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Comparative evaluation of numerical model and artificial neural network for simulating groundwater flow in Kathajodi–Surua Inter-basin of Odisha, India

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SUMMARY

In view of worldwide concern for the sustainability of groundwater resources, basin-wide modeling of groundwater flow is essential for the efficient planning and management of groundwater resources in a groundwater basin. The objective of the present study is to evaluate the performance of finite difference-based numerical model MODFLOW and the artificial neural network (ANN) model developed in this study in simulating groundwater levels in an alluvial aquifer system. Calibration of the MODFLOW was done by using weekly groundwater level data of 2 years and 4 months (February 2004 to May 2006) and validation of the model was done using 1 year of groundwater level data (June 2006 to May 2007). Calibration of the model was performed by a combination of trial-and-error method and automated calibration code PEST with a mean RMSE (root mean squared error) value of 0.62 m and a mean NSE (Nash–Sutcliffe efficiency) value of 0.915. Groundwater levels at 18 observation wells were simulated for the validation period. Moreover, artificial neural network models were developed to predict groundwater levels in 18 observation wells in the basin one time step (i.e., week) ahead. The inputs to the ANN model consisted of weekly rainfall, evaporation, river stage, water level in the drain, pumping rate of the tubewells 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 models. Out of the 174 data sets, 122 data sets were used for training and 52 data sets were used for testing. The simulated groundwater levels by MODFLOW and ANN model were compared with the observed groundwater levels. It was found that the ANN model provided better prediction of groundwater levels in the study area than the numerical model for short time-horizon predictions.

1. Introduction

Groundwater is an invaluable natural resource used for variety of purposes like domestic, agricultural and industrial uses. Almost all of the liquid freshwater in our planet (more than 98%) occurs as groundwater, while less than 2% occurs in the more visible form of streams and lakes which often are fed by groundwater (Bouwer, 2000; Russell, 2003). During the last few decades, groundwater has become an important source of freshwater throughout the world. It is estimated that groundwater provides about 50% of the current global domestic water supply, 40% of the industrial supply, and 20% of water use in irrigated agriculture (World Water Assessment Program, 2003). However, the aquifer depletion due to over-exploitation and the growing pollution of groundwater are threatening our eco-systems (Shah et al., 2000; Sophocleous, 2005; Evans and Sadler, 2008). The recent studies using GRACE satellite data have shown alarming decrease in groundwater levels in developing countries like India and Iran (Rodell et al., 2009; Voss et al., 2013). Hence, the key concern is how to maintain a long-term sustainable yield from aquifers (e.g., Hiscock et al., 2002; Alley and Leake, 2004).

The total annual replenishable groundwater resource of India is about 43 million ha m. However, in spite of national scenario on the availability of groundwater being favorable, there are pockets in certain areas of the country that face scarcity of water. This is because the groundwater development over different parts of the country is not uniform, being quite intensive in some areas (CGWB, 2006). Excessive pumping has led to alarming decrease in groundwater levels in several parts of the country like Gujarat, Tamil Nadu, West Bengal, Odisha, Rajasthan, Punjab and Haryana (CGWB, 2006; Mall et al., 2006). In studies using GRACE satellite data, it was found that the groundwater reserves in the states like Rajasthan, Punjab and Haryana are being depleted at a rate of

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$17.7 \pm 4.5\ km^3$/year. The same data suggest that between August 2002 and December 2008, the region lost 109 km^3 of groundwater which is double the capacity of India's largest reservoir Wainganga and almost triple the capacity of Lake Mead, the largest man-made reservoir in the United States (Rodell et al., 2009). This in turn has increased the cost of pumping, caused seawater intrusion in the coastal areas and has raised questions about the future availability of groundwater.

In order to avoid the overdraft and declining groundwater level, it is important to understand the behavior of an aquifer system subjected to artificial stresses. Simulation modeling is an excellent tool to achieve this goal. Groundwater simulation models are useful in simulating groundwater flow scenarios under different management options and thereby taking corrective measures for sustainable use of water resources by conjunctive use of surface water and groundwater. During the last 20 years various studies have been taken up for groundwater flow simulation in different basins using MODFLOW and other models (e.g., Reichard, 1995; Onta and Das Gupta, 1995; Ting et al., 1998; Reeve et al., 2001; Lin and Medina, 2003; Rodriguez et al., 2006; Zume and Tarhule, 2008; Al-Salamah et al., 2011; Gaur et al., 2011; Xu et al., 2012). However, the physically based groundwater simulation models are very data intensive, laborious and time consuming. Empirical models generally require less data and less effort in comparison to physically based models (Coppola et al., 2005). Artificial Neural Network (ANN) models are one of such models, which are treated as universal approximators and are very much suited to dynamic nonlinear system modeling (ASCE, 2000). The ability to learn and generalize from sufficient data pairs makes it possible for ANNs to solve large-scale complex problems. A number of studies have been done on the application of neural networks for groundwater level forecasting (e.g., Coulibaly et al., 2001; Coppola et al., 2003; Daliakopoulos et al., 2005; Lallahem et al., 2005; Nayak et al., 2006; Uddameri, 2007; Krishna et al., 2008; Trichakis et al., 2009; Mohanty et al., 2010; Ghose et al., 2010; Yoon et al., 2011; Adamowski and Chan, 2011; Li et al., 2012; Nourani et al., 2012).

The performance of numerical models evaluation like MODFLOW and empirical models like artificial neural network (ANN) in forecasting groundwater levels has been reported by Coppola et al. (2003). In their study, a neural network model was developed for predicting water levels at 12 monitoring well locations screened in different aquifers in a public supply well field, Florida, USA in response to changing pumping and climatic conditions. The developed neural network model predicted the groundwater level more accurately than the calibrated numerical model at the same location over the same time period. Parkin et al. (2007) developed a hybrid approach of numerical modeling and artificial neural networks to assess the impacts of groundwater abstractions on river flows in hydrogeologic settings representing most of England and Wales. The artificial neural network model was trained using the input and output data from SHETRAN numerical modeling system and tested using a field data from a case study site. They demonstrated the successful application of the approach for modeling river–aquifer interactions and its potential for modeling more complex hydrological systems. Nikolos et al. (2008) evaluated artificial neural network as an alternate approach to groundwater numerical modeling to optimize pumping strategy of production wells located in the northern part of Rhodes Island in Greece. They concluded that the use of neural network as an approximate model can significantly reduce the computational burden associated with numerical model and can provide very close to optimal solutions. Banerjee et al. (2011) evaluated the prospects of artificial neural network simulation over 2-D solute transport model (SUTRA) in estimating safe pumping rate to maintain groundwater salinity in Kavaratti island of Lakshadweep archipelago. 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 levels and comparison between both models has been done. For this, a study area named Kathajodi–Surua Inter-basin has been selected within the Mahanadi deltaic system of Odisha, eastern India. The present study has innovative elements concerning the methodology of groundwater-flow modeling and the study area.

2. Study area

The study area is a typical river island within Mahanadi deltaic system of eastern India and is surrounded on both sides by the Kathajodi River and its branch Surua (Figs. 1 and 2). It is locally called as 'Bayalish Mouza' and is located between 85°54′21″ to 86°00′41″ E longitude and 20°21′48″ to 20°26′00″ N latitude. The total area of the river island is 35 km^2. The study area has a tropical humid climate with an average annual rainfall of 1650 mm, of which 80% occurs during June to October months. The normal mean monthly maximum and minimum temperatures of the region are 38.8° C and 15.5° C in May and December, respectively. The mean monthly maximum and minimum evapotranspiration rates are 202.9 mm and 80.7 mm in May and December, respectively. Agriculture is the major occupation of the inhabitants and groundwater is the major source of irrigation in the area. There are 69 functioning government tubewells in the area, which constitute major sources of groundwater withdrawals for irrigation. These tubewells were constructed and managed by the Orissa Lift Irrigation Corporation, Government of Orissa, India. Now, they have been gradually handed over to the local water users' associations. There is no water shortage during the monsoon season in the study area, but in the summer season, the farm ponds dry up and the groundwater from tubewells is not sufficient to meet the entire water requirement of the farmers.

