International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
Maths 2021; 6(1): 01-07

www.mathsjournal.com
Received: 02-11-2020
Accepted: 08-12-2020

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Hydrological remote sensing periodic analysis on forecasting approach

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DOI: https://doi.org/10.22271/maths.2021.v6.i1a.627

Abstract
In this paper dynamics hydrological data sets are received using various sensors through internet by GPRS. The collected data are estimated using the more popular statistical models. Predictions are performed on those models explored from the stochastic process Thomas-Fiering is a more popular linear stochastic model to estimate Predictions through time series models explored from the stochastic processes of our work carried out. Sensitivity analysis is carried out for better understanding of the model with the stated context of hydro related data. For water, transport, trash, climate, and so forth, the IoT sensors can be utilized successfully.

Keywords: Central moving average, time series analysis, thomas-fiering model, hydrological data

1. Introduction

In today world, the analysis of hydrological data is benefit in many fields like water level, overflow protection, water power on hydrology measuring method. The application of stochastic process is a new trend on hydrology which predicts the management science, seasonal periods and climate change through stochastic development in ANOVA, ARIMA and MLE. Statistical downscaling is two-step process containing the development of statistical relationship between the variables such as climate variables and large-scale predictors. The second one is the application of the relationship to the output of the global climate model experiments to simulate local climate data sets in future.

The present paper is used to simulate the large-scale downscaling data taken from the water levels and discharge at mantralayam gauging site and predict the discharge data for future values. The application of stochastic process, which are trend on hydrology, management science, seasonal periods and climate change can be predicted stochastic linear normal equation useful in real life. This paper is organized in following manner. In section 2, the recent related works of hydrological methods are reviewed. The proposed work is discussed in next section. Finally, results and analysis are presented.

2. Related work

Lewis and Ray explained the characteristic of many types of hydrologic time series has periodically varying components. Data of this type may be modeled using a linear stochastic model that is commonly referred to as autoregressive integrated moving average ARIM [12]. Amitrano *et al*. Introduce a characteristic augmentation of this investigation is represented the nature of little repository for which high spatial and fleeting goal information are getting expanding accessible through advances in distant detecting innovation [2]. Ahmad *et al*. forecasted the daily maximum 1-hour ozone concentrations whereas Ahmad analyzed water quality data by using ARIMA model [1]. See and Openshaw enhanced flood forecasting on the river Ouse by using ARIMA model [16]. Hsu *et al*. used an ARMA model for the prediction of streamflow on a medium sized basin in Mississippi [9] Yurekli *et al*. applied the ARIMA model to monthly data from Kelkit Stream watershed [13] and a store was viewed as vaporous in the event that it didn't contain at any rate one pixel covered water all year. Yurekli *et al*. analyzed the residuals from the ARIMA models fitted to monthly streamflow data for three gauging stations located on Çekerek stream watershed by alternatives methods [10] Yeşilırmak River, Turkey. Grahs *et al*. Brought up the hydrology information utilized in this investigation comprise of mean month to month release time arrangement from the worldwide overflow server farm that were openly gotten to upon the undertaking acknowledgment [6]. U.S. Thakarel *et al*. IoT is the eventual fate of innovation which will choose how we control and communicate with our everyday gadgets and make them all the more effectively. The plan primary issue with IoT is ill-advised utilization of intensity, nonstandard addressing scheme and lake of device security [19].

