VARIATION OF TEMPERATURE AND RAINFALL IN INDIA

Debabrata Das and R. Srinivasan
Indus Business Academy, Plot No. 44, Knowledge Park-III,
Greater Noida, 201308, Uttar Pradesh, India

ABSTRACT

For an agriculture based economy like India fluctuations in the temperature and rainfall have profound socio-economic impact. To analyse the relationship between variations in temperature and precipitation due to changes in climatic condition, this paper uses Vector Error Correction Model. Past 106 years data of temperature and rainfall shows an inverse relationship. The average annual rise in temperature is found to be 0.03 percent with a mean of 24.28ºC; and the average annual decline in rainfall in India over the same period, is 0.002 percent, with a mean of 1085.98 mm. The temperature and rainfall levels are also projected up to the year 2020, which reveals an increase in average annual temperature by 0.001 percent and a decline in average annual rainfall at 0.005 percent. Based on the findings of this paper necessary measures need to be taken to mitigate the negative effects of temperature rise on environment.

KEYWORDS: *Climate Change, Temperature, Rainfall, Vector Autoregressive, Vector Error Correction, Cointegration.*

I. INTRODUCTION

Climate plays an important role in every sphere of human activity [1]. Climatic conditions over an area, is determined by the temperature, rainfall, wind, humidity, atmospheric pressure etc. prevailing in it [2]. Among the various climatic parameters, the temperature and rainfall assume special significance as they affect not only agriculture and economic activities, but also human health [3]. Depending on the region, location on earth, the altitude etc. the maximum and minimum temperature of a region over a specified time horizon, varies. Similar is the case of rainfall. Rainfall is affected by the change in atmospheric temperature [4] and temperature depends on global precipitation [5]. Changes in temperature and rainfall patterns increase the frequency, duration and intensity of other extreme weather events, such as floods, droughts, heat waves and tornadoes. Weather has a profound effect on human health and well-being as well. It has been associated with changes in birth rates, and sperm counts, with outbreaks of pneumonia, influenza and bronchitis, and is related to other morbidity effects linked to pollen concentrations and high pollution levels [6]. In the recent years scientific research based on reliable world climate data reveal that the climate is being affected by the greenhouse effect, as a result temperature and precipitation are changing globally. Cost of climate change makes of climate change are expected to be huge, as the Stern report on the economics of climatic change make it clear. The report estimates that not taking action could cost from five to twenty percent of global GDP every year, now and in future.

The fluctuations in the temperature and rainfall over India have a profound socio-economic impact. India is predominantly an agriculture based economy. About seventy percent of India’s population is dependent on agriculture; and, there is utter lack of irrigation facilities. Most of the cultivation is rain fed; and weak rainfall spells doom to agriculture. This leads to drought, crop failure and in the more extreme cases, famine. Strong monsoons are associated with devastating floods and the accompanying loss of life, property and crops [7]. Over the past few years monsoon patterns have shown a gradual change. All India summer monsoons have been stable, but the winter or the north-east monsoons have gradually intensified. There is an abrupt drop in the winter and spring temperature over north-central India and a gradual increase in the summer temperature over the peninsular India [8]. The changes in

rainfall and temperature patterns over India were detected using Mann-Kendall trend test, Bayesian change point analysis, and a hidden Markov model [9].
The objective of this paper is to analyze the variation in temperature and rainfall in India. In this paper an attempt is made to establish the relationship between temperature and rainfall; and to project the temperature and rainfall levels in India. Using the annual average data on temperature and rainfall from 1901 to 2006, Vector Autoregressive (VAR) model is applied for analysis. The paper is organized into the following sections. Section 2 describes the past trend in temperature and rainfall in India. The VAR model is discussed in Section 3 and the output of these models are analyzed in Section 4. The conclusion of the paper is drawn in Section 5.

