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Estimation of Autocorrelation function and partial Autocorrelation function of Evapotranspiration for Ranchi district, India, in context of time series Modelling.

Gautam Ratnesh [*1] and Sinha Anand Kumar[2]

[1]Department of Civil and Environmental Engineering, Birla Institute of Technology, Mesra-835215, India. E-mail: ratnesh_mishraji@yahoo.co.in

[2]Department of Civil and Environmental Engineering, Birla Institute of Technology, Mesra-835215, India. Email: aksinha@bitmesra.ac.in

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ABSTRACT

Auto correlation function (ACF) and Partial Auto correlation function(PACF) play important role in time series analysis. In this study ACF &PACF for reference crop evapotranspiration have been found. The data series of 102 years (1224 months) of Ranchi district are used for determination of ACF and PACF. This study is helpful for calculating parameters of different time series modelling like autoregressive (AR) Model, moving average (MA) Model, autoregressive moving average (ARMA)model, autoregressive integrated moving average (ARIMA)model, etc. Apart from that, these are also helpful for time series analysis of different data series of numerous fields. The study is beneficial for, Researcher in the field of hydrology, statistics, econometrics, big data series, predictions of sales in corporate field, forecasting of rainfall, temperature, to see the pattern of climate change, etc.

KEY WORDS: ACF, PACF, evapotranspiration, autoregressive, moving average

*Corresponding author

Ratnesh Gautam

Ph.D. Research Scholar,

Department of Civil and Environmental Engineering,

Birla Institute of Technology, Mesra-835215, India.

E-mail: ratnesh_mishraji@yahoo.co.in

1. INTRODUCTION

Autocorrelation means correlation of time series with its own past and future values. Autocorrelation is also denoted by serial correlation or lagged correlation, which indicate correlation between numbers of series of time dependent. Auto correlation may be positive or negative. Positive autocorrelation may be considered a particular form of persistence. Autocorrelation may be predictable, probabilistically, because future values depend on current and past values. There are three important tools for assessing the autocorrelation of a time series i.e. time series plot, the lagged scatter plot, the autocorrelation function. The partial autocorrelation function can be defined as regression of the series against its past lags. Generally, PACF helpful for possible order of autoregressive term and ACF confirming moving average term. Evapotranspiration is the important component of water cycle. Correct analysis of evapotranspiration is challenge for researcher and hydrologist to see the climate change. For analysis of evapotranspiration numbers of equations and formulas are given by different researchers. Present study is helpful for stochastic analysis of evapotranspiration. Mohan et al.[1] determined autocorrelation function and partial auto correlation function for forecasting weekly reference crop evapotranspiration series. Etuk et al.[2] used autocorrelation and partial auto correlation for modelling monthly Uganda shilling /US dollar Exchange rate by seasonal box-Jenkins techniques. Popale et al.[3] applied autocorrelation and partial autocorrelation function for stochastic generation and forecasting of weekly rainfall for Rahuri region. Jafri et al.[4] applied auto correlation and partial auto correlation function for stochastic approaches for time series forecasting of rate of dust fall. Helmy et al.[5] calculated auto correlation and partial autocorrelation for estimating monthly reference crop evapotranspiration in Najran region, KSA, using seasonal regression autoregressive model. Posilovikos et al.[6] used auto correlation function and partial auto correlation function for forecasting of remote sensed daily evapotranspiration data over Nile Delta Region, Egypt. Dabral et al.[7] determined auto correlation function and partial auto correlation function for time series modelling of pan evaporation a case study in the northeast India. Hamdi et al.[8] calculated auto correlation function and partial auto correlation function for developing reference crop evapotranspiration time series simulation model using class a pan, a case study for the Jordan valley Jordan. Asadi et al.[9]applied auto correlation function and partial auto correlation function for forecasting of potential evapotranspiration using time series analysis in humid and semi humid regions. Medelisation et al.[10] determined sample partial autocorrelation function of a multivariate time series. Trajkovic[11] used auto correlation function and partial auto correlation function for comparison of prediction models of reference crop evapotranspiration. Abolfazliet al.[12] forecasts rail transport petroleum consumption using an integrated model of auto correlation function and neural network. Gorwantiwarret al.[13] forecasting of Evapotranspiration for Makni Reservoir in Osmanabad District of Maharashtra, India using autocorrelation function and partial autocorrelation function.The main goal of this study is to determine correct value of auto correlation function (ACF)and partial auto correlation function (PACF) for reference crop evapotranspiration.