Predictive performances Ho and Xie [8] which is the popularity of ARIMA model in many areas resulted from having quite flexible of the model, due to the inclusion of both autoregressive and moving average terms. Larned *et al*. Developed the Hydrological ephemerality can fluctuate longitudinally along waterways with stream diligence changing in a non-straight way with the separation to/from the catchment's source [11] Snekler *et al*. Contributed the Indeed waterways with adequate calm head water contributing region can continue perpetual stream systems regardless of whether most of their stream length is through dry zones [18] Chang and Boyer estimate of low flows using watershed and climatic parameters are adequate for simulating perdays data sets [4] Vico *et al*. Determined the deciduousness, which would be obvious as a fast decrease in photosynthetic movement and following the finish of the wet season is a reasonable variation to a tropical occasionally dry atmosphere [20] Antopoulos *et al*. gives the statistical and trend analysis of water quality and quantity data for the hydrology and earth system science [3] Sharma *et.al*. The predicted data obtained from stream flow simulation approach for nonparametric method [17]. Fernando and Jayawardena generated and forecasting of monsoon rainfall data is strong model fit [5]. Hirsch *et al*. determined of trend analysis for monthly water quality data set are applications related to water resources research. Pradnya [7] A. Hukeri *et al*. ongoing advancement in RFID, savvy sensors, interchanges innovations, and Internet conventions empower IoT. The fundamental reason is to have a keen sensor working straightforwardly to convey another class of uses without human inclusion [14]. Sathish and Khadar Babu determined the food grains in the economic survey using Markovian estimation process. Our work attempts to predict the suitability of discharge level using various statistical parametric approach and comparing the statistical forecasting methods, which is best fit model accepted based on observed data sets [15].

3. Materials and Methods

In this section, the proposed works is presented in detail. The proposed works analyze time series of day-to-day discharge level data, which were collected through the sensor from the Sathanur Dam. The linear stochastic models were used: Thomas-Fiering model, MLE and ARIMA in this study.

Thomas-Fiering model recommended as the standard statistical model for the Hydrological applications. Maximum Likelihood Estimation is the best prediction using parameters of water level data sets. ARIMA model is rely heavily on autocorrelation patterns which is used to capture the forecasting effectively.

3.1 Extended thomas-fiering model

Thomas-Fiering model present daily discharge level data for linear stochastic model is used for generating perdays data. The well-known Thomas-Fiering model equation can be given as (Clarke, 1984):

$$\frac{\alpha_{i,j}-\overline{Q_J}}{\sigma_j} = \gamma_j \frac{\alpha_{i,j-1}-\overline{Q_{J-1}}}{\sigma_{j-1}} + \varepsilon_{ij}\sqrt{1-\gamma_j^2} + \beta_{ij}/n - 1\sqrt{1-\gamma_{j+1}^2} \qquad (3.1.1)$$

α_{ij} Predicted discharge for the jth month from the (j-1)th month at time i

$\overline{Q_J}$ The mean monthly discharge during month j

γ_j Correlation co-efficient for jth month to j-1th month

γ_{j+1} Correlation co-efficient for j+1th month to jth month

Extended Thomas-Fiering equation (3.1.1) was considered to estimate the comparison results of two error estimation

The first of them is the Root Mean Square Error (RMSE), which is given as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (3.1.2)$$

The second is the Mean Absolute Error (MAE), which is defined as

$$\text{MAE} = \frac{1}{n}\sum_{i=n}^{n}|y_i - \bar{y}| \qquad (3.1.3)$$

Extended Thomas-Fiering results are shown as follows

RMSE= 0.956

MAE= 0.03

3.2 Maximum likelihood Estimation for discharge data using Gaussian distribution (May 2016)

Calculate the maximum likelihood estimates of the parameter values of the Gaussian distribution μ and σ:

$$\text{P}(x; \mu, \sigma) = \prod_{x=1}^{15}\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

$$\text{P (15 Perdays}; \mu, \sigma) = \prod_{x=1}^{15}\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(91.9-\mu)^2}{2\sigma^2}\right) \times \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(91.5-\mu)^2}{2\sigma^2}\right)$$

$$\times \ldots\ldots\ldots\times \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(85.1-\mu)^2}{2\sigma^2}\right) \qquad (3.2.1)$$

Taking logs of the original expression is given us

$$\text{ʹIn}\,(P(x;\mu,\sigma)) = \prod_{x=1}^{15} \frac{1}{\sigma\sqrt{2\pi}}\left(\frac{1}{\sigma\sqrt{2\pi}}\right) - \frac{(91.9-\mu)^2}{2\sigma^2} + \text{ʹIn}\left(\frac{1}{\sigma\sqrt{2\pi}}\right) - \frac{(91.5-\mu)^2}{2\sigma^2} + \ldots\ldots\ \ldots\ldots + \text{ʹIn}\left(\frac{1}{\sigma\sqrt{2\pi}}\right) - \frac{(85.1-\mu)^2}{2\sigma^2} \qquad (3.2.2)$$

