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ORIGINAL ARTICLE

Forecasting of groundwater level in hard rock region using artificial neural network

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Abstract In hardrock terrain where seasonal streams are not perennial source of freshwater, increase in ground water exploitation has already resulted here in declining ground water levels and deteriorating its' quality. The aquifer system has shown signs of depletion and quality contamination. Thus, to secure water for the future, water resource estimation and management has urgently become the need of the hour. In order to manage groundwater resources, it is vital to have a tool to predict the aquifer response for a given stress (abstraction and recharge). Artificial neural network (ANN) has surfaced as a proven and potential methodology to forecast the groundwater levels. In this paper, Feed-Forward Network based ANN model is used as a method to predict the groundwater levels. The models are trained with the inputs collected from field and then used as prediction tool for various scenarios of stress on aquifer. Such predictions help in developing better strategies for sustainable development of groundwater resources.

Keywords Hard rock aquifer · Groundwater level · Artificial neural network · Forecasting

Introduction

In hard rock semi-arid terrain, groundwater is the largest fresh water resource. The groundwater potentiality in such region is largely limited to shallow weathered and fractured zones. Overall development and increasing population leads to increase in the demand of water supply. In order to meet demand for fresh water, there has been indiscriminate exploitation of groundwater resources. If pumping exceeds the total amount of recharge, groundwater mining occurs and the aquifer becomes no longer sustainable (Sophocleous 2005). The mismanagement of groundwater resources leads to the depletion of the aquifer storage, declining groundwater level and quality deterioration in hard rock aquifer (Voudouris 2006). In order to develop a sustainable management scheme, it is vital to prognose the behaviour of water level in the aquifer against a given stress.

In this paper, groundwater level has been estimated for the hard rock aquifer system of a small region of Andhra Pradesh named Kurmapally watershed (Fig. 1) using the method of ANN. It is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain processes information. It determines the relationship between inputs and outputs of physical systems by a network of interconnecting nodes adjusted by connecting weights based on the training samples, and extracts patterns and detects trends that are too complex to be noticed by either humans or other computational techniques. Neural network takes a different approach to problem solving than that of conventional computers. It has remarkable ability to derive meanings from complicated and imprecise data. An ANN can create its own organization or representation of the information it receives during learning time from the existing data. It has an ability to learn and apply the knowledge based on the data given for training or initial experience (Caulibaly et al. 2001***). Moreover, it validates the learning model with a chosen validation set from the input data to achieve a desired level of accuracy. The accuracy could be maximized by repeating the training process with different topological model. ANN can detect the pattern of complex natural systems accurately

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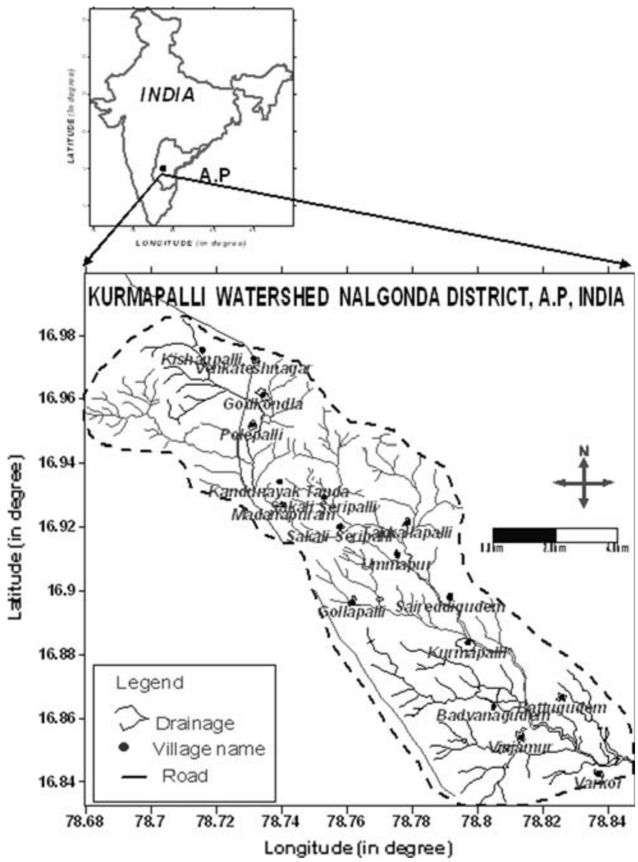