The river basin is underlain by a confined aquifer which mostly comprises coarse sand. The thickness of the aquifer varies from 20 to 55 m and the depth of the aquifer from 15 to 50 m over the basin (Mohanty et al., 2012). The aquifer hydraulic conductivity varies from 11.3 to 96.8 m/day, whereas the values of storage coefficient range between 1.43×10^{-4} and 9.9×10^{-4}.

3. Materials and methods

3.1. Data collection and analysis

Daily rainfall data of 20 years (1990–2009) and daily pan evaporation data of 4 years (2004–2007) were collected from a nearby meteorological observatory at Central Rice Research Institute (CRRI), Cuttack, Orissa located at about 2 km from the study area. The river-stage data available at an upstream site named Naraj (Fig. 1) were collected from the office of Central Water Commission (CWC), Bhubaneswar, Orissa. The lithologic investigations at 70 sites over the study area were carried out by test drilling method by Orissa Lift Irrigation Corporation (OLIC) Office, Cuttack, Orissa. The lithologic data were collected from the OLIC Office and analyzed by drawing geologic profiles along different sections in the study area. These lithologic analyses along with other field data were used for developing a numerical groundwater-flow model of the study area.

Since no groundwater data were available in the study area, a groundwater monitoring program was initiated by the authors. Monitoring of groundwater levels in the study area was done by selecting nineteen tubewells distributed over the study area. The locations of nineteen monitoring wells are shown as red circles in Fig. 2. Weekly groundwater-level data at the nineteen sites

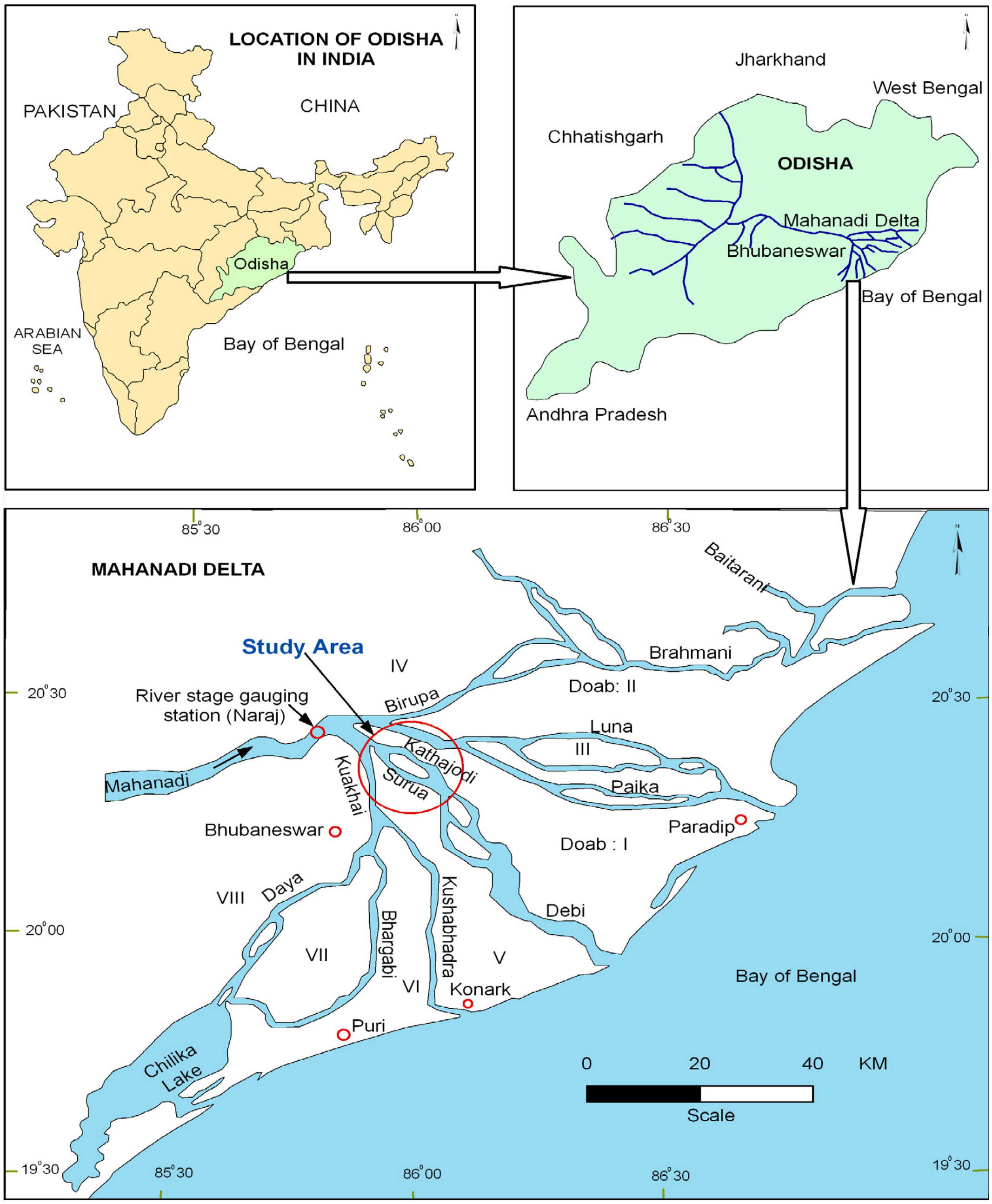

Fig. 1. Map of the study area showing geographical location and other details.

was monitored from February 2004 to October 2007, which was used for studying the groundwater characteristics in the study area, calibration of groundwater-flow simulation model, and training of neural network model for groundwater level forecasting.

3.2. Groundwater flow simulation using Visual MODFLOW

A groundwater flow simulation model was developed using Visual MODFLOW for simulating groundwater scenario in the study area. MODFLOW is a modular three-dimensional finite difference groundwater flow model (McDonald and Harbaugh, 1988), which simulates transient/steady groundwater flow in complex hydraulic conditions with various natural hydrological processes and/or artificial activities and, can be used for multi-aquifer modeling (Ting et al., 1998).

3.2.1. Conceptual model

A conceptual model of the study area was developed based on the hydrogeologic information and field investigation. The lithologic investigation indicates that a confined aquifer exists in the river basin. The thickness of the aquifer varies from 20 to 55 m and its depth from the ground surface varies from 15 to 50 m over the basin. The upper confining layer mostly consists of clay whereas the aquifer material comprises of medium sand to coarse sand. There are patches of medium sand and coarse sand within the clay bed which makes it act as a leaky confining layer. There are some clay lenses present in the confined aquifer. To simplify the model for simulation, those clay lenses were ignored while developing the conceptual model of the study area. The eastern boundary is bounded by the Kathajodi River and the western boundary is bounded by the Surua River (Fig. 2). Therefore, these boundaries were simulated as Cauchy (head-dependant flux)

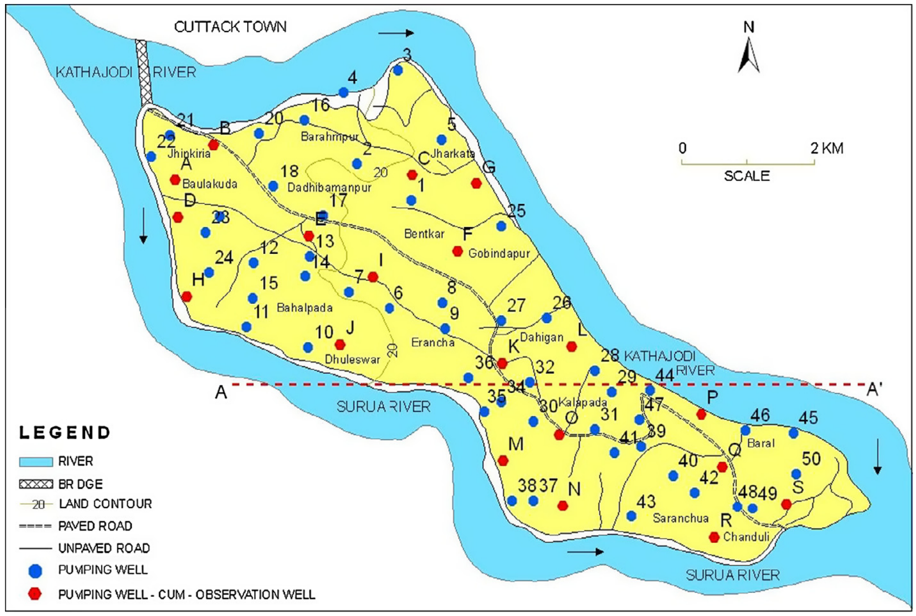

Fig. 2. Location of observation and pumping wells in the study area.

