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SIMULATING GROUNDWATER FLOW USING NUMERICAL MODEL AND ARTIFICIAL NEURAL NETWORK - A CASE STUDY

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Abstract: **There are many environmental concerns to the quantity of surface water and groundwater in the hydrological system. It is very important to estimate the groundwater levels by using readily available data for managing the water resources. Worldwide concern for the sustainability of groundwater resources, basin-wise modeling of groundwater flow is essential for the efficient planning and management of groundwater resources in a groundwater basin. This study aims to evaluate the performance of finite difference-based numerical model MODFLOW and an artificial neural network model, applied to simulate groundwater levels in Sindapalli Uppodai sub basin of Vaippar River basin, Tamilnadu, southern India. Among the different robust tools available, the Back-Propagation Neural Network (BPNN) model is commonly used to empirically forecast hydrological variables. Calibration of the MODFLOW was done by using monthly groundwater level data of 4 years from June 2006 to May 2010 and validation of the model was done using six month from June 2010 to December 2010 groundwater level data. Groundwater levels at 25 observation wells were simulated for the validation period. The inputs to the Artificial Neural Networks (ANN) model consisted of monthly rainfall, evaporation, water level in the small storage structures and groundwater levels in these wells at the previous time step. The time periods used in the MODFLOW were also considered for the training and testing of the developed ANN model. The simulated groundwater level by MODFLOW and ANN model were compared with the observed groundwater levels. The average regression coefficient for MODFLOW is 0.967 and back propagation neural network is 0.99 during fitting and 0.88 during forecasting respectively. It was found that the ANN model predicting the groundwater levels in the study area similar to the numerical model for short-horizon predictions.**

Keywords: **Groundwater flow modeling – MODFLOW Numerical - Artificial neural network – BPNN - Sindapalli Uppodai sub basin.**

1. INTRODUCTION

Across the world, the concern for water resources is growing as a result of population growth, climate change, and alarming signs that in some areas of the world, groundwater resources are being depleted at an unsustainable rate. This has prompted a re-examination of the world's water resources. In many countries, to meet the increased demand for water, groundwater resources must be tapped. However, to ensure sustainability, much greater emphasis must be put on groundwater management than on exploration for new groundwater resources in the drought prone and hard rock areas. Groundwater is particularly important in arid and semi-arid regions that lack perennial sources of surface water due to low rainfall and high evapotranspiration. (S.Ahmed et.al, 2008).

From the past three to four decades it was observed that the extensive use of groundwater resources in most of the irrigation area and public water supplies due to the scarce availability of the surface water. This situation is due to over exploitation of groundwater resources or monsoon failure results the reduction in recharge rate. However, the aquifer depletion due to over-exploitation and the growing pollution of groundwater are threatening our eco-systems water availability (Bouwer, 1999; Sophocleous, 2005, Sophocleous 2010). Thus, most of the weathered zones in hard rock regions become an unsaturated zone. Excessive pumping has led to alarming decrease in groundwater levels in several parts of the country like Gujarat, Haryana, Orissa, Punjab, Rajasthan, Tamil Nadu and West Bengal (CGWB, 2006). Hence, the key concern is how to maintain a long-term sustainable yield from aquifers (Hiscock et al., 2002; Alley et al., 2004) desires that the essential of the study and evaluation of the groundwater potential in micro watershed or sub basin scale. For the evaluation of the groundwater potential numerous variables comes into play like rainfall, effects of vadose zone, topography, land use, porosity, hydraulic conductivity, irrigation return flow and tank seepage, etc (MoWR, 1997)

Groundwater management in hard-rock areas in semiarid climates, where aquifers exist in the upper weathered-fissured section of the system; these aquifers receive little recharge, and have different and more complex characteristics than in classical sedimentary media. Specialized techniques are thus required to characterize and manage them. Groundwater modelling has produced answers to many difficult questions that arise in the course of hydrogeological investigations. During past two decades numerous of groundwater modelling studies have been carried out around the world for effective groundwater management in different basins using MODFLOW and other models (Corbet and Bethke 1992; Reichard, 1995; Gomboso et.al., 1996; Storm 1998; Rodriguez et al., 2006; Al-Salamah et al., 2011).

In recent years, the simulative capabilities of ground-water flow models have been enhanced by the development of increasingly sophisticated methods of representing the effects of external hydraulic influences on heads and flow patterns in ground-water systems. Heads in surficial aquifers, in particular, can be strongly affected by the hydraulic influence of bodies of surface water and by exchanges of water volumes with the overlying atmosphere. In particular the influence of surface water, such as lakes, that are in direct contact, vertically and laterally, with the surficial aquifer. Groundwater flow was simulated using the modular, three-dimensional, finite difference groundwater flow model MODFLOW-2000 (McDonald and Harbaugh, 1996, Harbaugh, et.al, 2000).

Traditional numerical methods, with specific boundary conditions, are able to depict the complex structures of aquifers including complicated prediction of groundwater levels (Singh et al., 2007). But the physically based groundwater simulation models are the vast and accurate data required and are difficult to obtain owing to spatial variations, characteristics of hydrogeology and their availability. Empirical models generally require less data and less effort in comparison to physically based models. ANN models are one of such models, which are treated as universal approximates and is very much suited to dynamic nonlinear system modeling (ASCE, 2000). Many hydrologists have attempted to use modern statistical models and techniques in water resources forecasting including ANN in recent years. The ability to learn and generalize from sufficient data pairs makes it possible for ANNs to solve large-scale complex problems. A few studies have been done on the use of neural networks for groundwater level forecasting (Coulibaly et al., 2001; Coppola et al., 2003, 2003a; Lallahem et al., 2005; Daliakopoulos et al., 2005; Nayak et al., 2006; Banerjee et al., 2009 and Ghose et al., 2010). Aziz and Wong (1992) illustrated the use of ANN for determining the aquifer parameter values from the normalized drawdown data obtained from the pumping test data, commonly referred as the inverse problem in groundwater hydrology. This study drew the pattern recognition ability of an ANN based on aquifer test data. From the measured drawdown the storativity (S) and Transmissivity (T) were found.

There are many different neural networks but for forecasting groundwater flow is almost always trained using back propagation. This may be due in part to the fact that BPNN were the first successful models to be implemented (Rumelhart et al., 1986, Shepherd, 1997), and because the algorithm is simple to program and apply. The BPNN has a simpler structure and algorithm than others, and is applied widely in groundwater and other fields with encouraging results, though it has some defects (Coulibaly et al., 2001). Many of the authors (Zakermoshfegh et.al, 2004, Napiorkowski and Piotrowski, 2005, Senthilkumar et.al, 2005, Piotrowski et.al, 2006) have applied BPANN for the prediction of various hydrological applications. In the present paper, a groundwater flow simulation model has been developed using Visual MODFLOW, an empirical ANN model has been developed for forecasting groundwater level and comparison between both the models has been done. For this study Sindapalli Uppodai sub basin area of Vaippar River basin, Tamilnadu, India has been selected.

2. STUDY AREA

Sindapalli Uppodai is a sub basin of Vaippar river basin which is shown in figure 1. It receives drainage from its own catchment. It originates from the plain terrain near Duraisamypuram village of Sivakasi taluk and it runs for a distance of 25 km and finally empties into Arjunanadhi River near Allampatti village and sub basin has a width of 17 km, which covers an area of 142 km^2. The Location of the sub basin is Latitude of 9º20’00”N to 9º27’00”N and Longitude 77º44’00”E to 77º58’00”E and in the Taluks of Sivakasi and Sathur in Virudhunagar district, Tamil Nadu, India. The altitude varies from 130 m in western side to 60 m in the eastern side above MSL. The maximum temperature ranges from 30.16˚C to 40.34˚C and the minimum temperature ranges from 20˚C to 27˚C respectively. The sub basin monthly average pan evaporation is 196.86 mm and average annual rainfall is 720 mm which is falls under the semi arid region. Geologically the entire sub basin can be classified in to hard rock and sedimentary formation of alluvium and tertiary. Major part of the sub basin is covered by gneissic groups of rocks which include garnetiferous gneissic, hornblende gneiss, mica gneiss, pink and grey granitic gneisses.

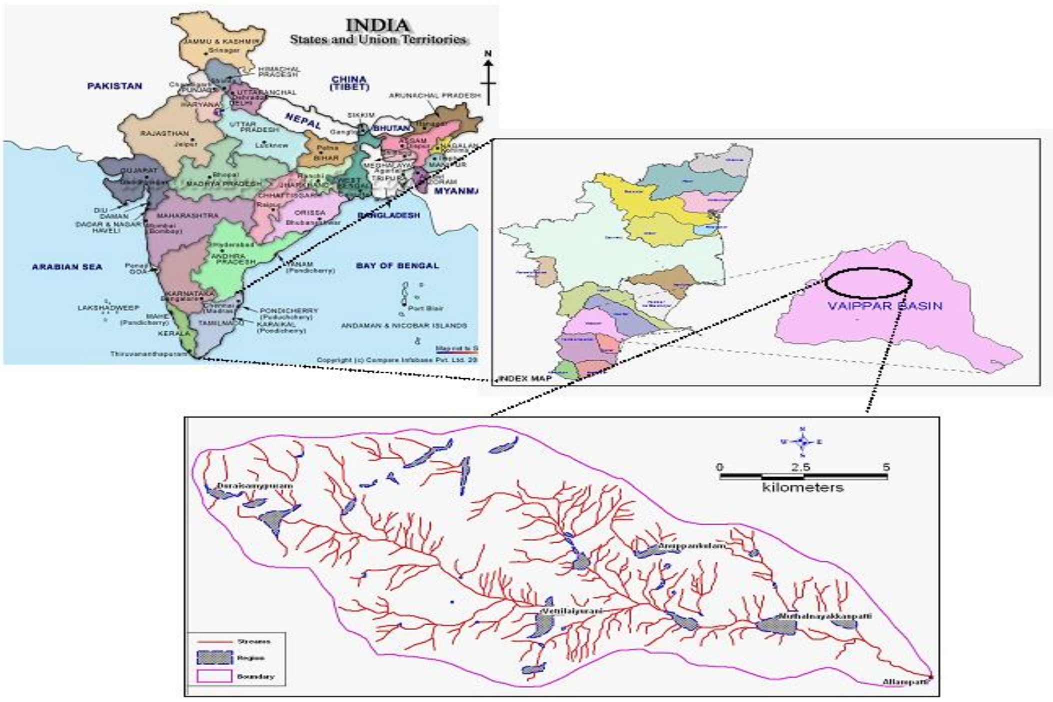

Fig. 1 Study Area Sindapalli Uppodai Sub basin

3. MATERIALS AND METHODS

3.1 Data Collection and Analysis:

The existing data on the aquifer extent, lithology, aquifer parameter, collection of maps, rainfall data, historic water level variations and meteorological data have been collected from the from the Institute for Water Studies (IWS) and surface and Groundwater data centre (SSGDC) of state Public Works Department of Tamilnadu. The meteorological data like rainfall, pan evaporation data, temperature, wind speed, humidity and sunshine hours etc, have been collected from the IMD Kavalur Meteorological station. The spatial data of study area such as soil, land use, geology, geomorphology and lineament were collected in the form of maps in the same scale of 1:50,000. The depth to water table and aquifer parameters are observed and calculated from the field measurements.

3. 2 Groundwater Flow Simulation using Visual MODFLOW:

Groundwater modelling can be used to simulate the flow and transport processes in an aquifer. A groundwater model can be used in an interpretative sense to gain insight into the head distribution and the flow pattern within a watershed. Further it is used to assess different scenarios that may occur in the future or to assess and better understanding processes that have already occurred. Over the last two decades the environmental industry has seen a dramatic increase in the application, understanding and acceptance of groundwater numerical modeling techniques for simulating groundwater flow and contaminant transport. A groundwater flow simulation model was developed using Visual MODFLOW for simulating groundwater scenario in the study area as shown in figure 2. Visual MODFLOW, which integrates the MODFLOW for simulating the flow, MODPATH for calculating advective flow pathlines, MT3D/RT3D for simulating the transport and SEAWAT for simulating coupled flow and transport processes is not only a versatile and robust model for simulating groundwater flow, but also an easily accessible model and is used by the researchers worldwide (Wilsnack et al., 2001; Fleckenstein et al., 2004) and become worldwide standards for 3-D groundwater flow and contaminant transport modeling. MODFLOW is a modular three-dimensional finite difference groundwater flow model (McDonald and Harbaugh 1988), which simulates steady/transient groundwater flow in complex hydraulic conditions with various natural hydrological processes and/or artificial activities.