Fig. 1 Study area

(Prochazka 1997). Recently, ANN has been used for forecasting groundwater level successfully (Coppola et al. 2005; Nayak et al. 2006; Lallahem et al. 2005; Daliakopoulos et al. 2005). Thus proper design and implementation of ANN models could provide an efficient tool in water resource management and forecasting. Moreover, ANN could be employed to predict various aspects in hydrology such as rainfall-runoff model, precipitation forecasting and water quality model (Govindaraju and Ramachandra 2000).

Study area

Kurmapally watershed (Fig. 1) is situated about 60 km southeast of Hyderabad, capital of Andhra Pradesh, and lies between longitude 78.67°–78.84°E and latitude 16.82°–16.98°N in Nalgonda District (Andhra Pradesh), India. Area covered by the watershed is 108 km^2. Annual rainfall in the area is about 400 mm. The study area is the drought prone. It is characterized by poor soil cover, erratic rainfall, lack of soil moisture and scarce vegetation for most part of the year. Most of the drainage originates from massive granite hills in the north of the study area, which divides it in small streams and flow towards southeast.

The groundwater potential map (Fig. 2) of this region has been prepared using various geoinformations such as geology, topography, slope, drainage density, etc., with the application of GIS and is categorized into five zones (Prasad et al. 2008). There are hilly terrains covering mainly northern and north-western part of the basin and mid-slope region with moderate undulating terrain and relatively flat region with gentle slope covering larger part of the basin. Most of the drainages are seasonal and remain dry in maximum period of the year. The basin is underlain by Archaean rocks and the hills (mostly in the north) are occupied by massive porphyritic granitic rocks. The southern part of the area is overlained with clay and *Kankar* (calcium concentrate) whereas the remaining part is occupied by weathered granite and gneisses.

Methodology

ANN based methods are data analysis methods and algorithms loosely based on nervous systems of humans and animals. Zhang et al. (1998) has explained that there is the class of cells in the human brain behave as functional units called dendrites as a receiver of information, cell body as a processor of information, axon as a carrier of the processed information to other neurons, synapse as a junction between axon end and dendrites of the other neurons. Similarly artificial neural network consists of a large number of simple processing units linked by weighted connections (Fig. 3). Feed Forward neural network (Baldi and Hornik 1989; Stinchcombe and White 1989), Radial Basis Function, Kohonen Self Organizing Network, Recurrent Network, Stochastic Neural Network and Associative Neural Network are the different ANN models for forecasting data. In this study, feed forward network based neural network is used for the input data set (Maier and Dandy 1998) to make the future predictions. In this network, the information moves in only forward direction from the input nodes to the output nodes, through the hidden nodes. There are no cycles or loops in the network. Input nodes are the resultant where identified weight functions (depending on the input data set) are applied to the inputs. Based on the topology it traverses through multiple intermediate weight functions before concluding to a resultant output (represented as output node). All these intermediate weighted resultants are known as hidden nodes and the cumulative application of weight function decides the number of hidden layers (depending on the topology) (Fig. 5).

