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Forecasting the groundwater levels using the stochastic time series models in hard rock region of Pollachi, Tamil Nadu

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ABSTRACT

The present study aims to investigate the potential impacts of rainfall variation on groundwater levels by analyzing the relationship between long term rainfall data (1936 to 2010) and groundwater levels (1971-2010) for ten observation wells in over exploited blocks (>100) of Pollachi Taluk, Coimbatore, Tamil Nadu. Correlation analysis between rainfall and groundwater level shows that annual rainfall display a moderate correlation with annual groundwater levels and any change in rainfall influences the water level. Groundwater level respond to rainfall variations with a time lag which was evaluated equal to one year using cross correlation. Forecasting of groundwater levels is very useful for planning integrated management of groundwater and surface water resources in a basin or region. In this study, linear stochastic time series models known as Autoregressive Integrated Moving Average (ARIMA) models were used to forecast groundwater levels for Pollachi based on the procedure of model development. The predicted results of the developed models are in close agreement with the observed data. Hence the developed models can be used to forecast groundwater levels with reasonably accuracy in the region under study.

1. INTRODUCTION

Groundwater is one of the major sources of water supply for domestic, agricultural and industrial demands. The increase in population, intensive agriculture practices without scientific manner and rapid industrialization is increasing the demand of water exponentially. Increased water demands will extract the maximum availability of surface water which creates the shortage of water. As scarcity of surface water will likely increase, there will be increasing pressure on groundwater resources (Sethi *et al.,* 2010). High pumping rates of groundwater in excess of replenishment leads to harmful environmental side effects such as water-level declines, drying up of wells, reduction of base flow into streams and lakes, water-quality degradation, increased pumping costs, land subsidence, and decreased well yields (Adamowski and Chan, 2011). In addition, climate change has a significant impact on the quantity and quality of groundwater resources.

Under normal climate conditions, maintaining a sustainable supply of groundwater is a major rising concern. In order to plan for sustainable development, climate change impacts particularly rainfall on groundwater supply need to be considered. Usually, groundwater resources are related to hydrologic processes, such as precipitation and evapotranspiration, and through interaction with surface water. However, the process of recharge the groundwater with rainfall is more complicated than recharge with surface water. Increased evapotranspiration and decreased precipitation as the result of climate change will result in declining groundwater levels, which would cause some wells to become dry while others would become less productive due to the loss of available drawdown (Chen *et al.,* 2004). Under natural conditions, annual groundwater level fluctuation depends on groundwater recharge, which is a function of total precipitation and evapotranspiration. Rainfall trends have good correlations with groundwater level variations (Chen *et al.,* 2002). In this circumstance, assessing the response of rainfall to groundwater is essential for ensuring a sustainable groundwater supply in this region.

The sustainable management of groundwater resources in conjunction with surface waters in a region is very important to ensure the sustainability of surface and groundwater resources. An important component of planning and implementing integrated management of groundwater and surface water resources is accurate and reliable forecasting of groundwater levels (Mohanty *et al.,* 2010). Accurate assessments of groundwater levels allow water managers, engineers, and stakeholders to develop better strategies to reduce adverse effects, to develop a better understanding of the dynamics that affect groundwater levels and to balance the water needs analyze the benefits and costs of water conservation. Forecasting of groundwater level have been attempted by various researchers around the world using time series technique (Zhou *et al.,* 2007; Aflatooni and Mardaneh, 2011) and Artificial Neural Networks (Nayak *et al.,* 2006; Pallavi *et al.,* 2009; Sreekanth *et al.,* 2009; Singh *et al.,* 2008). In this study, we examine the response of groundwater level to rainfall and develop accurate groundwater level forecasting models using time series techniques for Pollachi Taluk, Tamil Nadu.

