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## Factors affecting groundwater level fluctuation: A case study at Manvi

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**Abstract**

An accurate prediction of groundwater level is quite essential for ecological, sustainable development and management of groundwater resources. The soft computing models like ARIMA, ANN, FL, ANFIS and GA have been reported as the promising tools in prediction of accurate groundwater level. Now a day's, ANN is widely used by many researchers in groundwater level prediction. So, the present study was carried out to find best ANN model to predict groundwater level fluctuation at Manvi. Selection of significant input variables is the most important step in the development of ANN model. In general, all of the relevant input variables (Rainfall, ET, temperature, RH, recharge, discharge, aquifer properties, streams, infiltration, initial groundwater level and variable groundwater level in nearby wells) will be equally informative in many instances. Further some may be difficult to collect, noisy, correlated or have no significant relationship with the output variable (current groundwater level) being modelled. The statistical parameters viz., auto-correlation function (ACF), partial auto-correlation function (PACF) and cross-correlation function (CCF) were used to select the significant variables with significant lag times. MATLAB 7.14 was used for statistical analysis and interpretation. Results indicated that, rainfall, evapotranspiration and previous groundwater level showed a good correlation with current groundwater level. It was found that considerable lag time of one month in case of rainfall (R) and previous groundwater level (Wt) and four months lag time of evapotranspiration (ET). So, input with R (t-1), Wt (t-1) and ET (t-4) lags were selected for ANN modelling. Good prediction was observed by the developed model.

**Keywords:** ANN, groundwater level, auto-correlation, partial auto-correlation, cross-correlation

**Introduction**

Groundwater is a highly important, valuable and natural resource. A geologic formation from which significant amounts of groundwater can be pumped for domestic, municipal or agricultural uses is known as an aquifer. It is thus, clear how important groundwater is, for agricultural, domestic and industrial uses and is acquired by constructing and operating extraction wells (Umamaheswari and Kalamani, 2014a) [7]. The increasing population in the country reducing the national per capita annual availability of water by 15 per cent as recorded in 2011 (Anonymous, 2015) [1].

Groundwater reservoir is a complicated system and is exposed to either natural or artificial stresses on the aquifer in different chronological levels resulting in the fluctuations of groundwater level. Thus, to exploit and manage groundwater, mathematical models are needed. Conceptual and physically-based models are considered to be the main tools for depicting hydrological variables and understanding the physical processes taking place in a system (Prasenjit *et al.*, 2014) [3]. The development of artificial neural network model was used for modelling of groundwater level fluctuation. It is necessary to select appropriate inputs for the development of models. Inputs may affect the groundwater level fluctuation either directly or indirectly.

**Materials and Methods****Brief description of study area**

Study area lies under northern part of middle Krishna river basin of Karnataka, India. It is situated in Agro-Climatic Zone-II (North Eastern Dry Zone) of Karnataka, which is drought prone and falls in the arid tract of the country.

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It falls in the northern maidan region, between 15° 59' 45" N latitudes and 77° 3' 10" E longitudes. The drainage pattern of area is highly dendritic in nature. The drainage pattern in the area has been altered due to the irrigation practices in the area. The general slope of the terrain is towards the Tungabhadra river in the southern part.

### Temporal data

The monthly rainfall data and water table depth (m.bgl) of Manvi station for 18 years *i.e.*, from January 1999 to December 2016 were collected from Department of Mines and Geology, Raichur, were used for analysis. The meteorological data such as maximum and minimum temperature, relative humidity, wind speed and sunshine hour data for 18 years from January 1999 to December 2016 were collected from Main Agricultural Research Station, Raichur and used for calculating the evapotranspiration using CROPWAT 8.0 software. The present software used the Penman-Monteith method, the input parameters such as maximum temperature in °C, minimum temperature in °C, average relative humidity in per cent, wind speed in km per day and sunshine hour in hours were provided to calculate ET.