ANN model has got a couple of phases. The first one is *data analysis*. In this phase (French et al. 1992) ANN takes care of optimizing missing values, wrong type values if any and removing outliers. Outliers are the values that are far

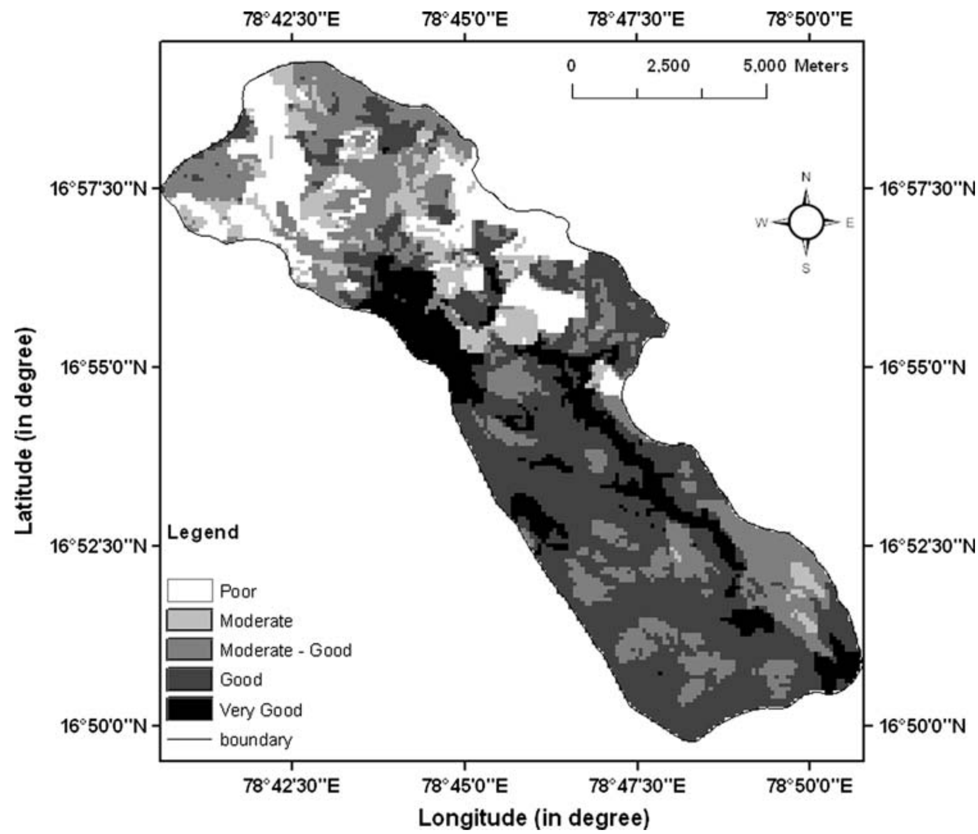


Fig. 2 Groundwater potential zone map

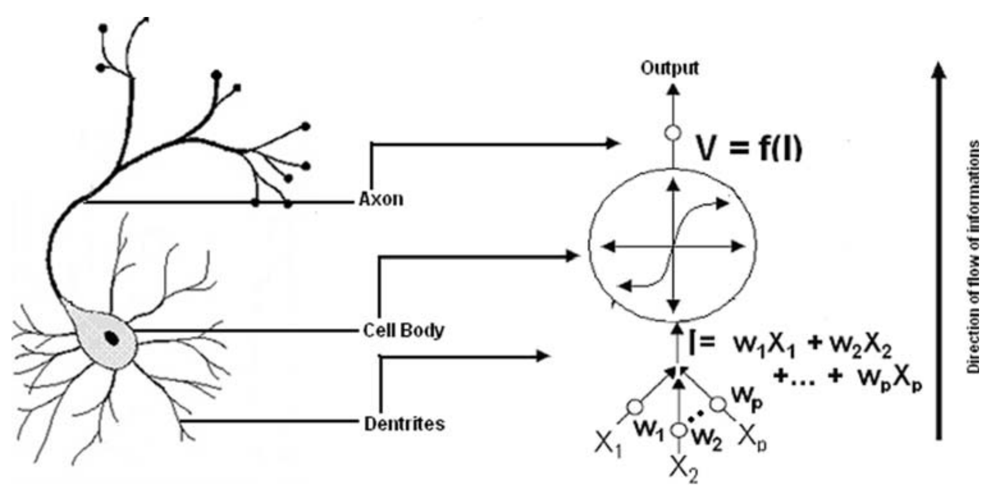