2. MATERIALS AND METHODS

Study Area

The study was conducted in the Pollachi Taluk of Coimbatore district, Tamil Nadu which covers an area of 1,16,552 ha. This Taluk is divided into 4 blocks (Anamalai, Pollachi North, Pollachi South and Kinathukadavu), which are further divided into 131 villages. Aliyar and Palar are the two important sub basins that drain water from Anamalai hills and flow in the North and Northeastern direction. The normal annual rainfall is 884 mm, of which 47% is contributed by the southwest monsoon and temperature varies from 15 to 37°C. The period from April to June is generally hot and dry. The taluk is underlain by both porous and fissured formations. The important aquifer systems are constituted by unconsolidated formations, weathered and fractured crystalline rocks. The depth of borewells ranged from 25 to 305 m and their yields range from 1.4 to 42 m^3 hr^{-1}. The major crops like paddy, coconut, groundnut, chillies are being grown in the medium to deep red calcareous soils whereas crops like maize, tobacco, sugarcane are sown in red non-calcareous soils.

Rapid increase in the demand of water needs has led to over exploitation of groundwater which has been reflected by the declined groundwater level. According to Central Ground Water Board, blocks in the Pollachi Taluk have been categorised as either over-exploited (>100%) or critical (85-100%). Government of Tamil Nadu, vide G.O. No. 53, has restricted the further groundwater development for irrigation in the over-exploited blocks (except the Anamalai block) of Pollachi. For this study, ten observation wells were considered to assess the groundwater fluctuations (Table 1). Monthly groundwater level of the mentioned observation wells located in Pollachi Taluk and rainfall data for the Pollachi station were obtained from the Office of Groundwater Division, Public Works Department, Coimbatore for the period of 1971 to 2010. The rainfall data was collected for the period of 1936-2010.

Relation between Rainfall and Groundwater Level

The relative importance of rainfall on groundwater level variation is examined by using cross-correlation analysis, which is defined as:

$$C_{xy}(k)=\frac{1}{n}\sum_{t=1}^{n-k}(x_t-\bar{x})(y_{t+k}-\bar{y})\ for\ k=0,1,2,3.. \quad ...(1)$$

$$C_{xy}(k)=\frac{1}{n}\sum_{t=1}^{n+k}(x_t-\bar{x})(y_{t+k}-\bar{y})\ for\ k=0,-1,-2,-3.. \quad ...(2)$$

$$r_{xy}(k)=\frac{c_{xy}(k)}{\sigma_x\,\sigma_y} \quad ...(3)$$

Where $C_{xy}(k)$ is the cross-correlogram, $r_{xy}(k)$ is the cross-correlation coefficient, x_t is the rainfall, y_t is the groundwater level and σ_x and σ_y are the standard deviations of the time series. Since groundwater level response to rainfall variation will display a time delay which is difficult to determine, an apparent time delay is defined as the time shift, in which the two time series reach a maximum correlation (Chen *et al.,* 2004):

$$\Delta t=t,\quad if\ r_{xy}(t)=\max(r_{xy}(1),...\ r_{xy}(n)) \quad ...(4)$$

A non-linear model, consisting of a linear trend can be written as:

$$v=a+b\tau \quad ...(5)$$

Long-term periodicity function used to model the variation of rainfall is written as:

$$w=\alpha+\beta\sin(2\pi(\tau-\omega))/T \quad ...(6)$$

Where, τ is time (yr); a, b, α and β are unknown coefficients; and ω and *T* are phase and periodicity length to be determined respectively. These unknown parameters can be estimated by minimizing ψ in the following equation:

$$\psi=\sum_{i=1}^{N}[y_{\tau}-(v_{\tau}+w_{\tau})]^2 \quad ...(7)$$

In Eq.(7), y_τ are the measured values of rainfall, and $v_\tau+w_\tau$ are the modeled values. The response time of