We can simplify above expression using the laws of logarithms to obtain

$$\text{ʹIn}\,(P(x;\mu,\sigma)) = -15\,\text{ʹIn}\,(\sigma) - \frac{15}{2}\,\text{ʹIn}\,(2\pi) - \frac{1}{2\sigma^2}[(91.9-\mu)^2 + (91.5-\mu)^2 + \ldots\ldots$$
$$\ldots\ldots + (85.1-\mu)^2] \qquad (3.2.3)$$

This expression can be differentiated to find the maximum. We can find the MLE of the mean μ. To do this we take the partial derivative of the function with respect to μ, giving

$$\frac{\partial\,\text{ʹIn}(P(x;\mu,\sigma))}{\partial\mu} = \frac{1}{\sigma^2}(91.9 + 91.5 + \ldots + 85.1 - 15\mu) \qquad (3.2.4)$$

Finally, setting the left hand side of the equation to zero and rearranging for μ gives

$$\mu = \frac{91.9+91.5+\cdots+85.1}{15} = 88.64$$

Similarly we have to get σ

$$\frac{\partial\,\text{ʹIn}(P(x;\mu,\sigma))}{\partial\,\sigma} = \frac{1}{2\,\sigma}(91.9 + 91.5 + \ldots + 85.1 - \mu) \qquad (3.2.5)$$

$2\,\sigma$ = [91.9+91.5+…+ (85.1—88.64]

σ = 620.5

μ = 88.64, σ = 620.5

3.3 ARIMA (p, d, q) model

P is the number of auto regression terms, d is the number of non-seasonal differences needed for stationarity and q is the number lagged forecast errors in the prediction equation.

$Y_t = \varphi_1 Y_{t-1} + \ldots + \varphi_p Y_{t-p} + a_t$

(1-$\varphi_1 B$-………- $\varphi_p B^p$) $Y_t = a_t$

4. Results and Discussions

The present models are very much useful to predict and forecast the water discharge level of the newly and existed barrage in our study area were useful. The Sathanur Freshwater is worked across Ponniar River close Sathanur town in Thandarampattu Taluk of Tiruvannamalai District. ZigBee remote sensor organization. In the observing territory, ZigBee remote sensor network is principally comprised by different sensors, for example, water meter, precipitation plan and the weight measure. Sensors and ZigBee remote module create ZigBee terminal hub. ZigBee terminal nodes connect into monitoring networks by star or mesh topology structure. According to the needs of the distance, ZigBee network accordance nodes distribute in monitoring area, and all hydrological data can be transmitted to the network by accordance nodes. GPRS networks. Hydrological information gathered by the ZigBee network is sent to information accepting focus through Internet by GPRS network, acknowledges significant distance information transmission. Checking focus. Checking focus worker interfaces with one GPRS module through the RS-232. The checking focus cycles and stockpiles the hydrological information gathered and dissects rundown by the product.

Table 1: Results of Sathanur Dam Discharge level 15 perdays data identification (May-2016)

S. No. Perdays (t)	Water Level Storage (m^3/s)-St	MA(3)	Fitted Values
1	91.9		88.42
2	91.5		88.44
3	91.05	425.7833	88.46
4	90.6	878.35	88.48
5	90.15	1507.6	88.5
6	89.7	2310.85	88.52
7	89.2	3284.583	88.54
8	88.75	4426.667	88.56
9	88.25	5733.017	88.58
10	87.75	7201.083	88.6
11	87.25	8826.833	88.62
12	86.7	10605.68	88.64
13	86.15	12533.8	88.66
14	85.65	14610.52	88.68
15	85.1		88.7

Reservoir and collect the water lever discharge data from the physical records of the Executive Engineer, Public works department, Sathanur Division, Tiruvannamalai District, Tamil Nadu, India for four divisional timings from the data results are follows.