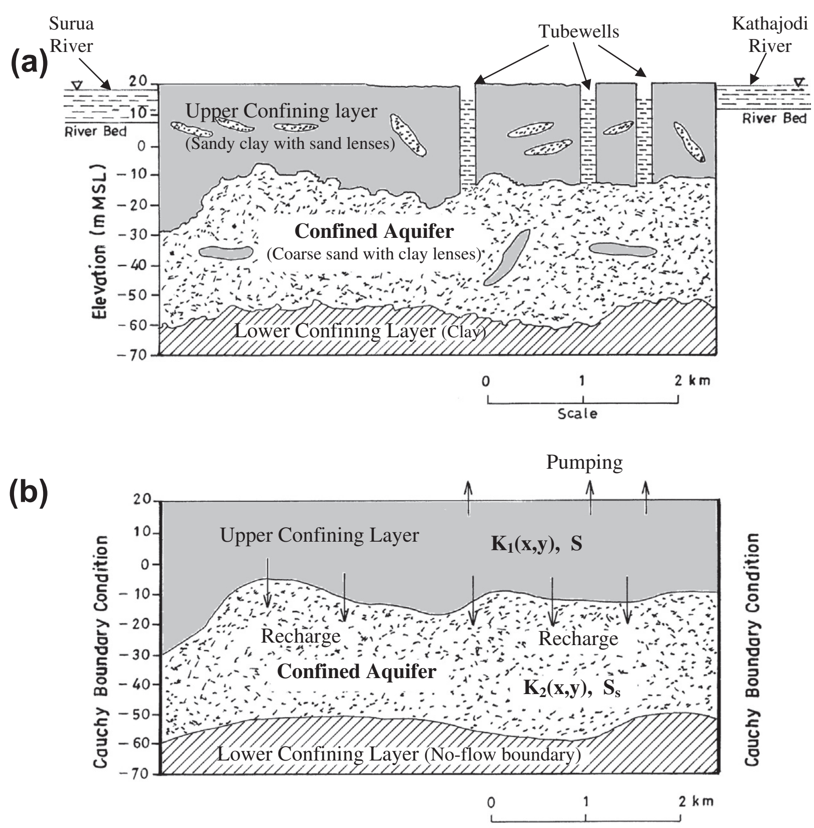

Fig. 3. (a) Representative lithiologic section of the Kathajodi–Surua Inter-basin. (b) Conceptual model of the Kathajodi–Surua Inter-basin.

boundary conditions. The conceptual model of the study area at Section A–A′ (Fig. 2) is shown in Fig. 3a and b, which provides a basis for the design and development of the numerical model of the study area using Visual MODFLOW software.

3.2.2. Discretization of the basin and model design

The study area was discretized into 40 rows and 60 columns using the Grid module of Visual MODFLOW software. This resulted in 2400 cells, each having a dimension of approximately 222 m ×

215 m. The cells lying outside the study area were assigned as inactive cells. The hydrogeologic setting of the study area as conceptualized earlier was divided into two model layers with the lower one representing the confined aquifer. The thickness of the two layers at different points was assigned considering the hydrogeologic framework of the basin. The data on surface elevation, bottom elevation of the top layer and bottom elevation of the aquifer layer at available 19 sites were imported to the MODFLOW software from the database prepared using MS-Excel files. Similarly, the location of pumping wells, observation wells and weekly groundwater levels of the model period were also imported from the MS-Excel databases.

3.2.3. Boundary conditions

The Kathajodi and Surua rivers completely surround the basin from the east and west directions, respectively making this study area a complete river island. Therefore, the boundaries of the groundwater basin were modeled as head-dependent flux or Cauchy boundary condition. The river heads were assigned as varying head boundary conditions using the 'River Package' of Visual MODFLOW software. The base of the aquifer was modeled as a no-flow boundary, because it consists of dense clay. The water flux between the rivers and the aquifer was simulated by dividing the rivers into 10 reaches. The input parameters such as river stage at different time steps, river-bed elevation, river-bed conductivity, river-bed thickness, and river width at the upstream and the downstream site for all the river reaches were assigned. MODFLOW linearly interpolates these values between both the ends of a river reach.

3.2.4. Initial conditions

Initial conditions refer to the head distribution everywhere in the system at the beginning of the simulation and thus are boundary conditions in time. It is a standard practice to select as the initial condition a steady state head solution generated by a calibrated model (Anderson and Woessner, 1992). In this study, steady-state head solution of 1st February 2004 groundwater level was used as the initial condition for the calibration period and steady-state head solution of 4th June 2006 groundwater level was used as the initial condition for the validation period.

3.2.5. Assigning model parameters

The model input includes hydrogeological parameters such as hydraulic conductivity and specific storage (S_s), and hydrological stresses like recharge, evapotranspiration and groundwater abstraction. The model parameters like hydraulic conductivity and specific storage were determined by conducting pumping tests at nine different sites of the study area. The hydraulic conductivity values ranged from a minimum of 11.25 m/day at Site B to a maximum of 96.80 m/day at Site O. Similarly the specific storage values ranged from a minimum of 4.3×10^{-6} at Site B to a maximum of 2.75×10^{-5} at Site O (Mohanty et al., 2012). The distribution of aquifer hydraulic conductivity over the study area was grouped into 9 zones based on pumping test data. For all the zones, a ratio of horizontal hydraulic conductivity (K_h) to vertical hydraulic conductivity (K_v) was assumed as 10 to account for aquifer anisotropy.

Since the historical records of pumping from these tubewells were not available, the data of groundwater abstractions were obtained by conducting a detailed survey in the study area. The pumping schedule, and position and extent of the well screens of respective pumping wells were assigned using the Well Package of the Visual MODFLOW software. The total groundwater recharge in the study area was estimated by adding the recharge from different sources such as rainfall, return flow from irrigation and water bodies. The recharge from rainfall was estimated using rainfall–recharge relationship for alluvial geological provinces of India given by Rangarajan and Athavale (2000). The recharge from the return flow from irrigation and water bodies were estimated according to the guidelines of Central Ground Water Board, New Delhi, India (CGWB, 1997). As the recharge estimated by empirical methods has a chance of uncertainty, they were used as a calibrating parameter.

3.2.6. Model calibration and validation

The developed groundwater-flow simulation model was firstly 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 19 observation wells during 1st February 2004. The solution of the steady-state calibration was used as an initial condition for the transient calibration. Transient calibration was performed using weekly groundwater level data of 19 selected sites for the period 01 February 2004 to 04 June 2006, 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. Initially, the sensitivity of hydraulic conductivity, specific storage and recharge to groundwater level fluctuation was studied by trial-and-error method. Based on the experience, their initial ranges were fixed for automated calibration, which were further refined during trial-and-error calibration. The lower and upper range of calibration parameters during automated calibration is given in Table 1. The calibration results were evaluated relative to the observed values of groundwater levels at 19 sites by using statistical indicators as well as by comparing observed and simulated groundwater-level hydrographs.

After calibrating the model, validation was performed using the observed groundwater level data from June 2006 to May 2007. The calibrated hydraulic conductivity and storage coefficient values were used during validation of the model whereas other input parameters like pumping, river stage, recharge and observation head of the corresponding validation period were used.