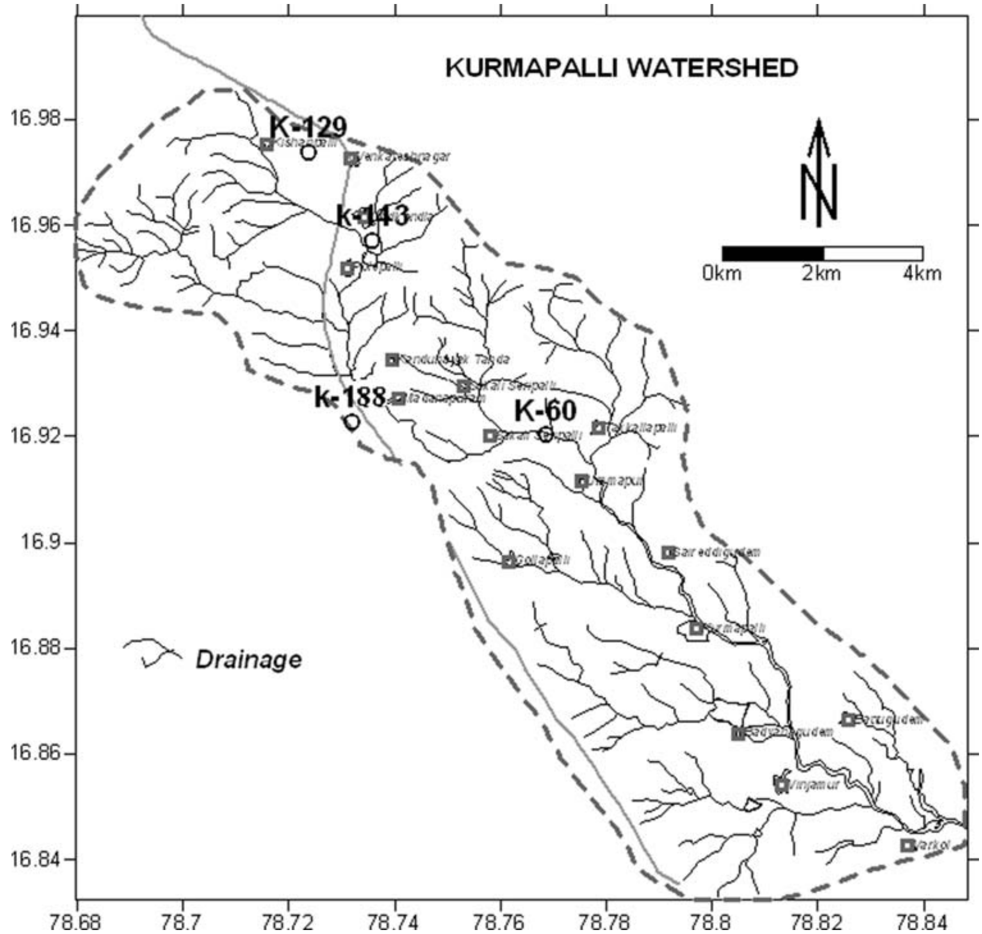


Fig. 3 Relation between ANN and biological neurons

from the majority of others, basically caused either by measurement errors or are extreme cases. Input data are collected from the study area for 23 months from four different wells (k60, k129, k143 and k188 as shown in Fig. 4).

