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# Autoregressive integrated moving average (Arima) model for simulation of groundwater level at Devasuguru Nala watershed, Raichur district

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**Abstract**
Groundwater is a significant source of water in India, with approximately 65-70% of irrigation and 85-90% of the rural domestic water supply dependent on groundwater. India is one of the world's largest groundwater users, with an estimated annual groundwater extraction of over 230 cubic kilometers (km³). This high rate of extraction raises concerns about over-exploitation in many regions. For the effective management of groundwater, it is important to model and predict fluctuations in groundwater levels. The most widely used technique for time series analysis is, the Box Jenkins' Autoregressive Integrated Moving Average (ARIMA) model is adopted for the study. Results showed that the groundwater levels had significantly declined from January 1999 to March 2017. The results indicated that seasonal decline in groundwater level for the observation well was 0.034 m/year and average annual decline was 0.7424 m/yr. The ARIMA candidate model [3, 0, 2] was identified as the best fit model for groundwater level time series modelling and forecasting in Devasuguru nala watershed region.

**Keywords:** ARIMA, ARMA, Groundwater level, time series

## Introduction
In arid and semi-arid environments, groundwater plays a significant role in the ecosystem and also plays an important role in irrigated agriculture in India. It has made significant contribution in increasing agricultural production and productivity, and has played the vital role in achieving the food security in India (Sharma, 2009) [19]. Its contribution in net irrigated area is about 61% (CGWB, 2010) [3]. In the last decades, groundwater levels have decreased due to the increasing demand for water, weak irrigation management and soil damage. For the effective management of groundwater, it is important to model and predict fluctuations in groundwater levels. A number of conceptual and physically based groundwater level forecasting models have been developed to depict hydrological parameters (precipitation, temperature, groundwater level etc) and to characterize the complex structures of aquifers. However, one of the disadvantages of these models is that, they require large and consistent quality data with detailed understanding of the underlying aquifer system. Time series forecasting model are suitable alternatives for limited data environment. They provide a powerful method for accurate and reliable results without a costly calibration time (Narayanam *et al.*, 2013) [12]. In recent fast, several authors have proved that, time series analysis are very effective in planning management strategies for development and utilization of groundwater resources (Mack *et al*. 2013; Patle *et al*. 2013; Abdulahi *et al*. 2015) [8, 14, 1].
The most widely used technique for time series analysis is, the Box Jenkins' Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model is statistical based stochastic process model. The ARIMA model is popular because of its simplicity and robust statistical properties. The ARIMA is a linear prediction model which assumes that, the current data has a direct relationship with the past data and its errors (Yurekli *et al*., 2007, Narayanam *et al*., 2013) [12, 21]. ARIMA has received wide application for forecasting of future trends in engineering and hydrological problems (Shahwan and Odening, 2007; Mitosek, 2000) [17, 10]. In hydrological studies.

ARIMA model was used for forecasting monthly temperature, humidity and precipitation (Jahanbakhsh and Babapour, 2003; Shamsnia *et al*., 2011) [5, 18], stream flow data (Karamouz and Zahraie, 2004; Samsudin *et al*., 2011) [6, 15] and groundwater level (Panda and Kumar, 2011; Mack *et al.*, 2013; Patle *et al*., 2013 and Abdulahi *et al*., 2015) [8, 14, 1, 13].