Table: 1
Location of Observation Wells (OW) in Pollachi Taluk

Sl. No.	OW No.	Location	Block	MSL (m)	Longitude	Latitude
1	63702	Andipalayam	Kinathukadavu	363.39	77°06'00"	10°48'00”
2	63703	Kattampatti	Kinathukadavu	397.49	77°08'40"	10°48'30”
3	63705	Poosaripatti	Pollachi North	378.11	77°07'00"	10°40'15”
4	63708	Puliampatty	Pollachi North	310.82	77°02'00"	10°40'40”
5	63709	Pollachi	Pollachi South	258.16	76°59'20"	10°39'00”
6	63710	M.n.palayam	Pollachi South	250.32	76°53'00"	10°37'45”
7	63716	Ponnayur	Pollachi South	252.94	76°56'15"	10°40'30”
8	63717	Gopalapuram	Pollachi South	211.67	76°52'45"	10°41'30”
9	63718	Poravipalayam	Pollachi South	255.51	76°56'56"	10°43'45”
10	63719	Kinathukadavu	Kinathukaduvu	331.80	77°01'00"	10°49'00"

groundwater level to rainfall (D_t) can be determined using maximum coefficient of correlation between two variables (water level, rainfall). These computations were done using Statistical Package for the Social Sciences (SPSS) software. Other techniques like moving average for revealing long-term rainfall trends, regression analysis to assess the presence of trends (slope estimates) for annual average groundwater levels, and seasonal index using simple average method for monthly mean groundwater levels are also used in the data analysis.

Description of the Stochastic Models

The stochastic models, which are often known as time series models have been used in scientific, economic and engineering applications for the analysis of time series. Time series modelling techniques have been shown to provide a systematic empirical method for simulating and forecasting the behaviour of uncertain hydrologic systems and for quantifying the expected accuracy of the forecasts (Mishra and Desai, 2005).

The autoregressive integrated moving average (ARIMA) model approach has several advantages over others such as exponential smoothing and neural network in particular, its forecasting capability, and its richer information on time-related changes. In most time series, there is a serial correlation among observations. This characteristic is effectively considered by ARIMA model. This model also provides systematic searching stage (*i.e.* identification, estimation and diagnostic check) for an appropriate model. Characteristic of many types of hydrologic time series has periodically varying components. Data of this type may be modelled using a linear stochastic model that is commonly referred to as ARIMA model.

Autoregressive (AR) models can be effectively coupled with moving average (MA) models to form a general and useful class of time series models called autoregressive moving average (ARMA) models. In ARMA model, the current value of the time series is expressed as a linear aggregate of *p* previous values and a weighted sum of *q* previous deviations (original value minus fitted value of previous data) plus a random parameter. However, they can be used when the data are stationary. This class of models can be extended to non-stationary series by allowing differencing of data series. These are called ARIMA models. Box and Jenkins (1976) popularized ARIMA models. The general non-seasonal ARIMA model is AR to order *p* and MA to order *q* and operates on d^{th} difference of the time series z_t; thus a model of the ARIMA family is classified by three parameters (*p, d, q*) that can have zero or positive integral values.

The general non-seasonal ARIMA model may be written as:

$$\phi\,(B)\nabla^d Z_t = \theta(B)a_t \qquad ...(8)$$

Where, ϕ (B) and θ(B) are polynomials of order p and q, respectively.

$$\phi\,(B) = (1 - \phi_1 B - \phi_2 B^2 - ...\ \phi_p B^p) \qquad ...(9)$$

$$\text{and } \theta\,(B) = (1 - \theta_1 B - \theta_2 B^2 - ...\ \phi_p B^p) \qquad ...(10)$$