### Selection of input vector

It is very important to identify the input vector, detailed correlation analysis using statistical parameters such as Auto-Correlation Function (ACF), Partial Auto-Correlation Function (PACF) and Cross-Correlation Function (CCF) were used to find out the significant lag values of input variables. Usually, not all of the potential input variables will be equally informative, because some may be correlated, noisy or have no significant relationship with the output variable being modeled (Sujatha and Kumar, 2009) [6]. Input variables were selected based on autocorrelation, partial autocorrelation and cross-correlation techniques. Many researchers successfully used correlation analysis for selection of input variables (Gharde *et al.* 2016) [2].

### Auto-correlation function

It is also known as serial correlation, the correlation of a signal with a delayed copy of itself as a function of delay. Informally, it is the similarity between observations as a function of the time lag between them. Auto-correlation function is defined by Eq. 1.

$$r_k = \frac{\sum_{t=1}^{N-k} (x_t - \bar{x}_t)(x_{t+k} - \bar{x}_{t+k})}{\left[ \sum_{t=1}^{N-k} (x_t - \bar{x}_t)^2 \sum_{t=1}^{N-k} (x_{t+k} - \bar{x}_{t+k})^2 \right]^{1/2}} \quad \dots (1)$$

### Where

- $r_k$  = The lag-k correlation coefficient, the serial correlation coefficient or ACF,
- $X_t$  = Time series for  $t = 1, \dots, N$ ,
- $X_{t+k}$  = Lagged time series for  $t = 1, \dots, N-k$ ,
- $\bar{X}_t$  = Sample mean for  $t = 1, \dots, N$ ,
- $\bar{X}_{t+k}$  = Sample mean for  $t = 1, \dots, N-k$ ,  $N$  is the sample size.

### Partial auto-correlation function

In the analysis, the partial autocorrelation function gives the partial correlation of a time series with its own lagged values, controlling for the values of the time series at all shorter lags. It contrasts with the autocorrelation function, which does not

control for other lags. Partial auto correlation function was defined by Eq. 2.

$$r_k = \frac{\rho_k - \sum_{t=1}^{k-1} r_{k-1,t} \rho_{k-t}}{1 - \sum_{t=1}^{k-1} r_{k-1,t} \rho_{k-t}} \quad \dots (2)$$

### Where

- $r_k$  = The lag-k correlation coefficient, the serial correlation coefficient or PACF,
- $\rho_k$  = Auto correlation coefficient with lag-k,
- $r_{k-1,t}$  = The serial correlation coefficient or PACF, lag for  $k = 1, \dots, N-1$ ,
- $\rho_{k-t}$  = Auto correlation coefficient with lagged time series for  $k=1 \dots k-t$ .

### Cross-correlation function

In signal processing, cross-correlation is a measure of similarity of two series as a function of the displacement of one relative to the other. This is also known as a sliding dot product or sliding inner-product. It is commonly used for searching a long signal for a shorter, known feature. Cross-correlation function was defined by Eq. 3.

$$r_k^{ij} = \frac{\sum_{t=1}^{N-k} (x_t^{(i)} - \bar{x}_t^{(i)})(x_{t+k}^{(j)} - \bar{x}_{t+k}^{(j)})}{\left[ \sum_{t=1}^{N-k} (x_t^{(i)} - \bar{x}_t^{(i)})^2 \sum_{t=1}^{N-k} (x_{t+k}^{(j)} - \bar{x}_{t+k}^{(j)})^2 \right]^{1/2}} \quad \dots (3)$$

### Where

- $r_k^{ij}$  = The lag-k cross-correlation coefficient,
- $X_t^{(i)}$  = The time series values of series i,
- $X_t^{(j)}$  = The time series values of series j,
- $\bar{X}_t^{(i)}$  = The mean of the first  $N-k$  values of series i, and
- $\bar{X}_{t+k}^{(j)}$  = The mean of the last  $N-k$  values of series j.

