Environ Geol (2007) 51:885–895
DOI 10.1007/s00254-006-0452-5

ORIGINAL ARTICLE

Using statistical and artificial neural network models to forecast potentiometric levels at a deep well in South Texas

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Received: 27 February 2006 / Accepted: 12 July 2006 / Published online: 22 August 2006

Abstract Reliable forecasts of monthly and quarterly fluctuations in groundwater levels are necessary for short- and medium-term planning and management of aquifers to ensure proper service of seasonal demands within a region. Development of physically based transient mathematical models at this time scale poses considerable challenges due to lack of suitable data and other uncertainties. Artificial neural networks (ANN) possess flexible mathematical structures and are capable of mapping highly nonlinear relationships. Feed-forward neural network models were constructed and trained using the back-percolation algorithm to forecast monthly and quarterly time-series water levels at a well that taps into the deeper Evangeline formation of the Gulf Coast aquifer in Victoria, TX. Unlike unconfined formations, no causal relationships exist between water levels and hydro-meteorological variables measured near the vicinity of the well. As such, an endogenous forecasting model using dummy variables to capture short-term seasonal fluctuations and longer-term (decadal) trends was constructed. The root mean square error, mean absolute deviation and correlation coefficient (R) were noted to be 1.40, 0.33 and 0.77 m, respectively, for an evaluation dataset of quarterly measurements and 1.17, 0.46, and 0.88 m for an evaluative monthly dataset not used to train or test the model. These statistics were better for the ANN model than those developed using statistical regression techniques.

Keywords ANN · Back percolation · Time-series modeling · Coastal aquifers · Texas · USA

Introduction

Accurate short- and medium-term forecasts of groundwater levels are critical to ensure that water demands of different user groups within a region are met in a proper manner. Such forecasts are often used to help trigger drought management practices and other conservation measures and also to help farmers meet their crop water requirements. Mathematical models based on the conservation laws of physics can be calibrated and used to obtain monthly and quarterly forecasts of groundwater levels. However, the development of such models requires considerable data of not just the groundwater levels but also of other hydrogeologic parameters such as hydraulic conductivity and storage coefficients. In addition, the characterization of hydrologic processes such as recharge and surface water–groundwater interactions is data intensive and introduces considerable uncertainty in the modeling results.

Regional-scale groundwater models are useful for long-term planning and understanding of how various hydrologic and hydrogeologic processes affect large-scale groundwater movement. However, these models are typically not suitable for short- and medium-term forecasting, as their large grid sizes will effectively average out any local responses that may be produced in the short run. The focus on the localized responses during the short-term planning calls for alternative approaches that lead to better forecasts even if these tools do not provide pertinent physical insights into the

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mechanisms causing the noted response (Ahmad and Simonovic 2005).

Artificial neural networks (ANN) are modeled after the human brain in that they learn the behavior of the system from the data. They do not require extensive characterization of the system using conservation laws. Instead, the system response is correlated to a known set of inputs, which are presumably easy to measure and control the response of the system. Mathematically, ANNs have been shown to be universal approximators capable of mapping highly nonlinear relationships (Hornik et al. 1989).

The applications of ANNs to hydrology started in early 1990s and since then have been used extensively in several surface water hydrology problems including: developing rainfall–runoff relationships (Rajurkar et al. 2004; Tokar and Markus 2000; Fernando and Jayawardena 1998), predicting stream flows (Moradkhani et al. 2004; Anctil et al. 2004), estimating river stages (Thirumalaiah and Deo 1998) and generating runoff hydrographs (Ahmad and Simonovic 2005; Muttiah et al. 1997). The reader is referred to ASCE (2000a, b) for a more thorough discussion on the theory and applications of neural networks to hydrologic problems.

In contrast, the applications of ANNs in groundwater hydrology have been more recent (Coulibaly et al. 2001; Coppola et al. 2003; Daliakopoulos et al. 2005). The primary focus of these applications has been to forecast water table fluctuations in shallow unconfined aquifer using hydro-climatic variables such as precipitation, temperature and streamflow (Daliakopoulos et al. 2005). Coppola et al. (2003) considered ANNs to predict water table fluctuations in semiconfined formations of multilayered systems. Again, they utilized pumping as well as other hydro-climatic information such as temperature, relative humidity and wind speed as input parameters. In all these studies, neural network models were noted to perform well and in some instances their predictive capabilities exceeded those of physically based models developed using MODFLOW (Coppola et al. 2003).

While the prediction of water table fluctuations using exogenous hydro-climatic variables is possible in unconfined and shallow semiconfined aquifers, these inputs may not be useful for modeling potentiometric heads in deeper formations that are not as affected by climatic influences. This task is further exacerbated when anthropogenic pumping information is also not available. The econometric strategy of using dummy variables for modeling time-series data (Gujarati 1979) is coupled with neural networks and evaluated in this study to obtain groundwater level forecasts when surrogate information is not available or suitable for making predictions.