Next phase is *network training*. In this paper, Levenberg–Marquardt algorithm (LMA) (Levenberg 1944) has been used to train the ANN and it has surfaced as the best model resulting high level of accuracy and efficiency with 23 months data. LMA is used to find an optimum solution to minimize the problem. This algorithm is the modification of classical Newton algorithm. The LMA interpolates between the Gauss–Newton algorithm (GNA) and the method of gradient descent. It uses approximation of Hessian matrix for the weight updates. This is mainly applied in the least squares curve fitting problem (Marquardt 1963) where given a set of empirical data pairs of independent (x_i) and dependent variables (y_i), it optimizes the parameter β of the model curve $f(x, \beta)$ so that the sum of the squares of the deviations

Fig. 4 Wells' location map



$$S(\beta) = \sum_{i=1}^{m} \left[y_i - f\left(x_i, \beta\right)\right]^2 \tag{1}$$

in above Eq. 1 becomes minimal. Like other numeric minimization algorithms, the LMA is an iterative procedure. To start a minimization, the user has to provide an initial input (i.e. field data) for the parameter vector β. In each iteration step, the parameter vector β is replaced by a new estimate $\beta + \delta$. To determine δ, the functions $f(\beta + \delta)$ are approximated by their linearization as given below:

$$f(\beta + \delta) \approx f(\beta) + J\delta \tag{2}$$

where J is the Jacobian of f at β. At a minimum of the sum of squares S, the gradient of S with respect to δ is 0. Differentiating the square of the right hand side of the equation above and setting to zero leads to following expression:

$$\left(J^{\mathrm{T}} J\right)\delta = J^{\mathrm{T}}[y - f(\beta)] \tag{3}$$

that is a set of linear equations which can be solved for δ. J^{T} is the transpose matrix of J and $J^{\mathrm{T}} J$ is the Hessian matrix. The key hallmark of the LMA is to replace this equation by a 'damped version' in Eq. 4

$$\left(J^T J + \lambda I\right)\delta = J^T[y - f(\beta)] \tag{4}$$

where I is the identity matrix, giving as the increment δ to the estimated parameter vector β. The damping factor λ is adjusted at each iteration (Philip and Walter 1978). A similar damping factor appears in Tikhonov regularization (Tikhonov 1963), which is used to solve linear ill-posed problems, as well as in ridge regression, an estimation technique in statistics. Various more or less heuristic arguments have been put forward for the best choice for the damping parameter λ. Theoretical arguments exist showing why some of these choices guaranteed local convergence of the algorithm; however, these choices can make the global convergence of the algorithm suffer from the undesirable properties of steepest-descent, in particular very slow convergence close to the optimum. Marquardt recommended starting with a value λ_0 and a factor $v > 1$. Initially setting $\lambda = \lambda_0$ and computing the residual sum of squares $S(\beta)$ after one step from the starting point with the damping factor of $\lambda = \lambda_0$ and second with λ/v. If both of these are worse than the initial point then the damping is increased by successive multiplication by v until a better point is found with a new damping factor of λv^{k} for some k. If use of the damping factor λ/v results in a reduction in