3.2.1 Conceptual model:

The conceptual model of the hydrogeologic system was derived from a detailed study of the geology, borehole lithology and water table fluctuations in the wells. Groundwater of the study area was found in the top 20 m weathered zone of gneisses and charnokites. In this study, the weathered rock formation zone was considered because none of the wells enter below the weathered rocks, so that nothing can be said about the size and main direction of the fractures. To simulate the groundwater flow in the study basin as a single unconfined aquifer consist of two sub layers, the upper layer having clay as a soil and lower as weathered rock layer and this aquifer was conceptualized as an unconfined two – layered aquifer. The upper layer represents the shallow topsoil with a thickness ranging from 1 to 2 m. The bottom layer represents the weathered rocks with a thickness ranging from 2 to 20 m. Layer data have been arrived by interpolating values from borehole lithologs, which provides a basis for the design and development of the numerical model of the study area using Visual MODFLOW software.

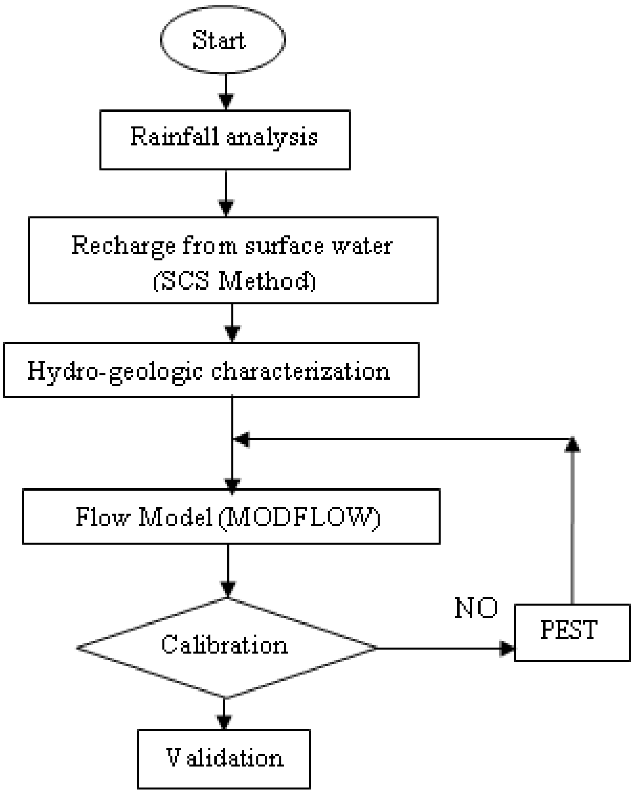

Fig. 2 Flowcharts for Groundwater Flow Modelling

3.2.2 Governing Equation:

Based on the conceptual model of the study basin, the governing groundwater flow equation given below is restricted to fluids with a constant density or in cases where the differences in density or viscosity are extremely small or absent (Anderson and Woessner, 1992; Barends and Uffink, 1997). This equation is derived mathematically by combining a water balance equation with Darcy's law.

$$\frac{\partial}{\partial x}\left(K_x \frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(K_y \frac{\partial h}{\partial y}\right)+\frac{\partial}{\partial z}\left(K_z \frac{\partial h}{\partial z}\right)=S_s \frac{\partial h}{\partial t}-W^* \tag{1}$$

Where, Kx, Ky, Kz = components of the hydraulic conductivity tensor [LT-1]; Ss= specific storage [L-1]; W* is the general sink/source term that is intrinsically positive and defines the volume of inflow to the system per unit volume of aquifer per unit of time [T-1]; h= is the groundwater head [L]; x, y, z = Cartesian coordinates [L]; t = time [T]

3.2.3 Topography and Grid Development:

The study area was discretized into 42,500 cells with 170 rows and 250 columns Grid module of Visual MODFLOW software. The length of the each cell was 100 m along the east–west and north-south direction. The cells lying outside the study area were assigned as inactive cells. The grid elevation was obtained from the Engineering survey and GPS survey which was carried out in the field and also the remote sensing data Shuttle Radar Topographic Mission (SRTM) 90m resolution data were utilized for developing the model grid elevation. The SRTM collected interferometric radar data that were used to generate global, high-quality DEMs at resolutions of 1 and 3 arc seconds, for latitudes less than 60° (Rodriguez et al. 2004, Rabus et.al 2003). The Digital Elevation Model is shown in figure 3 and Grid cells were shown in figure 4.

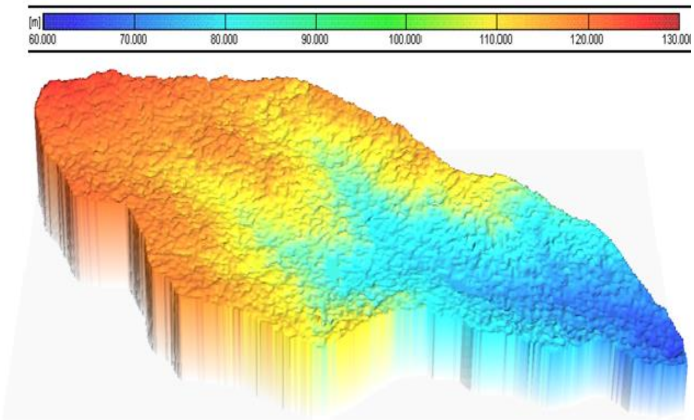

Fig. 3 Digital Elevation Model of Sindapalli Uppodai Sub basin

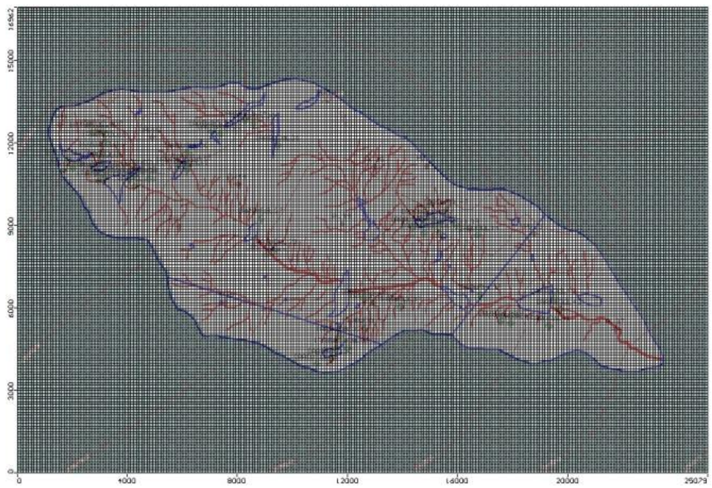

Fig. 4 Grid cells of the Model area with active and inactive cells

The elevation database was created for all the 25 well locations using excel for importing elevations to the model and interpreted to the entire model domain. The following fig. 5, fig.6 and fig.7 shows the ground surface elevation contour varies from 132 m at upstream side and 66 m at downstream side and variations of elevation in longitudinal and transverse direction.

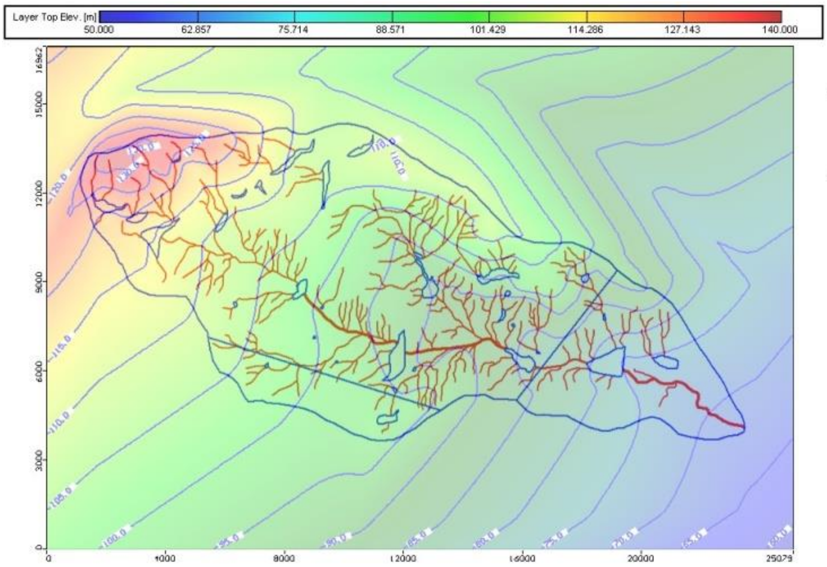

Fig. 5 Ground surface elevation contour

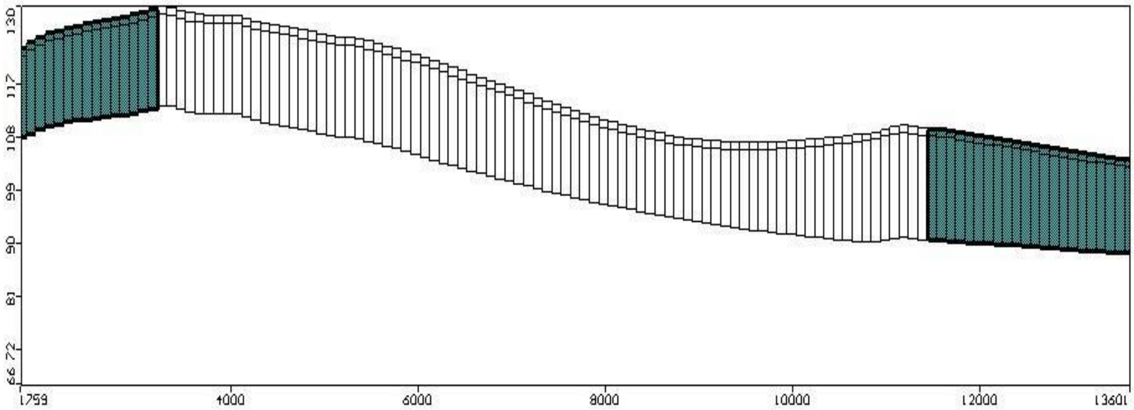

Fig. 6 Variations of elevation in longitudinal direction

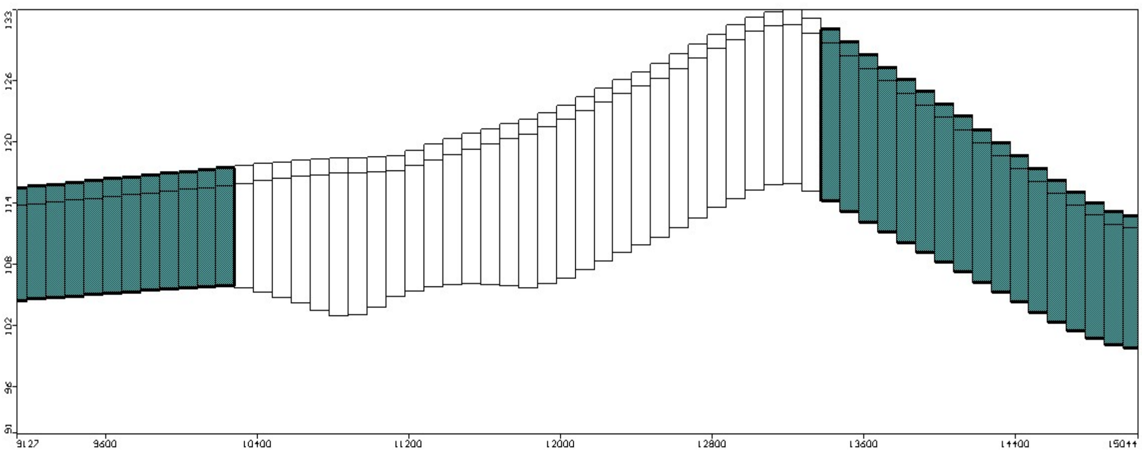

Fig. 7 Variations of elevation in transverse direction

3.2.4 Water level data:

The monthly water level data collected from PWD in three observation wells in the study area from the period of June 2006 to May 2010 have been taken for model calibration. In addition, groundwater levels from the 25 wells spread over the study area were monitored month wise. Water level fluctuations are found to be varying from 2 m to 12m.

The location of observation wells and pumping wells are imported from database. The observation wells consist of the Irrigation wells which are monitored and the data obtained from the Public Works Department has been considered for the flow modeling. The pumping well locations were taken based on the demand of that area and located as the representative pumping well of the area.

3.2.5 Aquifer Characteristics:

The aquifer properties such as horizontal and vertical hydraulic conductivity (K_x & K_y), specific yield (S_y), used in this model were obtained from the pumping test analysis carried out in the field both dug wells as well as bore wells and results from Public Works Department (PWD) were used. By using Theis method the Time vs. Drawdown and Residual drawdown vs. t/t' at Vetrilaiyurani location is obtained and presented in figure 9 and figure 10. These were tabulated in table 1.