Materials and methods

Data collection and preprocessing

Historical data (collected approximately once every 5 days) between the period January 1973 and December 1996 at a well (USGS well # TX001 284105096564501 YT-80-17-502) in Victoria, TX, with geographic coordinates, latitude—28°41′05″W, longitude—96°56′45″N with a land surface datum (LSD) 20.73 m above mean sea level, were selected for this study. The well penetrates 312.72 m below the land surface and is screened in the Goliad and Lissie hydrologic units of the Plieocine and Pleistocene series and is referred to as the Evangeline formation (Baker 1979). The raw data consisted of 2,822 records from which monthly average water levels were extracted using the Pivot Table operation in MS-EXCEL®. The average water levels were missing for 22 months, which were interpolated using successive moving average models with two, three, eight and twelve periods. The average root mean square error (RMSE) of the all the moving average predictions was less than 1.52 m with the maximum error of about 1.83 m. As such, the potential errors introduced due to the interpolation procedure are within the natural variability observed at the well and were deemed not to bias the study. The data were also used to obtain quarterly average water level elevations. Wherever possible, interpolated data were excluded to obtain quarterly averages to further minimize any errors introduced by interpolation. Only three quarters during the years 1973–1996 were based on the interpolated data. In addition to water level measurements, monthly temperature and precipitation data collected at Victoria, TX, were obtained from the National Climatic Data Center (NCDC 2004).

Exploratory data analysis and model specification

The Evangeline formation of the Gulf Coast aquifer outcrops several tens of kilometers westwards away from the well. The stratigraphic thickness of the Evangeline formation increases towards the east (Baker 1979). As such, precipitation and temperature measurements collected near the well may not be good indicators of groundwater levels observed in the well and this reasoning was confirmed by cross-plots presented in Figs. 1 and 2. Furthermore, the water levels in the well were influenced by pumping from several

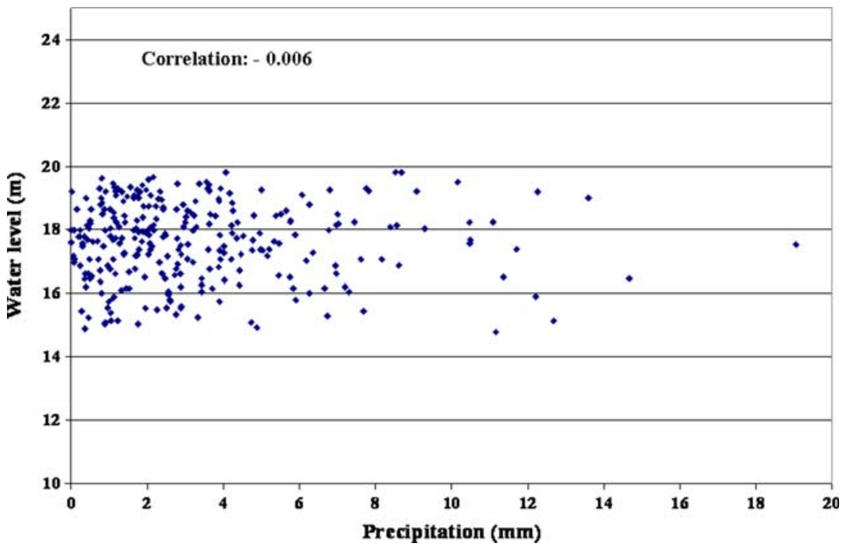

Fig. 1 Cross-plot between average monthly groundwater levels and total monthly precipitation

different municipal, industrial and agricultural water users in the region. As detailed historical records of these usages were not available, pumping could not be used as one of the inputs. Therefore, the modeling had to be carried out endogenously using time as the input. The long-term intraseasonal variability depicted in Fig. 3 suggested that separate dummy variables were necessary to alter the intercept and capture these seasonal variations (Gujarati 1979). Based on visual inspections, the water level dataset was divided into three parts (1973–1982, 1983–1992, 1992–1996) and a one-way ANOVA was carried out to identify the presence of any long-term trends due to decadal changes in land use and urbanization. The results presented in Table 1 indicated that the average water levels were different in at least two time periods. As such, additional dummy variables were used to modify the regression slopes in the second and third time periods. Mathematically, the relationship between inputs and outputs can be generically written as

$$\mathrm{WL} = f\left(t, \mathrm{DUM}_i, X_j t, C\right) \quad (1)$$

$$\begin{aligned} &\mathrm{DUM}_i = 1 \quad \text{if month (quarter)} = i; \\ &\mathrm{DUM}_i = 0 \quad \text{otherwise } \forall i = 2, \ldots, 12 \text{ monthly or } 2, \ldots, 4 \\ &\text{(quarterly)} \end{aligned} \quad (2)$$

$$\begin{aligned} &X_j = 1 \quad \text{if decade} = j \\ &X_j = 0 \quad \text{otherwise } \forall j = 1(1983{-}1992), 2(1993{-}1996). \end{aligned} \quad (3)$$

where WL is the water level (potentiometric level) in the well measured from the LSD; t is the time variable