2. MATERIAL AND METHOD

Study area Ranchi district is the capital district of Jharkhand state of India, which is situated at latitude 23.35˚N, Longitude 85.23˚E,the geographical area is approximately 5231 sq.km.Elevation from the mean sea level is 2140 ft, annual rainfall is 1530mm of rainy, winter, summer seasons. The main minerals are lime stone, coal, asbestos and ornamental stones etc. and crops are rice, millets, pulses and oil seeds. The total population is around 2912022. Data series is taken from the same Ranchi district. A autocorrelation function is a bar chart of correlation coefficients between the given series and its lags. The partial autocorrelation function is the bar chart of partial correlation coefficient between the given data series and its lags. If Y variable is regressing on variable X1,X2,and X3, then the partialCorrelation between Y and X3 is not determined by their relations with X1and X2.This correlation can be determined as the reduction in variance square root , which is computed by adding X3 to the regression of Y on X1 and X2.The autocorrelation of a Y time series at lag1 is the correlation coefficient between Y_t and Y_{t-1}, which is also correlation between Y_{t-1} and Y_{t-2}.In a series, if partial autocorrelation function shows sharp cutoff whereas autocorrelation function decays more slowly, that series represent AR signature, and if vice-versa then MA signature.The autocorrelation function (ACF) is widely known for identifying the presence of serial correlation.

Mathematical expression of the autocorrelation function for the series $y_1, y_2, \ldots, y_n$, the sample autocorrelation at lag k is

$$r_k = \frac{\sum_{t=1}^{n-k}(y_t-\bar{y})(y_{t+k}-\bar{y})}{\sum_{t=1}^{n}(y_t-\bar{y})^2} \qquad [1]$$

Where $\bar{y} = \frac{\sum_{t=1}^{n} y_t}{n}$

r_k is known as autocorrelation coefficient at lag k. The plot of ACF is also known as correlogram.

The standard error of r_k is $s_{r_k} = \left(\frac{1+2\sum_{j=1}^{k-1} r_j^2}{n}\right)^{0.5}$ [2]

The limits for the values of the ACF are given by $\pm\frac{Z_{1-\alpha/2}}{\sqrt{n}}$, Where $z_{1-\alpha/2}$ is the standard normal deviate for 1-α/2 level of confidence (usually 95% level of confidence and the value for Z =1.96).

The sample partial autocorrelation at lag *k* is

$r_{11} = r_1$ [3]

$r_{22} = (r_2 - r_1^2)/(1-r_1^2)$ [4]

$r_{kj} = r_{k-1,j} - r_{kk}\, r_{k-1,k-j}$, k = 2,…., j = 1,2,…..,k-1 [5]

$r_{kk} = \frac{r_{k} - \sum_{j=1}^{k-1} r_{k-1,j}.r_{k-j}}{1-\sum_{j=1}^{k-1} r_{k-1,j}.r_j}$, k=3,……. [6]

Where $r_{kj} = r_{k-1,j} - r_{kk}.\, r_{k-1,k-j}$

The limits for the values of the PACF are given by

$\pm\frac{Z_{1-\alpha/2}}{\sqrt{n}}$, Where $z_{1-\alpha/2}$ is the standard normal deviate for 1-α/2 level of confidence (usually 95% level of confidence and the value for Z =1.96).