Panda and Kumar (2011) [13] analysed the groundwater levels using seasonal auto regressive integrated moving average (SARIMA) for an over exploited aquifer of north-eastern districts in Orissa (India). They reported that groundwater exploitation vary from 25 to 60 m below surface. They showed that SARIMA model was suitable for forecasting the temporal behavior of groundwater tables. The above review support that non-parametric approaches can be used for detecting trend in groundwater levels and Auto Regressive Integrated Moving Average (ARIMA) models for forecasting groundwater levels were applied several time series models to predict groundwater level forecasting in Kashan plain, Isfahan province, Iran. The five time series models of autoregressive (AR), moving-average (MA), auto-regressive moving-average (ARMA), autoregressive integrated moving-average (ARIMA) and seasonal auto-regressive integrated moving-average (SARIMA) were applied. The results showed that the AR model with a two-times lag (AR(2)), shows the best forecasting of groundwater level for 60 months ahead with a high accuracy of R2. According to the results, the average groundwater level fluctuation in 2010 and 2016 was 74.58 and 80.71 m, respectively. With these conditions, the groundwater depletion rate would be 1.02 m per year in 2016. G. T. Patle *et al.*, (2013) [14] carried out a study for time series modelling of groundwater levels for forecasting the pre and post-monsoon water levels in Karnal district of Haryana. Results showed that the ARIMA (0, 1, 2) was identified as the appropriate model for time series modeling and forecasting. The forecasted results showed that the pre and post monsoon groundwater level in 2050 would decline by 12.97 m and 12.00 m over the observed water level in 2010, and reach to a level of 29.95 m and 28.14 m below ground surface. The average rate of decline of pre and post-monsoon groundwater level in the district during this period would be 0.32 and 0.30 m/year, respectively used non parametric tool to study trends in rainfall, temperature and groundwater levels from 2005 to 2014 using Mann-Kendall test, Sen's slope estimator and ARIMA models in the Upper East Region of Ghana. The results showed on the seasonal scale, both the Mann-Kendall and Sen's slope estimator have shown rising seasonal trends in all the wells except Kabingo which showed a declining seasonal trend of 0.312 to 0.097 m/year. Forecast for rainfall and groundwater levels using ARIMA models indicates that there will be a significant decline in rainfall at a rate of 4.779 mm/year by 2020 and an average rate of decline of 1.008 m/yr at Kabingo where the groundwater level expected to decline to about 12 m by 2020.

## Study Area

Study area Devasugur nala watershed covers part of Raichur taluk of Raichur district and is located at northern part of middle Krishna river basin of Karnataka, India (Fig. 1). Raichur district is situated in north-eastern part of Karnataka state which is drought prone and falls in the arid tract of the country. It falls in the northern maidan region, between 15º 33' to 16º 34' N latitudes and 76º 14' to 77º 36' E longitudes. The two important rivers in the district are the Krishna and the Tungabhadra. The drainage pattern is highly dendritic in nature.

The climate of the district can be termed as mild to severe, with mild winters and hot summers. December is the coldest month with mean daily minimum of 17.7 °C, while May is the hottest month with mean daily maximum temperature of 39.8 °C. Relative humidity of over 75 per cent is common during monsoon period. Wind speeds exceeding 15 km. $h^{-1}$ are common during the months of June and July. The recorded annual potential evaporation is around 1950 mm with May registering over 220 mm and December around 120 mm. The normal annual rainfall of the district is 621 mm. The annual number of the rainy days is about 49 days. Nearly 67 per cent of the rain is received during the southwest monsoon period (June to September) and the northeast monsoon contributes about 24 per cent, during the post monsoon period. The general slope of the terrain is towards the Krishna River in the northern part of the district and towards the Tungabhadra River in the southern part.

The stage of groundwater development in the district, as per the norms is only 20 per cent. Except for small pockets in Lingsugur and Raichur taluks, which are categorized as overexploited, the rest of the district is safe from groundwater point of view. The available groundwater resources for irrigation are to be utilized by construction of abstraction structures of suitable designs based on the hydrogeological conditions prevailing in the area. The annual replenishable groundwater resources of the district are 673.66 MCM and the net annual groundwater draft is 131.77 MCM. As already some parts of the district are canal irrigated, conjunctive use of surface and groundwater is to be practiced for sustained development, and adequate surface water availability to tail end users.

## Data used

The observation well located in Raichur of Devasuguru nala watershed was selected for the study. The monthly groundwater level (Below ground level) of Raichur station for 19 years *i.e.*, from January 1999 to March 2017 were collected from Department of Mines and Geology, Raichur, and used for analysis. The location map of the study area and observation well is presented in Fig. 1. The time series plot of monthly groundwater level for 19 years data is presented in Fig. 2.