Seasonal Models

Many hydrologic time series contain cyclic features. These features are primarily due to the earth's rotation about the sun. Such series are cyclically non-stationary. Once the deterministic cyclic effects have been removed from a series, the ARIMA approach can be applied to obtain a linear model for the stochastic part of the series. Box *et al.* (1994) have generalized the ARIMA model to deal with seasonality and define a general multiplicative seasonal ARIMA model, which are commonly known as Seasonal ARIMA (SARIMA) models. In short notation the SARIMA model described as ARIMA (*p, d, q*) (*P, D, Q*)s, where (*p, d, q*) is the non-seasonal part of the model and (*P, D, Q*)s is the seasonal part of the model, which is mentioned below:

$$\phi_P(B)\Phi_p(B^s)\nabla^d \nabla_S^D Z_t = \theta_q(B)\Theta_Q(B^s)a_t \qquad ...(11)$$

Where, *p* is the order of non-seasonal autoregression, *d* is the number of regular differencing, *q* is the order of non-seasonal moving average, *P* is the order of seasonal autoregression, *D* is the number of seasonal differencing, *Q* is the order of seasonal moving average, and *s* is the length of season.

Time series model development consists of three stages which include identification, estimation, and diagnostic checking (Box and Jenkins, 1976). The identification stage involves transforming the data (if necessary) to improve the normality and the stationarity of the time series and determining the general form of the model to be estimated. During the estimation stage the model parameters are calculated using the method of moments, least square methods, or maximum likelihood methods. Finally, diagnostic checks of the model are performed to reveal possible model inadequacies and to assist in selecting the best model. The best model is selected based on a) Low Akaike Information Criteria (AIC) and Schwarz Bayesian Criterion (SBC), b) Insignificance of auto correlations for residuals (Q-tests), and c) Significance of the parameters. Standard computer packages like SAS, SPSS *etc.* are available for finding the estimates of relevant parameters using iterative procedures.

ARIMA parameters are estimated using best fit model so that the statistical criteria such that stationary R-square, R-square (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), maximum absolute error (MaxAE), maximum absolute percentage error (MaxAPE), normalized Bayesian information criterion (BIC) be the least. The monthly groundwater level data from 1972 to 2010 is used for model development and forecasting.

3. RESULTS AND DISCUSSION

In the present study, we evolved the relation between groundwater level and rainfall, built seasonal models to forecast the groundwater level using the time series techniques and discussed in the following sub-sections.

Response of Groundwater Level to Rainfall

The annual mean and 3-year moving average of rainfall monitored at Pollachi for the period 1936-2010 is shown in Fig. 1a. In the stipulated period, rainfall trend in four different seasons *viz.*, (i) Southwest (June to Sep), ii) Northeast (Oct to Dec) (iii) winter (Jan to Feb) and summer (March to May) are presented in Fig. 1b to Fig. 1e. It has been noticed that northeast monsoon is showing steady increase in rainfall, whereas rainfall in all other seasons is declining. The linear regression analysis of annual groundwater (Table 2) level has showed that 50% of the wells had increasing trend (positive trend slope). This indicates that if the current situation persists in future, groundwater level will decline even if we consider that water consumption level will remain same.

Variation of seasonal index of groundwater level for each well and monthly average rainfall is given in Fig. 2. Highest index value of 135% has been noticed for the month June when the groundwater level was highest in the OW 63710, whereas lowest index of 72% is noticed for the OW 63703 in the month of December.

Analyses of annual rainfall and its relation to water level variations show that the annual average water level in all OWs is positively correlated to annual rainfall with a certain time lag. Observation wells having lesser correlation with annual rainfall are in extensive seasonal withdrawal areas. The calculated average correlation coefficient between

Table: 2
Correlation analysis between mean annual groundwater level and annual average rainfall

Sl. No.	OW No	Regression coefficient	Correlation coefficient	Time delay (Year)	Maximum cross correlation
1	63702	0.0991	0.46	1	0.462
2	63703	-0.1081	0.20	1	0.197
3	63705	-0.1374	0.48	1	0.450
4	63708	0.0736	0.43	1	0.494
5	63709	0.0133	0.64	1	0.567
6	63710	-0.0296	-0.05	3	0.187
7	63716	0.0099	0.46	1	0.444
8	63717	-0.0310	0.62	1	0.571
9	63718	0.1042	0.52	1	0.594
10	63719	-0.0300	0.52	1	0.469