Q is the Box- LjungStatistics , the equation of Q value is-

$Qk=n(n+2)\sum_{k=1}^{m}\frac{r_k^2}{n-k}$ [7]

In case of n is large ,$Q_k$has the chi-square distribution having degree of freedom of freedom k-p-q, where p is the autoregressive operator and q is the moving average operator.

In any time series study the pattern of autocorrelation is modelled, for itself, in preparation for test of intervention, forecasting. To check the linear or quadric pattern in data series, effect of previous value to the current one. Due to rotation of sun, seasonal pattern occur in the data series, the data series are examined for the seasonality.

3. DATA COLLECTION AND ITS ANALYSIS

The data series is collected from 'http://indiawaterportal.org/met data. To know the properties of data, it is plotted on the simple graph at excel sheet. Figure[1] shows there are no trends in data series but there is strong periodicity. For time series analysis, the data should be free from periodicity. Figure [2] is the plot of seasonally differenced data series with no periodicity. For making data series stationary, seasonal differenced data is re differenced by difference of one month. Figure[3] is the time series plot of seasonal and non-seasonal differenced data series. For determination of ACF and PACF SPSS16 Software was used. Table1 shows autocorrelation functionand partial autocorrelation of evapotranspiration data series at lag16. Standard error and L-jung statistics (Q-value) is also located corresponding to the autocorrelation and partial autocorrelation values. Table 2 shows autocorrelation and partial autocorrelation of seasonally differenced evapotranspiration data series at lag16. Table3 has the numerical values of autocorrelation and partial autocorrelation function of seasonally and non- seasonally differenced evapotranspiration data series at lag 16.Figure [4] to Figure [9] shows plots of autocorrelation function and partial autocorrelation function corresponding to the numerical values of Table1, Table 2and Table 3.

4. RESULT AND DISCUSSION

Figure 4 and Figure 5 represents autocorrelation function and partial autocorrelation function at 16 lags and 95% confidence limit respectively. The patterns of spikes shows cyclic pattern in the data series. Figure 6 and Figure 7 shows auto correlation function partial auto correlation function of seasonally differenced data series respectively at lag16. In this figures autocorrelation function is slowly decay whereas partial autocorrelation function shows sharp cut off, this indicate presence of autoregressive(AR) in the data series. Figure 8and Figure9 shows autocorrelation and partial autocorrelation of seasonally and non-seasonally differenced data series at lag 16. In these figures autocorrelation function shows sharp cut off and autocorrelation function decay slowly, this indicate presence of moving average (MA) in the data series.In this way on the basis of spikes appear in the figure of autocorrelation and partial autocorrelation, the presence of AR, MA are identified. These finding are beneficial for different time series modelling like autoregressive(MA) model, moving Average(MA) model, autoregressive moving average(ARMA)model,autoregressive integrated moving average(ARIMA) model etc. Randomness in data can also be checked by autocorrelation function at time lags. Autocorrelation also check, relationship of observation to the adjacent observation, white noise condition of observation, sinusoidal properties of data series,and appropriate model for the time series.

5. CONCLUSION

This paper is inspired by conjecture that evapotranspiration series would contain little amount of autocorrelation, but persistent for different lags.Data series did not show any inherent trends, but show strong periodicity. Auto correlation function and partial autocorrelation are determined upto lags 16. Autocorrelation function and partial autocorrelation have both negative and positive values. As per requirements lags of auto correlation function and partial autocorrelation can be changed. These results are useful for time series modelling especially for auto regressive integrated moving average modelling.Auto correlation function and partial autocorrelation may also be applying for prediction and forecasting purposes. They gives autoregressive or moving average present in the models.The presence of autocorrelation and partial autocorrelation is evapotranspiration data is important, because for modelling and forecasting of evapotranspiration, the regression model assume that error terms should free from autocorrelation, when autocorrelation is present, the regression model is misidentified. So alternative model may produce a better modelling and forecasting of evapotranspiration.