The above statistical parameters were performed in MATLAB 7.14 software by using suitable syntax.

### Result and Discussion

Generally, the significant lags of input variable were found out by trial and error method. A statistical procedure was suggested by Sudheer *et al.* (2002) to avoid the trial and error method. The statistical parameters such as auto-correlation function (ACF), partial auto-correlation function (PACF) and cross-correlation function (CCF) could be used to find out the significant lag values of input variables. The obtained lag values for the input variables were used for the development of model (Table 1).

It was observed that the autocorrelation value of groundwater level for the observation well located at the Manvi (Fig. 1) was highly correlated (0.8963) at one month time lag ( $t-1$ ). Partial autocorrelation analysis (Fig. 2) was carried out for more clarification in selection of input. It was also high (0.9223) at one time lag which lied above 95 per cent upper confidence bound. Selected input for groundwater level was groundwater level data with one month lag time ( $t-1$ ). The cross correlation values between rainfall with groundwater level (Fig. 3) was maximum correlation (0.2563) at 14<sup>th</sup> month but one month time lag (0.1665) was considered as significant lag (Sujatha and Kumar, 2009) [6]. The cross correlation between evapotranspiration with groundwater

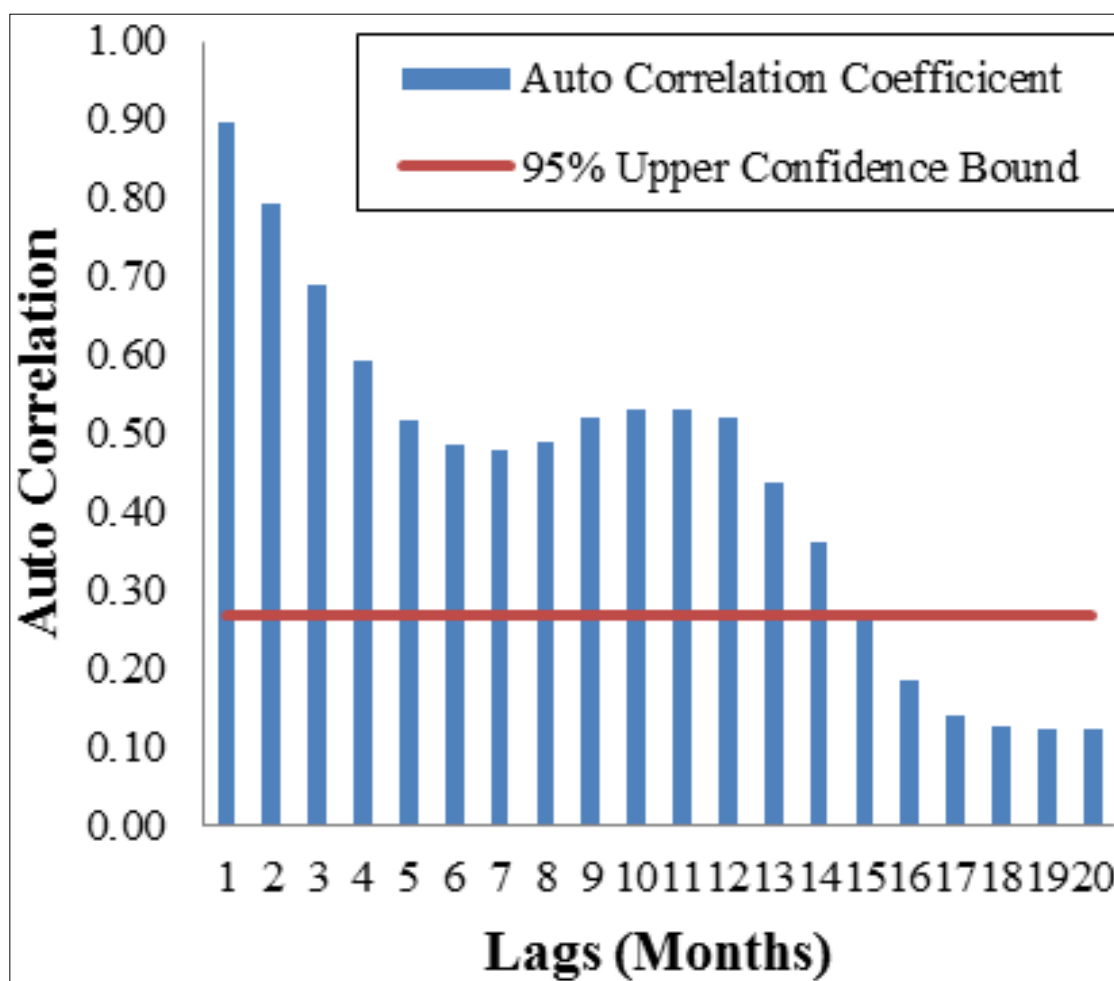
level (Fig. 4) shown maximum correlation (0.2883) at 11<sup>th</sup> month but four month time lag (0.2481) was considered as significant lag (Sujatha and Kumar, 2009) [6] and lied above the line of 95 per cent upper confidence bound.