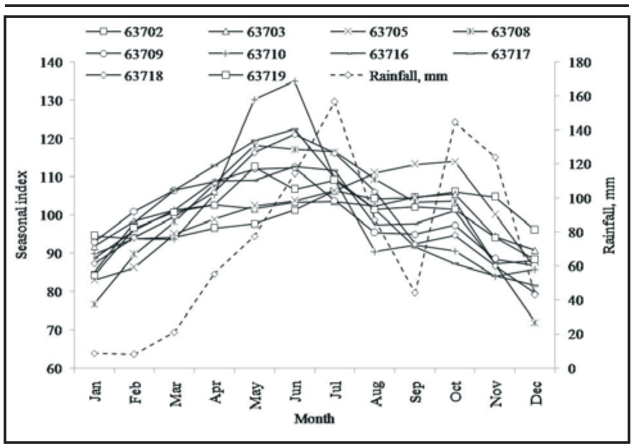

Fig. 2. Seasonal index of groundwater level and monthly mean rainfall of Pollachi

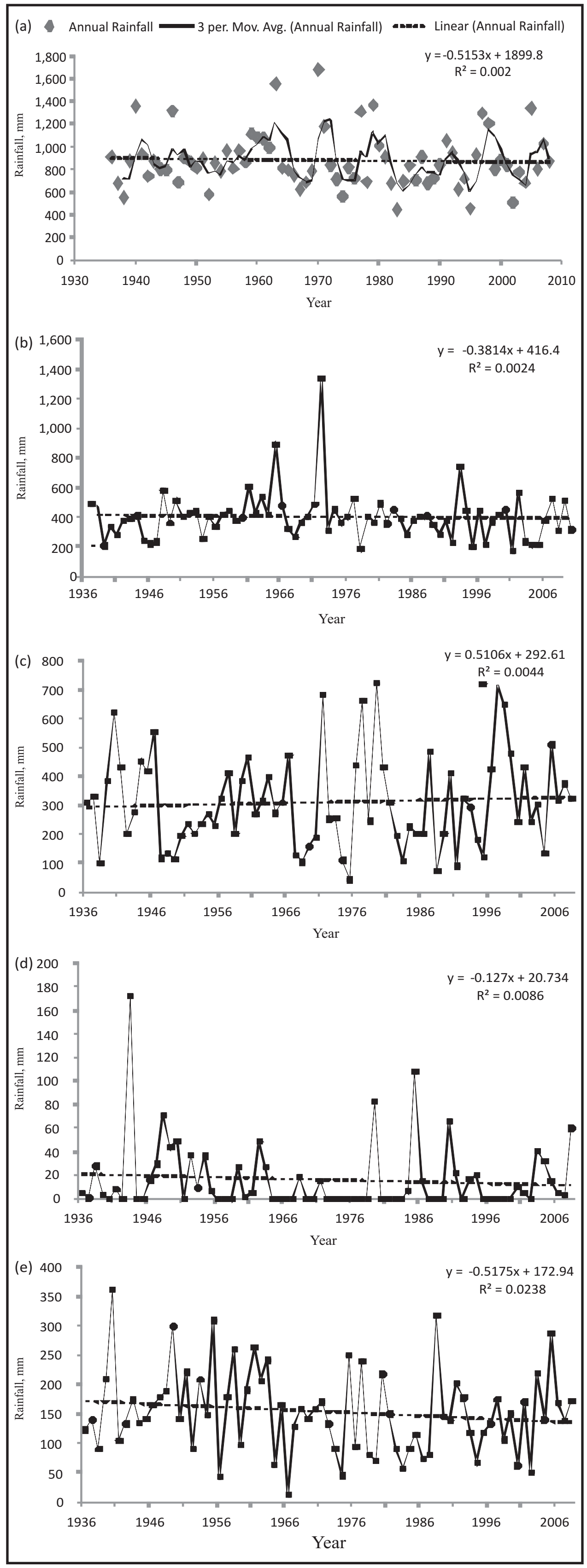

Fig. 1. Distribution of rainfall during 1936 to 2010 (a) annual rainfall, (b) south west monsoon rainfall, (c) north east monsoon rainfall, (d) winter rainfall, (e) summer rainfall