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LIST OF FIGURES

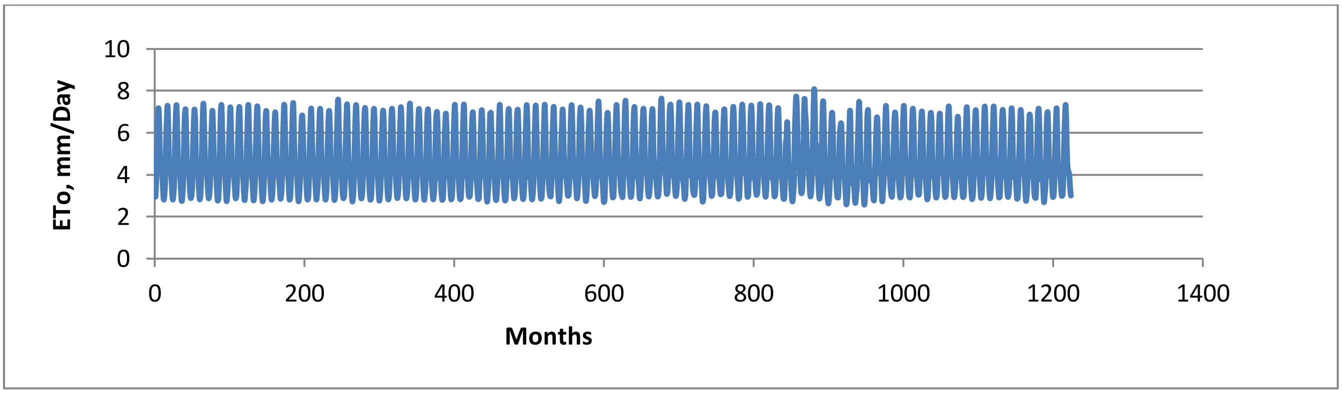

Figure1 time series plot of reference crop evapotranspiration (ETo)

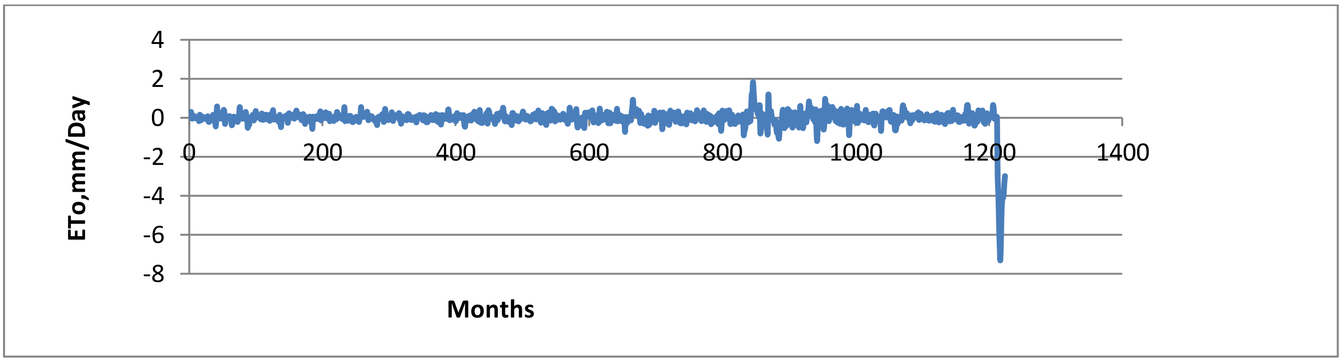

Figure 2. Graph of the Seasonally Differenced Eto(Sdiff.Eto) Data Series(Difference of 12 months)

