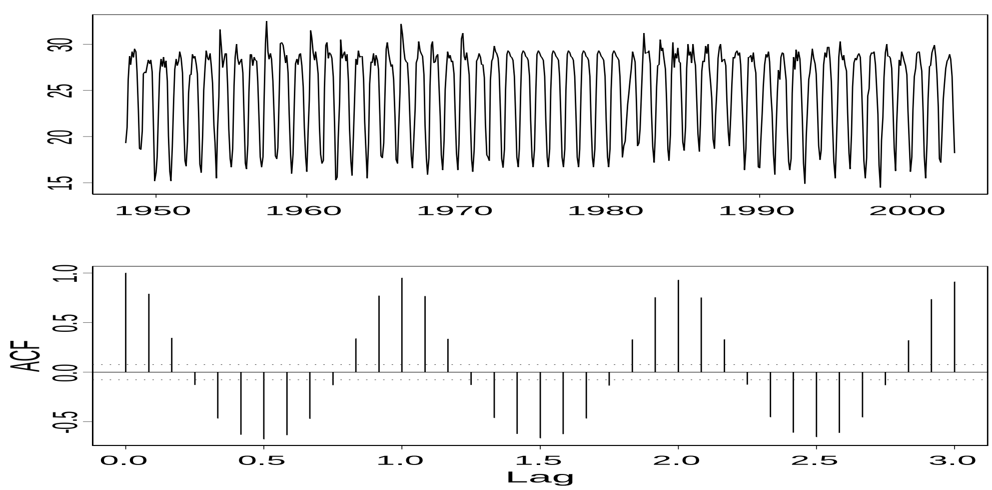

Fig. 5.3. Time series plot and SACF of Temperature for 1948:1 – 2002:12

Figs. 5.1, 5.2 and 5.3 show that the time series plots does not shows any trend in each series and the variance is constant over time. The data seem to move around a constant overall mean; but certain observations are regularly above or regularly below this overall mean. That is, the level of these series shifts in a seasonal fashion. SACF also supports this statement. SACF shows that a given month of each series is similar to the same month one year earlier, two years earlier and so on. These evidences imply that humidity, rainfall and temperature series of Dinajpur district have strong seasonal patters.

It will be better to show that whether each seasonally occurring series have the same degree and variation through the years. It can be explicitly shown by boxplot. Figs. 5.4, 5.5, 5.6 show the monthly degrees and variations through the years which are almost different for each climatic series.

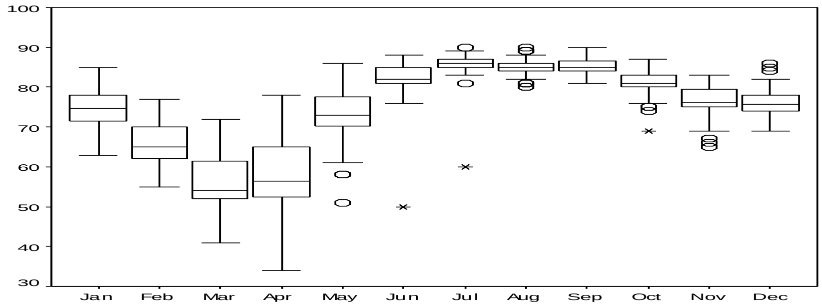

Fig. 5.4. Boxplots of humidity

Fig-5.4 shows monthly average humidity of Dinajpur district ranges from 34 (April, 1960) to 90 (August, 1966). Humidity increases gradually from April and remains almost high (82-90) through July to September and then starts to decrease gradually from October. That is, the period from June to September is very highly humid.

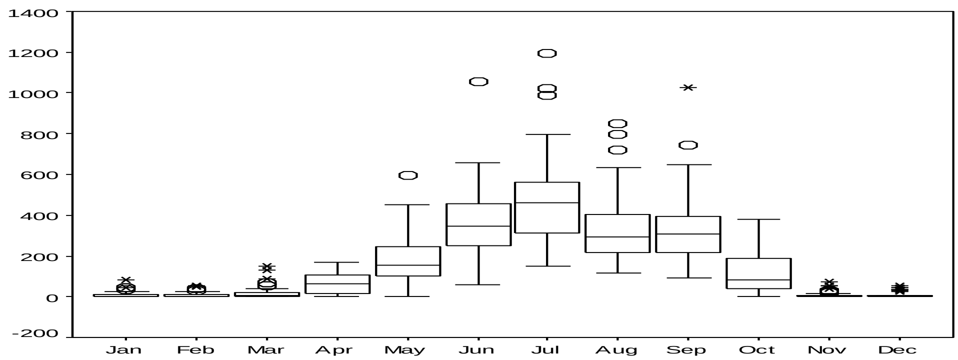

Fig. 5.5. Boxplots of Rainfall

It can be shown from Fig. 5.5 that monthly averaged rainfall of Dinajpur district starts to increase gradually from April and remain almost heavy for the period June to July and gradually decreases from August. Rainfall is very minimal during the period November to March. That is, the monthly mean rainfall ranges from 0 mm to 1196 mm and the period June to September can be characterized by heavy rainfall.