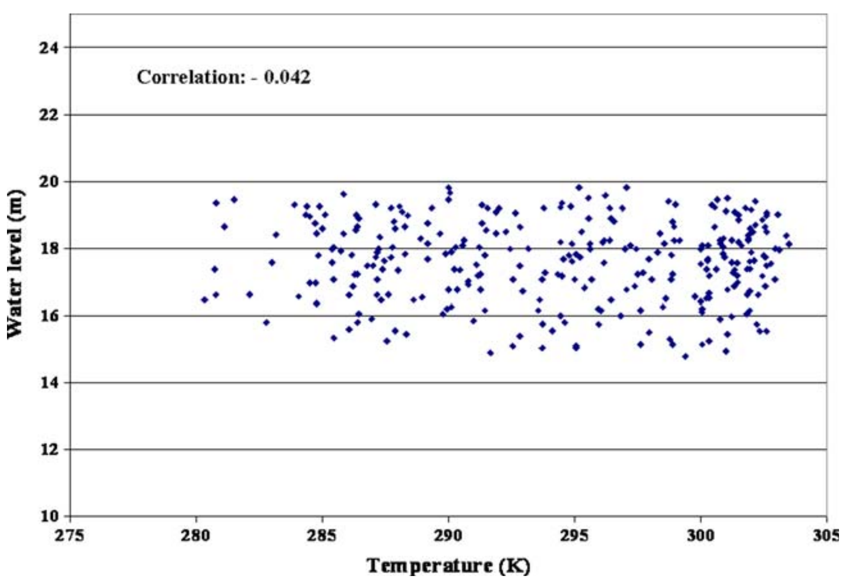

Fig. 2 Cross-plot between average monthly groundwater levels and mean monthly temperature

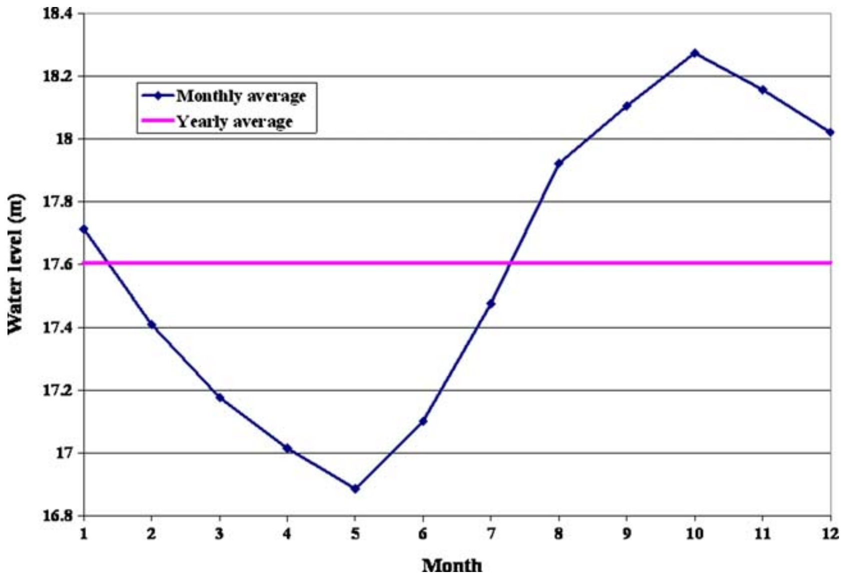

Fig. 3 Long-term monthly average groundwater levels during the period 1973–1996

representing the month (or quarter) since the start of the simulation period. DUM_i is the intercept dummy variable where the index i stands for the month or the quarter under consideration. A total of 11 dummy intercepts are required to represent monthly variations and a total of three dummy intercepts are required for modeling quarterly variations. These dummy variables alter the intercept C, which represents the variability of the first month (quarter). Similarly, the dummy variable X_j alters the slope to better fit the land use and urbanization trends in subsequent decades. Initially, the function (Eq. 1) was assumed to be linear and regression coefficients were obtained using ordinary least squares. The intercept C is referred as the bias unit in neural network models.

Artificial neural networks

Artificial neural networks are a general class of black box models derived from the theories of artificial intelligence and suited to model highly nonlinear systems. While a variety of neural network architectures and learning algorithms exist, feed-forward networks with error back-propagation are commonly used in many practical applications, as it has proven to be a universal approximator (Hornik et al. 1989). The fundamental concept corresponding to feed-forward network is the artificial neuron (Fig. 4). The neuron performs two functions—first it computes the weighted sum of all the inputs fed into it and this computed sum is then passed through a transfer function to compute the output. Usually a logistic sigmoid function is used for this purpose. A training dataset is used to ascertain the unknown connection weights by minimizing the

Table 1 Results of the ANOVA analysis used to test the differences in means of various time-periods

Source	DOF	SSE	MSE	F statistic	Probability
Observations	2	147.69	73.84	76.4	0
Error	285	275.45	0.97		
Total	287	423.14			

Periods	Observations	Mean	SD
1973–1982	120	16.92	1.31
1983–1992	120	18.44	0.70
1993–1996	48	17.22	0.56

The means are different between at least two time periods

DOF degrees of freedom, *SSE* sum of squared error, *MSE* mean square error, *SD* standard deviation