## Methodology

The Mann-Kendall (Mann, 1945; Kendall, 1975) [9, 7] and Sen's slope estimator (Sen, 1968) [16] were used for trend analysis and detection of slope of the trends. Auto Regressive Integrated Moving Average (ARIMA) model (Box and Jenkins, 1976) [1] was used for groundwater levels modeling and forecasting. GIS was used to visualize the spatial distribution of the groundwater levels.

## Mann-Kendall Test

The Mann-Kendall test is a non-parametric statistical test for trend analysis of time series data. The Mann-Kendall statistic provides an indication of whether a trend exists and whether the trend is positive or negative. Major advantage of this test is that it is free from statistical distributions which are required for parametric method (Kendall, 1975) [7]. Considering $X_1$, $X_2$........$X_n$ as a time series data, the null hypothesis ($H_0$) for the Mann-Kendall test is that there is no trend or serial correlation among the analyzed population against the alternative hypothesis ($H_1$), which assumes increasing or decreasing monotonic trend.

The Mann-Kendall statistic S is given as

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn(X_j - X_i) \quad ...(1)$$

Where, S is Mann-Kendall statistics, n is number of data points, $X_j$ and $X_i$ are the data values of the time series i and j respectively such that i>j, sign is the signum function. The application of trend test is done to a time series $X_i$ that is ranked from i = 1, 2,………n-1 and $X_j$, which is ranked from j = i+1, 2,……….n. Each of the data point $X_i$ is taken as a reference point which is compared with the rest of the data points $X_j$ so that,

$$\text{Sgn}(X_j - X_i) = \begin{Bmatrix} 1\ if(X_j - X_i) > 0 \\ 0\ if(X_j - X_i) = 0 \\ -1\ if(X_j - X_i) < 0 \end{Bmatrix} \quad ...(2)$$

A positive value of S indicates an upward trend and negative value indicates downward trend (Salmi *et al*. 2002; Luo *et al*. 2008) [6]. For n = 10, the statistic S is approximately normally distributed with the mean E(s) = 0 and variance (Var (s)).
The variance statistic is given as

$$\text{Var(S)} = \frac{n(n-1)(2n+5)-\sum_{i=1}^{m} t_i(i)(i-1)(2i+5)}{18} \quad ...(3)$$

Where, $t_i$ is considered as the number of ties up to sample i. In this method, the presence of a statistically significant trend is evaluated using the $Z_c$ value.

$$Z_c = \begin{Bmatrix} \frac{S-1}{\sqrt{Var(S)}}\ if\ S > 0 \\ 0\ if\ S = 0 \\ \frac{S-1}{\sqrt{Var(S)}}\ if\ S > 0 \end{Bmatrix} \quad ...(4)$$

It follows that the null hypothesis (No trend) is rejected when the $Z_c$ value calculated from the above equations is greater than in absolute value than the critical value Zα, at a chosen level of significance α. In this study, Zα and α were taken as ±1.96 and 5% respectively as widely used by several authors (Patle *et al*. 2013; Vousoughi *et al*. 2013) [14, 20]. Positive values of Zs indicate increasing trends while negative Zs values show decreasing trends.

**Sen's Slope Estimator Test**

True slope in time series data (change per unit time) is estimated by procedure described by Sen (1968) [16] in case the trend is linear. The magnitude of trend is predicted by the Sen's slope estimator ($Q_i$).

$$Q_i = \frac{X_j - X_k}{j-k}\ for\ i = 1,2, \ldots\ldots, N \quad ...(5)$$

Where, $X_j$ and $X_k$ are data values at times $j$ and $k$ ($j > k$) respectively. The median of these $N$ values of $Q_i$ is represented as Sen's estimator. $Q_{med} = Q_{(N+1)/2}$ if $N$ is odd, and $Q_{med} = [Q_{N/2} + Q_{(N+2)/2}]/2$ if $N$ is even. Positive value of $Q_i$ indicates an increasing trend and a negative value of $Q_i$ shows decreasing trend in the time series.