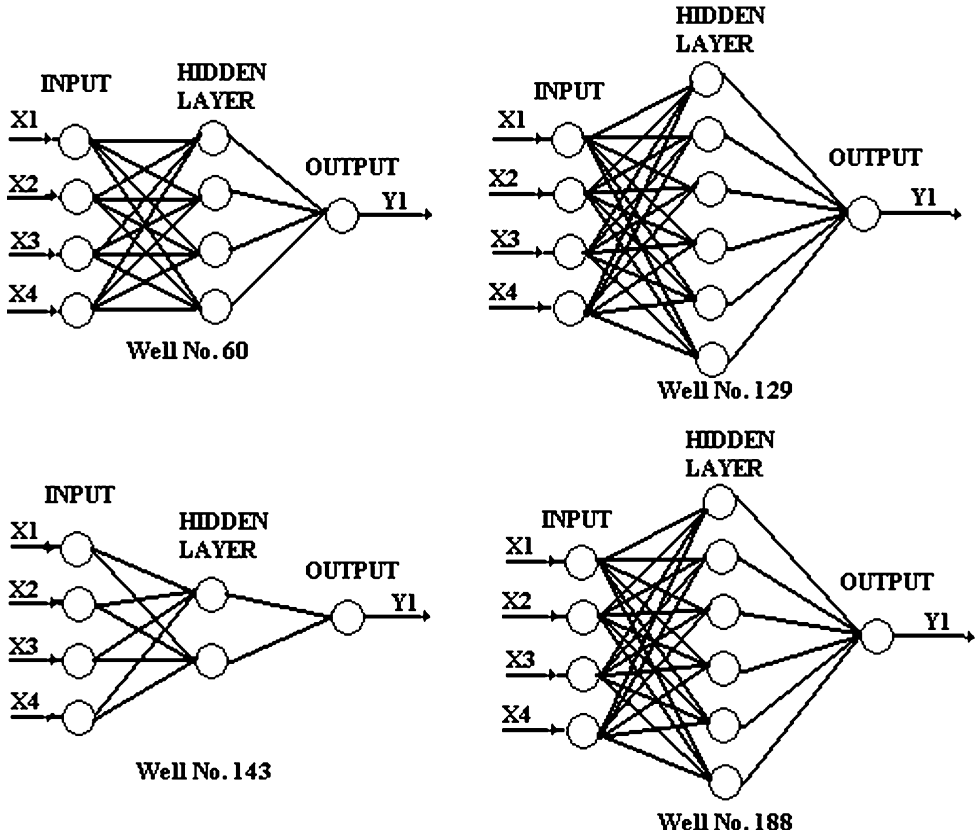


Fig. 5 ANN architecture for the well's data

squared residual then this is taken as the new value of λ (and the new optimum location is taken as that obtained with this damping factor) and the process continues; if using λ/v resulted in a worse residual, but using λ resulted in a better residual then λ is left unchanged and the new optimum is taken as the value obtained with λ as damping factor.

Next is *Network Topology Selection*. In this phase, search algorithm is run for finding the best topology for the given data. It decides the number of hidden layers and number of neurons (weight distribution) in each hidden layer based on the above steps (Coulibaly et al. 2000). In our study, different topologies (Fig. 5) are found suitable for different well locations.

Next Phase is *Training Parameters Selection*. In this phase, training algorithm's parameters like quick propagation coefficient, learning rate, momentum and a condition to stop the network training process, mean square error

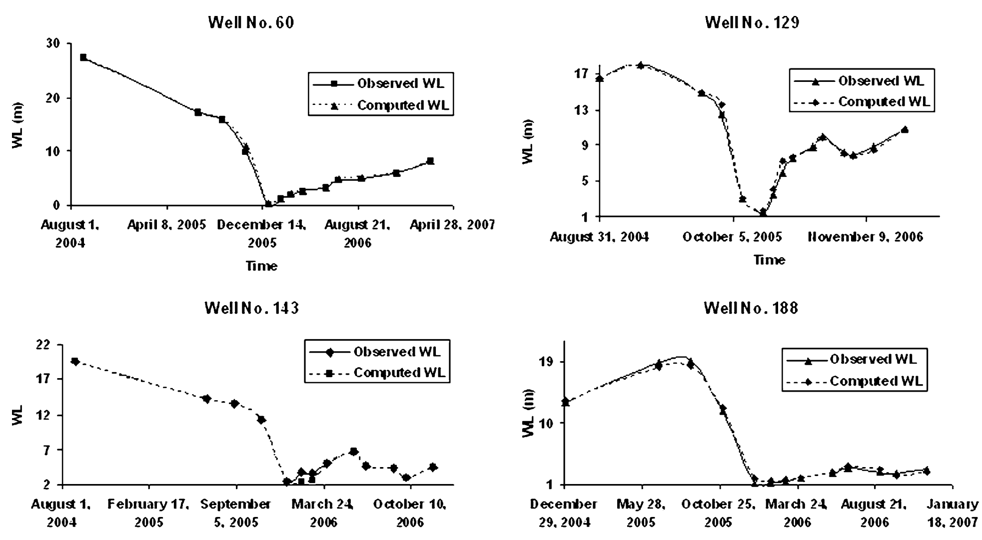


Fig. 6 Comparison between observed and predicted water levels

and minimum improvement has been decided. Error is the kind of conditions based on which training process are said to be reached at the permissible level for forecasting. In this phase the ANN validates its' authenticity forecasting from the training subset and comparing it with the validation subset (Fig. 6). Once it achieves this, it certifies itself for forecasting.