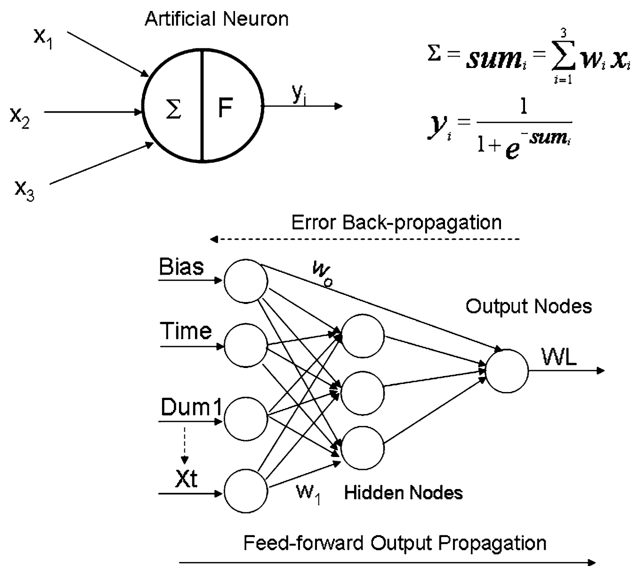

Fig. 4 Salient features of feed-forward artificial neural networks depicting neuron functionality and computations

Table 2 Regression coefficients and the 95% confidence intervals for the regression models developed to forecast quarterly groundwater levels

Summary statistics	Regression-1Q	Regression-2Q
Dataset	Training only	Training + testing
Observations	50	75
F statistic	63.240	62.020
Adj. coefficient of determination (R^2)	0.884	0.832
Coefficients (numbers in parenthesis are 95% confidence interval)		
Intercept	15.018 ± 0.375	15.074 ± 0.386
Time	0.302 ± 0.048	0.294 ± 0.049
Dummy intercept (2nd quarter)	**–0.220** ± 0.350	–0.348 ± 0.341
Dummy intercept (3rd quarter)	0.326 ± 0.320	0.357 ± 0.318
Dummy intercept (4th quarter)	0.902 ± 0.394	0.677 ± 0.341
Slope dummy variable 1983–1992	–0.039 ± 0.011	–0.038 ± 0.011
Slope dummy variable 1993–1996	–0.071 ± 0.012	–0.071 ± 0.012

Statistically insignificant coefficients are highlighted in bold

RMSE. In the conventional back-propagation algorithm, the weights are changed according to the error of the output layer (Fig. 4). This approach, while practical, suffers from the presence of local optima and can have large regions of poor sensitivity (Hsu et al. 1995). The back-percolation is a variant of the back-propagation formulated to improve its convergence capabilities (Jurik 1990). Unlike back-propagation, the errors in the hidden nodes are considered separately from those in the output nodes in back-percolation causing a reduction in the amount of training cycles needed to converge (Jurik 1990; Ahmad and Simonovic 2005).

Results and discussion

To correctly model the datasets a reasonable number of sample data must be used to generate both regression coefficients and neural network weights. Therefore, the available monthly (quarterly) data were randomly shuffled and divided into three datasets. The training dataset comprised 192 monthly records (50 quarterly) and was used to train the neural network model to obtain connection weights. Another dataset, termed as testing dataset, consisting of 48 monthly (25 quarterly) records was used to identify the best neural network configuration from a set of different configured networks. Finally, an evaluative dataset consisting of 48 monthly (25 quarterly) records was used to independently evaluate the performance of the final (selected) model. The outputs from all these datasets were finally rearranged to develop the predictive time series plots.

Two sets of regression models having the same underlying mathematical structure were developed at both quarterly and monthly time-scales. The first model was developed using just the training dataset and is termed as "regression 1" model while the second one was developed using training and testing datasets and termed "regression 2" model. The results for the regressions performed on a quarterly time-step are summarized in Table 2 and indicate that the overall fits provided by these regressions are statistically significant. The regression coefficients obtained for the quarterly time-scale indicate that the performance of both the models is fairly similar. However, the dummy intercept for the second quarter is only significant in the model developed using the training and testing dataset. Thus, additional data are necessary to notice a statistically significant alteration in the average water levels for the months of April–June. However, as evidenced from the adjusted R^2 values, the inclusion of this additional data introduces added variability that cannot be explained using current model specifications.

The calculated residuals were analyzed qualitatively using histograms, normal plots and other exploratory data analysis tools (Hamilton 1993) and residual plots for quarterly data are presented in Figs. 5 and 6. In addition, Durbin–Watson statistic and Spearman rank correlation analysis (Gujarati 1979) were used to assess the presence of autocorrelation and heteroscedasticity, respectively. The results indicated that the residuals were reasonably normal and did not suffer from extensive autocorrelation and heteroscedasticity problems.

The model fits and other evaluative statistics for the regressions developed using monthly water level data are presented in Table 3. The results again indicate excellent overall model fits. However, the dummy intercept variables for the months August–December were noted to be statistically indifferent from zero. Nonetheless, the exclusion of these variables did affect the variance explained by the models and as such were retained. As with the quarterly dataset, the regression coefficients developed using training data alone and those employing both training and testing data were statistically similar. Again, the inclusion of additional