II. TREND IN TEMPERATURE AND RAINFALL IN INDIA

Round the year the weather is generally hot, with some variations from region to region. In the Northern hemisphere, the coolest weather lasts from around December to February, with fresh mornings and evenings; with the day time remaining predominantly sunny. The real hot weather is, when it is dry, dusty and unpleasant; between March and June. Monsoon rains occur in most regions in summer anywhere between June and early October. India's unique geography strongly influences its climate; this is particularly true of the Himalayas in the north and the Thar Desert in the northwest.
The Indian Meteorological Department (IMD) designates four official seasons. Winter months occur from December to early March. The year's coldest months are December and January, when temperatures average around 10–15 °C in the northwest; temperatures rise as one proceeds towards the equator, peaking around 20–25 °C in mainland India's southeast. Summer or pre-monsoon season lasts from March to June (April to July in north western India). In western and southern regions, the hottest month is April; whereas, for northern regions, May is the hottest month. Temperatures average around 32–40 °C in most of the interior. Monsoon or rainy season lasts from June to September. The season is dominated by the humid southwest summer monsoon, which slowly sweeps across the country beginning late May or early June. Monsoon rains begin to recede from North India at the beginning of October. South India typically receives more precipitation. Post-monsoon season lasts from October to December. In north western India, October and November are usually cloudless, clear sky with pleasant and comfortable temperature.
Indian Meteorological Department provides the monthly maximum and minimum temperature of India in degrees Celsius, based on homogeneous regions of India such as Western Himalaya, North West, North Central, North East, West Coast, East Cost and Interior Peninsula. Similarly, the rainfall in India is measured in millimeters, based on rainfall in homogeneous regions of India such as Northwest, Central Northwest, Northeast, West Central, Peninsular and Hilly region. The average temperature and the average rainfall in India over the year are presented in figure (see Fig.1).
It can be observed that the average annual temperatures in India, over the years have been fluctuating, showing a marginally increasing trend. The 106 years of available data, shows a marginal increase of 0.03 percent with mean temperature of 24.28ºC, and a standard deviation of 0.29ºC. The increase in average annual temperature is found to be more rapid after the year 1960. Especially, since the year 1998, the average temperature can be seen lying above the trend line. In contrast, when we look at the rainfall graph (see Fig.1), over the years, it has shown a decreasing trend, oscillating about the long-term trend line. In the past 106 years, the average annual decrease in rainfall is -0.002 percent.

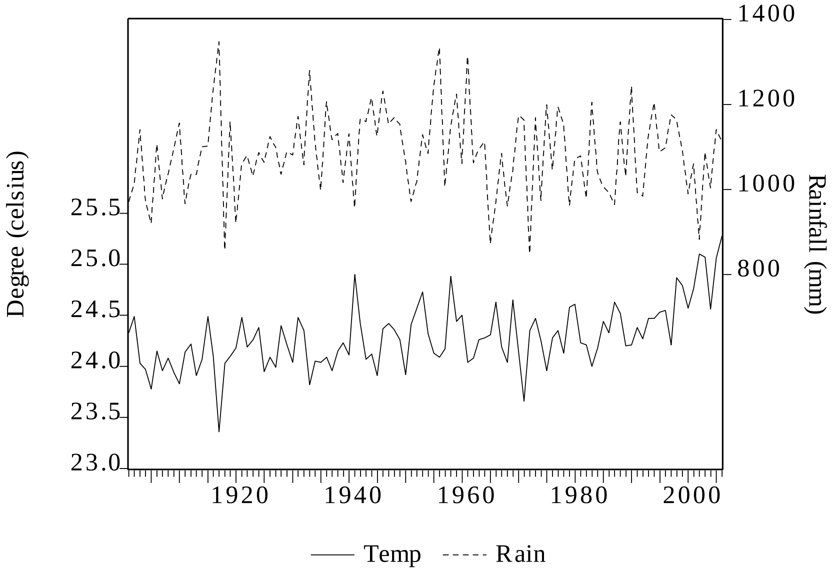


Figure: 1 Annual Average Temperature and Rainfall in India

The mean rainfall has been 1085.98 mm, with a standard deviation of 100 mm. In line with the rise in temperature over the years, there is an observable decreasing trend in rainfall, after the year 1960 [6]. The statistical testing of temperature and rainfall reveals an inverse (-0.24), relationship, at 98 percent confidence level. From the figure 1, it can be understood that the temperature and rainfall over the years have been irregular. More variations in rainfall figures can be observed over the years. Intuitively also, it can be said that the increase in temperature leads to decline in rainfall; and vice-versa. Statistical testing of the data appears to substantiate this intuition. Hence, when there is interdependency and cointegration among multiple variables, VAR model fits well in capturing the behavior and characteristics of a data series.