The results of lags for groundwater level at all the observation wells in the study area were showing the dependency of consecutive month groundwater level with each other. The present findings were similar with the study carried out at

Tirupati mandal by Sujatha and Kumar (2009) [6]. They identified input variables for the observation wells located in study area were RF (t-1), RF (t-2), GWL (t-1), GWL (t-2) and ET (t-1) and Sourabh *et al.* (2016) selected monthly rainfall, ambient temperature and mean river stage and considerable lag for 1 month and 2 month of rainfall, temperature and mean river stage of selected sites as inputs for prediction of groundwater.

**Table 1:** ACF, PACF and CCF of the Manvi observation well

Lags, in months	ACF	PACF	CCF	
			RF with GWL	ET with GWL
1	0.90	0.92	0.17	-0.09
2	0.79	-0.07	0.10	0.11
3	0.69	-0.05	0.16	0.00
4	0.59	-0.01	0.10	0.25
5	0.51	0.07	0.05	-0.14
6	0.48	0.21	-0.01	-0.10
7	0.48	0.13	-0.05	-0.03
8	0.49	0.11	-0.07	0.08
9	0.52	0.11	-0.01	0.20
10	0.53	0.03	0.06	0.27
11	0.53	0.06	0.11	0.29
12	0.52	0.04	0.18	0.26
13	0.44	-0.41	0.24	0.18
14	0.36	0.07	0.26	0.09
15	0.28	-0.13	0.23	0.01
16	0.18	-0.15	0.19	-0.08
17	0.14	0.25	0.15	-0.14
18	0.12	-0.09	0.06	-0.12
19	0.12	-0.04	0.01	-0.06
20	0.12	-0.02	-0.03	0.05