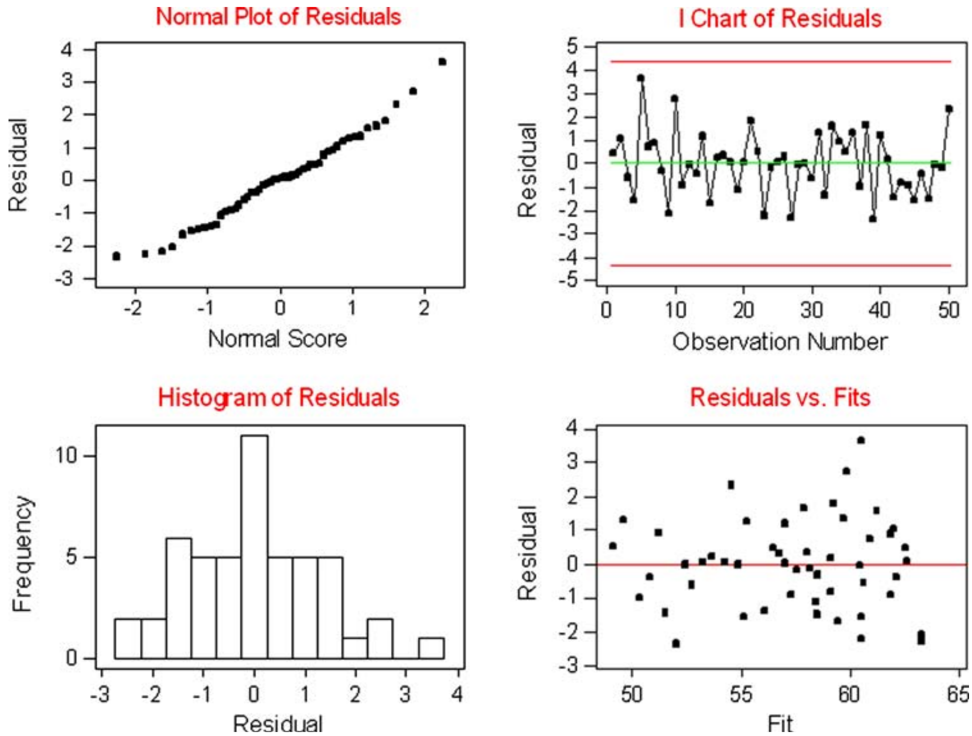

Fig. 5 Diagnostic residual analysis plots for the regression-1Q model developed using quarterly training dataset

data reduced the models' ability to explain the variability in the data. However, unlike quarterly data models, the additional data were not sufficient to obtain statistically significant intercepts for the later months of the year. The residuals obtained from monthly scale models were analyzed using visual and statistical tests for autocorrelation and heteroscedasticity and the results presented in Figs. 7 and 8 indicated that the developed regressions were minimally influenced by autocorrelation and heteroscedasticity and as such the regression estimates and confidence levels were deemed to be fairly unbiased and reliable.

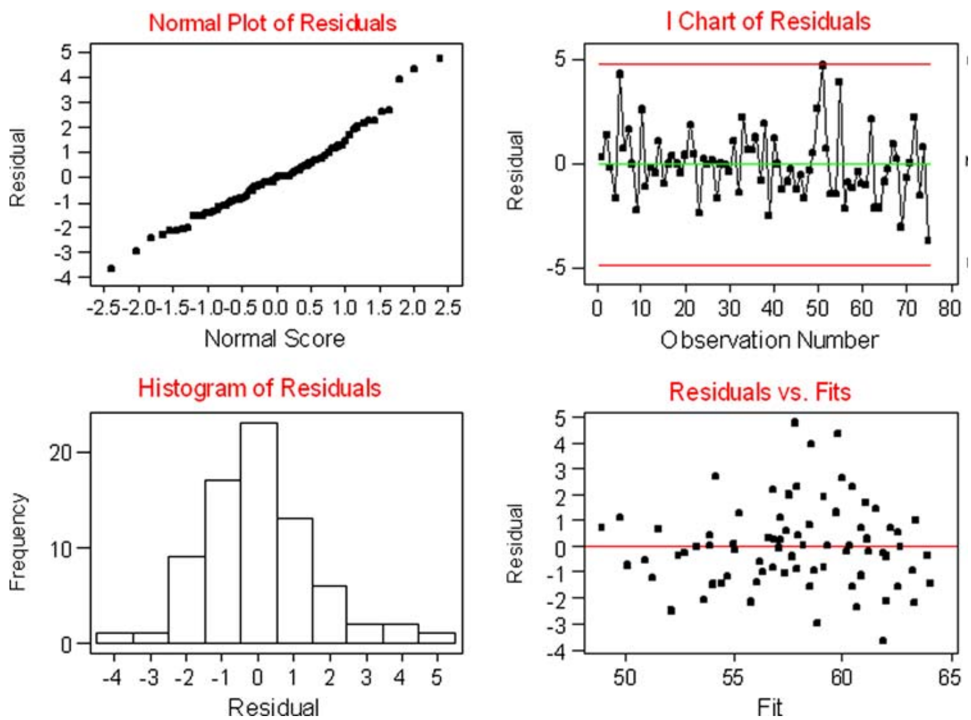

Fig. 6 Diagnostic residual analysis plots for the regression-2Q model developed using quarterly training and testing dataset

Table 3 Regression coefficients and the 95% confidence levels for the regression models developed to forecast monthly groundwater levels