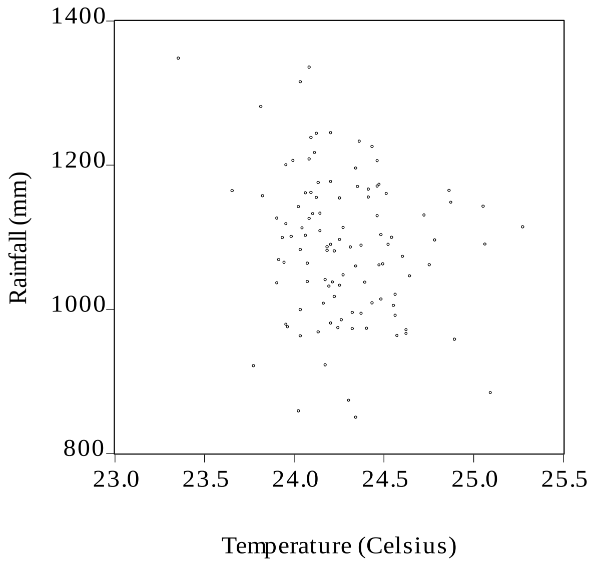


Figure: 2 Annual average temperatures Vs. rainfall

Figure 2 is the plot of scatter diagram for rainfall and temperature. It reveals a cluster formation; with the temperature ranging between 23.9ºC and 24.7ºC and the rainfall ranging between 950 mm and 1250 mm per year. These seem to be ideal range of temperature and rainfall, as far as India is concerned. However, in the recent years, the annual average temperatures have remained above the long-term trend lines, which can become a major cause for worry in the times to come. This may also explain the lack of rainfall in India in the recent years.

III. VECTOR AUTOREGRESSIVE MODEL

The interdependency of the climatic variables suggests for multivariate stochastic analysis. Vector Autoregressive (VAR) is one of the multivariate stochastic model, is a natural extension from the conventional univariate time series analysis [10], [11], [12]. This VAR model includes two particularly important variables for climatic condition analysis: temperature and rainfall. There are many other input data that are potentially relevant to climate, such as humidity, wind, atmospheric pressure, catchment characteristics, land use, atmospheric circulation and even human facilities and activities. Undoubtedly climatic condition of a particular geographical area is a complex phenomena. In order to keep the model simple and tractable, only temperature and rainfall are selected, largely due to data availability. However, there may be a sense that a bias exists in projected temperature and rainfall in many climate models [13], [14].

The VAR model seems appropriate to examine climatic data for three reasons. First, it is expected to uncover dynamic interactions among the variables of interest; because, intuitively it is known that the rainfall is affected by temperature. Both belong to the world water cycle, and climatic time series data tends to exhibit a set of statistical properties necessary for VAR, such as stationarity [11], [15]. Finally, the fundamental assumption for estimating a VAR model is that the first two moments exist and are covariance stationary. Therefore, stationarity is a key requirement for performing the VAR model. Many studies have shown that majority of time series variables are non stationary or integrated of order 1 [16]. Using non stationary time series in a regression analysis may result in spurious regression which was firstly pointed out by Granger and Newbold. Thus before analyzing time series data in an empirical study, it should make stationarity test which is commonly done by unit root test. There are a variety of unit root tests used in econometric literature principally Augmented Dickey-Fuller (ADF) test, Phillip-Perron (PP) test etc. This paper is used ADF unit root tests to investigate whether the time series data used in this study are stationary or not. Augmented Dickey-Fuller [17] test is obtained by the following regression

$$\Delta T_t = \beta_1 + \beta_2 t + \delta T_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta T_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta R_t = \beta_1 + \beta_2 t + \delta R_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta R_{t-i} + \varepsilon_t \quad (2)$$

where Δ is the difference operator, β, δ, and α are the coefficients to be estimated, T and R are temperature and rainfall variables whose time series properties are examined and ε is the white-noise error term.

The next step is to investigate the existence of a long-term relationship between variables temperature and rainfall, in the climate model. If the temperature and rainfall variables are co-integrated with each other, then this will provide statistical evidence for the existence of a long-run relationship. Though, a set of time series are not stationary, there may exist some linear combination of the variables which exhibit a dynamic equilibrium in the long run [16]. The maximum-likelihood test procedure established by Johansen is used as to the test for cointegration [18]. Johansen's method is to test the restrictions imposed by cointegration on the unrestricted VAR involving the series. Consider a VAR of order p:

$$T_t = \gamma_0 + \gamma_1 T_{t-1} + \ldots\ldots + \gamma_p T_{t-p} + \lambda_1 R_{t-1} + \ldots\ldots + \lambda_p R_{t-p} + \omega_t \quad (3)$$