Result and ground water level forecasting

Forecasting of the ground water level has been carried out for five geographically diversified wells for five years (Fig. 7). Moreover, the study forecasted the behavioral changes by changing the input parameters so as to determine the future trend with varying water usage and hydrologeological conditions (Fig. 8). A plot has been included with the forecasted data against the observed field data for the initial training period and it shows an unprecedented level of accuracy for the ANN model (Fig. 6).

The result shows well no. k60 lies in moderate to good groundwater potential zone; well no. k129 lies in moderate zone and well no. k143 and k188 lies in moderate to poor zone (Fig. 7). The study demonstrates the same result of groundwater potential zone observed through the application of GIS (Fig. 2).

The result forecasts the groundwater level in well number k60 is not changing with time but in well number k129, k143 and k188 the level is decreasing with time (Fig. 7). This shows the potentiality of the aquifers is different for the different parts of the hard rock basin. Well no. k60 will not be affected more but for other wells abstraction should be reduced. The study indicates,

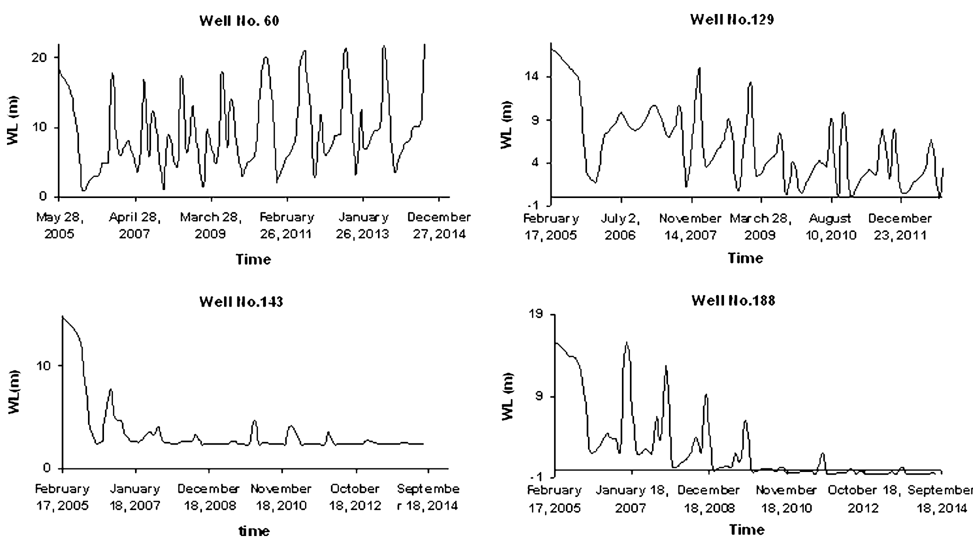


Fig. 7 Groundwater level forecasting with the actual condition (**a**) well no 60 (**b**) well no. 129 (**c**) well no. 143 (**d**) well no. 188