**Auto Regressive Integrated Moving Average (ARIMA) Model**

ARIMA model (Box and Jenkins, 1976) [1] is one of the most popular tools for modeling of time series data and forecasting. It contains autoregressive (AR), integrated (I) and moving average (MA) parts which are expressed as ARIMA (p, d, q). Where, p is autoregressive part, d is integrated part and q is moving average part. In present study, time series of groundwater levels represented by $Y_t$ were used for modeling and forecasting as a function of time. A time series was represented by $Y_t$ as

$$Yt = Y_1, Y_2, Y_3 \ldots.Y_t \quad ...(6)$$

where, $Y_1$, $Y_2$, $Y_3$….. are observation at time $t_1$, $t_2$, $t_3$….
The autoregressive part explains the relationship between present and previous p observations. If p = 1, then each observation is a function of only one previous observation i.e.

$$Y_t = c + f1Y_{t-1} + et \quad ...(7)$$

where, $Y_t$ is the observed value at time t, $Y_{t-1}$ is the previous observed value at time t-1, et is random error and c and f1 are constants.
Other observed values of the series can be included in the right hand side of the equation if p > 1

$$Y_t = c + f1Y_{t-1} + f2Y_{t-2} + \cdot \cdot \cdot + fpY_{t-p} + et \quad ...(8)$$

The integrate part of the model determines whether the observed values are modelled directly, or differentiated. When the series is modelled directly, then d=0. However, in practice, d can be 1 or 2. The need for differencing to make the series stationary has been thoroughly explained by Dickey and Fuller (1979) [4].
The moving average part of the model identifies the relationship between observation and previous q errors, if q=1, each observation is a function of only one previous error i.e.

$$Yt = c + q1_{et-1} + et \quad ...(9)$$

where, c is a constant term; et represents the random error at time t and et-1 represents the previous random error at time t - 1. Other errors can be included in the right hand side of the equation if q > 1.
The ARIMA modeling consists of four steps *viz*., model identification, parameter estimation, diagnostic testing and forecasting (Patle *et al*., 2013 and Abass *et al*., 2017) [14]. In model identification, the stationarity and normality of the time series data is tested by looking into the behavior of the autocorrelation function (ACF) and partial autocorrelation function (PACF) after which the tentative model is chosen by matching ACF and PACF of stationary series. In parameter estimation step, the parameters estimates (p, d, q) are usually obtained by the method of maximum likelihood. In the diagnostic testing stage, the model adequacy is examined to check if the model assumptions about the errors are satisfactory. If the selected model is unsatisfactory, the above procedure is repeated with a new model until the new model fits the assumptions around the errors. Finally best fit model will be used for predicting the future trend of the time series.
The R software was used for building and testing the ARIMA model. The groundwater level data were divided into two set in the ratio 70:30. The first part was used for model identification while the second part was used for validation of the model. The goodness fit criteria used to evaluate the performance of the models are Root Mean Square Error (RMSE), MAPE, MAE, MASE and AIC. The observed and

forecasted results were compared in order to select the best model.

## Results and Discussions

### Water table fluctuation trends

The monthly groundwater level (below ground level) of Raichur station for 19 years i.e., from January 1999 to March 2017 were collected from Department of Mines and Geology, Raichur, and used for analysis. To determine the trend in time series data of groundwater level in study area the Mann-Kendal test (Zc) and Sen's slope (Q med) estimates were applied. Earlier than the application of both Mann-Kendal and Sen's slope estimates, autocorrelation test were carried out on groundwater time series data in order to check for randomness in the data. The lag-1 serial correlation coefficients of the observation well were statistically not significant, hence, no need to pre-white the data. Therefore, the statistical tests described above were applied to the original time series data.

The results of the statistical test on the seasonal Zc and Qmed of the Mann-Kendall and Sen's slope of the groundwater levels in the study are presented in Table 1.

Values of Zc recorded for the groundwater data was 0.7424 which is greater than the P value which was 0.458 at 5% significance level. This indicated that there was a significant trend in time series data of groundwater level. The positive sign suggests that the groundwater level is declining with respect to ground surface. Sen's slope estimator was used to find out the slope of trend line (i.e. rate of water level decline, m/yr). The positive value of slope indicated the declining trend (i.e. depth of water level with respect to ground surface is increasing) of ground water level during the period of 19 years. The results indicated that seasonal decline in groundwater level for the observation well was 0.034 m/year and average annual decline was 0.7424 m/yr.