$$R_t = \gamma_0 + \gamma_1 T_{t-1} + \ldots\ldots + \gamma_p T_{t-p} + \lambda_1 R_{t-1} + \ldots\ldots + \lambda_p R_{t-p} + \omega_t \quad (4)$$

where the γ_t's and the λ_t's are coefficients and ω_t's are white noise error term of innovations.
If the two variables are cointegrated, then the VAR can be rewritten as:

$$T_t = \mu_0 + \mu_1 R_t + \sum_{i=-p}^{p} \mu_i \Delta R_{t-i} + \upsilon_t \quad (5)$$

$$R_t = \mu_0 + \mu_1 T_t + \sum_{i=-p}^{p} \mu_i \Delta T_{t-i} + \upsilon_t \quad (6)$$

where μ's are cointegrating coefficients and ν_t's are white noise error term of innovations.

Finally, causality testing in Granger sense is conventionally conducted by estimating autoregressive or vector autoregressive models. Based upon the Representation Theorem, [19] Granger (1988) shows that if a pair of I(1) series are co-integrated there must be a unidirectional causation in either way. Thus, a usual methodology of testing for (non) causality between two time series involves pretesting for a unit root and cointegration. The causality test may be conducted in two ways. In the absence of any co-integrating relationship between the variables, the standard Granger causality test can be applied [19]. The Granger method involves the estimation of the following equations:

$$\Delta T_t = \varphi_0 + \sum_{i=1}^{p} \varphi_{1i} \Delta T_{t-i} + \sum_{i=1}^{p} \varphi_{2i} \Delta R_{t-i} + \eta_t \quad (7)$$

$$\Delta R_t = \varphi_0 + \sum_{i=1}^{p} \varphi_{1i} \Delta R_{t-i} + \sum_{i=1}^{p} \varphi_{2i} \Delta T_{t-i} + \eta_t \quad (8)$$

where ϕ's are coefficients to be determine and η_t's are white noise error term of innovations.
If cointegration exists between T and R, the Vector Error Correction method is required in testing Granger causality as shown below:

$$\Delta T_t = \tau_0 + \sum_{i=1}^{q} \tau_{1i} \Delta T_{t-i} + \sum_{i=1}^{q} \tau_{2i} \Delta R_{t-i} + \chi_1 z_{t-1} + \xi_t \quad (9)$$

$$\Delta R_t = \tau_0 + \sum_{i=1}^{p} \tau_{1i} \Delta R_{t-i} + \sum_{i=1}^{p} \tau_{2i} \Delta T_{t-i} + \chi_1 z_{t-1} + \xi_t \quad (10)$$

where z_{t-1} is the error correction term obtained from the co-integrating equation , so that changes in the variables T_t and R_t are partly driven by the past values of z_t. The first difference operator is marked by Δ and ξ_t is the error term. The error correction coefficients,τ's and χ's are expected to capture the adjustments of T_t and R_t towards long-run equilibrium, whereas the coefficients on T_{t-i} and R_{t-i} are expected to capture the short-run dynamics of the model. In order to analyze the effects of shocks in one climatic variable in the other, the paper uses a well-known technique called impulse response functions. A vector autoregressive can be written in a vector moving average form such as

$$T_t = \mu + \omega_t + \psi_1 \omega_{t-1} + .\psi_2 \omega_{t-2} + \psi_3 \omega_{t-3} + ... + \psi_p \omega_{t-p} \quad (11)$$

$$R_t = \mu + \omega_t + \psi_1 \omega_{t-1} + .\psi_2 \omega_{t-2} + \psi_3 \omega_{t-3} + ... + \psi_p \omega_{t-p} \quad (12)$$

In this case the matrix ψ has the following interpretation:

$$\psi_p = \frac{\partial T_{t+p}}{\partial \omega_t} \text{ or } \frac{\partial R_{t+p}}{\partial \omega_t} \quad (13)$$

The ψ'S identify the consequences of a one-unit increase in the ith variable's innovation at time period t, holding all other innovations constant. These are called impulse response functions (IRF). We can use these IRF to analyze the impact of shocks in the temperature on rainfall in India and vice versa.
In specifying a VAR model, number of lags to be included cannot be determined arbitrarily. Various criteria are available to choose proper lag length for the VAR model such as Akaike's Information Criterion (AIC), Schwarz information criterion (SC), Hannan-Quinn information criterion (HQ), Log Likelihood, etc. All the criteria indicated a maximum lag length equal to four, the number of lags used in the vector auto-regression is chosen, based on the evidence provided by Akaike's Information Criterion (AIC) and Schwarz information criterion (SC) [20]. Finally the forecasting is made by using VAR specifying model. The selected model is not necessarily the one that provides best forecasting. Therefore, further accuracy test such as normalized mean square error (NMSE) should be conducted to ensure the selection of the appropriate model. NMSE ranges from 0 to $+\infty$. When NMSE is closer to zero, the model is perfect and when NMSE is greater than one, the model is poor.