Mean = 88.64, Standard Deviation = 2.105

Table 2: CMA Results of Sathanur Dam Discharge level 15 perdays data identification

t*St	t^2	$t^2 S_t$	CMA(3)
91.9	1	91.9	
183	4	366	
273.15	9	819.45	652.0667
362.4	16	1449.6	1192.975
450.75	25	2253.75	1909.225
538.2	36	3229.2	2797.717
624.4	49	4370.8	3855.625
710	64	5680	5079.842
794.25	81	7148.25	6467.05
877.5	100	8775	8013.958
959.75	121	10557.25	9716.258
1040.4	144	12484.8	11569.74
1119.95	169	14559.35	13572.16
1199.1	196	16787.4	14610.52
10501.25	1240	107720.25	

Hydrological data, which given in Table 1 are received in the center. Statistical models using R languages. Determine whether the errors in our ARIMA forecast are normally distributed with a mean of 0 and constant variance, we can also visualize our forecast errors with a time plot.

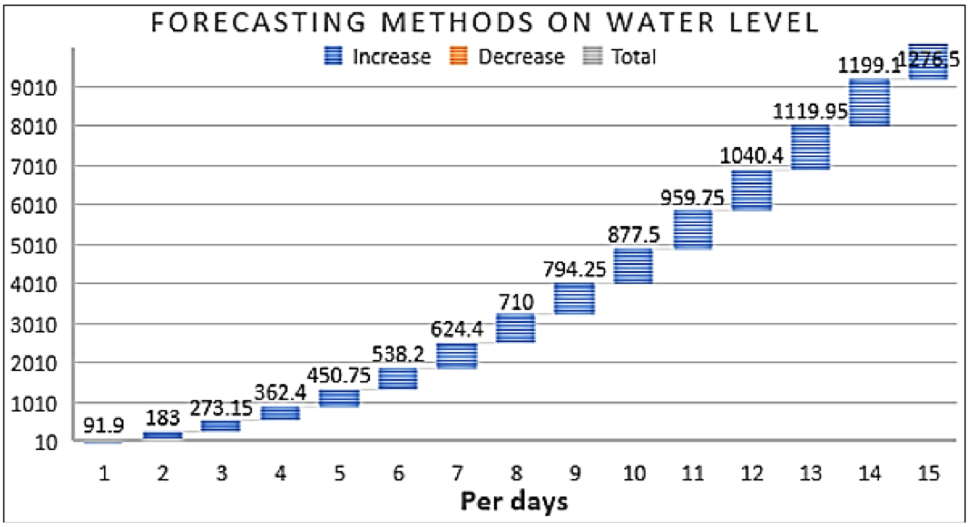

Fig 1: MA and CMA Results for Discharge Level (m^3/s)

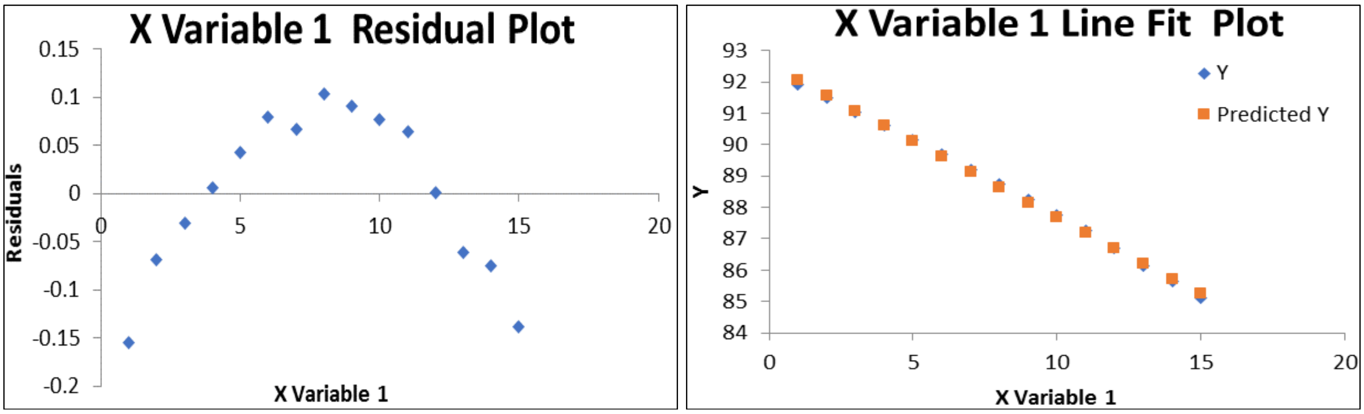

Fig 2: Residual values and Fitted values for Discharge Level (m^3/s)