Table 1 Pumping Test Analysis

Well No	Name of the Village	Lithology	K (m/day)	S
PW1	Maraneri	2.3m Clay with Sand and Silt, 5.8m Weathered Granite, 12.3m Granite Gneiss (Hard)	16	0.02
PW2	Duraisamypuram	0.8 m Clay with Sand 5.2m Weathered Granite, 12.5m Granite Gneiss (Hard)	14	0.02
PW3	Vetrilaiyurani	0.6m Top Soil, 1.5m Sand stone, 2.6m Lime Stone, 3.4m Gneiss Weathered, 5.78m Granite	16	0.022
PW4	Annuppankulam	1.2m Top Soil, 3m Sand, 9.1m Gneiss Weathered, 12.5 Granite	10	0.016
PW5	Muthalnayakkanpatti	1.1mTop Soil, 2.1m Sand stone, 5.6m Gneiss Weathered, 10.75m Granite	20	0.027

3.2.6 Aquifer properties:

Based on the lithology, aquifer properties such as hydraulic conductivity, porosity, specific yield and initial head were assigned for 25 well locations. These point values were then converted into spatial distribution through construction of thiessen polygon with 25 wells as a nodal point for thiessen polygon construction. The aquifer is assumed to have horizontal isotropic (k_x = k_y) and vertical conductivity is taken as 0.1 times of k_x. The distribution of hydraulic conductivity, porosity and specific yield for each layer is shown in Table 2.

Table 2 Range of Aquifer Properties

Layer	Hydraulic Conductivity (m/s)	Porosity	Specific Yield
1	1.05 E^{-06} to 1 E^{-04}	0.26 to 0.48	0.018 to 0.028
2	1.2 E^{-08} to 5.5 E^{-06}	0.28 to 0.50	0.022 to 0.036

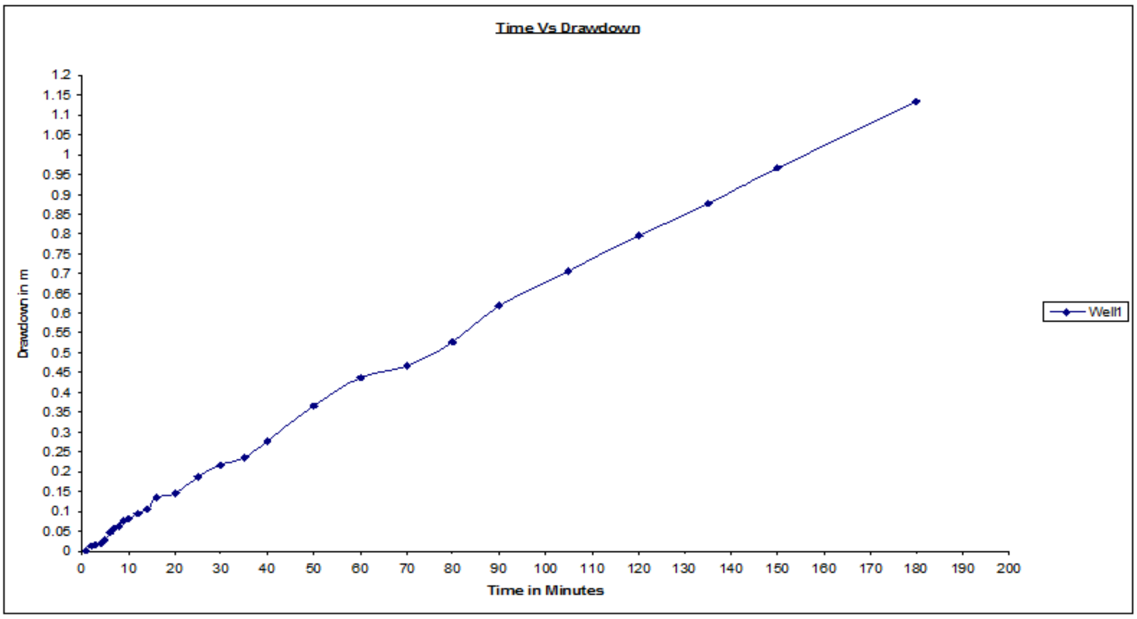

Fig. 8 Time Vs Drawdown of the Pumping Test analyses at Vetrilaiyurani

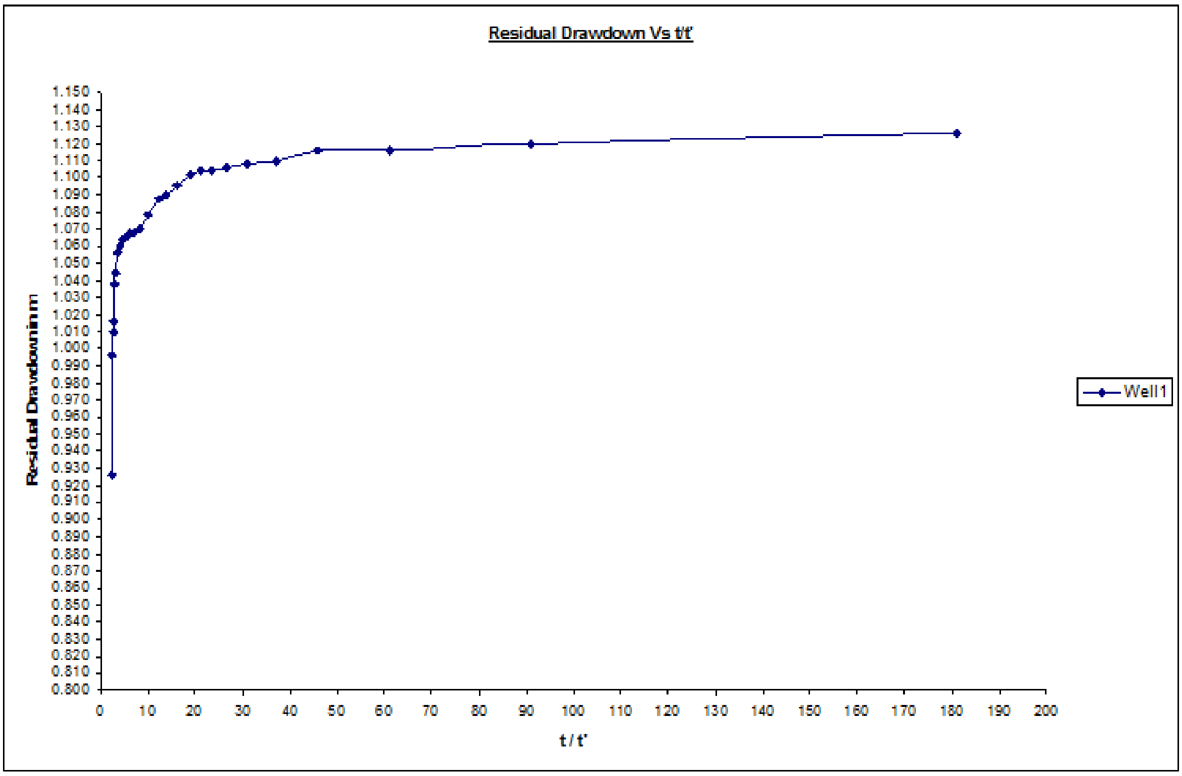

Fig. 9 Residual drawdown Vs t/t'of the Pumping Test analyses at Vetrilaiyurani

3.2.7 Boundary conditions:

Boundary conditions were assigned for the study area based on the interpretation made using borehole lithology and physiography. The sub basin boundary conditions of east, south and north was considered as general flow boundary because of the subsurface flow which was identified based on the water table contours over the long term analysis. Ridge lines along the Western and some parts of the Northern boundaries were taken as no flow boundaries in the groundwater model because it is typical for the groundwater divides to closely follows surface water divides in the study area. Other boundary condition was given as stream head boundary along the stream course of the Sindapalli Uppodai Sub basin.

3.2.8 Groundwater Abstraction:

In this study region prior to 1975, groundwater was withdrawn mostly from shallow, open dug wells. They were more than 10 m in diameter and reached depths of 12 to 18 m, tapping mostly the weathered zone, which was fully saturated with water; fluctuations in water levels typically occurred about 3 to 5 m below ground level. This scenario has changed totally because of well drilling from 1975 to 1985. Bore wells 15 cm in diameter started tapping the fractured aquifer. The depths of the bores initially ranged from 25 to 30m in 1970–80. These wells tapped both the weathered and weathered-fractured zones and the dug wells were also used as reservoirs to store water. Due to increasing demands commensurate with a large increase in the rural population, bore wells were drilled to depths of more than 60 to 70m in the period 1980–90. The average yield of wells in these rocks ranges from 10 to 100m^3/d. The net result of the drilling has been that a large part of the weathered zone has dried up. The dug wells have become defunct due to water-level decline, and, presently, most of them are abandoned. Historical data of Indian water levels for the past two decades indicate that they have typically declined by 6 to 8m in the discharge zones, and by 12 to 15m on average and up to 25m in the withdrawal areas (Subrahmanyam et al., 2000).

Groundwater is extracted through dug well, dug-cum-bore wells for agriculture, industrial and other purposes. In summer season most of the dug wells get dry. Pumping rate was calculated based on number of wells and duration of pumping hours in a day. The pumping rate of the sub basin works out to be 16 MCM per year, which is cross verified with the PWD records. Figure 10 shows the monthly groundwater pumping at the sub basin.

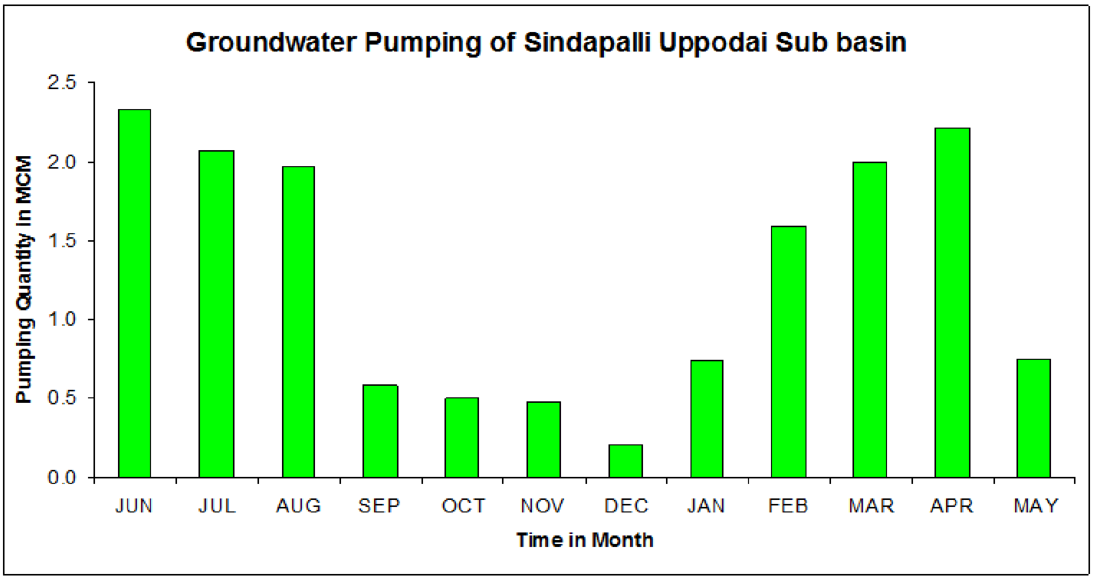

Fig. 10 Monthly Average Groundwater pumping of Sindapalli Uppodai Sub basin

3.2.9 Estimation of recharge rate:

A GIS based Soil Water Balance approach was used to determine groundwater recharge in the study area. Surface runoff from rainfall was calculated from SCS-CN method combined with GIS technique. The rainfall data and evaporation values were collected from Kavalur meteorological station, PWD, Virudhunagar. Based on this method rainfall recharge rate was computed. The recharge rates are found to vary from 8% to 16% of rainfall and the same is adopted for each year as input to the model. These recharge rates were used for the model calibration. The computed recharge values are within the range of values recommended by the Groundwater Estimation Committee (GEC 1997) norms. It is estimated that the stream recharge, return flow from irrigation field and infiltration for each month as per GEC-1997 norms and the average recharge rates are presented in figure 12.