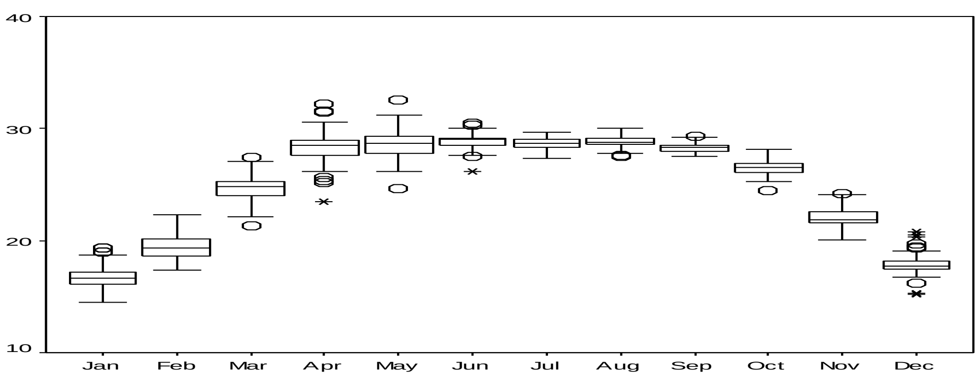

Fig. 5.6. Box plots of Temperature

Fig. 5.6 shows monthly average temperature of Dinajpur district ranges from 14.5 ^{o}C to 32.5 ^{0}C. Temperature increases gradually from January and remains almost high (82-90) for the long period April to September and then starts to decrease gradually from October. That is, the temperature remains hot from April to September. From the Figs. 5.4, 5.5 and 5.6, we also can summarize that in summer (June to September) the three climatic variables of Dinajpur district are positively related among each other;

though such relationship can not be found in winter (November to February).

Results of tests for stochastic trends

In this subsection, four tests were used to determine the presence of stochastic trends in a selected group of climate change data of Dinajpur district. Here four time series were considered namely, average, maximum, minimum and difference (i.e., difference between maximum and minimum) for each of the three annual climatic variables; humidity, rainfall and temperature over the period 1948 to 2002. That is, we perform four test procedures for stochastic trends on twelve time series over the period 1948 to 2002. Time series plots (Figs. 5.1, 5.2 and 5.3) of all the series are far less clear. Almost all the series are trending but the graphs cut a deterministic linear regression line repeatedly, which hint that these series could be trend stationary. So, we conduct the tests under the null hypothesis that the series is a random walk with drift whilethe alternative hypothesis is that the series is a trend stationary. Summary of the tests are given in Table 5.1

Table 5.1. Univariate tests for the order of integration under the null hypothesis that the series is a random walk with a drift

Series	**Test Procedures**				
	Lags	**ADF**	**P-P**	**KPSS**	**Bootstrap**
Humidity (ave)	2	I(1)	I(1)	I(1)	I(1)
Humidity (max)	1	TS*	TS	TS	TS
Humidity (min)	2	I(1)	TS	I(1)	TS
Humidity (diff)	2	I(1)	TS	I(1)	TS
Rainfall (ave)	2	TS	TS	I(1)	TS
Rainfall (max)	3	TS	TS	TS	TS
Rainfall (min)	5	TS	TS	TS	TS
Rainfall (diff)	3	TS	TS	TS	TS
Temperature (ave)	2	TS	TS	TS	TS
Temperature (max)	2	TS	TS	TS	TS
Temperature (min)	1	I(1)	TS	I(1)	TS
Temperature (diff)	2	I(1)	TS	I(1)	TS

* TS = Trend Stationary

Table 5.1 shows that ADF and KPSS give identical results. They show that three humidity series (average, minimum and difference) and two temperature series (minimum and difference) are I(1) and all other series are tend stationary. Though Bootstrap and P-P also shows identical results, they say that only humidity (average) series is I(1) rather than trend stationary. That is, except four series, all test procedures used here give same results. We also conduct the tests under the null hypothesis that the series is a random walk while the alternative hypothesis is that the series is stationary. Results of these tests are shown in Table 5.2.