### Model selection and forecasting of groundwater levels

Autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for groundwater level time series for study area was presented in Fig.3 and 4. The plot of ACF (Fig. 3) without differencing indicates there are many spikes above the confidence limits and ACF coefficient is decaying slowly. Fig. 4 shows the plot of PACF drop off sharply after the first lag indicates that the time series is more volatile. Based on the plots of ACF and PACF the order of p and q were decided for developing tentative ARIMA models for time series of groundwater levels.

Eight tentative ARIMA models were selected with different values of p, d, q which were within the reasonable range. To examine if the selected four models contained any systematic pattern which could be removed to improve the predictability of selected models, autocorrelation function (ACF) and partial autocorrelation function (PACF) of residuals were further examined. The ACF and PACF of residuals of selected model groundwater level time series are plotted in Fig. 5 and 6. It is observed from this figure that ACF and PACF of residuals are within the confidence limit and were not significantly different from zero except first lag in ACF. This indicated that the models were appropriately selected.

Out of the eight selected models best model for groundwater levels time series was selected on the basis of root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and Akaike's Information Criterion (AIC) as indicated in Table 2. The model which had lowest value of these parameters was selected for validation. The ARIMA candidate model [3, 0, 2] is having lowest RMSE (0.8510), MAPE (6.5500), MAE (0.5980), MASE (0.8544), AIC (590.75) and Log Likehood (-288.38). Therefore, ARIMA [3, 0, 2] was identified as the best fitted model for groundwater levels time series.

### Model validation

The selected candidate model (ARIMA [3, 0, 2]) was further validated by comparing the forecasted and observed groundwater levels for the period 2007 to 2017. The model validation parameters are presented in Table 3. It is observed that RSME, MAPE, MAE, MASE were within the permissible limit. Comparison of observed and forecasted groundwater levels are presented in Fig. 7. It is observed that observed and forecasted groundwater levels are in close agreement with R2 values of 0.934. Therefore, ARIMA candidate model [3, 0, 2] was selected as best fit model groundwater level forecasting in the Devasuguru nala Watershed, Raichur District region.