Summary statistics	Regression-1M	Regression-2M
Dataset	Training only	Training + testing
Observations	192	250
F statistic	43.536	53.567
Adj. coefficient of determination (R^2)	0.757	0.755
Coefficients (numbers in parenthesis are 95% confidence interval)		
Intercept	15.805 ± 0.399	15.699 ± 0.347
Time	0.088 ± 0.012	0.087 ± 0.011
Dummy intercept (Feb)	–0.596 ± 0.457	–0.4514 ± 0.396
Dummy intercept (Mar)	–0.644 ± 0.445	–0.554 ± 0.401
Dummy intercept (Apr)	–0.969 ± 0.473	–0.772 ± 0.407
Dummy intercept (May)	–1.135 ± 0.429	–1.03 ± 0.388
Dummy intercept (June)	–0.978 ± 0.439	–0.777 ± 0.384
Dummy intercept (July)	–0.507 ± 0.457	–0.403 ± 0.401
Dummy intercept (Aug)	**–0.117** ± 0.444	**0.030** ± 0.392
Dummy intercept (Sep)	**–0.001** ± 0.450	**0.085** ± 0.397
Dummy intercept (Oct)	**0.026** ± 0.457	**0.316** ± 0.398
Dummy intercept (Nov)	**–0.088** ± 0.451	**0.140** ± 0.402
Dummy intercept (Dec)	**–0.042** ± 0.445	**–0.021** ± 0.389
Slope dummy variable 1983–1992	–0.010 ± 0.002	–0.009 ± 0.002
Slope dummy variable 1993–1996	–0.019 ± 0.003	–0.019 ± 0.002

Statistically insignificant coefficients are highlighted in bold

The comparison of the developed quarterly and monthly models indicates that the variability in the observed data is better explained by quarterly models than monthly models. This result is to be expected as the averaging process filters out the short-term variability in the data. Even with additional variability in the dataset, the monthly models were able to explain over 75% variability in the data without having to resort to autoregressive parameters. A simple model with time and intercept as two variables was seen to explain roughly 55% of the variability. As such, the use of dummy variables to include seasonal effects was deemed useful to increase forecasting abilities of the regression models.

While the linear regression models were able to explain at least 75% of the variability in the data, it is hypothesized that nonlinear relationships could exist between the observed water levels and some of the

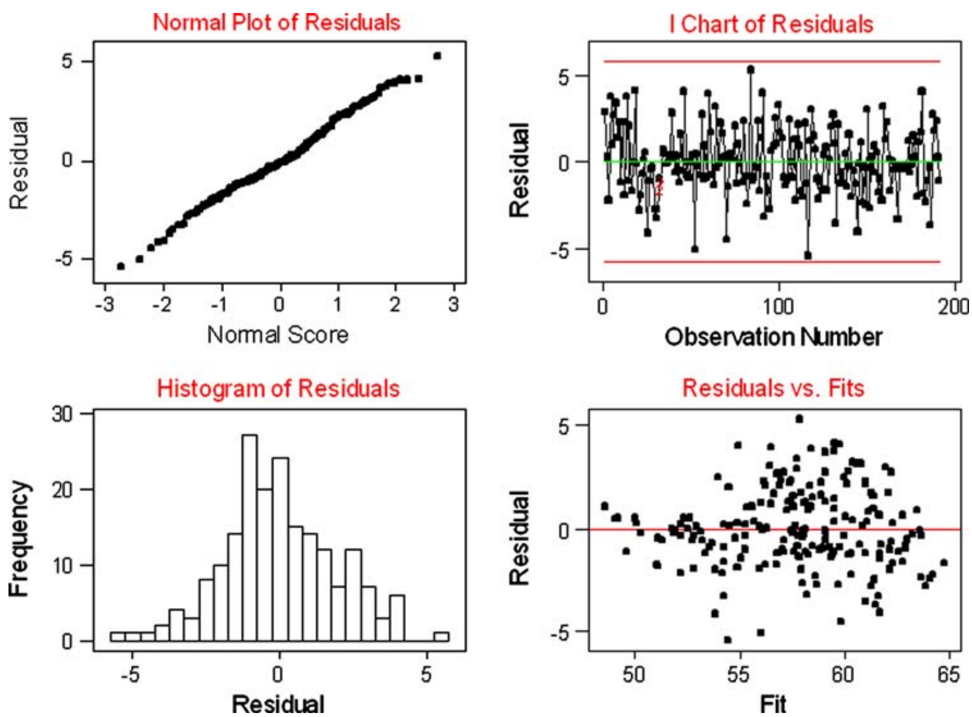

Fig. 7 Diagnostic residual analysis plots for the regression-1M model developed using monthly training dataset