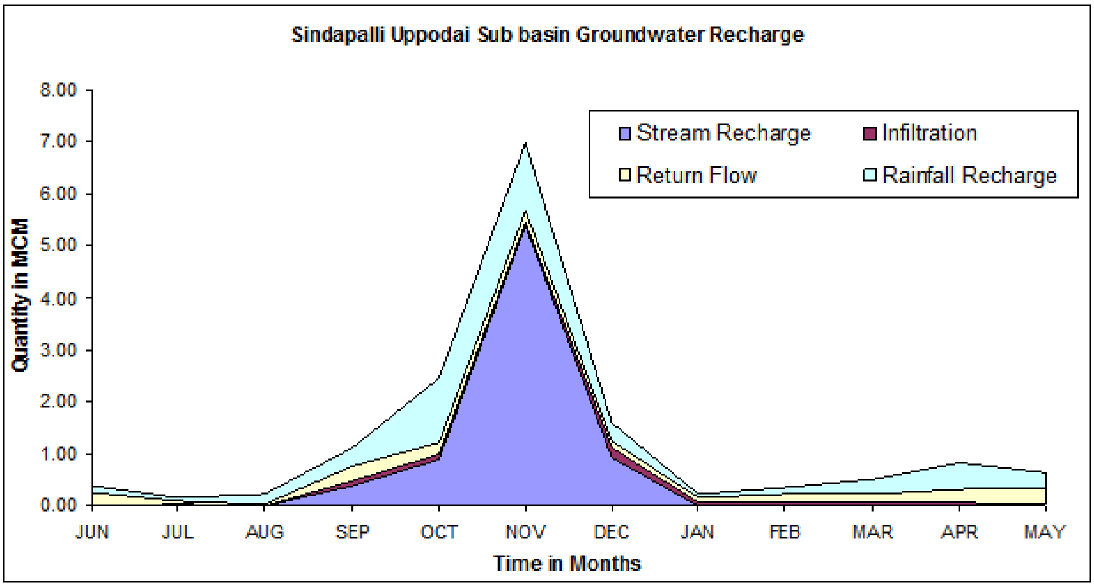

Fig. 11 Monthly Groundwater Recharge of Sindapalli Uppodai Sub basin

The recharge in this area varies considerably due to land use pattern, soil types and topography. Rainfall is the prime source for groundwater recharge. A comparison between the monthly rainfall value and consequent variation in the groundwater table over a span of 30 years revealed that the groundwater is replenished whenever the monthly rainfall exceeds 70 mm. The other sources of groundwater recharge in this area are small storage tanks and it was arrived at the model from difference between the water level in the tank and the groundwater table.

3.2.10 Model calibration and validation:

The developed groundwater-flow simulation model was first calibrated for the steady-state condition and then for the transient condition. The steady-state calibration was achieved by matching the model-calculated groundwater levels with average groundwater-levels observed in the 25 observation wells during 1st June 2006. The solution of the steady-state calibration was used as an initial condition for the transient calibration. Transient calibration was performed using monthly groundwater level data of 25 selected sites for the period June 2006 to May 2010, following the standard procedures (Anderson and Woessner, 1992; Zheng and Bennett, 2002; Bear and Cheng, 2010). A combination of trial and error technique and automated calibration code PEST was used to calibrate the developed flow model by adjusting the hydraulic conductivity, specific storage and recharge within reasonable ranges. The calibration results were evaluated relative to the observed values at the 25 sites by using statistical indicators and comparing observed and simulated groundwater level hydrographs.

After calibrating the model, validation was performed using the observed groundwater level data from June 2010 to December 2010. The calibrated hydraulic conductivity and storage coefficient values were used during validation of the model whereas other input parameters like pumping, heads in the small storage, recharge and observation head of the corresponding validation period were also used.

3.2.11 Sensitivity Analysis:

Sensitivity analysis quantifies the uncertainty of the calibrated model, aquifer parameters, stresses and boundary conditions (Scanlon et al 2003). The nonuniqueness of the calibrated model can be evaluated using sensitivity analysis. The hydrologic parameters that have the greatest impact on simulated water levels can be identified through sensitivity analyses. The sensitivity analysis is carried out in the calibrated model to assess the effect of recharge. The sensitivity of model input parameters on change of head is shown in Figure 12.

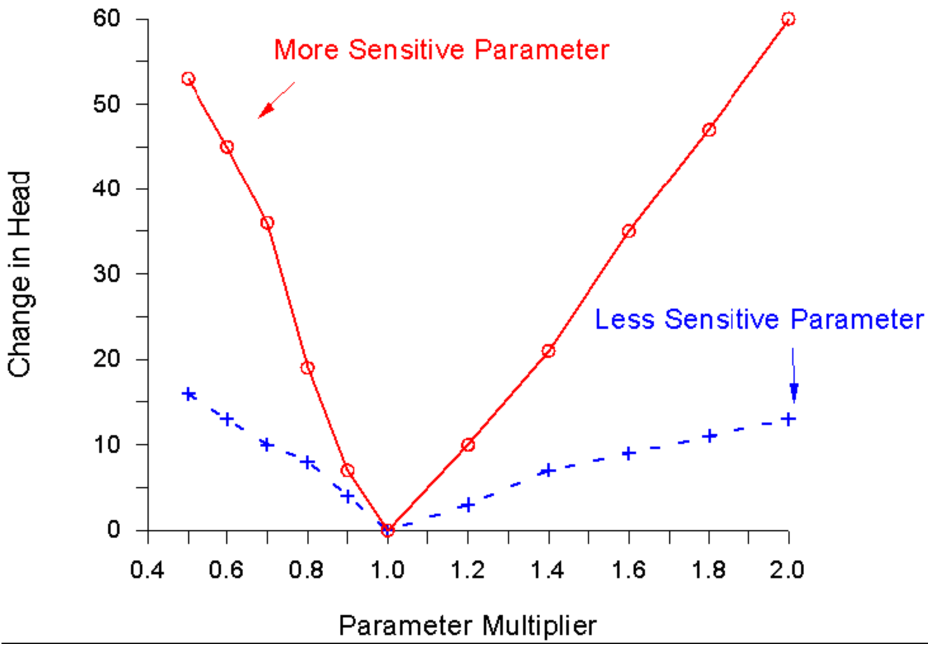

Fig. 12 Sensitivity analysis on the model input parameters

3.3 Groundwater Level Forecasting using Artificial Neural Networks:

BPNN is a widely used and effective model due to their popularity, and their flexibility in modeling a wide spectrum of problems in many application areas. A back propagation (BP) network consists of (i) an input layer with nodes representing input variables to the problem, (ii) an output layer with nodes representing the dependent variables and (iii) one or more hidden layers containing nodes to help capture the nonlinearity in the data. Back-propagation (BP) is perhaps the most commonly used training algorithm for ANNs (Wasserman, 1989 and Fausett, 1994). In the network, the data are fed forward into the network without feedback, all links between neurons are unidirectional and there is no neuron-to-neuron of the input layer, the hidden layer and output layer possess computational property. In fact, BP refers to the way the error computed at the output side is propagated backward from the output layer, to the hidden layer, and finally to the input layer as shown in Fig. 13 (a), (b) & (c). BP is based on searching an error surface using gradient descent for point(s) with minimum error. Each, iteration in BP constitutes two sweeps: forward activation to produce a solution, and a backward propagation of the computed error to modify the weights. A clear systematic document about the BP algorithm and methods for designing the BPNN are given by Jiang et.al, (2008) and Basheer et.al, (2000).

Each input pattern of the training dataset is passed through the network from the input layer to the output layer. It is essentially a gradient descent technique that minimizes the network error function and the network output is compared with the desired target output and an error computed by using Eqn. 2. This error is propagated backward through the network to each node, and correspondingly the connection weights are readjusted based on Eqn. 3.

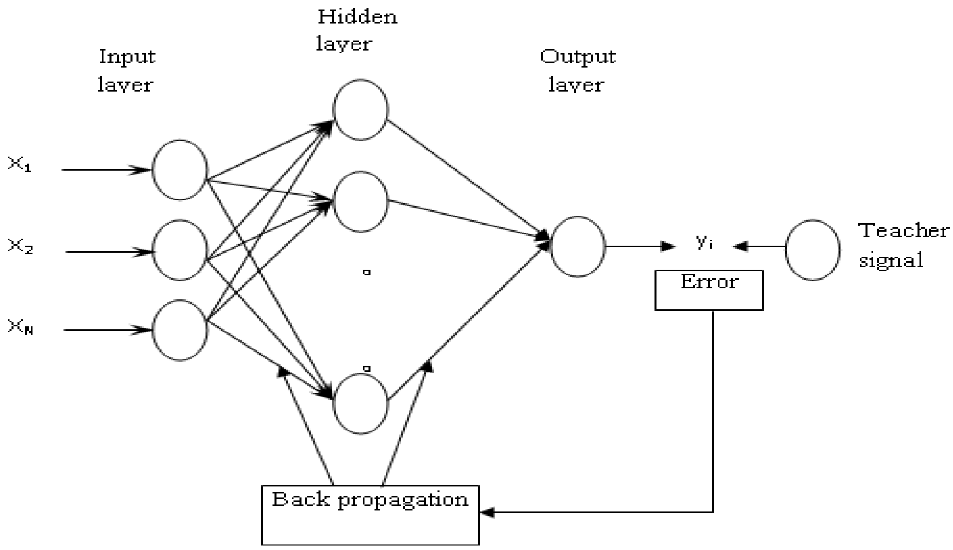

Figure 13 (a) A typical ANN architecture with three layers

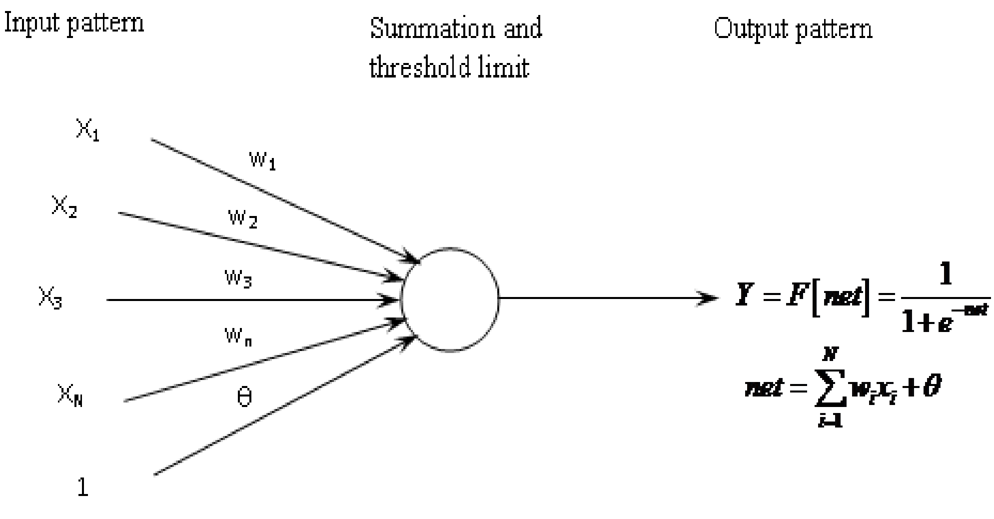

Fig. 13 (b) Schematic diagram of a typical j^th node

However, the common BP algorithm has the following defects: it is easily trapped in a local minimum; has a slow convergence rate; and the studying process is apt to oscillate. In view of these defects, we improved the algorithm by combining learning rate self-adaptation and adding momentum (Govindaraju & Rao, 2000). The updated formula for weight and valve value is as follows:

$$w(t+1) = w(t) + \eta(t).D(t) + a[w(t) - w(t-1)] \quad \dots (2)$$

$$\theta(t+1) = \theta(t) + \eta(t)e(t) \quad \dots (3)$$

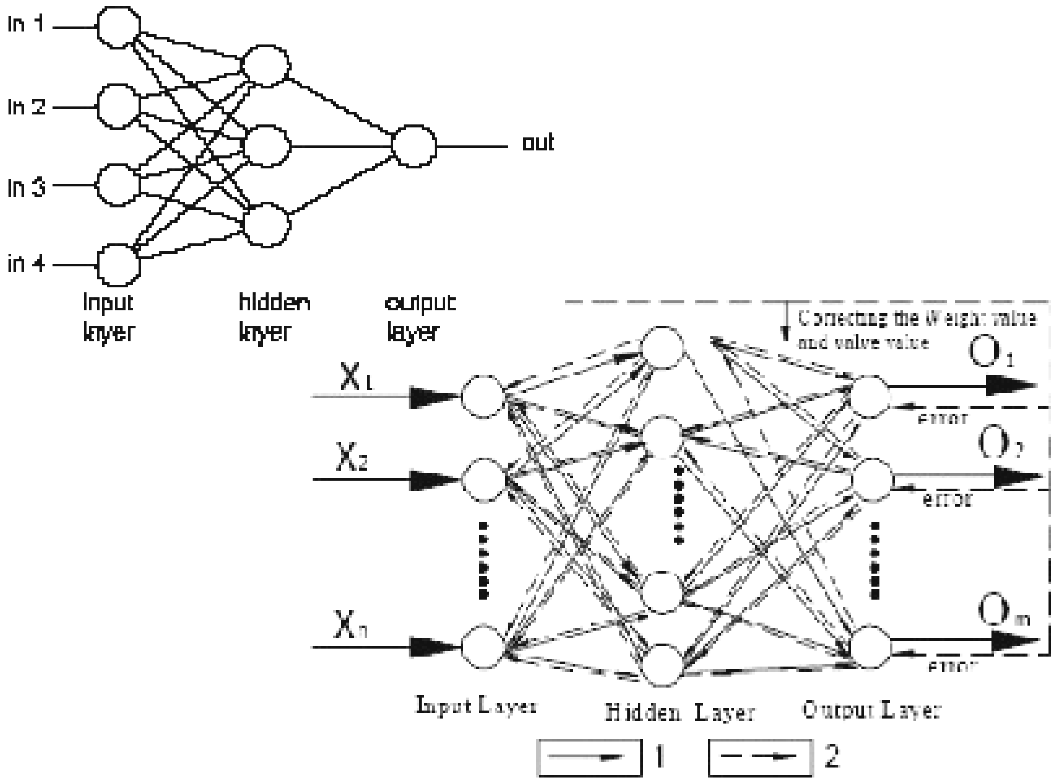

Fig. 13 (c) the typical structure and working basics of Back Propagation Algorithm

Where w (t) is weight value, D (t) = −∂E/∂w (t) is the negative gradient at t0, θ (t) is the valve, e (t) is the general error at t, and a is momentum, which is generally equal to 0.9 (Swingler 1996 & Wong et.al, 2007). After momentum is added, the weight is adjusted toward the average direction of the error surface. This can diminish oscillate during network-convergence processes and improve convergence. η (t) is the rate of learning at t ; which changes with the training process. The arithmetic is as follows:

$$\eta(t) = 2^{\lambda}\eta(t-1)\lambda = sign\left[D(t).D(t-1)\right] \qquad \ldots (4)$$

Equation.4 shows that when the two successive iterative gradients have the same direction, it means that the error falls too slowly and we can double the step length. In contrast, when the two directions are opposite, the fall is exaggerated and we can halve the step length. Meanwhile, to avoid vibration and divergence caused by an excessive learning rate, we should limit η to the range 0.01–0.1 (Basheer et.al, 2000).