IV. ANALYSIS OF OUTPUT

To find out the appropriate lag for testing unit root, cointegration and Granger causality test, unrestricted VAR (equation 3 and 4) was first run on the differenced series with the lag values taken from one to four. The optimal lag length or order of the VAR was found to be four by the Akaike Information Criterion, Schwarz Criteria, and Likelihood Ratio test statistics (Table 1).

Table 1: Information criteria for VAR model

Lag Length	One	Two	Three	Four
Log Likelihood	-647.66	-626.76	-616.34	-600.47
Akaike Information Criteria	12.57	12.36	12.36	12.25
Schwarz Criteria	12.72	12.72	12.72	12.71

In table 2 and 3, result of equation (1) and (2) for unit root tests are presented. The result shows that both temperature and rainfall were not stationary at levels. This can be seen by comparing the observed values (in absolute terms) of the ADF test statistic with the critical values (also in absolute terms) of the test statistics at the 1%, 5% and 10% level of significance. Therefore, the null hypothesis is accepted and it is sufficient to conclude that there is a presence of unit root in the variables at levels. However, from the tables it is revealed that all the variables were stationary at first difference, on the basis of this, the null hypothesis of non-stationarity is rejected and it is safe to conclude that the variables are stationary. This implies that the variables are integrated of order one, i.e. I (1).

Table 2. Augmented Dickey Fuller Test Statistic for Temperature

Include in test equation	Level	First Difference	Critical Value at Significance Level		
			1%	5%	10%
None	1.07	-7.76	-2.59	-1.94	-1.62
Intercept	-1.02	-7.85	-3.50	-2.89	-2.58
Trend and Intercept	-2.78	-7.96	-4.05	-3.45	-3.15

Table 3. Augmented Dickey Fuller Test Statistic for Rainfall

Include in test equation	Level	First Difference	Critical Value at Significance Level		
			1%	5%	10%
None	0.05	-7.31	-2.59	-1.94	-1.62
Intercept	-5.10	-7.28	-3.50	-2.89	-2.58
Trend and Intercept	-5.08	-7.25	-4.05	-3.45	-3.15

Since the two variables are noted to be I(1), there exists the possibility that they share a long-run equilibrium relationship, as was pointed out by Engle and Granger [16]. To test this, a VAR-based cointegration tests developed by Johansen is used [18], [21]. In formulating the dynamic model for the test, the question of whether an intercept and trend should enter the short- and/or long-run model is raised [22]. Therefore, all four linear deterministic trend models are considered by Johansen [21]. The number of cointegrating relations from all four models, on the basis of likelihood ratio and the eigenvalue statistic using critical values at 5 percent and 1 percent level are summarized in table 4 (equation 5 and 6). In the table, the maximal eigenvalue and the likelihood ratio strongly rejected the null hypothesis that the variables are not co-integrated. It showed that there is one co-integrating relationship between the variables (i.e., at most 1) for both these time periods.

Table 4 Johansen Cointegration Test

Test assume no deterministic trend in data				
No intercept or trend in CE or Test VAR				
Eigen value	Likelihood Ratio	5% Critical Value	1% Critical Value	Hypothesized No. of CE(s)
0.2183	26.9262	12.53	16.31	None **
0.0201	2.0514	3.84	6.51	At most 1
Intercept (no trend) in CE or no intercept in VAR				
0.2184	27.3898	19.96	24.6	None **
0.0245	2.5029	9.24	12.97	At most 1
Intercept (no trend) in CE and test VAR				
0.2177	25.2482	15.41	20.04	None **
0.0043	0.4394	3.76	6.65	At most 1