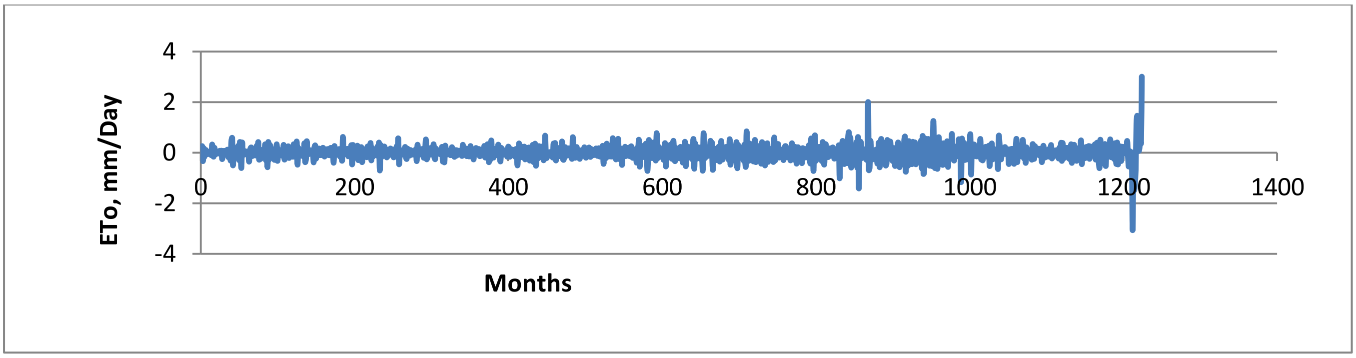

Figure 3. Graph of Seasonally and then non- seasonal differenced Eto (Nsdiff.Eto) data series(Differenced of one month)

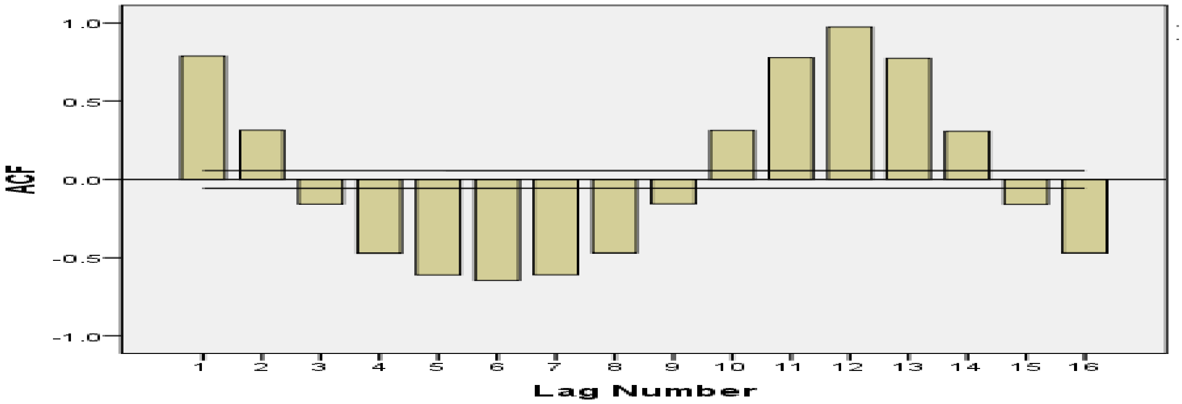

Figure 4 Autocorrelation function (ACF) plot at 16 Lags.