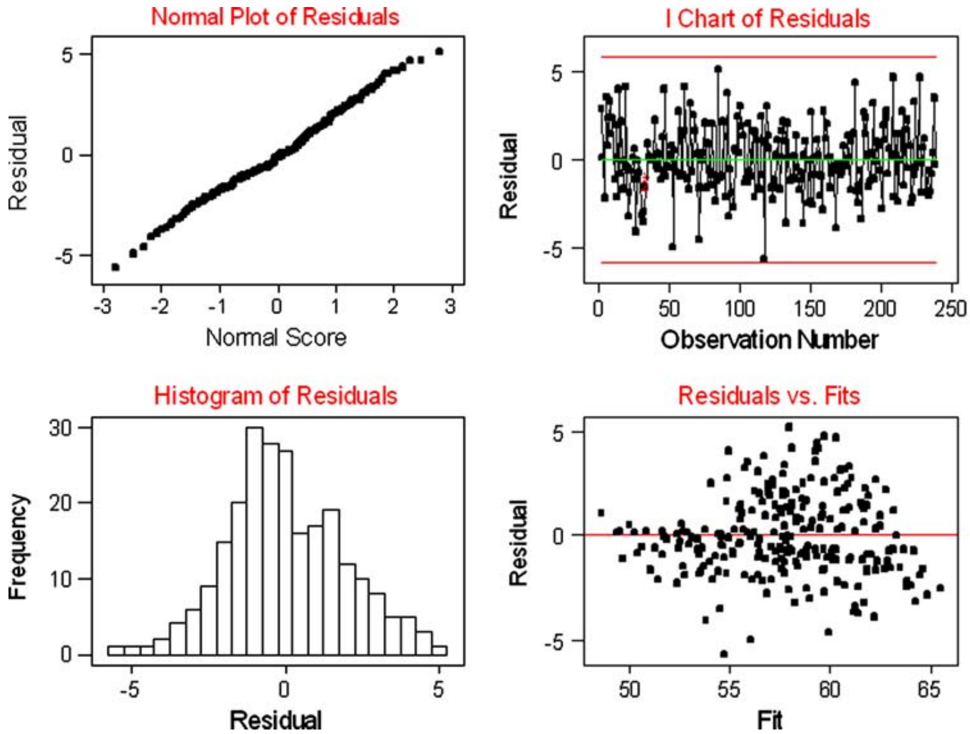

Fig. 8 Diagnostic residual analysis plots for the regression-1Q model developed using monthly training and testing dataset

independent variables. A diagnostic lack-of-fit test (Burn and Ryan 1983) was used to test for the possibility of nonlinear relationships. The results of this testing indicated a possible lack of fit with the data due to potential curvature in time and slope for the decade 1983–1992 for quarterly and monthly data as well as a potential curvature in the dummy regression of the intercept for the month of November. Therefore, neural network models were hypothesized to provide better fits than the regression models.

The training data were used to train several feed-forward neural network models with varying number of hidden nodes. The forecasting abilities of these networks were tested using the testing dataset and absolute percent error metric. The best network was then selected for comparison with regression models. For the quarterly dataset, the best network had an error of 6.356% and the testing error was equal to 8.662% after 453 cycles. The model had six inputs excluding the bias node and three hidden nodes and one output node (6-3-1 architecture) whose connection weights are presented in Table 4. As can be seen, none of these connection weights are anomalously low, indicating that all the connections affect the predicted quarterly water levels.

The developed model was further tested for its predictive capabilities by computing RMSE, mean absolute deviation (MAD) and correlation coefficient metrics (Daliakopoulos et al. 2005) for an independent evaluative dataset. The evaluation statistics for all the datasets for quarterly water level data are presented in Table 5. It is important to note that both testing and evaluative data have not been used to obtain necessary network weights and provide independent checks on

Table 4 Connection weights for the artificial neural network model developed for obtaining quarterly groundwater level forecasts

From node	To node	Weight
Bias	Hidden	–0.222
Time	node 1	0.326
Dummy intercept quarter 2		–0.119
Dummy intercept quarter 3		–0.189
Slope dummy variable 1983–1992		–0.166
Slope dummy variable 1993–1996		–0.115
Bias	Hidden	–0.468
Time	node 2	–2.103
Dummy intercept quarter 2		0.101
Dummy intercept quarter 3		–0.098
Slope dummy variable 1983–1992		–0.275
Slope dummy variable 1993–1996		0.344
Bias	Hidden	0.681
Time	node 3	–0.551
Dummy intercept quarter 2		–0.377
Dummy intercept quarter 3		–0.043
Slope dummy variable 1983–1992		–0.115
Slope dummy variable 1993–1996		–0.088
Bias	Quarterly	–1.472
Hidden node 1	water levels	0.348
Hidden node 2		–1.332
Hidden node 3		–1.514

Table 5 Connection weights for the artificial neural network model developed for obtaining monthly groundwater level forecasts

From node	To node	Weight
Bias	Hidden node 1	–0.036
Time		0.061
Dummy intercept (Feb)		–0.080
Dummy intercept (Mar)		–0.126
Dummy intercept (Apr)		–0.260
Dummy intercept (May)		–0.276
Dummy intercept (June)		–0.087
Dummy intercept (July)		–0.079
Dummy intercept (Aug)		–0.072
Dummy intercept (Sep)		0.025
Dummy intercept (Oct)		0.048
Dummy intercept (Nov)		0.014
Dummy intercept (Dec)		0.001
Slope dummy variable 1983–1992		–0.564
Slope dummy variable 1993–1996		–0.089
Bias	Hidden node 2	0.449
Time		–2.395
Dummy intercept (Feb)		0.068
Dummy intercept (Mar)		0.077
Dummy intercept (Apr)		0.127
Dummy intercept (May)		0.149
Dummy intercept (June)		0.169
Dummy intercept (July)		0.061
Dummy intercept (Aug)		–0.114
Dummy intercept (Sep)		–0.065
Dummy intercept (Oct)		–0.136
Dummy intercept (Nov)		–0.087
Dummy intercept (Dec)		–0.050
Slope dummy variable 1983–1992		0.007
Slope dummy variable 1993–1996		1.746
Bias	Monthly water levels	–0.766
Hidden node 1		0.893
Hidden node 2		–1.165

the model. However, the testing dataset has been used to identify the best network from a set of alternatives. The correlation coefficients were fairly high (>0.75) indicating that the neural network model was able to explain the observed variability in the data. The RMSE and the MAD were deemed reasonable as well.