3.3.1 Evaluation Criteria:

The Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and coefficient of efficiency (R^2) are used in order to assess the effectiveness of this model and its ability to make precise predictions. The RMSE calculated by

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t}^{n}(\mathrm{H}_t - \hat{\mathrm{H}}_t)^2} \qquad \ldots\ldots\ldots. (5)$$

and, the MAE calculated by

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\mathrm{H}_t - \hat{\mathrm{H}}_t\right| \qquad \ldots\ldots\ldots.. (6)$$

Proposed R^2, a non-dimensional criterion on the basis of standardization of the residual variance with initial variance, can be used to compare the relative performance of the model used different method. It is estimated as

$$R^2 = \frac{\sum_{t=1}^{n}(H_t - \overline{H}_t)^2 - \sum_{t=1}^{n}(H_t - \hat{H}_t)^2}{\sum_{t=1}^{n}(H_t - \overline{H}_t)^2} \quad \ldots\ldots (7)$$

Where H_t, $\hat{H}_t$ and $\overline{H}_t$ are the observed, predicted and mean observed data respectively; n is the number of observations. RMSE and MAE indicate the discrepancy between the observed and calculated values. The Lowest the RMSE and MAE, the more accurate the prediction is. R^2 represent the percentage of the initial uncertainty explained by the model. The best fit between observed and calculated values would have $R^2=1$ (Daliakopoulos, et.al, 2005).

3.3.2 Data and Data Normalization:

The monthly average groundwater table of an observation well No. 831933 from 1976 to 2010; the Hydrology and Water Resources Division, Vaippar River Basin and Institute for Water Studies, Chennai provided data. Fig. 14 shows the changes in the level of the groundwater table with the rainfall over the observation period. With an approximate balance maintained between recharge and discharge; however, from 1976, the groundwater table fell sharply, and the trend became increasingly steep due to low rainfall and over exploitation of groundwater.

The monthly groundwater depths time series were divided into two data sets, one subset for training the neural network (1976–2003); for testing (2004-2009) and the other for validation (2010). For BPNN model, normalization of data within a uniform range is essential to prevent larger numbers from overriding smaller ones, and to prevent premature saturation of hidden nodes, which impedes the learning process. This is especially true when actual input data take large values, which is to scale input and output variables in interval (0,1) corresponding to the range of the transfer function.

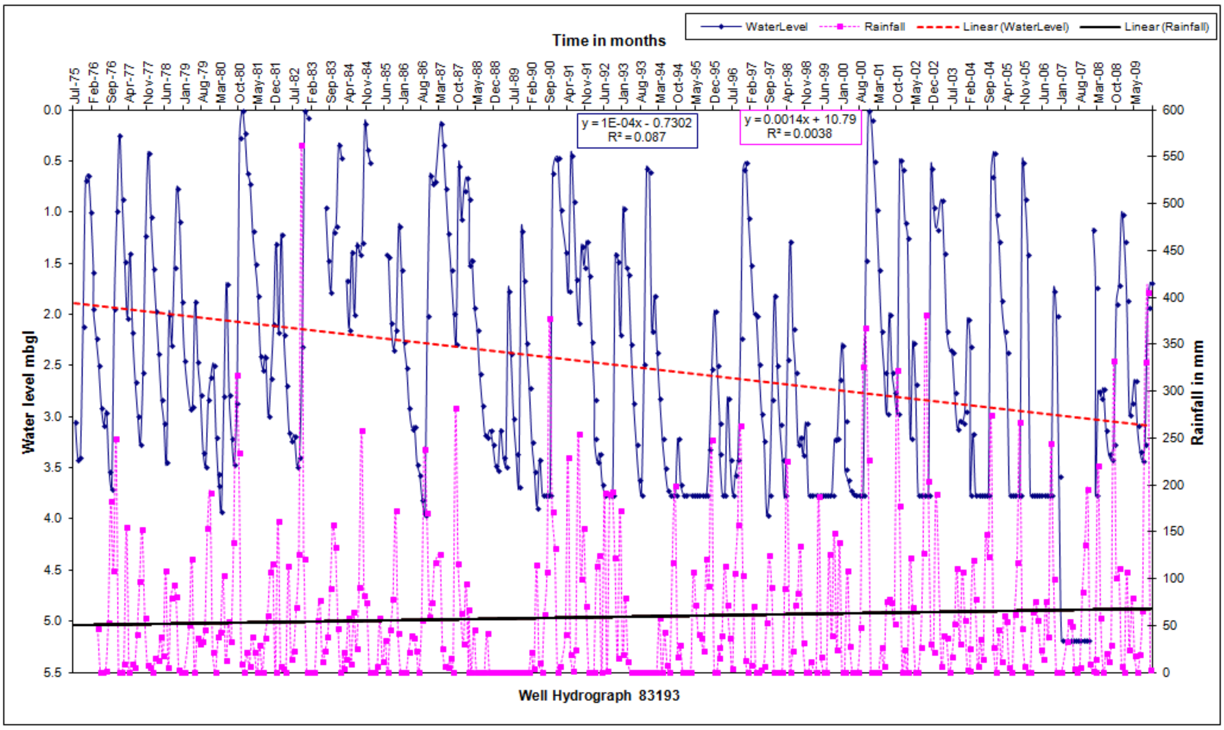

Fig. 14 Observed groundwater level and rainfall time series of well No.83193

Data normalization is performed before the training process. From this, the actual data is normalized between 0-1 using equation 8. After training the network, the de-normalization is performed at the output nodes.

$$x_n = \frac{x_0}{x_{\max}} \quad \ldots\ldots (8)$$

where, x_n and x_o represents the normalized and original data; x_{max} is the maximum values of the selected variable.

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4. RESULTS AND DISCUSSION

4.1 Groundwater Simulation by Numerical Model:

Monthly water levels from 25 wells being monitored over the study region to analyse the variability and to calibrate the groundwater flow model. The finite difference computer code MODFLOW which numerically approximates this equation, was used to simulate the groundwater flow in the study area. The model was calibrated in two stages, which involved a steady state condition and a transient state condition.

4.1.1 Steady state calibration:

The water level condition of the month June 2006 was assumed to be the initial condition for the steady state model calibration. A number of trial runs were made by varying the hydraulic conductivity values for all the two layers. The computed versus observed heads for the observation points are shown in figure 15.

The resulting calibration graph shows very good agreement with observed value and the normalized root mean squared error is 2.696%. The residual mean and the absolute residual mean are 3.634 and 3.769 m respectively. A linear regression analysis of the simulated and observed values of hydraulic head for all of the observation wells yields a coefficient of correlation of 0.998. Most of the points are located into or on the edge of the 95% confidence interval. The calibration indicates that there is a very good agreement between the computed and observed water levels in most of the wells.

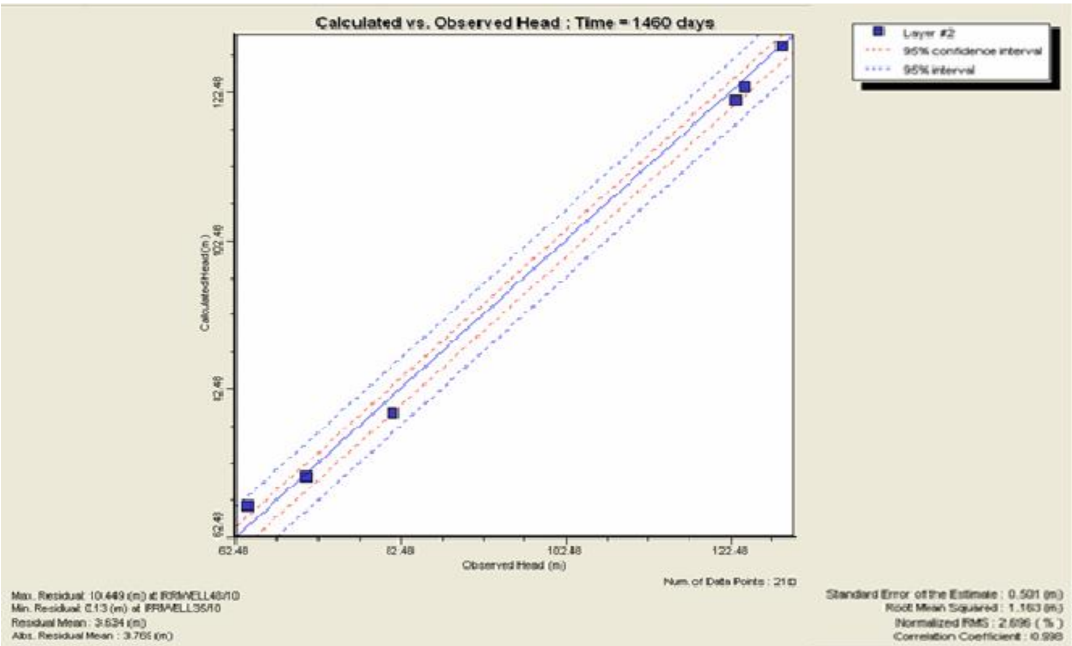

Fig. 15 Observed vs. calibrated head for steady state condition

4.1.2 Transient state calibration:

The transient calibration was carried out for the time period of June 2006 to May 2010. The hydraulic conductivity values, boundary conditions and water levels arrived through the steady state model calibration was used as the initial condition in the transient model calibration. They are used along with the specific storage, specific yield values, time variable recharge and pumping distribution.

The calibration of the transient flow model was based on records of periodic water level measurements in observation wells over 4 years. Each month was considered as a stress period with specified values of recharge and discharge rates for a total of 48 stress periods. Numbers of trial runs were made by varying the storage coefficient values in an appropriate way so that a reasonably good correlation was obtained between the computed and observed water levels.

The scattered plot for the computed and observed water levels at the end of transient model calibration is shown in figure 16. From this transient simulation, the residual mean and absolute residual mean are 3.63 m and 3.79 m respectively. Similarly the root mean squared error is 5.004 m.

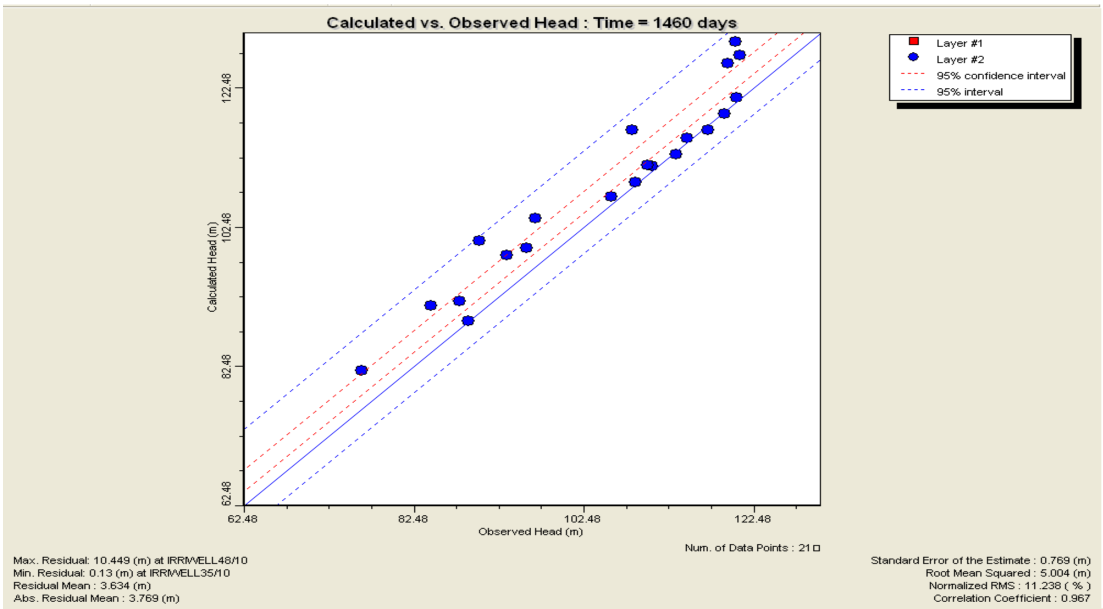

Fig. 16 Observed versus calibrated head for transient state condition

A linear regression analysis of simulated and observed values of hydraulic head for the six observation wells yields a coefficient of correlation of 0.967. The very good matching of computed water levels and observation water levels in the study area indicates that the model reasonably represents the true aquifer system. It was found that the computed heads are varying with seasonal change in the water table and the majority of the heads falls in the 90 per cent confidence level.