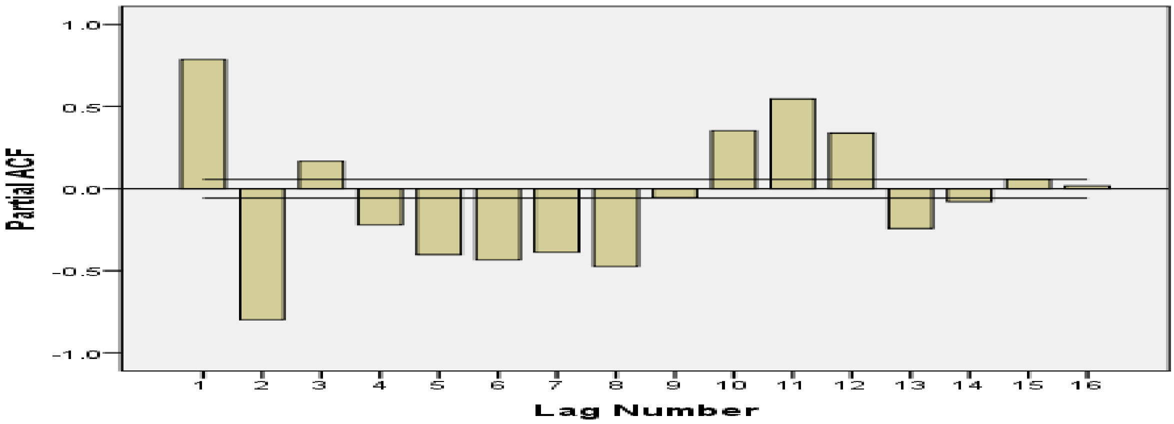

Figure 5 Partial autocorrelation function (PACF) plot at 16 lags

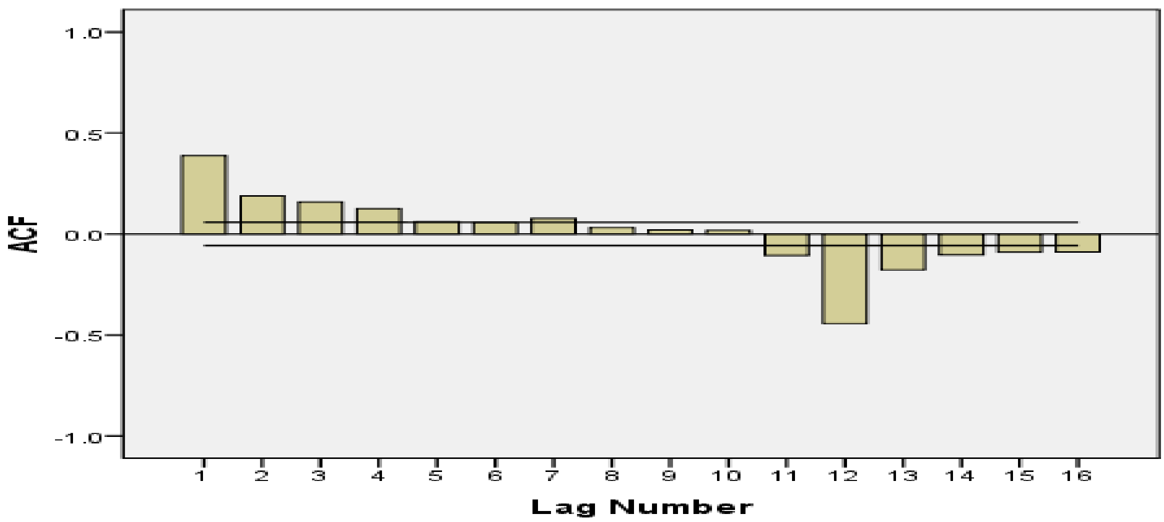

Figure 6.Autocorrelation function (ACF) plot of seasonally differenced data at 16 Lags.