3.2.7. Criteria of model evaluation

In order to evaluate the performance of the calibration and validation of the MODFLOW-based numerical model, six statistical criteria were used. They are bias, mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), mean percent deviation (D_v) and Nash–Sutcliffe efficiency (NSE) and are given by the following equations:

$$\text{Bias} = \frac{1}{N}\sum_{i=1}^{N}(h_{si} - h_{oi}) \tag{1}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|h_{si} - h_{oi}|. \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(h_{si} - h_{oi})^2}{N}}. \tag{3}$$

Table 1
Range of calibration parameters during automated calibration.

Calibration parameter	Hydraulic conductivity	Specific storage	Recharge
Lower range	50% of measured value	50% of measured value	90% of estimated value
Upper range	200% of measured value	200% of measured value	110% of estimated value

$$R^2 = \frac{(\sum_{i=1}^{N}(h_{oi} - \bar{h}_o)(h_{si} - \bar{h}_s))^2}{\sum_{i=1}^{N}(h_{oi} - \bar{h}_o)^2 \sum_{i=1}^{N}(h_{si} - \bar{h}_s)^2}. \quad (4)$$

$$D_v = \frac{1}{N}\sum_{i=1}^{N}\frac{h_{si} - h_{oi}}{h_{oi}} \times 100 \quad (5)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}(h_{oi} - h_{si})^2}{\sum_{i=1}^{N}(h_{oi} - \bar{h}_o)^2} \quad (6)$$

where h_{oi} is the observed groundwater level of the ith data [L], h_{si} the simulated/predicted groundwater level of the ith data, $\bar{h}_o$ the mean of observed groundwater levels [L], $\bar{h}_s$ the mean of simulated groundwater levels [L], and N is the number of observations. The best-fit between observed and simulated groundwater levels under ideal conditions would yield bias = 0, MAE = 0, SEE = 0, RMSE = 0, normalized RMSE = 0, R^2 = 1, D_v = 0 and NSE = 1.

Moreover, the observed groundwater level hydrographs and MODFLOW-based numerical model simulated groundwater level hydrographs were plotted for a visual checking of model performance. Scatter plots (together with 1:1 line, 95% interval lines and 95% confidence interval lines) of observed versus simulated groundwater levels were also prepared for calibration and validation periods for examining the efficiency of the models in simulating groundwater levels. The 95% interval is the interval where 95% of the total number of data points is expected to occur. The 95% confidence interval shows the range of calculated values for each observed value with 95% confidence that the simulation results will be acceptable for a given observed value. For an ideal calibration, the 1:1 line should lie within the 95% confidence interval lines (WHI, 2005).

3.2.8. Prediction of future groundwater scenario

In a predictive simulation, the parameters optimized during calibration are used to predict the system response to future events. Predictive simulations were performed to examine the response of the aquifer to simulate groundwater levels in the long run under existing pumping conditions. Under this scenario, keeping all the existing conditions constant, the effect of continuation of existing pumpage on groundwater levels during 2007–2020 period was examined.

3.3. Groundwater level forecasting using artificial neural network model

Besides the development of a groundwater-flow simulation model, ANN models were also developed to assess their efficacy in predicting groundwater levels in the study area. In most of the past studies on groundwater level prediction by ANN, the ANN models have been developed for predicting groundwater levels either in a single well or in a few selected wells using a varying set of input parameters (Daliakopoulos et al., 2005; Nayak et al., 2006; Uddameri, 2007; Krishna et al., 2008). However, in the present study, an attempt was made to predict groundwater levels simultaneously in a large number of wells over the basin by using ANN technique.

3.3.1. Design of ANN model

In this study, widely applied feedforward neural network (FNN) architecture was used. It is one of the simplest neural networks and has been successfully used for water resources variable modeling and prediction (Maier and Dandy, 2000; ASCE, 2000). In a feedforward network, the nodes are generally arranged in layers, starting from a first input layer and ending at the final output layer. The nodes in one layer are connected to those in the next, but not to those in the same layer. Thus, the output of a node in a layer is only dependant on the input it receives from previous layers and corresponding weights. Fig. 4 shows the feedforward network for the current study having one hidden layer with 40 nodes in the input layer and 18 nodes in the output layer.

As the Bayesian regularization performed better than Levenberg–Marquardt and GDX algorithms (Mohanty et al., 2010), it was used in this study for groundwater level forecasting. The ANN model was designed to predict groundwater levels in 18 tubewells (Fig. 2) with 1-week lead time using a set of suitable input parameters. Based on the correlation analysis between groundwater level and the selected input parameters, groundwater level at 1-week lag time, weekly rainfall, river stage, weekly evaporation, water level in the main drain and weekly pumping from the tubewells were considered as final input parameters. There were altogether 40 input nodes and 18 output nodes in the initial ANN model of the study area. The 40 input nodes represent groundwater levels with 1-week lag time at the 18 sites, groundwater pumping rates of the 18 tubewells, weekly rainfall, average weekly pan evaporation, average weekly river stage, and average weekly water level at the drain outlet. The 18 output nodes represent groundwater levels at the 18 sites in the next time step (i.e., 1 week ahead).

3.3.2. Clustering of study area

The ANN model having 40 input nodes and 18 output nodes was difficult to be trained by the trial and error method while using Bayesian regularization (BR) algorithm; it proved to be time and computer memory consuming. Maier and Dandy (1998) reported that the Levenberg–Marquardt algorithm has a great computational and memory requirement, and hence it is mostly useful for

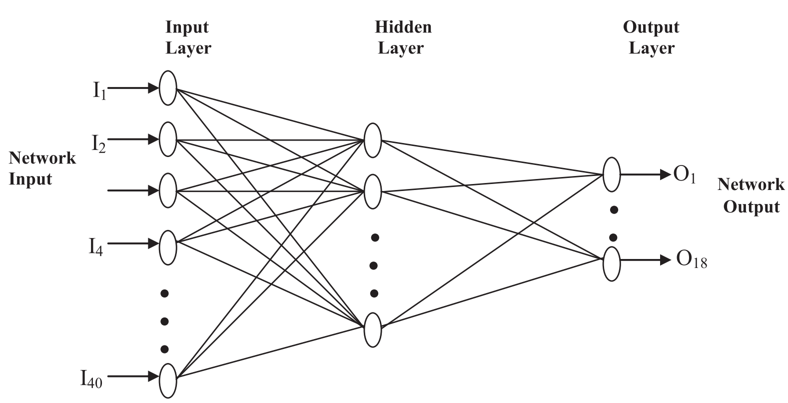

Fig. 4. Configuration of feedforward three-layer ANN for the study area.

small networks. In order to run the model effectively, an effort was made to reduce the size of the neural network by dividing the study area into three clusters (Mohanty et al., 2010) and developing three separate ANN models for the three clusters to predict groundwater levels 1 week advance at the sites present in a particular cluster. Cluster 1 contains 7 sites namely A, B, D, E, H, I and J. Cluster 2 contains 5 sites namely C, F, G, K and L, and Cluster 3 contains 6 sites namely M, O, P, Q, R and S (Fig. 2). The division of the study area into three clusters and modeling groundwater separately in three clusters would not have any effect on the final output as the pumping of the tubewells in a given cluster has a very minor effect on the water level in the tubewells of other clusters.

In each cluster, groundwater levels at the sites in the previous time step, pumping rates of the tubewells, weekly total rainfall, weekly pan evaporation and weekly river stage were considered as input parameters. In the third cluster, however, an additional input parameter weekly water level in the drain was considered as it has potential to affect the groundwater level in this cluster only. Thus, Cluster 1 had 17 input nodes and 7 output nodes, Cluster 2 had 13 input nodes and 5 output nodes and Cluster 3 had 16 input nodes and 6 output nodes.

3.3.3. Model training and testing

The structure of the neural network consisted of one hidden layer along with the input and output layer. The optimal number of nodes in the hidden layer was optimized by trial and error and the number of hidden nodes corresponding to the least root mean squared error (RMSE) was selected as the optimal number of hidden neuron. The activation function of the hidden layer and output layer was set as log-sigmoid transfer function as this proved to be the best by trial and error among a set of other options. In this study, supervised type of learning with a batch mode of data feeding was used for ANN modeling. Out of the 174 weeks datasets available, 122 datasets were used for training the ANN models and 52 datasets were used for testing the models. The ANN modeling was performed by using MATLAB 6.5 software. The six statistical indicators described in Section 3.2.7 were used to evaluate the performance of the developed ANN models during training and testing.