The computed water level contours along with velocity vector profiles for the end of the calibration period in May 2010 for the lower aquifers is shown in figure 17. The flow direction in second layers for the simulation period and there is no flow occurred in the first layer and has maximum dry cell than the second layer. This is because of low water table level in this region as well as the thickness of the layer is very small compared to the second layer. The dry cells in the smaller portion of lower aquifer may be due to presence of higher pumping rates and water table is lower when compared to the bottom of its elevation. Hence, the flow rate is poor in the first layer and the second layer has good groundwater flow which can be seen through the velocity vectors. The water level contours and velocity vectors of groundwater flow in the second layer are pointing predominantly towards Sindapalli Uppodai River. Generally the flow direction of the river moves from West to East. Similar results were reported by Bobba (1993) while investigating the fresh water aquifer of Lambton, Canada.

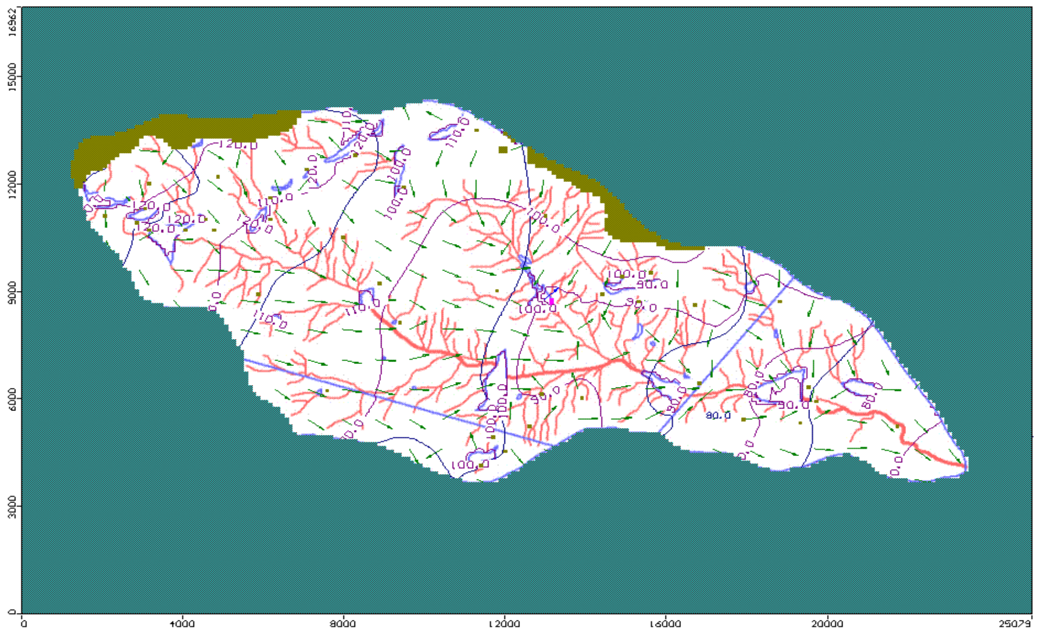

Fig. 17 Velocity vector profile along with water level contours for lower aquifer

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Flow lines more or less followed the general slope of the land. But in the ridge of the study basin in the some parts of the northern, southern and western boundary the flow direction is changing due to the outflow from the basin. The horizontal component of flow is accelerated through the weathered zones overlying the impermeable layer in the hard rock surface, which reduces the downward movement of water results in reduce of recharges. Therefore the horizontal component becomes dominant to outflow to the adjacent basins. Other such reasons are excessive pumping quantity on the other side of the basin boundary.

From the simulation model it is observed that the drawdown of a well is more in the upstream side as well as in the northern and southern side of the boundary. Because, in this region's the irrigation activities are good when compared to the middle and downstream side of the basin and also the recharge are less due to presence of the rock outcrops.

In the upstream side of the basin the drawdown goes up to 8 to 10 m, in the middle and downstream of the basin it is up to 2 to 4 m due to the presence of the water in the tanks for a longer period and recharge due to stream course. This shows that the good groundwater potential along side of the stream course and tanks having the water for a longer period. The water table generally goes down as we travel from river to boundaries within the basin; the contours are wider spaced indicating a lower hydraulic gradient for the groundwater flow (Bear 1979, Raghunath, 1985). Figure 18 shows the drawdown map of the Sindapalli Uppodai sub basin for the period of calibration.

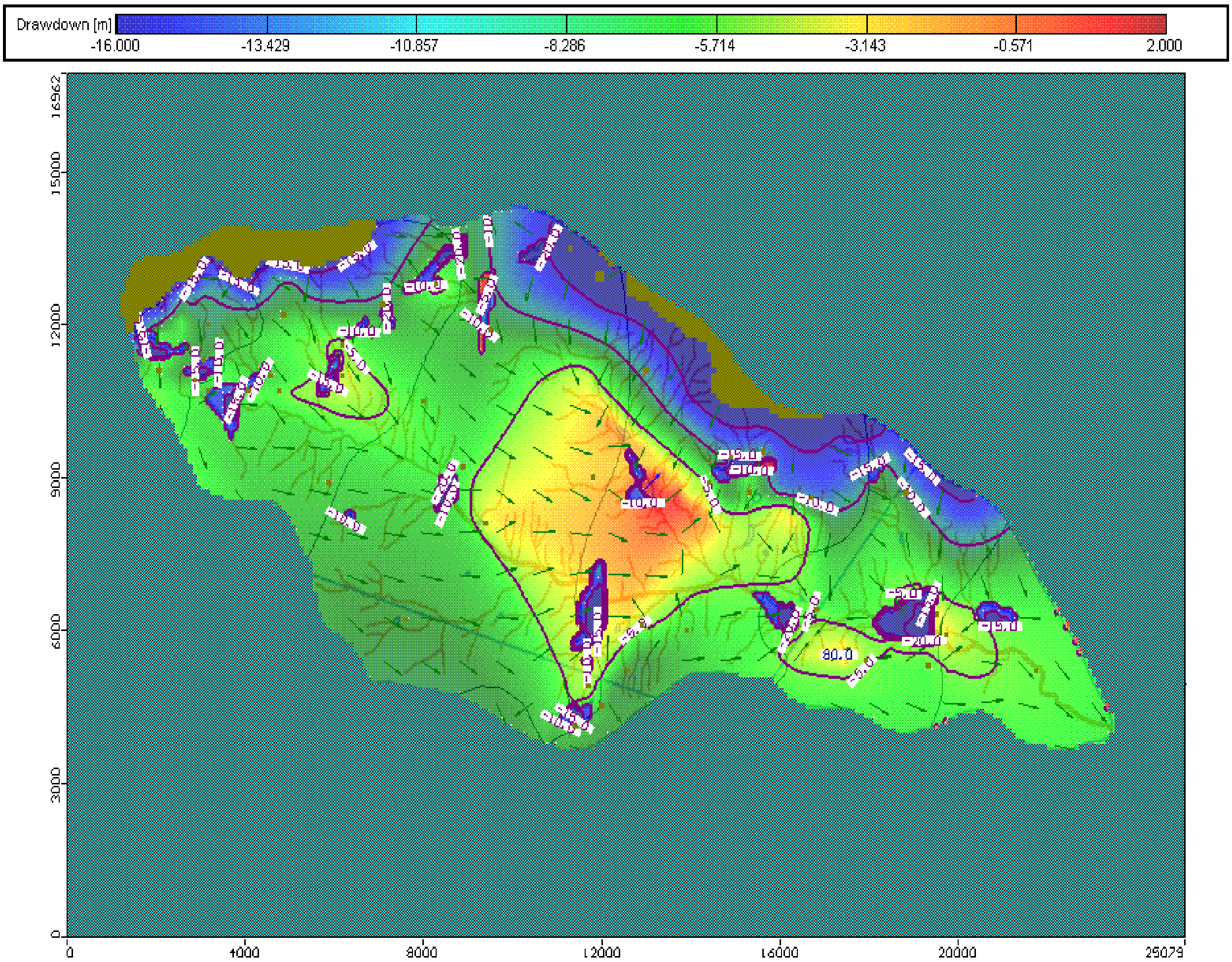

Fig. 18 Drawdown map of Sindapalli Uppodai sub basin lower aquifer

The computed and observed well hydrographs at the end of model calibration period in May 2010 are shown in Figure 17 and Figure 18. The trends shown in the hydrographs follows a similar pattern of observed water level. The computed well hydrographs for all the observation wells shows a good agreement with the observed values. The comparisons of computed and observed well hydrographs for Irrigation well 01 at the upstream side and OB10 in the middle part of the study area show a very good agreement.

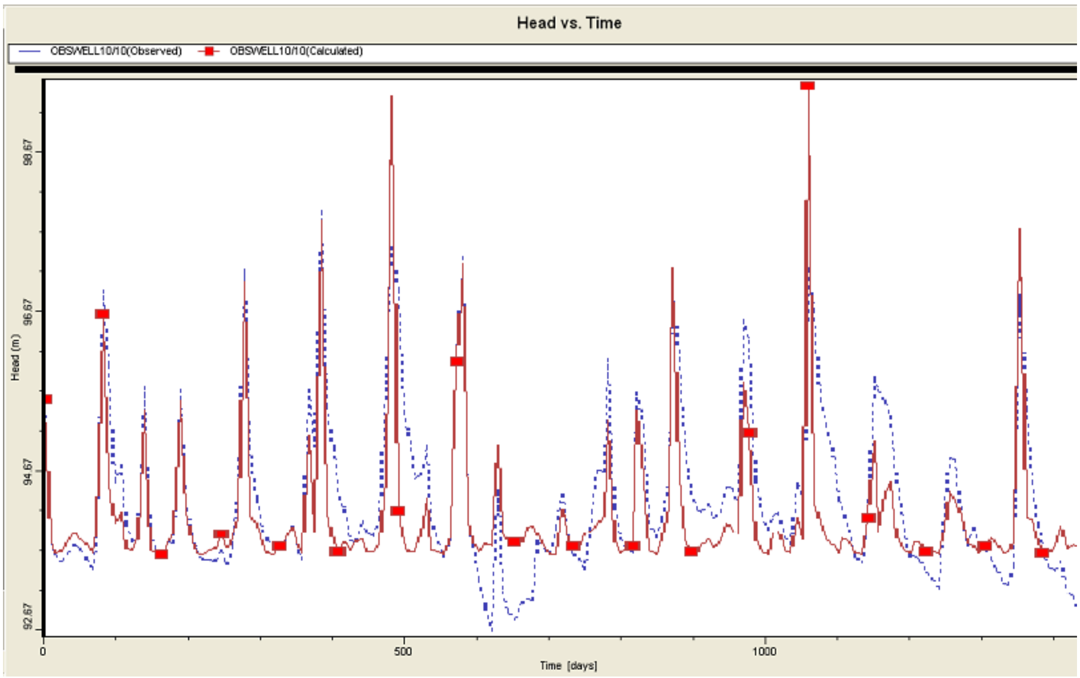

Fig. 19 Computed versus observed heads at observation well No.10

Both the simulated and observed hydrographs show a general decline in water level during the year 2007. This may be due to the lower rainfall values which reduced the rainfall recharge during that period. There is a rise of water level in both calibrated and observed hydrographs is observed during the month of October, November and December. This shows that the increased rainfall recharge resulted from Northeast monsoon which contributes maximum amount of rainfall during these months.