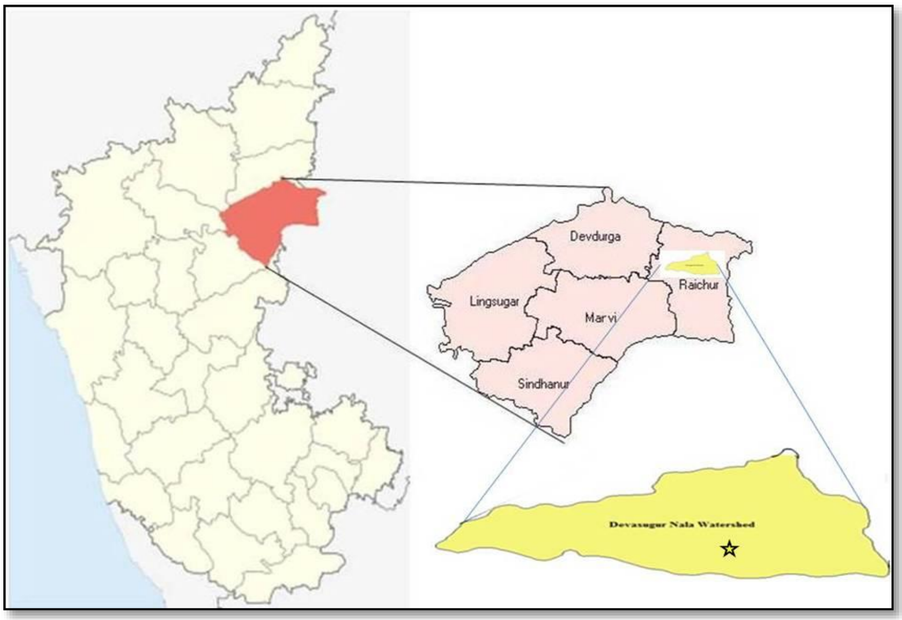



**Fig 1:** Location map indicating the study area in Devasugur Nala Watershed

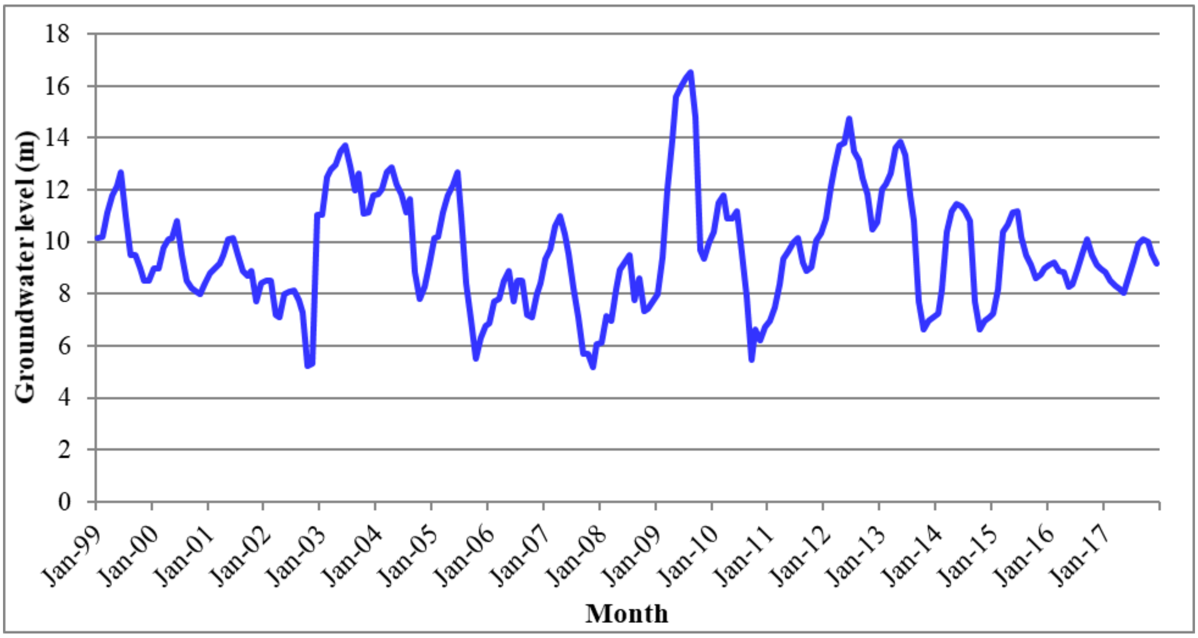
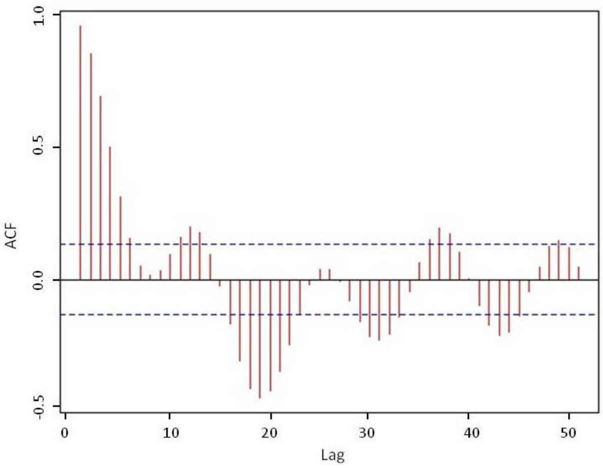