ANOVA

Table 3: ANOVA Results of 15 perdays data identification

Groups	Count	Sum	Average	Variance
Perdays (t)	15	120	8	20
Water Level Storage (m^3/s)-St	15	1329.7	88.64667	4.74981

The observed discharge level (m^3/s) estimation process presence in Table 1 and corresponds to moving average and fitted values are analyzed similar way of forecasting approach. The significance prediction analysis of central moving average results and ANOVA variance values are shown in Table 2, 3.

Table 4: ANOVA variation with forecasting approach on Extended R^2 and Regression:

Source of Variation	SS	df	MS	F	P-value	F Crit
Between water level	48779.14	1	48779.14	3941.779	1.13E-31	4.195972
Within Water level	346.4973	28	12.3749			
Total	49125.63	29				
R Square	0.998499895					
Adjusted R Square	0.998384502					
Standard Error	0.087597408					
Observations	15					

Further from Table 4 and Table 5, the statistical fit based R^2 values of standard error analyses that forecasting trend with residuals predictions are presence. The prediction of best residual results for water level (Table 6).

Table 5: Standard Error analysis on forecasting approach

	df	SS	MS
Regression	1	66.39758036	66.39758036
Residual	13	0.099752976	0.007673306
Total	14	66.49733333	
	Coefficients	Standard Error	t Stat
Intercept	92.54238095	0.047596767	1944.299734
X Variable 1	-0.486964286	0.005234946	-93.02182844

Table 6: Residual Results (Water level m^3/s)

Observation	Predicted Y	Residuals	Standard Residuals
1	92.05541667	-0.155416667	-1.841190295
2	91.56845238	-0.068452381	-0.810941723
3	91.0814881	-0.031488095	-0.373033193
4	90.59452381	0.00547619	0.064875338
5	90.10755952	0.042440476	0.502783868
6	89.62059524	0.079404762	0.940692399
7	89.13363095	0.066369048	0.786260888
8	88.64666667	0.103333333	1.224169418
9	88.15970238	0.090297619	1.069737908
10	87.6727381	0.077261905	0.915306397
11	87.18577381	0.06422619	0.760874886
12	86.69880952	0.001190476	0.014103334
13	86.21184524	-0.061845238	-0.732668218
14	85.72488095	-0.074880952	-0.887099728
15	85.23791667	-0.137916667	-1.63387128

Table 7: Comparison of results from at Sathanur Dam discharge level data on Extended Thomas-Fiering and MLE method (May-2016)

Extended Thomas-Fiering	Maximum likelihood estimation	Error Estimates
RMSE = 0.95, Mean = 88.64	Mean = 88.6	RMSE = 0.956
MAE = 0.03, Standard deviation = 2.1	Standard deviation = 620.5	MAE = 0.03

Estimate on comparison of result from Sathanur dam discharge level in Extended Thomas Fiering, MLE and Error estimates are predicted in Table 7. The discharge level predicted data using Moving average and Central moving average observed by the researcher are shown in Fig 1. Data relating to monthly generation of water level has been indicated using residual with fitted values for plot in basis Fig 2. Show the Auto correlation and Partial correlation forecasting methods using R language shown in Fig 3. And Fig 4. Future values predicted and the data generated is identified.