Table 5.2. Univariate tests for the order of integration under the null hypothesis that the series is a random walk

Series	**Test Procedures**				
	Lags	**ADF**	**P-P**	**KPSS**	**Bootstrap**
Humidity (ave)	2	I(1)	I(1)	I(1)	I(1)
Humidity (max)	1	I(1)	I(1)	I(0)	I(1)
Humidity (min)	2	I(1)	I(1)	I(1)	I(1)
Humidity (diff)	2	I(1)	I(1)	I(1)	I(1)
Rainfall (ave)	2	I(1)	I(1)	I(1)	I(1)
Rainfall (max)	3	I(1)	I(1)	I(0)	I(1)
Rainfall (min)	5	I(0)	I(0)	I(0)	I(0)
Rainfall (diff)	3	I(1)	I(1)	I(0)	I(1)
Temperature (ave)	2	I(1)	I(1)	I(0)	I(1)
Temperature (max)	2	I(1)	I(1)	I(0)	I(1)
Temperature (min)	1	I(1)	I(1)	I(1)	I(1)
Temperature (diff)	2	I(1)	I(1)	I(1)	I(1)

Table 5.2 shows that three test procedure; ADF, P-P and Bootstrap, show identical results for all series while KPSS test procedure differs with them. From these test results we conclude that except rainfall

(min), all the series is integrated of order 1, that is, they contain stochastic trends.

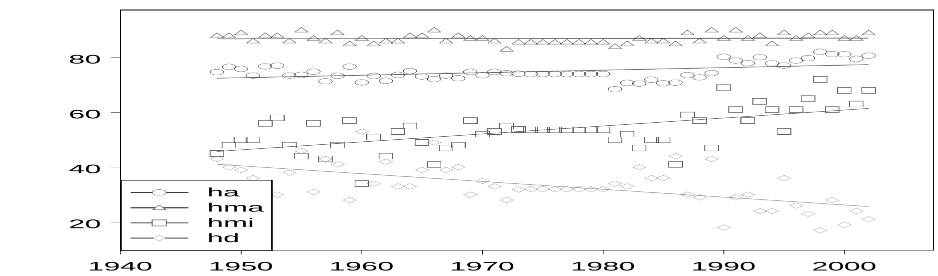

Fig. 5.7. Deterministic regression line of 4 humidity series

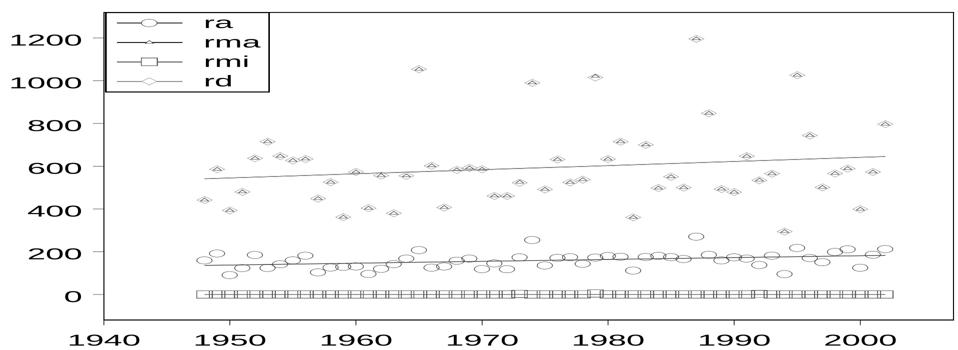

Fig. 5.8. Deterministic regression line of 4 Rainfall series

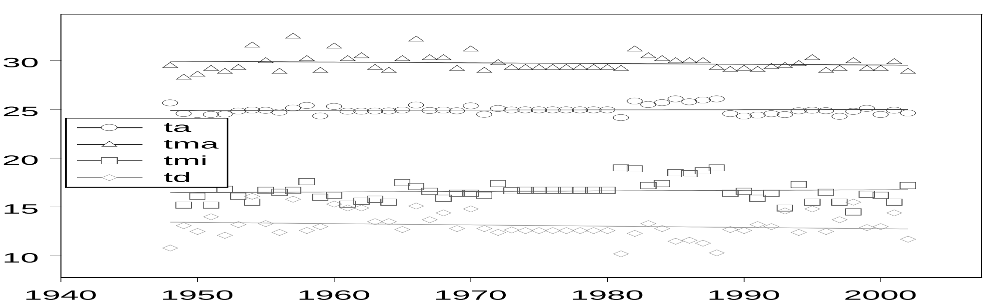

Fig. 5.9. Deterministic regression line of 4 Temperature series

Conclusions

The overall findings obtained from the Dickey-Fuller (Dickey and Fuller, 1979, 1981), Phillips-Perron (Phillips and Perron, 1988), KPSS (Kwiatowski, Phillips, Schmidt, and Shin, 1992) and Bootstrap test demonstrate that the annual average, minimum, maximum and difference series for humidity, temperature and rainfall of Dinajpur district are integrated of order 1, that is, these contain stochastic trends except the minimum rainfall series. So, we should be careful about being trapped in spurious regression in case of climatic variables in regression where we need the help of co-integration technique for showing causal relationship among climatic variables / economic and climatic variables.

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