3.4. Comparison of numerical model and neural network model

A comparison of the performance of the MODFLOW-based numerical model with that of the ANN model was carried out to study their efficacy in simulating/predicting groundwater levels. In order to have a fair comparison between the models, the training and testing periods of the ANN model were maintained same as the corresponding period of the numerical model. The predicted groundwater levels by the ANN model at 18 sites during the testing period were compared with the groundwater levels simulated by the numerical model during the validation period using statistical indicators like bias, MAE, RMSE, R^2, D_v and NSE as described in Section 3.2.7. In addition, groundwater levels simulated by both the models were plotted along with the observed groundwater levels for visual comparison of performance of the two models.

4. Results and discussion

4.1. Groundwater simulation by numerical model

4.1.1. Calibration results

During calibration, the groundwater flow-simulation model was found more sensitive to aquifer hydraulic conductivity values in comparison to aquifer specific storage. The statistical indicators along with the calibrated hydraulic conductivity values at nineteen

Table 2
Performance statistics of numerical model during calibration period.

Site	Calibration period (February 2004 to May 2006)						
	Bias (m)	MAE (m)	RMSE (m)	R^2	D_v (%)	NSE	K_h (m/day)
A	0.347	0.505	0.589	0.891	2.396	0.831	20
B	−0.490	0.508	0.616	0.910	−3.012	0.693	20
C	−0.267	0.593	0.660	0.869	−1.788	0.602	27
D	0.006	0.344	0.442	0.895	0.118	0.895	32
E	−0.175	0.655	0.765	0.843	−1.280	0.700	23
F	0.006	0.382	0.485	0.901	−0.012	0.872	27
G	−0.517	0.616	0.768	0.794	−3.154	0.613	27
H	0.012	0.335	0.444	0.927	0.264	0.907	32
I	−0.090	0.515	0.642	0.856	−0.683	0.792	23
J	0.117	0.370	0.472	0.949	1.065	0.918	41
K	−0.081	0.496	0.686	0.817	−0.598	0.782	44
L	−0.253	0.462	0.682	0.812	−1.793	0.775	44
M	0.161	0.486	0.632	0.878	1.604	0.857	52
N	0.542	0.722	0.850	0.799	4.457	0.681	52
O	0.182	0.577	0.809	0.762	1.436	0.680	52
P	−0.407	0.449	0.617	0.903	−3.098	0.828	45
Q	0.031	0.397	0.581	0.869	0.400	0.861	45
R	−0.210	0.663	0.817	0.852	−1.076	0.809	47
S	0.273	0.473	0.600	0.899	2.564	0.863	47

calibration sites are presented in Table 2. It is observed that the bias, MAE, RMSE, R^2, D_v and NSE values vary in the range of 0.006 to 0.517 m, 0.335 to 0.663 m, 0.442 to 0.817 m, 0.762 to 0.949, −0.012 to −3.154% and 0.602 to 0.918 respectively, after calibration of the model. The statistical indicators in the table indicate that the simulated groundwater levels at sites D, F, H, J and N are more accurate compared to other sites (relatively low values of MAE and RMSE, and high values of R^2 and NSE). On the other hand, there has been relatively inferior simulation of groundwater levels at sites C, E, G and R as the MAE and RMSE values are on a higher side, and R^2 and NSE values are on a lower side. The bias values at sites B, C, E, G, I, K, L, P and R are negative, which indicates there is overall under-simulation at these sites. There is overall over-simulation at the remaining sites. However, there is an overall good calibration because the values of bias, MAE, RMSE, and D_v for almost all the sites are reasonably low and within acceptable limits. Also,

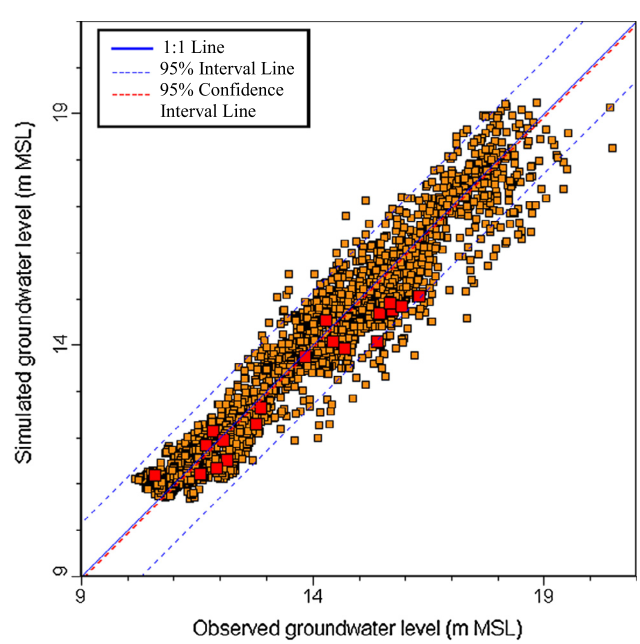

Fig. 5. Scatter diagram of observed versus simulated groundwater levels for the calibration period.

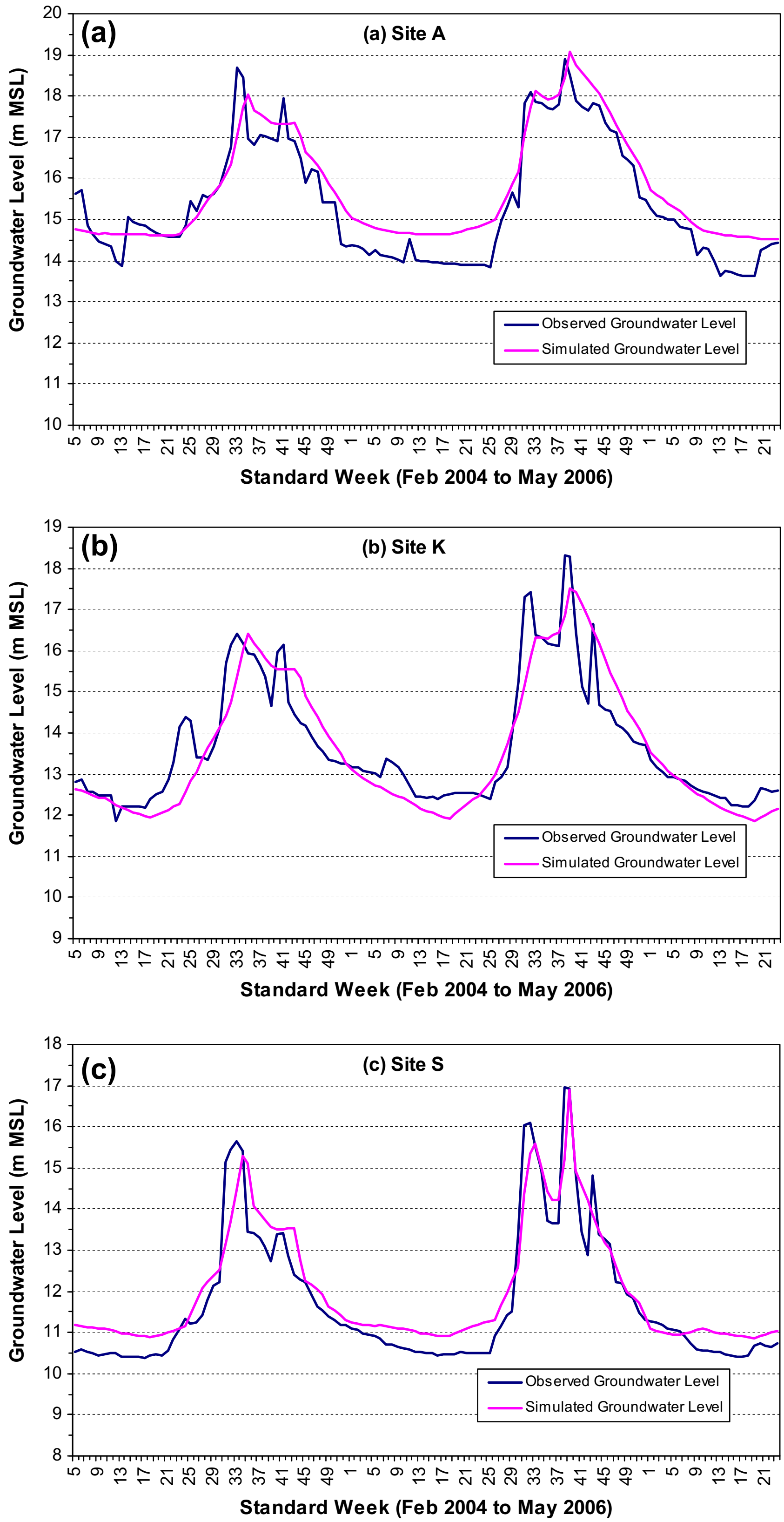

Fig. 6. (a–c) Comparison between observed and simulated groundwater levels at sites A, K and S for the calibration period.