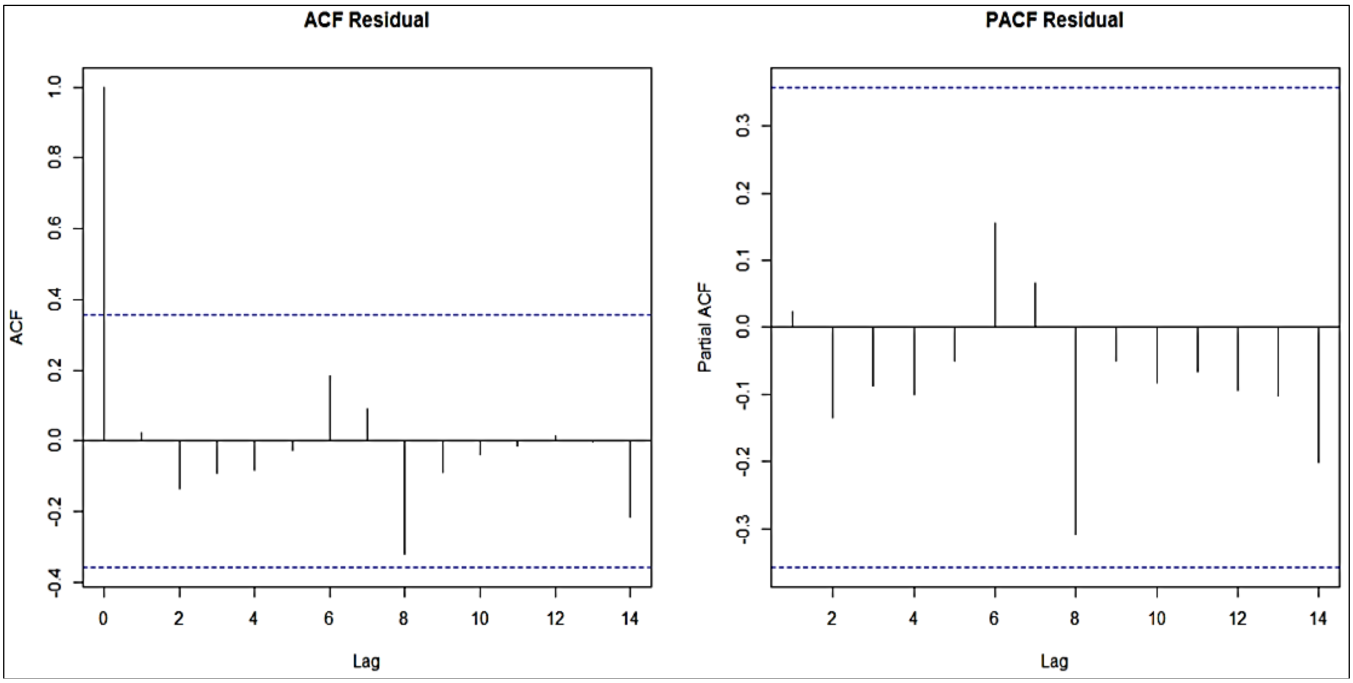

Fig 3: Residual values for ACF and PACF

Information gathered throughout the preliminary were looked at utilizing a single direction or a multifaceted rehashed measures ANOVA ($p< 0.05$). A nonparametric Mann-Whitney U test or a Kruskal-Wallis ANOVA was utilized to look at the information between medicines. All investigations were performed utilizing the Statistica (rendition 10) programming bundle (StatSoft Inc, Tulsa, USA), finally we close release level information utilizing R language progressed factual strategies. Remaining standard mistake: 0.003595 on 13 levels of opportunity, Multiple R-squared: 0.9985, Adjusted R-squared: 0.9984, F-measurement: 8653 on 1 and 13 DF, p-esteem: < 2.2e-16.