**Fig 2:** Time series plot of monthly groundwater level



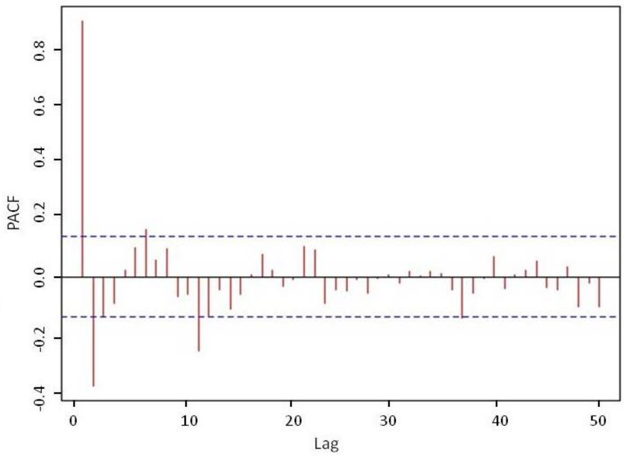
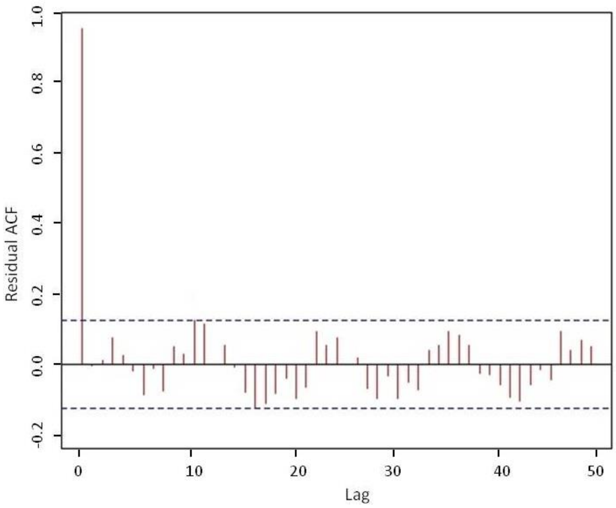