**Fig 1:** ACF of groundwater level for Manvi observation well

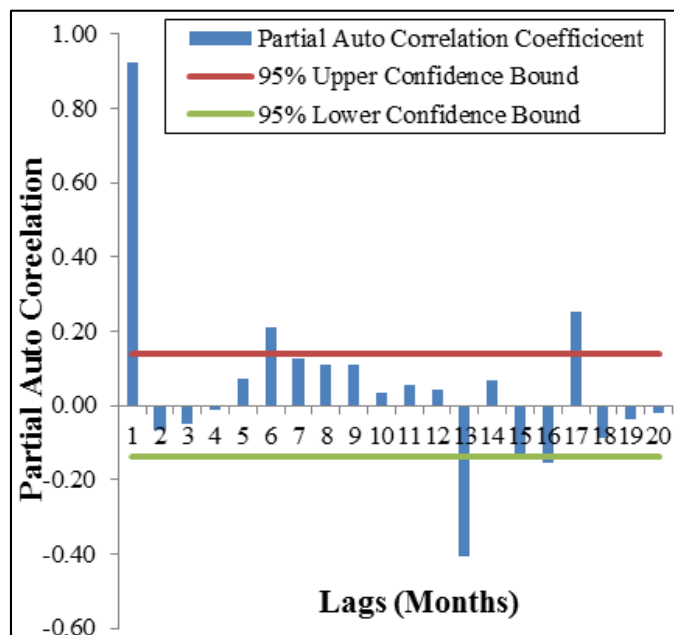


Fig 2: PACF of groundwater level for Manvi observation well

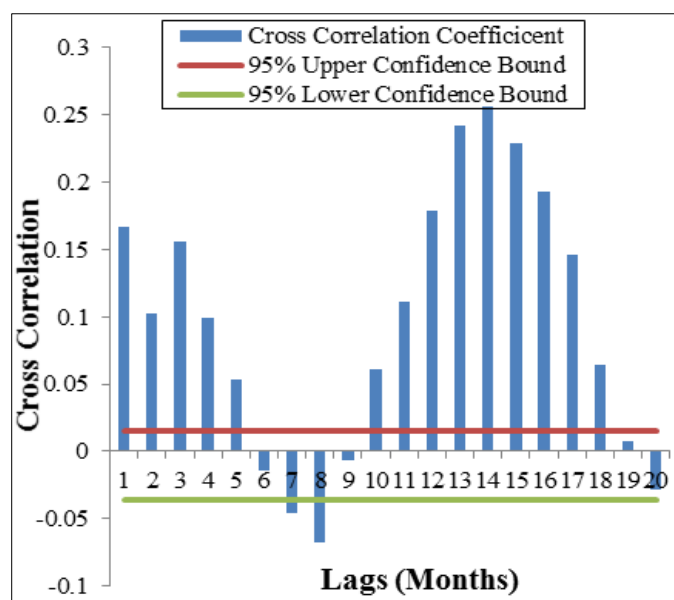


Fig 3: CCF between RF and GWL for Manvi observation well

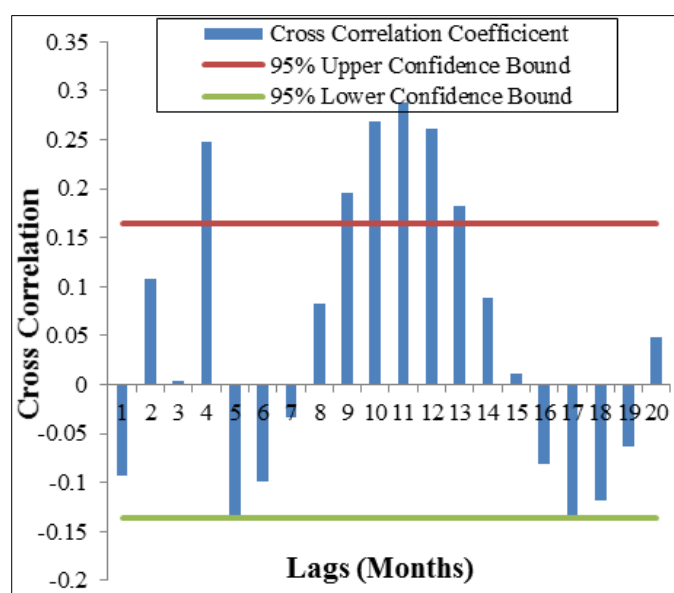


Fig 4: CCF between ET and GWL for Manvi observation well

## Conclusion

Based on the auto correlation function (ACF), partial auto correlation function (PACF) and cross correlation function (CCF) the final inputs were selected optimum lags were RF (t-1), ET (t-4), GWL (t-1) for the selected observation well. The present study shown that, auto correlation function, partial auto correlation function and cross correlation functions were found to be promising methods for selection of desirable input for the modelling.

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