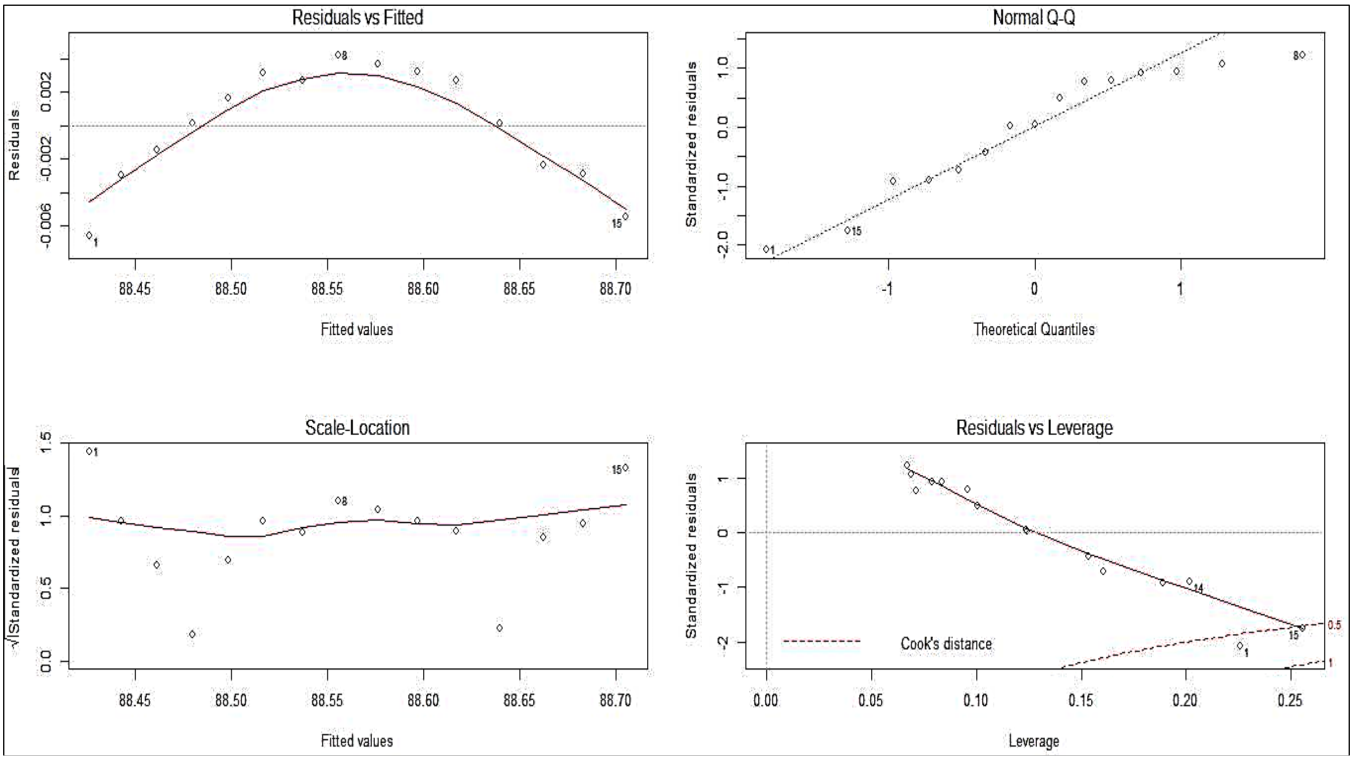

Fig 4: Original-Fitted values (2016-May)

5. Conclusion

The existence of statistical gaps between discharge levels and not having a coherent time series of the data, it is inevitable to use modeling in presenting an appropriate trend and close to the calculated data. In present study, to find the future trend among the discharge levels of the local downscaling time series models were used. Time series models have rich level of different and diverse structure in modeling discharge level forecast. However, the present model is perfectly suitable for discharge data to predict local future time series can be generated. Therefore, the mentioned method can be used for being aware of the discharge levels and the probability of occurrence of the flow in future years. The application of various statistical methods is very significantly for prediction process due to the environment hazards like earthquake, volcano, dams. The improvement of logical capacity to distinguish and foresee changes to the water cycle in light of common and human-prompted atmosphere fluctuation is a key need research territory. The improvement of such logical establishments requires key interests in both estimation and fundamental exploration programs. Flow hydrological water assets cycle and sensor exercises have a solid accentuation on atmosphere and because of maritime and environmental cycles on atmosphere.

6. Acknowledgments

This research was supported by my research supervisor SK. Khadar Babu, form Vellore Institute of Technology, Vellore. Special thanks go to Vishnu Priya from M.A.N.I.T Bhopal. Many people have made great efforts in the subject, thank you for the help of my teacher and my colleagues. This work is partially supported by Department of Mathematics, Bioinformatics and Computer Applications at M.A.N.I.T Bhopal.

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