Test allows for linear deterministic trend in data

Intercept and trend in CE –no trend in VAR

0.2565	34.0234	25.32	30.45	None **
0.0396	4.0822	12.25	16.26	At most 1

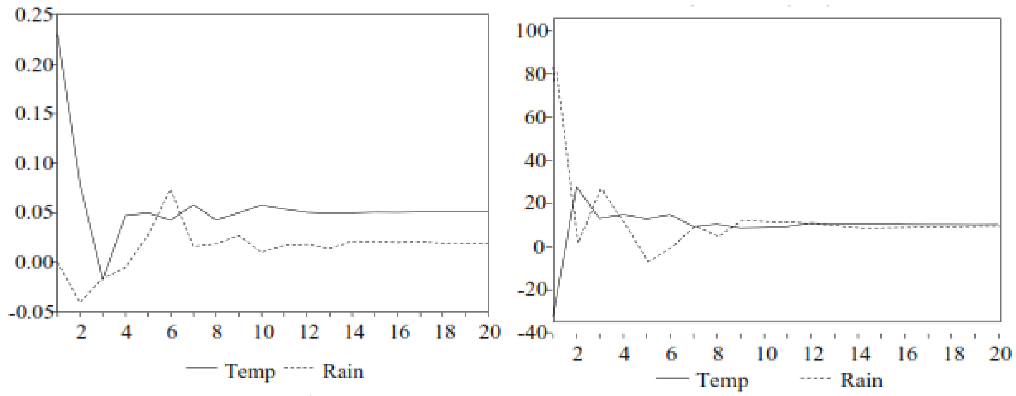
*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

Table 5. Vector Error Correction model

Error Correction:	**ΔT**	**t-statistic**	**ΔR**	**t-statistic**
CointEq1	-0.17*	-1.96	-0.95*	-5.60
ΔT(-1)	-0.55*	-4.18	-0.09	-0.55
ΔT(-2)	-0.68*	-4.98	0.22	-1.36
ΔT(-3)	-0.36*	-2.87	0.36*	-2.42
ΔT(-4)	-0.23*	-2.09	0.18*	-1.74
ΔR(-1)	-0.01*	-3.29	-80.85	-1.57
ΔR(-2)	-0.01*	-3.44	-13.65	-0.26
ΔR(-3)	-0.01*	-3.59	22.30	-0.45
ΔR(-4)	-0.01*	-3.20	-10.00	-0.24
C	0.03	-1.18	3.13	-0.33
R-squared	0.46		0.62	
F-statistic	8.59*		16.58*	

Note: * significance at 5% level

Having found clear evidence in favor of the changes in temperature and rainfall being cointegrated, we investigate the causal structure and the adjustment processes of the changes using the vector error correction method. The number of lags is the same as specified in the Johansens cointegration Test. The final model is chosen on the basis of the minimization of the Akaike Information Criterion and Schwarz Criteria, with individual significance of the variables at 95% level. An important point worth noting is that in the vector autoregressive or vector error correction method output, some of the coefficients may turn out to be individually insignificant. In that case we check the F-Statistic for the joint significance of all the variables included and it turns out to be positive, justifying the inclusion of the variables. The better vector error correction model found in VAR assume linear trend in data (intercept or trend in cointegration equation) with four lag. Though the models are significant at 95% level, but some of the individual coefficients in rainfall model are significant at very low levels. The results of equation (9) and (10) are presented in Table 5, which shows that the error correction coefficients of temperature and rainfall models are significant and have negative signs implying that the series cannot drift too far apart and convergence is achieved in the long run. More specifically, each error correction term coefficient indicates that a deviation from the long equilibrium value in one period is corrected in the next period by the size of that coefficient. For temperature and rainfall models the corrections are around seventeen and ninety five percent, respectively. In the short run, it can be observed that fluctuation-type relationships exist in general. Further, almost all adjustments take place within the same or following time periods, implying that the system settles down quickly.



(a) Temperature (^{0}C.) (b) Rainfall (mm)

Figure 3: Impulse Response to One S.D

The Vector Error Correction model with four lags assuming linear trend provides the minimum normalized mean square error (NMSE) i.e. 0.04 and 0.006 for temperature and rainfall, which is closer to zero therefore, the model is nearly perfect for forecasting. Having adequately tested and validated these time series models using historical data it is believed that they can be used to make at least short time forecasts up to the year 2020. The forecasting of average annual temperature and rainfall are presented in Figure 4 and Figure 5. It can be observed that, in the forecasting period, the maximum average temperature of 25.40 ^{0}C is likely to be seen in the year 2018. The average annual rate of rise in temperature is expected to be 0.001 percent. On the other hand, the annual rainfall may decrease at the rate of 0.005 percent per annum.