the 3-year moving average rainfall and annual groundwater levels is 0.43. Eighty percent of the wells have a coefficient greater than 0.43 with a maximum on 0.64 (Table 2). The analysis of correlation shows that in majority of wells, change in rainfall influences the groundwater level.

Cross correlation analysis was performed to find out the time delay *i.e.,* response of groundwater to rainfall (Table 2). Results of cross correlation with time lag between rainfall and water table for individual wells have shown that the corresponding time delay with the maximum cross correlation was one year. This means that the rainfall received today will not significantly affect the groundwater level at that well location for about one year.

Forecasting of Groundwater Level

The time series stochastic models for forecasting the groundwater level are developed and the estimates of model parameters along with their statics (standard error, t-ratios and p-values) have been presented in Table 3. The standard errors calculated for the model parameters were generally small compared to the parameter values. Therefore, most of the estimates of parameters are statistically significant and these parameters should be included in the models.

Table: 3

Description of models and statistical analysis of model parameters for ten observation wells

Sl. No.	OW	Model	Parameters			Standard error	t-ratio	Significance P<0.05
1	63702	ARIMA(0,0,4)(1,0,0)12	Constant		345.852	0.549	630.291	0
				Lag 1	-1.044	0.054	-19.235	0
				Lag 2	-0.757	0.076	-9.966	0
				Lag 3	-0.441	0.076	-5.83	0
				Lag 4	-0.27	0.055	-4.918	0
			AR, Seasonal	Lag 1	0.239	0.054	4.454	0
2	63703	ARIMA(1,1,1)(1,0,1)12	MA	Lag 1	-0.009	0.324	-0.029	0.977
			AR, Seasonal	Lag 1	0.996	0.015	64.833	0
			AR	Lag 1	-0.157	0.319	-0.492	0.623
			Difference		1			
			MA, Seasonal	Lag 1	0.972	0.059	16.433	0
3	63705	ARIMA(2,1,5)(1,0,1)12	MA	Lag 2	0.404	0.214	1.885	0.06
				Lag 5	0.181	0.048	3.783	0
			AR, Seasonal	Lag 1	0.999	0.01	97.024	0
			AR	Lag 2	0.377	0.219	1.719	0.086
			MA, Seasonal	Lag 1	0.982	0.094	10.402	0
			Difference		1			
4	63708	ARIMA(2,0,1)(1,0,1)12	MA	Lag 1	-0.932	0.025	-37.997	0
			AR, Seasonal	Lag 1	-0.896	0.061	-14.797	0
			AR	Lag 2	0.799	0.038	21.095	0
			MA, Seasonal	Lag 1	-0.992	0.19	-5.213	0
			Constant		305.305	0.73	418.044	0
5	63709	ARIMA(1,0,5)(0,0,0)12	MA	Lag 1	0.297	0.055	5.403	0
				Lag 2	0.131	0.053	2.498	0.013
				Lag 5	0.253	0.051	4.996	0
			AR	Lag 1	0.958	0.024	39.217	0
			Constant		254.005	0.238	1069	0
6	63710	ARIMA(1,0,0)(1,0,1)12	AR, Seasonal	Lag 1	0.965	0.021	46.624	0
			AR	Lag 1	0.589	0.038	15.37	0
			MA, Seasonal	Lag 1	0.874	0.043	20.185	0
			Constant		246.091	0.346	711.982	0
7	63716	ARIMA(1,0,2)(1,0,0)12	MA	Lag 2	-0.064	0.054	-1.184	0.237
			AR, Seasonal	Lag 1	0.172	0.048	3.605	0
			AR	Lag 1	0.822	0.031	26.903	0
			Constant		245.836	0.503	488.645	0
8	63717	ARIMA(0,1,5)(1,0,1)12	MA	Lag 1	0.191	0.047	4.055	0
				Lag 2	0.159	0.047	3.364	0.001
				Lag 5	0.324	0.047	6.941	0
		AR, Seasonal	Lag 1	0.993	0.015	65.977	0	
			MA, Seasonal	Lag 1	0.957	0.048	20	0
			Difference		1			
9	63718	ARIMA(2,1,2)(1,0,1)12	MA	Lag 1	0.208	0.027	7.694	0
				Lag 2	-0.999	0.19	-5.262	0
			AR, Seasonal	Lag 1	0.943	0.035	27.039	0
			AR	Lag 1	0.212	0.026	8.04	0
				Lag 2	-0.963	0.028	-34.133	0
			MA, Seasonal	Lag 1	0.858	0.058	14.819	0
			Difference		1			
10	63719	ARIMA(1,1,0)(0,0,0)12	AR	Lag 1	-0.277	0.047	-5.948	0
			Difference		1			