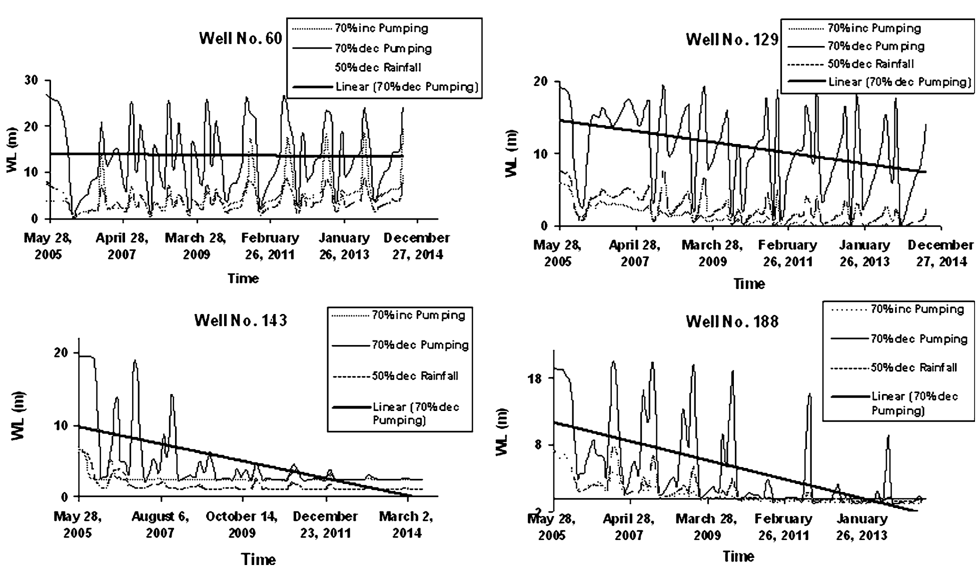


Fig. 8 Groundwater level forecasting with varying recharge and pumping condition (**a**) well no 60 (**b**) well no. 129 (**c**) well no. 143 (**d**) well no. 188

controlled pumping could sustain the groundwater level but over exploitation of aquifer will cause aquifer mining in the moderate to poor zone. This observation draws attention to take care of each area in particular due to their difference in aquifer characteristics with different groundwater management strategy.

Moreover, attempt has been made to forecast the trend of the groundwater level by varying the attributes. In the first case, future projection is done with the *70% increase in groundwater pumping*. This situation is very common in this drought prone area. It shows the increase in groundwater pumping could cause 6–10 m of decrease in the groundwater level in all the four wells even while recharge prevails. The level could go down to zero in the dry months. The worst affected is well no. k188 where the forecast indicates an occurrence of groundwater mining within shortest time (Fig. 8).

In the second case *pumping rate is decreased by 70%*. With this variation, it is observed that the groundwater level could go up by 8–10 m in the months of recharge. Moreover, the model indicates that the decrease in pumping rate could prevent the groundwater mining of the aquifer basins even in the dry seasons (Fig. 8).

Drought is very common and frequent in this study area and rainfall decreases even up to 100% by that time.

In the third case, we have *decreased the rainfall by 50%* and the result shows an overall decreasing trend in groundwater level in all seasons (Fig. 8). Moreover, the study has captured the trend line over a period of five years for all the wells (Fig. 8).

Conclusion

Increasing population causes greater necessity of groundwater for irrigation and domestic purposes and leads to widespread exploitation of the resource. But as the aquifer conditions are not uniform everywhere, an unmanaged pumping practice could cause the aquifer mining in the moderate and poor aquifer zone. Application of ANN has successfully demonstrated that the groundwater levels can be forcasted considering different scenarios. The forecasted result will help to develop awareness among the residents and moreover will draw an attention of the state and central government to devise and formulate a clear groundwater management policy for this region.

ANN could be very useful in hydrological forecasting of different aquifer conditions as it does not disturb the aquifer dynamics. ANN is capable of understanding poorly defined relations and advantageous when the vaguely defined problem does not post for any specific solution. It is nonlinear in nature and thus is the exceptionally powerful method of analyzing real-world data allowing modeling of complex dependencies. By nature, ANN recognizes the hidden pattern of data, trains itself, validates its' own knowledge set and makes use of that knowledge in forecasting. Thus hydrological data which relates to high level of diversity within it, with loose level of relations among the parameters, draws a potential attention from the field of ANN intelligence.

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