the R^2 and NSE values are reasonably high at most of the sites. The calibration was done keeping in view the mean statistical indicators, and hence there was very good calibration at some sites and there was average calibration at other sites. The variation of degree of accuracy at different calibration sites is not unusual at a basin scale. This variation can be attributed to the influence of local factors and/or errors in field data measurement. The calibrated values of hydraulic conductivity varied from a minimum of 20 m/day (sites A and B) to a maximum of 52 m/day (sites M, N and O) (Table 2), whereas the calibrated values of aquifer specific storage remained more or less the same (varying from 1.43×10^{-4} to 9.9×10^{-4}) as the measured values.

The MODFLOW-generated scatter diagram along with 1:1 line, 95% interval lines and 95% confidence interval lines for the entire calibration period is shown in Fig. 5. The figure shows that the 1:1 line lies within the 95% confidence interval lines indicating a good calibration of the developed groundwater flow model. The observed and calibrated groundwater levels at three sites, i.e., Baulakuda (Site A) in the upstream portion of the basin, Dahigan (Site K) in the middle portion of the basin and Chanduli (Site S) in the downstream portion of the basin are shown in Figs. 6a–c, respectively. The visual comparison of observed and calibrated groundwater level hydrographs at all the sites including the above 3 sites indicated a reasonably good match between observed and calibrated groundwater levels at almost all the sites except sites C and E having under-simulation of groundwater levels during dry periods, Site G having under-simulation during both dry and wet periods, and Site R having over-simulation during dry periods and under-simulation during wet periods.

4.1.2. Validation results

The scatter diagram along with 1:1 line, 95% interval lines and 95% confidence interval lines for the entire validation period is shown in Fig. 7. The figure shows that the 1:1 line lies within the 95% confidence interval lines which indicates satisfactory validation of the developed groundwater flow model. The comparison between the observed and simulated groundwater levels by graphical as well as statistical methods is described in succeeding section dealing with comparison of MODFLOW-based numerical model and ANN model. Table 3 shows the comparison of statistical indicators during the calibration and validation of the model. The statistical indicators MAE, RMSE, D_v are only marginally higher and NSE is only marginally lower during validation in comparison to the calibration period. This signifies satisfactory calibration and validation of the model.

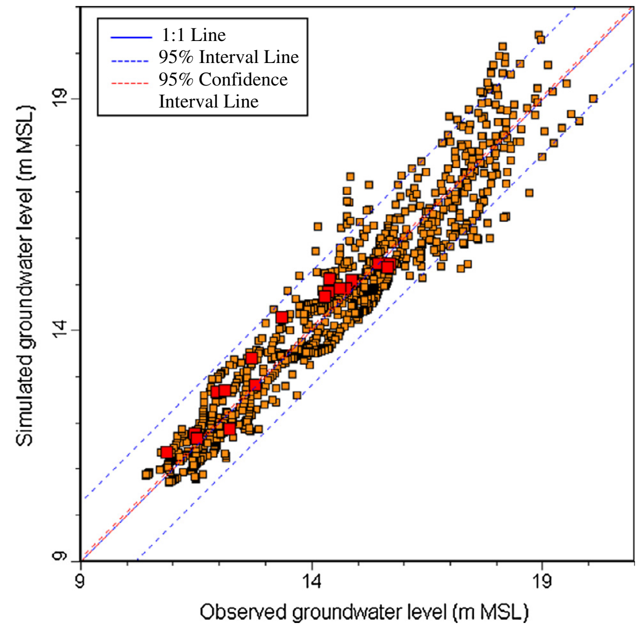

Fig. 7. Scatter diagram of observed versus simulated groundwater levels for the validation period.

Table 3
Comparison of performance statistics during calibration and validation of the model.

	Bias (m)	MAE (m)	RMSE (m)	R^2	D_v (%)	NSE
Calibration	−0.063	0.478	0.620	0.916	−0.27	0.915
Validation	0.044	0.489	0.632	0.918	0.37	0.914

4.1.3. Simulating future groundwater scenario

Fig. 8 shows the simulated groundwater levels at five sites distributed over the study area during the period (2007–2020), keeping all the parameters constant. It is clear that there is no significant change in groundwater levels up to the year 2020 at all the sites. The groundwater levels at sites O and S are relatively lower than the other 3 sites, and that scenario is maintained throughout the simulation period. The Kathajodi–Surua Inter-basin is a complete river island surrounded by two rivers and due to this, the effect of the boundary conditions on groundwater levels has been found very significant. The water that is pumped from the aquifer is being replenished by the river, and hence there is no significant change in groundwater levels even in the long run (by 2020). Thus, if the existing conditions continue, there is no threat to the groundwater lowering in the study area in the near future.

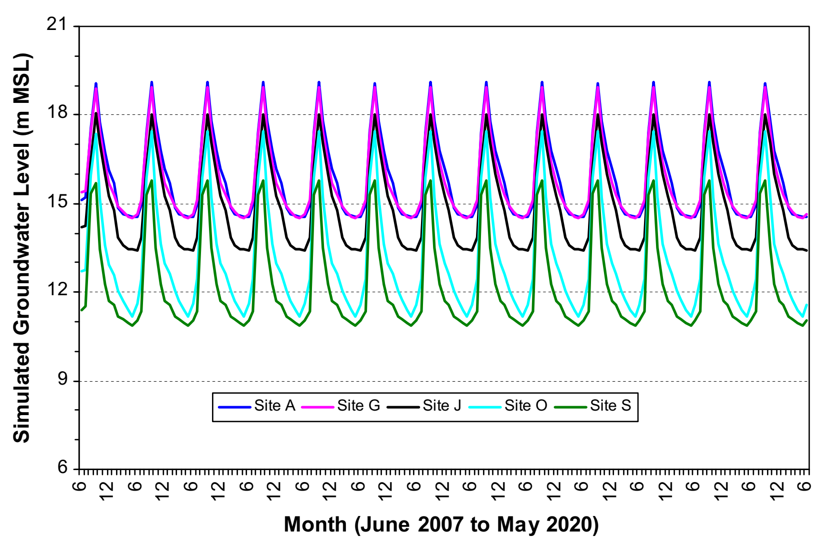

Fig. 8. Simulated groundwater levels during the period 2007–2020.