Goodness-of-fit measures such as stationary R-square, R-square (R^2), RMSE, MAE, MAPE, MaxAE, MaxAPE, BIC and Ljung-Box Q for best fit model of individual well to assess the model efficiency and accuracy is presented in Table 4. The plot between observed and predicted groundwater levels using the selected best model for all observation wells is shown in Fig. 3. From the Figures, it could be seen that the predicted values of groundwater levels follow the observed values of groundwater level very closely.

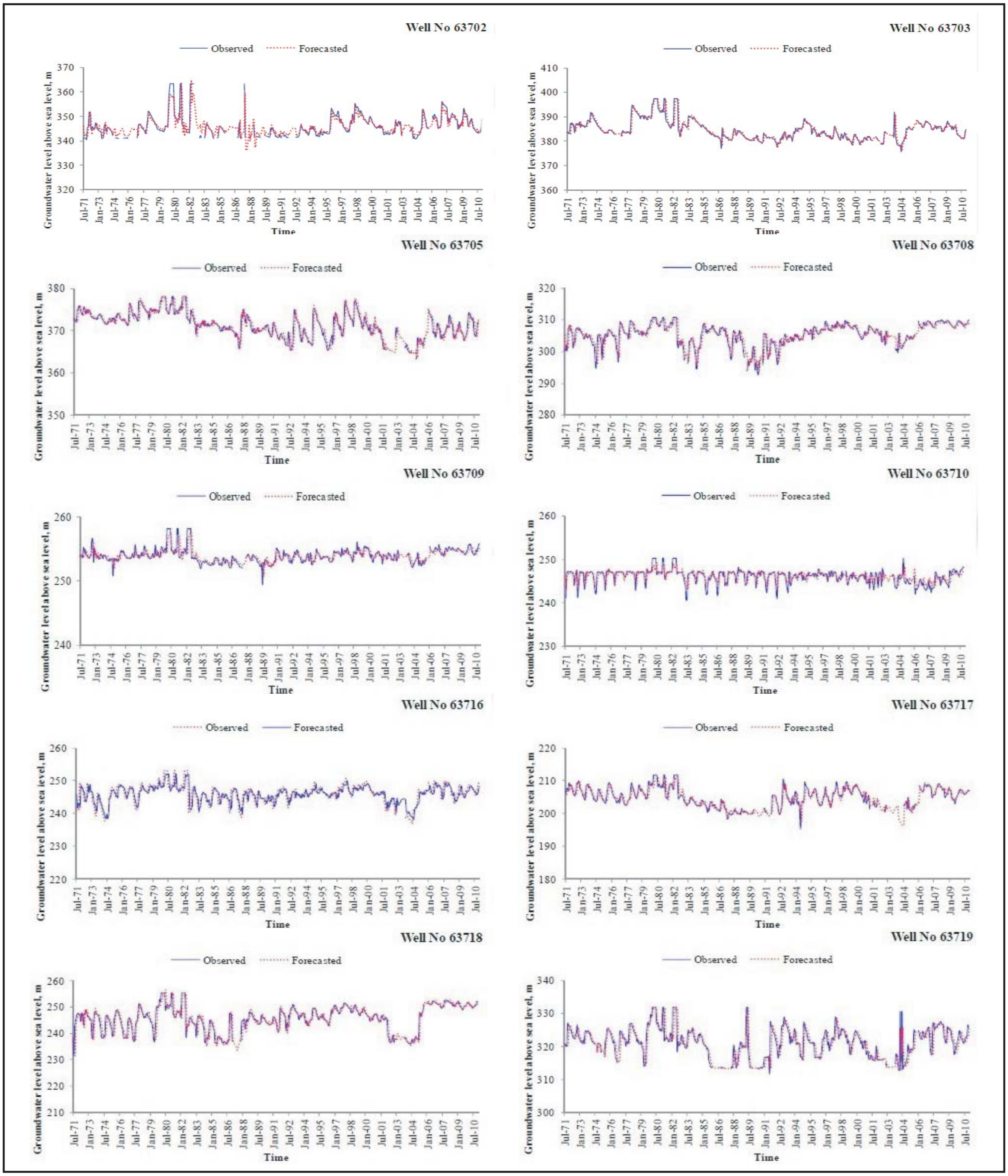

Fig. 3. Comparison of observed groundwater level with forecasted results using ARIMA models

Table: 4
Statistical fit measures for best model of ten observation wells

Sl. No.	Observation wells	Model Fit statistics								Ljung-Box Q(18)		
		Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.
1	63702	0.664	0.664	2.761	0.470	1.639	5.327	18.187	2.122	46.767	13	0.000
2	63703	0.061	0.836	1.648	0.235	0.908	3.425	13.156	1.054	28.689	14	0.012
3	63705	0.150	0.832	1.232	0.210	0.780	2.163	8.113	0.485	22.992	13	0.042
4	63708	0.789	0.789	1.668	0.354	1.074	2.708	8.278	1.090	15.479	14	0.346
5	63709	0.603	0.603	0.705	0.180	0.458	1.438	3.713	-0.632	23.945	14	0.047
6	63710	0.418	0.418	1.239	0.337	0.828	2.369	5.717	0.482	23.967	15	0.066
7	63716	0.699	0.699	1.580	0.429	1.052	4.744	11.405	0.968	19.626	15	0.187
8	63717	0.186	0.795	1.343	0.426	0.874	3.095	6.190	0.660	21.405	13	0.065
9	63718	0.062	0.794	2.166	0.485	1.188	6.772	16.179	1.627	24.628	12	0.017
10	63719	0.077	0.588	2.794	0.490	1.579	5.436	17.972	2.069	30.008	17	0.026

4. CONCLUSIONS

Potential impacts of rainfall on groundwater levels are investigated by analyzing the relationship between historical rainfall records and water levels in the observation wells in Pollachi Taluk of Coimbatore district, Tamil Nadu. Analysis of seasonal and annual rainfall indicated that Northeast monsoon is showing steady increase in rainfall, whereas rainfall in all other seasons is declining. The linear regression analysis indicated that decreasing trend was observed in the half of the total observation wells studied. Seasonal variation of groundwater with rainfall was high in June month and low in December. The analysis of correlation shows that in majority of wells, change in rainfall influences the groundwater level. Maximum cross correlation analysis indicates that response of groundwater to rainfall was one year. Time series ARIMA models have been developed to estimate the future pattern of groundwater for water resource planning and management.

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