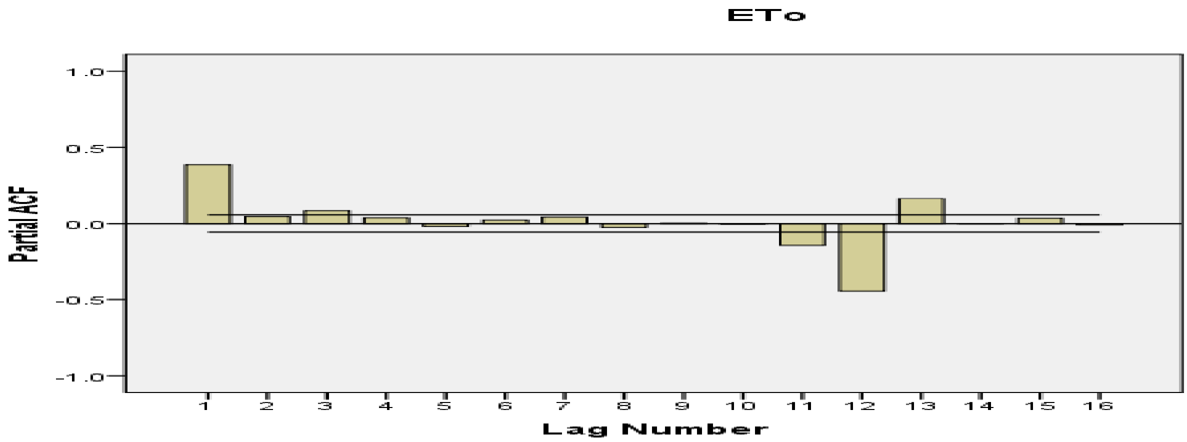

Figure 7.Partial autocorrelation function (PACF) plot of seasonally differenced data at 16 Lags.

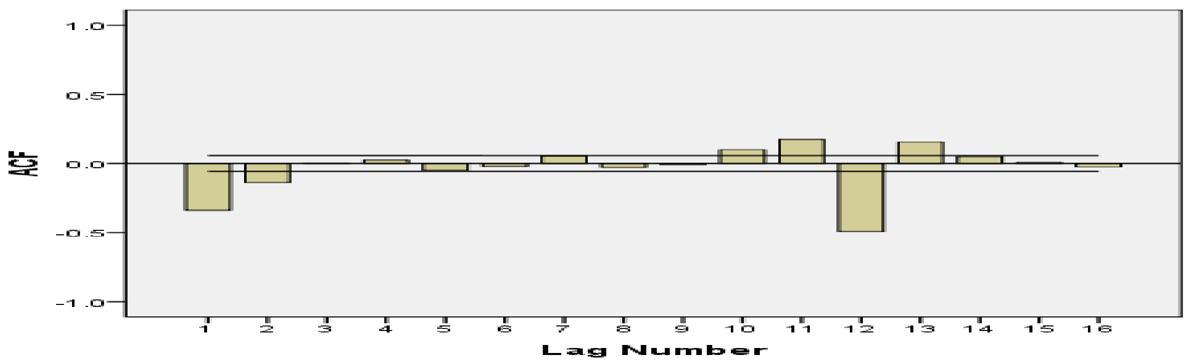

Figure 8. Autocorrelation function (ACF) plot of seasonally and non- seasonally differenced data at 16 Lags.