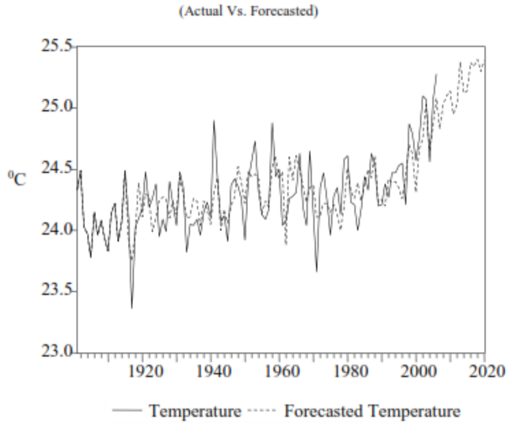


Figure 4: Average Annual Temperature (^{0}C)

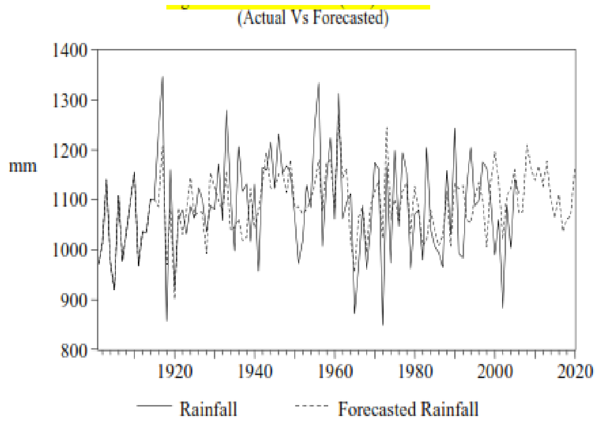


Figure 5: Annual Rainfall (mm) in India

V. SCOPE FOR FUTURE WORK

This study has tried to give the insight on modelling some aspect of climate change i.e. temperature and rainfall in India. Since changes in climate are not only due to changes in temperature and rainfall alone, but also include some other variables like humidity, wind etc. which are not available in this study. Yet, it always leaves scope for further research. Presently, India is in the phase of rapid economic growth, which has led to urbanization and industrialization. Therefore, both growth in population, industries and motor vehicle has put a lot of pressure on the atmosphere, which in turn has increased the problems associated with changes in climatic conditions. By studying the interrelationship among the variables, the researchers try to understand and suggest ways to minimise fluctuation in temperature and rainfall. The variation in temperature not only affects precipitation but has an impact on health of human, animal and plant life.

VI. CONCLUSION

India is faced with considerable risk and uncertainty due to climate change. The fluctuations in the temperature and rainfall in India has a profound impact on climate, thus on socio-economic conditions as well. In this paper Vector Error Correction model is used to study the variation in temperature and rainfall in India and establish relationship between the two variables. Over the past 106 years, there is an average annual rise in temperature of 0.03 percent with a mean 24.28ºC; and a decrease in average annual rainfall in India over the years at the rate of 0.002 percent, with mean of 1085.98 mm. This substantiates our intuition. There is a long-term inverse (-0.24%) relationship between temperature and rainfall at 98 percent confidence level. This is reinforced by Johanson cointegration test and Granger causality test of integrated climatic variables. The Vector Error Correction model fits well to project the temperature and rainfall up to the year 2020. Thus it is expected that the future rise in average annual temperature is likely to be 0.001 percent; with a corresponding decline in average annual rainfall of 0.005 percent. The maximum annual average temperature in India may reach up to 25.4ºC by 2020. Another finding from the analysis is that while the temperature appears to have increased over the years, the rainfall has shown only a marginal decline. To maintain the normal rainfall there is a need to control temperature by way of proper urban planning, increased tree plantation and reduction in air pollution [23].