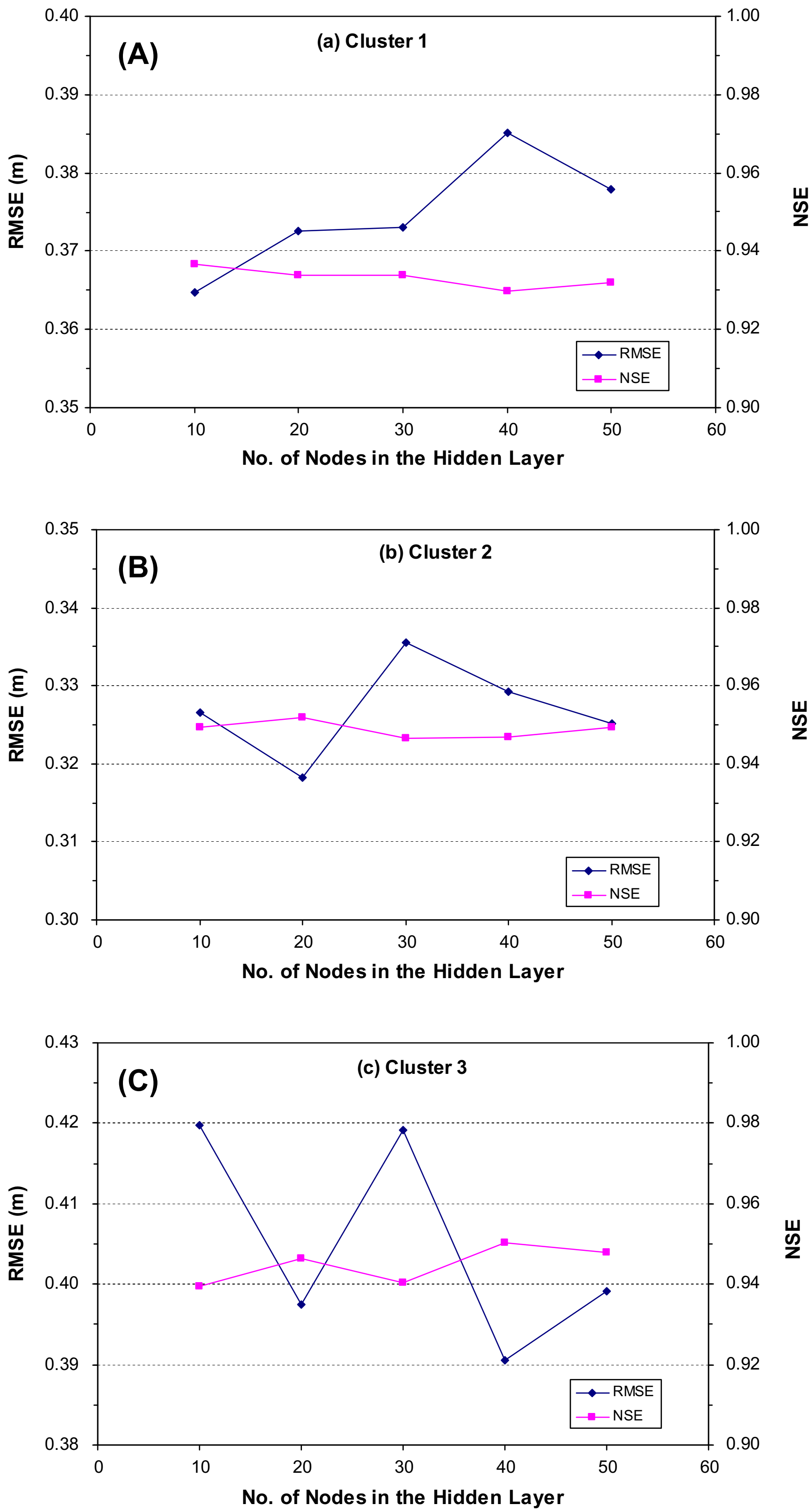

Fig. 9. (a–c) Variation of RMSE and NSE with number of nodes in the hidden layer at three clusters.

4.2. Groundwater level forecasting using neural network model

4.2.1. Model training results

The optimum number of hidden neurons in the neural network model was found 10, 20 and 40 for clusters 1, 2 and 3, respectively. Fig. 9a–c show the variation of RMSE and NSE values with the number of nodes in hidden layer for three different clusters respectively. The RMSE values are the lowest and the NSE values are the highest in all the figures with respect to the optimum number of hidden neurons.

Table 4
Performance statistics of ANN model during training period.

Site	Calibration period (February 2004 to May 2006)					
	Bias (m)	MAE (m)	RMSE (m)	R^2	D_v (%)	NSE
A	−0.044	0.189	0.249	0.970	−0.262	0.970
B	−0.018	0.116	0.149	0.982	−0.097	0.982
C	0.019	0.139	0.184	0.970	0.074	0.969
D	−0.032	0.176	0.241	0.970	−0.169	0.969
E	0.011	0.147	0.188	0.982	0.105	0.982
F	0.011	0.168	0.214	0.976	0.104	0.975
G	−0.003	0.210	0.304	0.941	0.022	0.940
H	−0.030	0.181	0.235	0.974	−0.176	0.974
I	−0.005	0.121	0.159	0.988	−0.005	0.987
J	−0.018	0.150	0.200	0.986	−0.087	0.985
K	0.006	0.224	0.328	0.951	0.106	0.951
L	0.019	0.251	0.359	0.939	0.237	0.938
M	0.020	0.276	0.394	0.945	0.284	0.945
O	0.024	0.266	0.389	0.927	0.311	0.926
P	0.030	0.228	0.367	0.941	0.349	0.940
Q	0.022	0.258	0.385	0.941	0.309	0.939
R	0.057	0.361	0.478	0.939	0.714	0.935
S	0.037	0.237	0.391	0.943	0.455	0.942

The statistical indicators for the training period at eighteen sites are presented in Table 4. It is observed that the bias, MAE, RMSE, R^2, D_v and NSE values for the training period vary in the range of −0.003 to 0.057 m, 0.116 to 0.361 m, 0.149 to 0.478 m, 0.927 to 0.988, −0.005 to −0.714% and 0.926 to 0.987 respectively. The statistical indicators indicate that the training of the model is very satisfactory as the values of bias, MAE, RMSE, and D_v are reasonably low and the R^2 and NSE values are reasonably high at all the sites.

4.3. Comparison between the numerical model and ANN model

The comparison between the MODFLOW-based numerical model and the ANN model in terms of bias, MAE, RMSE, R^2, D_v and NSE statistical indicators during validation period is shown in Table 5. The bias, MAE, RMSE, R^2, D_v and NSE values in numerical model vary in the range of −0.025 to −0.505 m, 0.297–0.709 m, 0.38–0.827 m, 0.85–0.964, 0.36% to −3.78% and 0.55–0.95 respectively. The corresponding values in neural network model varies in the range of 0.01–0.239 m, 0.178–0.464 m, 0.24–0.522 m, 0.918–0.976, −0.06% to 1.82% and 0.90–0.96 respectively. The values of R^2 and NSE are generally higher and the values of bias, MAE, RMSE and D_v are lower for the ANN model at all the sites compared to the numerical model. Hence, it can be inferred that the ANN model predicted groundwater levels with higher accuracy than the numerical model.

Furthermore, simultaneous plots of the groundwater levels simulated by the MODFLOW-based numerical model and the ANN model along with the observed groundwater levels for three sites, i.e., Baulakuda (Site A) in the upstream portion of the basin, Dahigan (Site K) in the middle portion of the basin and Chanduli (Site S) in the downstream portion of the basin are shown in Figs. 10a–c, respectively. The visual comparison of observed, numerical model-simulated and ANN model-simulated groundwater level hydrographs at all the sites including the above 3 sites indicated that the groundwater levels predicted by the ANN model matched better with the observed groundwater levels than the groundwater levels simulated by the numerical model. It is only at Site Q and to some extent Site R, the accuracy of groundwater levels prediction by the numerical model almost matched with that of ANN model. Thus, the visual checking of observed and simulated groundwater levels also confirms that the ANN model is superior to the numerical model in simulating groundwater levels.

A closer look at the quantitative indicators and graphical comparisons show that there is very little difference between the R^2 values obtained for the numerical and ANN models (Table 5), even though the graphical comparisons and other statistical indicators indicate a clear difference between the performances of both the models. Similarly, the values of bias and D_v at sites C, F and H are significantly less in case of numerical model, even though other statistical indicators and graphical comparisons do not show a good matching between the observed and simulated groundwater levels. It can be attributed to the reason that in some cases, the over-calculated and under-calculated values negate each other, and produce a bias value close to zero. Sometimes, this can lead to false interpretation of model calibration (WHI, 2005). The same logic holds true for D_v also. On the other hand, the MAE, RMSE and NSE indicators are consistently found superior in ANN model than the numerical model, except at sites Q and R, where they are comparable. This is also in agreement with the graphical comparison of observed and simulated groundwater levels. Based on the above analysis, it is inferred that the MAE, RMSE and NSE statistical indicators are more powerful than the bias, D_v and R^2 in evaluating the model performance.