**Fig 3:** ACF of groundwater level **Fig 4**: PACF of groundwater level



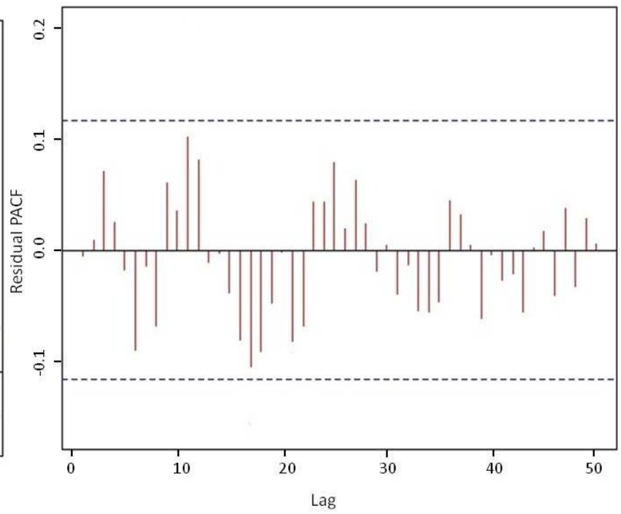




**Fig 5:** Residual ACF of groundwater level **Fig 6:** Residual PACF of groundwater level

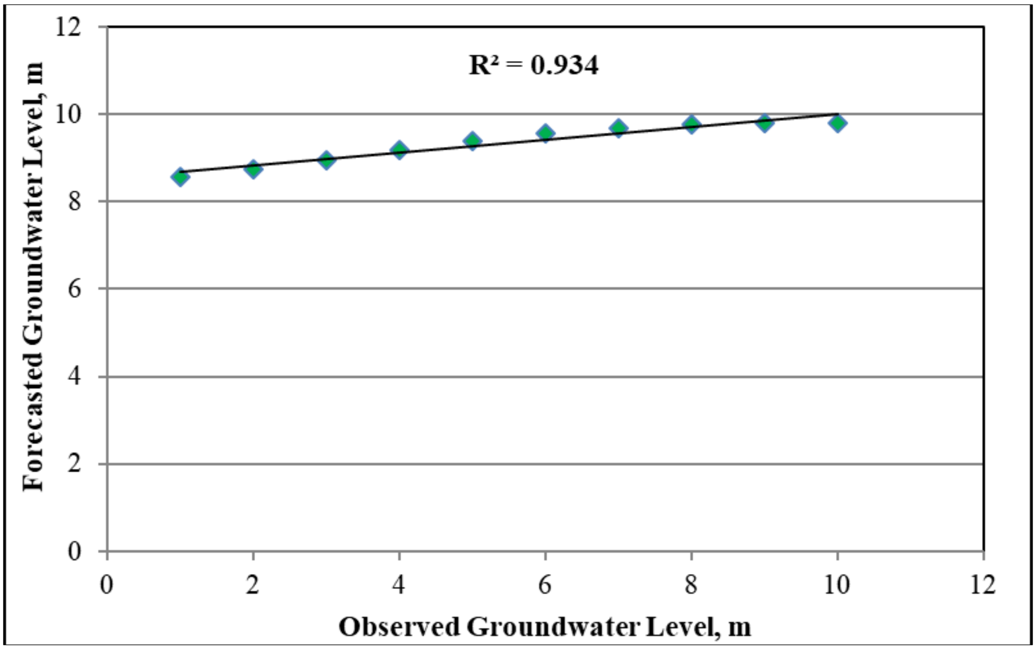



**Fig 7:** Observed and forecasted groundwater levels

**Table 1:** Mann-Kendall's statistic's and sen's slope for monthly groundwater level

| Parameter | Zc | P value | Q med | Trend (m/yr) | Seasonal Trend (m/yr) | Remarks |
|---|---|---|---|---|---|---|
| Groundwater level | 0.7424 | 0.458 | 0.034 | 0.7424 | 0.034 | ** |

Zc: Mann-Kendall test, Qmed: Sen's slope estimator, m: meter, yr: years,
**Statistically insignificant trend at 5% significant level

**Table 2:** ARIMA candidate models

| ARIMA Candidate model | RMSE | MAPE | MAE | MASE | AIC | Log Likehood |
|---|---|---|---|---|---|---|
| ARIMA [1, 0, 1] | 0.9317 | 7.1334 | 0.6518 | 0.9313 | 624.6 | -308.3 |
| ARIMA [1, 0, 2] | 0.9184 | 7.0150 | 0.6428 | 0.9184 | 620.08 | -305.04 |
| ARIMA [2, 0, 1] | 0.8994 | 6.8243 | 0.6245 | 0.8923 | 610.69 | -300.34 |
| ARIMA [2, 0, 2] | 0.8986 | 6.8075 | 0.6232 | 0.8905 | 612.31 | -300.16 |
| ARIMA [3, 0, 1] | 0.8990 | 6.8142 | 0.6238 | 0.8913 | 612.48 | -300.24 |
| ARIMA [3, 0, 2] | 0.8510 | 6.5500 | 0.5980 | 0.8544 | 590.75 | -288.38 |
| ARIMA [4, 0, 1] | 0.8958 | 6.8061 | 0.6231 | 0.8902 | 612.92 | -299.46 |
| ARIMA [4, 0, 2] | 0.8952 | 6.8021 | 0.6237 | 0.8906 | 619.62 | -299.31 |

**Table 3:** Validation of Selected ARIMA candidate models

| ARIMA Candidate model | $R^2$ | RMSE | MAPE | MAE | MASE |
|---|---|---|---|---|---|
| ARIMA [3, 0, 2] | 0.934 | 0.8711 | 6.8200 | 0.6238 | 0.8654 |

## Conclusion

Long term groundwater fluctuation trends indicate the effect of groundwater withdrawal and recharge on changes in water stored in aquifer, which is required for assessing the groundwater potential available for utilization. The most widely used technique for time series analysis is, the Box Jenkins' Autoregressive Integrated Moving Average (ARIMA) model is adopted for the study. The Mann-Kendall and Sen's slope estimator were used for trend analysis and detection of slope of the trends. Results showed that the groundwater levels had significantly declined from January 1999 to March 2017. The results indicated that seasonal decline in groundwater level for the observation well was 0.034 m/year and average annual decline was 0.7424 m/yr. The ARIMA candidate model [3, 0, 2] was identified as the best fit model for groundwater level time series modelling and forecasting in Devasuguru nala watershed region.

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