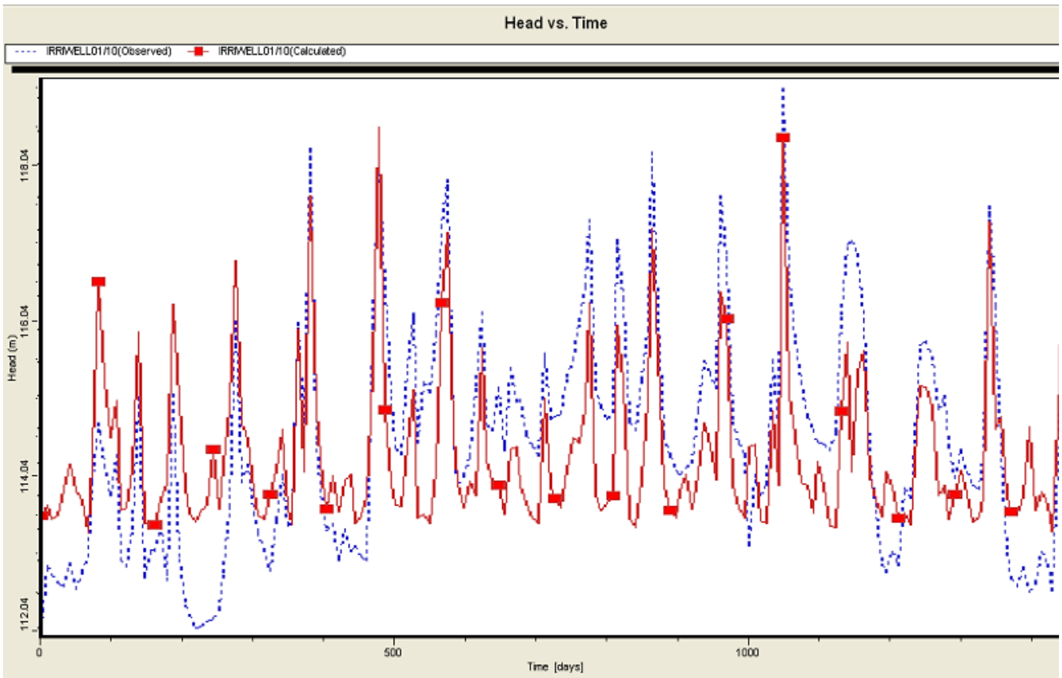

Fig. 20 Computed versus observed heads at observation well No.Irri.Well01

4.1.3 Model Validation:

After the model calibration, model was validated from the period from June 2010 to December 2010. The general trend of the calibrated water level matches reasonably well that of the field measured water level as shown in figures 19 to 20. Both the calibrated and measured hydrographs show a general decrease of the water level during the year 2007. This general decrease in the water level could be related to the precipitations being lower than the 38-year average rainfall.

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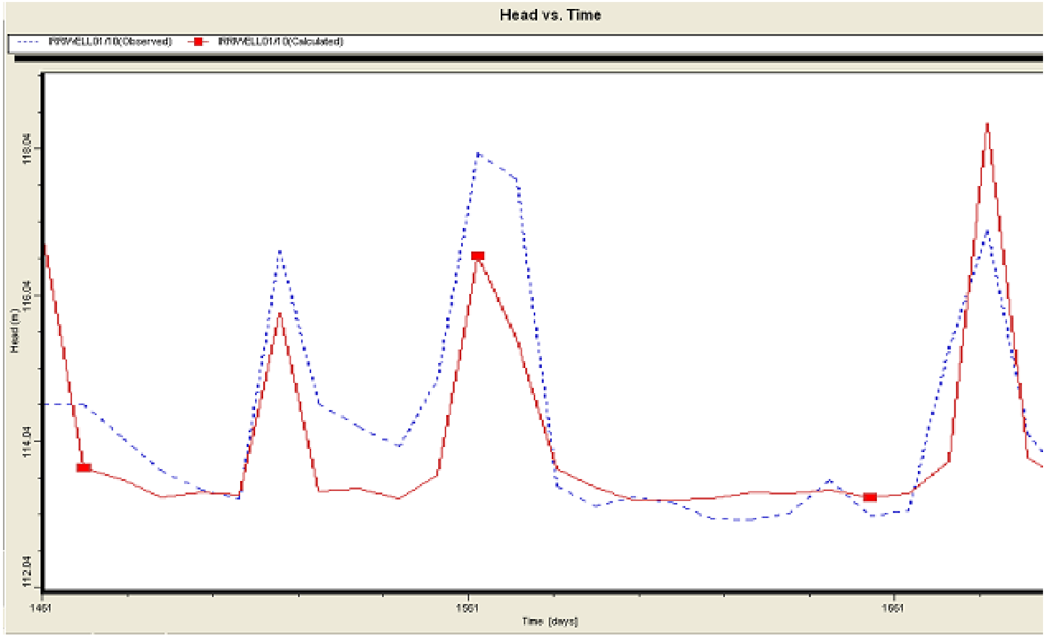

Fig. 21 Computed vs. observed heads at well No.Irri.Well01 during Validation

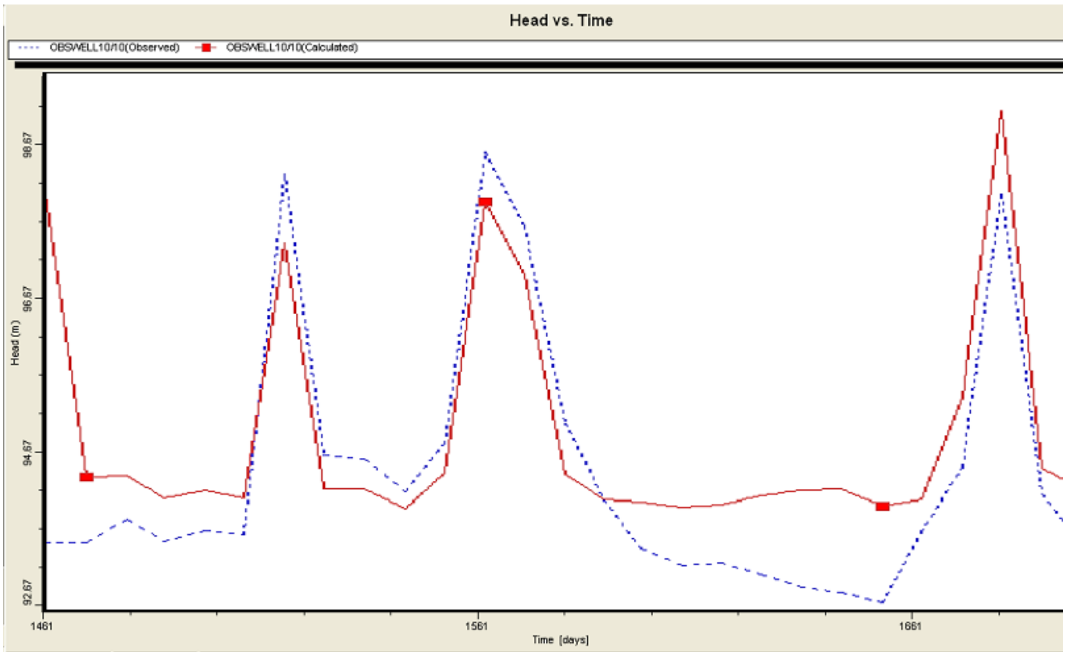

Fig. 22 Computed vs. observed heads at well No.10 during Validation

4.2 Groundwater Level Forecasting using BPNN:

Relevant data for the investigation area was limited, and the dynamic variation in groundwater belonged to univariate time series. Therefore, the correlation analysis technique was used to implement the pretreatment. The auto-regressive order was 4, with correlation coefficient R = 0.99 under a 95% level of significance; this means that the monthly groundwater table showed a strong relation with the groundwater table measured over the preceding 6 months. Therefore, it is imported the groundwater tables for the preceding 6 months and acquired the groundwater table for the present month.

Numerous studies have shown theoretically that three layered BP networks can precisely describe any non-linear mapping relation (Jiang, 2008). Therefore, three-layered BP networks were used here. Four nodes and one node were defined as the input and output layers, respectively. The number of hidden layer nodes was calculated by the trial-and-error method. Ten nodes were initially chosen; five nodes were finally selected after debugging.

All tests and results derived through programming in MATLAB Ver.7.6. The weights and thresholds of all connections links were assigned initial random values in a relatively small range between 0 and 1. Provided the initialization learning rate was 0.3 (Fu.L,1995), the momentum coefficient was equal to 0.9. The sum-of–squared–errors (SSE) calculated for the training or test subsets were chosen as the convergence criteria (Fu.L, 1995). The training examples were presented to the network random. After 12211 training repetitions, the error was 5.0552 x10^{-04}, which is less than the allowable error; the learning rate was 0.35 at this time. The error variance and is shown in figure 23.

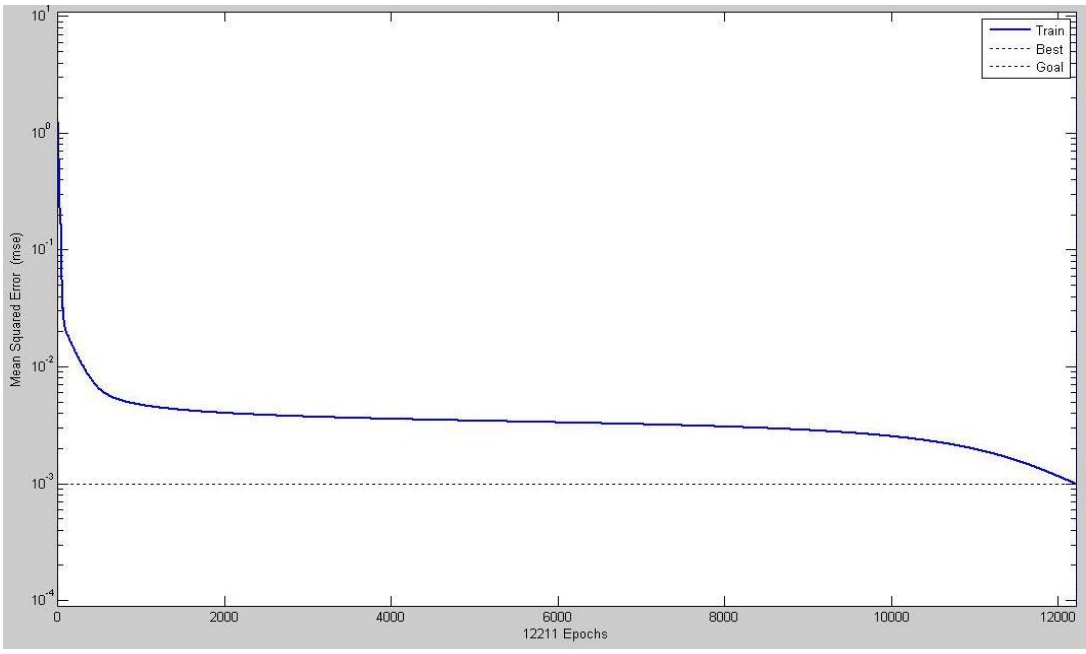

Fig. 23 Error function during Training

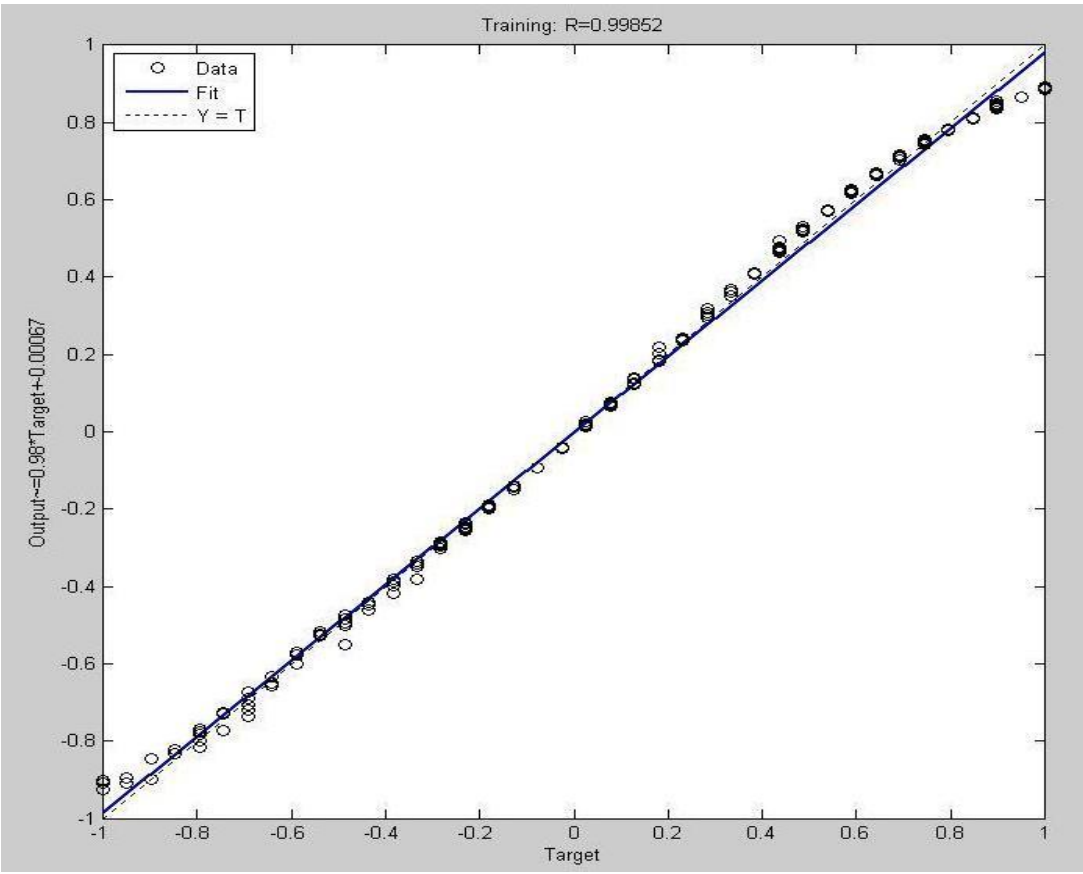

Fig. 24 Fitting Line during Training

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Figure 24 and figure 25 shows a comparison of observed and calculated groundwater levels by BPNN models. It is obvious that the simulated results agree well with the observed. It can be observed that the RMSE for BPNN is 0.1, this error evaluates the residual between observed and predicted by the models (Aqil.M, 2007); the MAE is 0.09, which measures the mean absolute error between observed and predicted by the models; and R^2 is 0.99, which evaluates the capability of the model in predicting groundwater heads away from the mean (Castellano-Méndez, W, 2004). All this suggested that BPNN are able to reproduce the groundwater levels time series well.