REFERENCES

[1]. Dhorde A, Dhordel A. and Gadgil A. S. (2009) Long-term Temperature Trends at Four Largest Cities of India during the Twentieth Century. Journal of Industrial Geophysics. 13 (2): 85-97
[2]. John P P J (2012) Seasonal Variation in Water Temperature on the South East Coast of Tamil Nadu, India. Journal of Environmental Science, Computer Science and Engineering & Technology. 1 (3): 488-491
[3]. Tiwari R C (2006) Analytical Study on Variation of Climatic Parameters at Aizawl, Mizoram (India). Bulletine of Arunachal Forest Research. 22 (1&2): 33-39
[4]. Hengchun YE (2008) Changes in frequency of precipitation types associated with surface air temperature over northern Eurasia during 1936-90. Journal of climate. 21 (22): 5807-5819
[5]. Liu S C, Fu C, Shiu C J, Chen J P and Wu F (2009) Temperature dependence of global precipitation extremes. Geophys. Res. Lett., 36, L17702, doi: 10.1029/2009GL040218.
[6]. Kalkstein L S and Valimont K M (1987) Climate effects on human health. In Potential effects of future climate changes on forests and vegetation, agriculture, water resources, and human health. EPA Science and Advisory Committee Monograph no. 25389: 122-52. Washington D.C. USA. Environmental Protection Agency.
[7]. Eugene M R and Thomas H C (1983) The relationship between eastern equatorial Pacific sea surface temperatures and rainfall over and Sri Lanka. Monthly Weather Review. 111: 517-528
[8]. Kothyari U C and Singh V P (1998) Rainfall and temperature trends in India. Hydrological Processes. 10 (3): 357 – 372
[9]. Tripathi S and Rao S G (2009) On the identification of intra-seasonal changes in the Indian summer monsoon. Proceedings of the Third International Workshop on Knowledge Discovery from Sensor Data. June 28-28. Paris France.doi: 10.1145/1601966.1601979
[10]. Lettenmaier Dennis and Wood Eric (1993) Hydrologic forecasting in Handbook of Hydrology. Edited by David M. pp 19.1-19.72. McGraw-Hill Inc. New York.
[11]. Salas J (1993). Analysis and modeling of hydrologic time series in Handbook of Hydrology. Edited by David M. pp 19.1-19.72. McGraw-Hill Inc. New York.
[12]. Wong H, Wai-cheung I, Riquan Z and Jun X (2007) Hon-parametric time series models for hydrologic forecasting. Journal of Hydrology. 332: 337-347.
[13]. Bergström S, Bengt C, Marie G, Göran L, Anna P and Markku R 2001. Climate change impacts on runoff in Sweden— assessments by global climate models, dynamical downscaling and hydrological modeling. Climate Research. 16: 101-112.
[14]. World Bank (2007) Addressing climate change-driven increased hydrological variability in environmental assessments for hydropower projects—a scoping study. Mimeograph.
[15]. Koutsoyiannis D (2006) Non-stationarity versus scaling in hydrology. Journal of Hydrology. 324: 239-254.
[16]. Engle R F and Granger C W (1987) Co-integration and error correction: representation, estimation, and testing. Econometrica, 55, 251-276
[17]. Dickey D A and Fuller W A (1979) Distribution of the estimates for the autoregressive time series with a unit root. Journal of the American Statistical Association. 74: 427-431
[18]. Johansen S (1991) Estimation and hypothesis testing of cointegration vectors in Gaussian vector auto regression models. Econometrica. 59: 1551-1580
[19]. Granger C W J (1988) Some recent developments in a concept of causality. Journal of Econometrics. 39: 199– 212
[20]. Gujarati D N and Sangeetha (2003) Basic Econometrics (Fourth Edition). Tata McGraw-Hill Education Private Limited. New Delhi
[21]. Johansen S (1995) Likelihood-based inference in cointegrated vector autoregressive models. Oxford University Press. New Delhi
[22]. Haris R (1995) Cointegration analysis in econometric modeling. Prentice Hall India, New Delhi
[23]. Das D, Srinivasan R and Sharfuddin A (2011) Fossil fuel consumption carbon emission and temperature variation in India. Energy and Environment. 22 (6): 695-709

AUTHORS

Debabrata Das is currently associated with the Indus Business Academy (IBA), UP, India as Director and Professor. He has more than two decades of teaching and research experience in the area of quantitative business. Before joining IBA, he worked with International Management Institute (IMI) , New Delhi, India, about a decade. He has a number of research publications in refereed national and international journals of different countries. He has conducted a number of research projects for national and international agencies (Government of India; German agency for technical cooperation; global economic advantage, etc.). His research interests are in the areas quantitative modelling in transportation, energy, environment, climate, socio economy and business research.

R. Srinivasan is currently associated with Indus Business Academy, UP, India as a Professor (Finance). He is pursuing his PhD from Faculty of Management Studies, Delhi. He has more than a couple of decades of experience in various capacities in the industry as well as academia. He has assisted in development of cases for the European Union funded research project on CSR, during his association with International Management Institute (IMI), New Delhi, India. His areas of research interests include econometric modelling, risk assessment and management, business valuations, etc. His research works are in the areas of finance and socio economic research.