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

Table 5
Goodness-of-fit statistics for the numerical and ANN models at 18 sites during validation period (June 2006 to May 2007).

Site	Numerical model						ANN model					
	Bias (m)	MAE (m)	RMSE (m)	R^2	D_v (%)	NSE	Bias (m)	MAE (m)	RMSE (m)	R^2	D_v (%)	NSE
A	0.473	0.536	0.717	0.867	3.162	0.763	0.023	0.253	0.365	0.941	0.167	0.939
B	−0.438	0.568	0.677	0.854	−2.620	0.718	−0.022	0.281	0.331	0.937	−0.060	0.933
C	−0.072	0.657	0.775	0.891	−0.657	0.550	0.010	0.178	0.240	0.958	0.095	0.957
D	0.236	0.343	0.493	0.912	1.565	0.884	0.127	0.239	0.342	0.953	0.859	0.945
E	0.182	0.658	0.827	0.937	0.825	0.670	0.023	0.216	0.299	0.956	0.183	0.957
F	0.082	0.613	0.737	0.874	0.356	0.706	−0.067	0.277	0.365	0.939	−0.454	0.928
G	−0.399	0.436	0.542	0.935	−2.396	0.855	0.079	0.201	0.288	0.964	0.491	0.960
H	0.081	0.511	0.657	0.850	0.804	0.826	0.084	0.271	0.358	0.953	0.617	0.949
I	0.369	0.529	0.697	0.962	2.177	0.775	0.211	0.297	0.380	0.955	1.431	0.934
J	0.124	0.417	0.600	0.850	0.947	0.841	−0.016	0.375	0.480	0.918	−0.166	0.898
K	0.284	0.400	0.505	0.947	2.041	0.912	0.239	0.291	0.353	0.976	1.816	0.957
L	−0.277	0.379	0.522	0.929	−1.958	0.900	−0.047	0.228	0.345	0.958	−0.299	0.957
M	0.312	0.709	0.812	0.937	3.114	0.843	0.109	0.365	0.444	0.972	1.171	0.954
O	0.369	0.424	0.563	0.949	2.790	0.885	0.097	0.259	0.355	0.958	0.844	0.955
P	−0.505	0.520	0.631	0.953	−3.778	0.853	−0.079	0.247	0.324	0.964	−0.566	0.962
Q	−0.025	0.297	0.380	0.964	−0.373	0.945	−0.136	0.292	0.343	0.966	−1.170	0.955
R	−0.279	0.396	0.552	0.945	−1.974	0.907	−0.042	0.464	0.522	0.922	−0.350	0.918
S	0.282	0.416	0.486	0.955	2.587	0.922	0.036	0.244	0.356	0.960	0.300	0.958

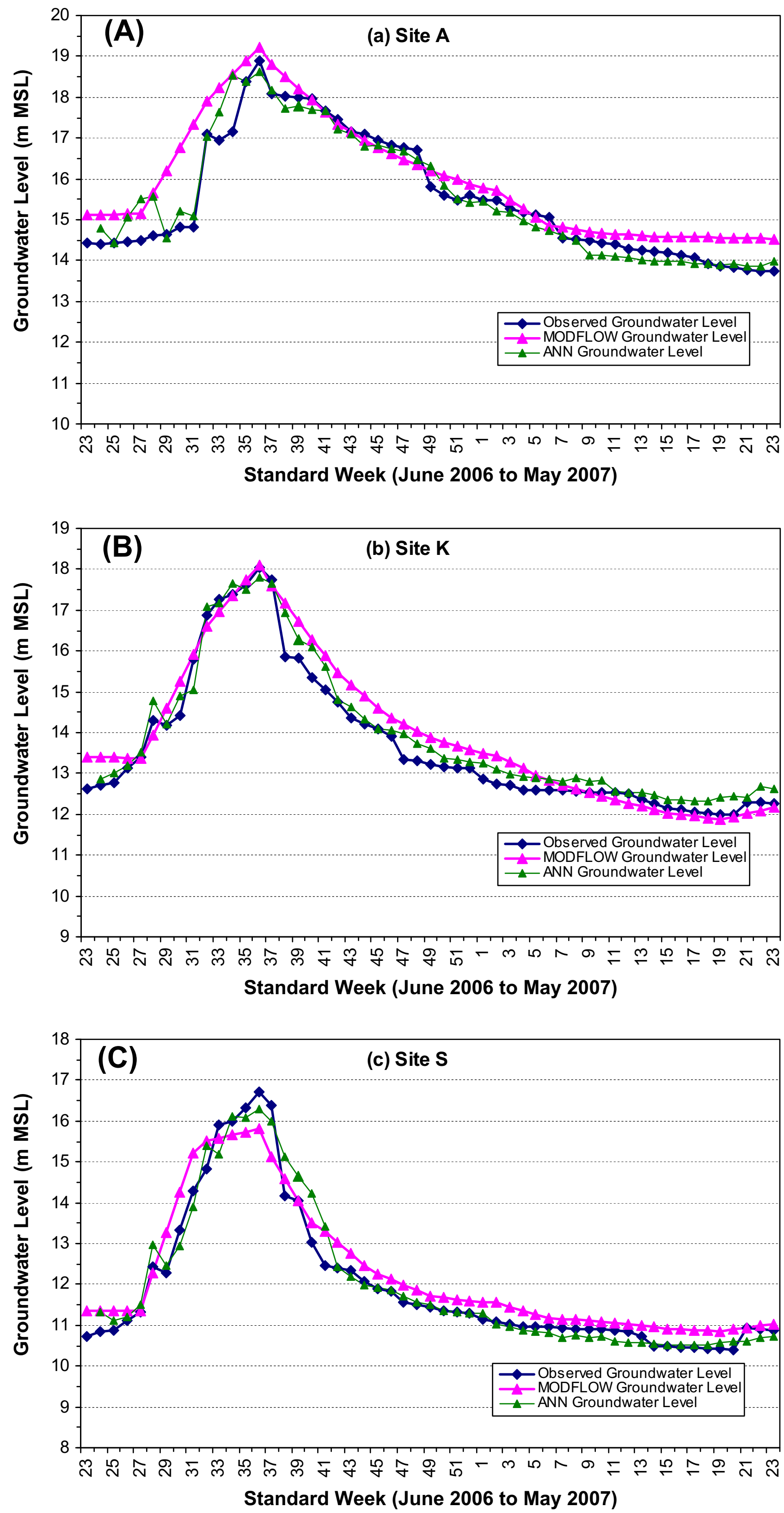

Fig. 10. (a–c) Comparison between groundwater level simulated by numerical model and ANN model at site A, K and S.

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 models, 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 provide total water balance of the system under study, whereas the ANN models are 'black box' models and they do not provide any information about the processes of a system. Also, the numerical models can help provide insights into the hydrogeologic framework and properties, and simulate future conditions (Coppola et al., 2003). They can also generate detailed output regarding head, flow, and water budget components over 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-term predictions at selected locations that require a high accuracy (Coppola et al., 2005).

5. Conclusions

A groundwater flow simulation model was developed for the Kathajodi–Surua Inter-basin of Odisha, India using finite difference-based Visual MODFLOW software for simulating groundwater levels. Additionally, artificial neural network (ANN) models were also developed for forecasting groundwater levels in the study area. The comparison of these two different types of models revealed that the ANN model can provide better prediction of groundwater levels than the MODFLOW-based numerical model for short time-horizon predictions. ANNs have also the advantage of not requiring explicit characterization and quantification of physical properties of the system. 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 models, any changes in the input or output parameters will require total modeling of the system from the beginning, but this is not the case in case of numerical models. Furthermore, the numerical models are more appropriate for long-term predictions, whereas the ANN technique is better for short-term predictions that require a high accuracy. Thus, there are different advantages offered by the ANN technology and numerical models, and therefore they should be selected in accordance with the type of problems. In some cases, they can be used as complementary to each other for making sound decisions concerning groundwater management problems.

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