It is necessary to validate the forecasting method before using the model for practical application. The groundwater level for 2010, which was not used in development of the model, was used to assess forecasting accuracy. The validated results are presented in Table 3 and Figure 26. It can be observed that the RMSE, MAE and R^2 for BPNN model are 0.085, 0.076 and 0.88, respectively. It is obvious that the BPNN is able to predict the groundwater levels reasonable well.

From the present exercise, one could conclude that ANN could be used as an effective tool in modeling groundwater table. By implementing this model it is possible to quickly predict the water levels of a particular location to assess its suitability for different agricultural practices. Further improvements to the current model could be achieved by incorporating additional input variables and through a revised training incorporating more observed data.

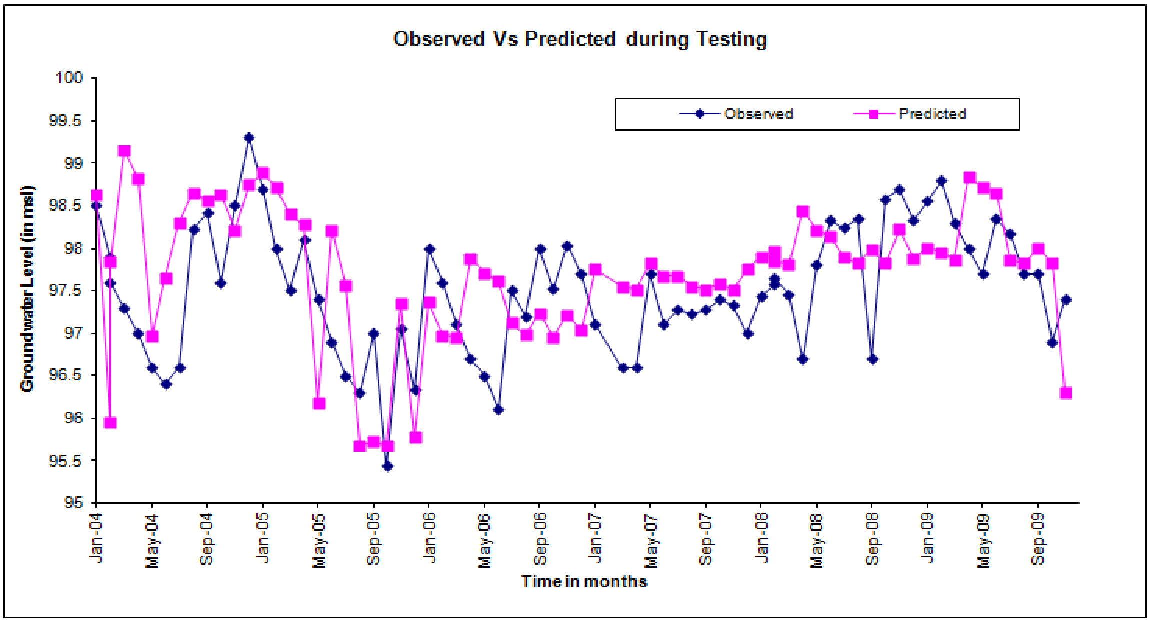

Fig. 25 Observed and Predicated GWL during testing

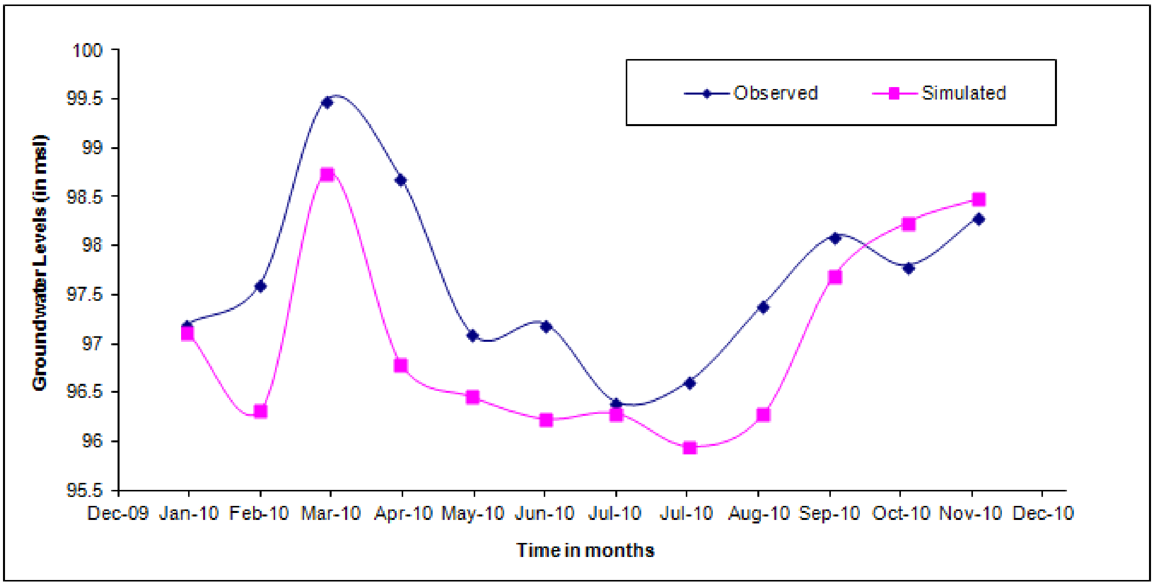

Figure 26 Observed and Forecasted Groundwater Levels

Table 3 Error and R^2 Values for BPNN Model

Model	Training			Forecasting		
	RMSE	MAE	R^2	RMSE	MAE	R^2
BPNN 4-5-1	0.1	0.09	0.99	0.085	0.076	0.88

4.3 Model Comparison:

The simulated groundwater levels from Artificial Neural Network and MODFLOW for the year 2010 is shown in Figure 27. The ANN model that can capture the complex dynamics of water table fluctuations, even with relatively short length of training data when compared to physically based models. The correlation coefficient of the numerical model prediction is 0.967 and by BPNN is 0.88. From the figure it is observed that the water levels simulated form the MODFLOW and ANN are relatively closer to the observed data.

Coppola et.al, (2003) have discussed, despite the limited data; the ANN model provides better prediction of groundwater levels. The neural networks also have the advantage of not requiring explicit characterization and quantification of the physical properties and condition of the aquifer system. Also, the data requirement of ANNs is generally easier to collect and quantify than the physically based models. However in case of ANN model, any changes in the input or output parameters will require total modeling of the system from the beginning, whereas this is not the case in case of numerical model. The numerical models provide total water balance of the system, whereas the ANN models are 'black box' models and they do not provide any information about the process of a system. The numerical models can help provide insights into the hydrogeologic framework and properties, and simulate future conditions.

Numerical models can also generate detailed output regarding head, flow, and water budget components across the study area. Thus, the numerical models can be more appropriate for long-term predictions, whereas the ANN technique may be better for real-time short-horizon predictions at selected locations that require a high accuracy (Coppola et al., 2005). If sufficient ANN prediction coverage exists for the study area, head and flow fields and water budget components can be estimated by using interpolation and estimations methods. In cases where sufficient coverage is not available, numerical modeling approach would have to be used for predictions. The ANN models can replace the numerical models as an approximate simulator in the simulation-optimization models as has been reported by some researchers (Rao et al., 2004; Bhattacharya and Datta, 2005; Safavi et al., 2010). The replacement of the numerical model by the ANN model can help reduce the computational burden in distributed modeling.

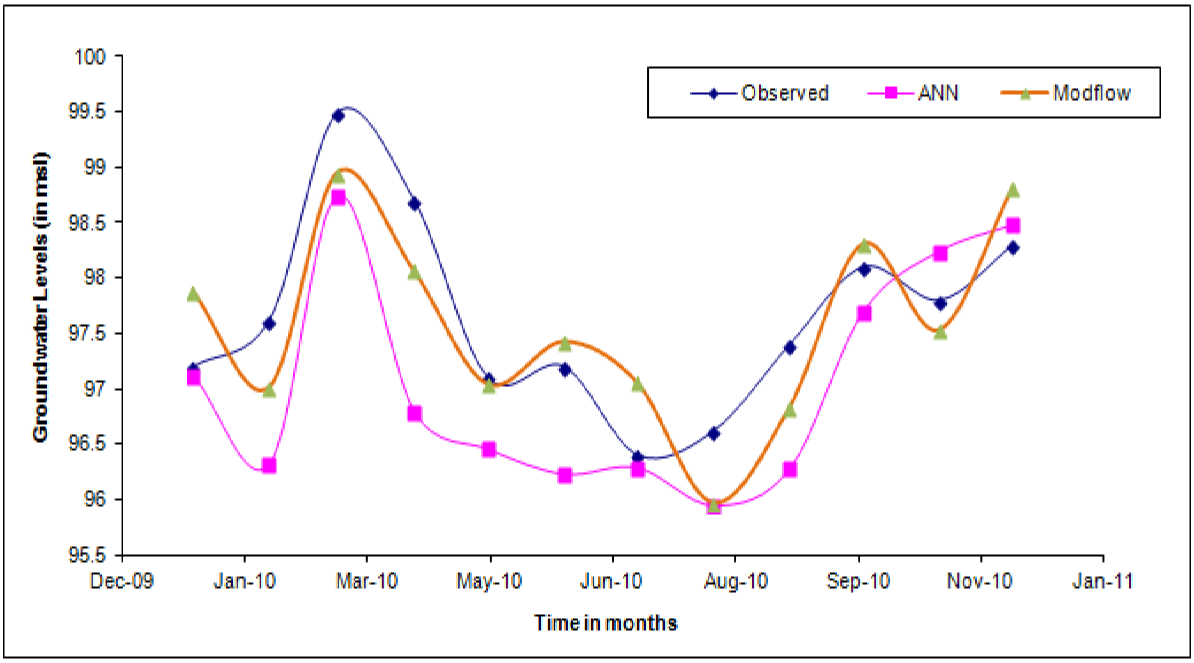

Fig. 27 Model Comparison between simulated heads of ANN and MODFLOW for Well No. 10

5. CONCLUSION

A groundwater flow simulation model was developed for the Sindapalli Uppodai Sub basin of Vaippar River Basin, Tamilnadu, Southern India, using Visual MODFLOW model for simulating groundwater scenarios. Artificial neural network models were also developed for forecasting groundwater level in the study area. The comparison of both the models showed that the ANN model can provide better prediction of groundwater level than the MODFLOW-based numerical model for short-horizon predictions with the limited data availability. The data requirement in case of ANN models is also substantially less than the numerical models. The correlation coefficient of the numerical model prediction is 0.967 and by BPNN is 0.88 for the observation well no.10 and observed that each one is closer to each other.

However, numerical models like MODFLOW provide the total water balance of the system whereas the ANN models are like a 'black box' and they do not describe the entire physics of the system. In case of ANN model, any changes in the input or output parameters will require total modeling of the system from the beginning whereas this is not the case in case of numerical models. The numerical models can be more appropriate for long-term predictions, whereas the ANN technique may be better for real-time short-horizon predictions at selected locations that require a high accuracy. Thus, there are different advantages offered by the ANN technique and numerical models, and each should be selected in accordance with the problem. In some cases, both the models can act complimentary to each other like using numerical model for long term predictions and ANN model for short term predictions.

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