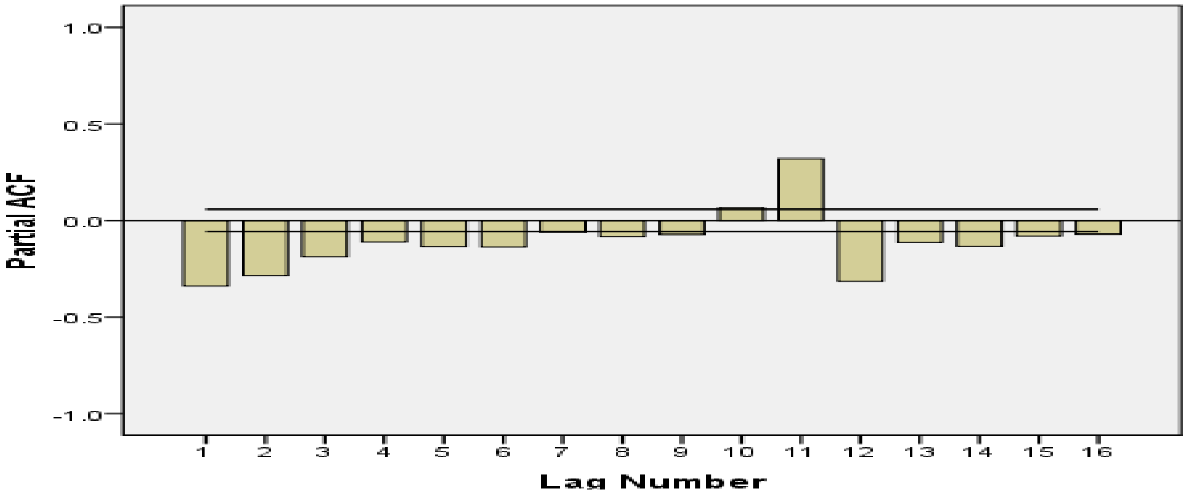

Figure 9. Partial autocorrelation function (PACF) plot of seasonally and non- seasonally differenced data at 16 Lags.

Table1. Autocorrelation function (ACF) and partial autocorrelation function(PACF) at 16 lags

Lag No	ACF	S.E.	Q-Value	PACF	SE
1	0.787	0.029	759.990	0.787	0.029
2	0.315	0.029	882.066	-.799	0.029
3	-.159	0.029	913.259	0.168	0.029
4	-.471	0.029	1.186E3	-.221	0.029
5	-.610	0.029	1.645E3	-.402	0.029
6	-.646	0.028	2.159E3	-.434	0.029
7	-.609	0.028	2.617E3	-.388	0.029
8	-.470	0.028	2.889E3	-.474	0.029
9	-.159	0.028	2.920E3	-.054	0.029
10	0.313	0.028	3.041E3	0.352	0.029
11	0.776	0.028	3.787E3	0.546	0.029
12	0.975	0.028	4.964E3	0.339	0.029
13	0.773	0.028	5.703E3	-.243	0.029
14	0.308	0.028	5.821E3	-.079	0.029
15	-.161	0.028	5.853E3	.057	0.029
16	-.470	0.028	6.127E3	.017	0.029

Table 2. Autocorrelation function (ACF) and partial autocorrelation function (PACF) of seasonally difference evapotranspiration data at 16 lags.

Lag No	ACF	SE	Q- Value	PACF	SE
1	.388	.029	182.478	.388	.029
2	.189	.029	226.013	.046	.029
3	.159	.029	256.683	.084	.029
4	.125	.029	275.859	.038	.029
5	.062	.029	280.478	-.017	.029
6	.057	.029	284.376	.023	.029
7	.077	.029	291.603	.043	.029
8	.032	.029	292.832	-.024	.029
9	.021	.029	293.349	.003	.029
10	.018	.029	293.757	-.002	.029
11	-.106	.029	307.549	-.143	.029
12	-.444	.029	549.083	-.443	.029
13	-.178	.029	588.004	.164	.029
14	-.103	.029	601.111	.001	.029
15	-.090	.029	611.110	.035	.029
16	-.089	.029	620.882	-.007	.029

Table 3 .Autocorrelation function (ACF) and partial autocorrelation function (PACF) of seasonally and non-seasonally difference evapotranspiration data at 16 lags.

Lag No	ACF	SE	Q- Value	PACF	SE
1	-.338	.029	138.726	-.338	.029
2	-.137	.029	161.668	-.284	.029
3	.003	.029	161.677	-.188	.029
4	.025	.029	162.425	-.112	.029
5	-.048	.029	165.229	-.136	.029
6	-.021	.029	165.757	-.138	.029
7	.054	.029	169.255	-.062	.029
8	-.028	.029	170.195	-.084	.029
9	-.007	.029	170.258	-.073	.029
10	.100	.029	182.405	.064	.029
11	.174	.029	219.550	.321	.029
12	-.493	.029	517.008	-.314	.029
13	.156	.029	546.880	-.114	.029
14	.050	.029	550.007	-.134	.029
15	.009	.029	550.114	-.080	.029
16	-.024	.029	550.850	-.071	.029