However, the metrics are relatively better for the training dataset than those for the testing and evaluative datasets, respectively. Therefore, the possibility of over-fitting, a phenomenon where the model has memorized the training dataset and is not capable of predicting newer data, cannot be ruled out. Any over-fitting in the neural network is probably caused due to using of the limited number of observations to train the data and can possibly be improved by adding small random values to the training dataset (Principie et al. 2000). The time-series plots depicting the predictive capabilities of the regression and neural network model are shown in Fig. 9. While all these models are not able to capture some of the extreme variabilities in the quarterly water levels, the neural network is seen to do a better job than the regression counterparts.

Using the monthly testing dataset, a 14-2-1 neural network model was identified as the optimal model and possessed a training error of 8.603% and a testing error of 7.95%. The connection weights for this network are presented in Tables 6 and 7, which indicate that the connection strength of the intercept dummy variables for the months of August–December is relatively lower for hidden node one. Also, hidden node one has a relatively lesser impact on the predicted water levels than the bias node and the other hidden node and as such do not contribute significantly to the forecasted estimates.

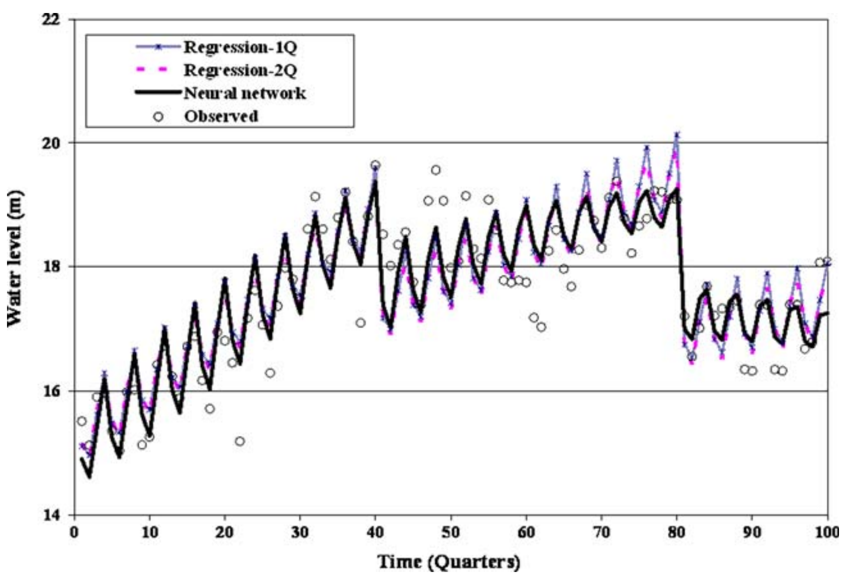

Fig. 9 Visual comparison of the abilities of regression and neural network models to predict quarterly water levels at the well

Table 6 Evaluation statistics for regression and artificial neural network models developed to predict average quarterly groundwater levels

Dataset	Statistic	Regression-1M	Regression-2M	ANN
Training	Correlation coefficient	0.948	0.945	0.956
Testing	Correlation coefficient	0.838	0.855	0.872
Evaluation	Correlation coefficient	0.715	0.733	0.771
Training	RMSE	5.610	6.001	5.052
Testing	RMSE	15.269	12.871	11.572
Evaluation	RMSE	21.280	17.841	15.089
Training	MAD	3.333	3.294	3.366
Testing	MAD	5.541	5.164	4.587
Evaluation	MAD	7.208	6.535	5.915

RMSE and MAD values in meter

Table 7 Evaluation statistics for regression and artificial neural network models developed to predict average monthly groundwater levels

Dataset	Statistic	ANN	Regression-1M	Regression-2M
Training	Correlation coefficient	0.906	0.880	0.878
Testing	Correlation coefficient	0.924	0.855	0.878
Evaluation	Correlation coefficient	0.876	0.880	0.884
Training	RMSE	10.499	12.152	12.392
Testing	RMSE	7.520	14.216	11.991
Evaluation	RMSE	11.608	11.079	11.079
Training	MAD	4.554	4.977	5.072
Testing	MAD	4.039	5.371	5.072
Evaluation	MAD	4.954	5.049	5.121

RMSE and MAD values in meter

The evaluative statistics presented in Table 6 indicated that the RMSE, MAD and correlation coefficient were slightly lower for the monthly dataset than those observed for the quarterly dataset. However, the predictive capabilities of the monthly model for the testing and evaluative datasets were relatively better than the quarterly counterparts. Also, the relative differences in these metrics between the training, testing and evaluative datasets are fairly low indicating that the monthly model probably does not suffer from over-fitting. The time-series plot for monthly water levels shown in Fig. 10 indicates that all the models have difficulties in capturing the water table dynamics during the 1980s (time steps 120–240). However, the neural network models do a better job of predicting the drought conditions (high water level elevation from the LSD), while the regression models appear to be closer to the low water levels of the wet years.

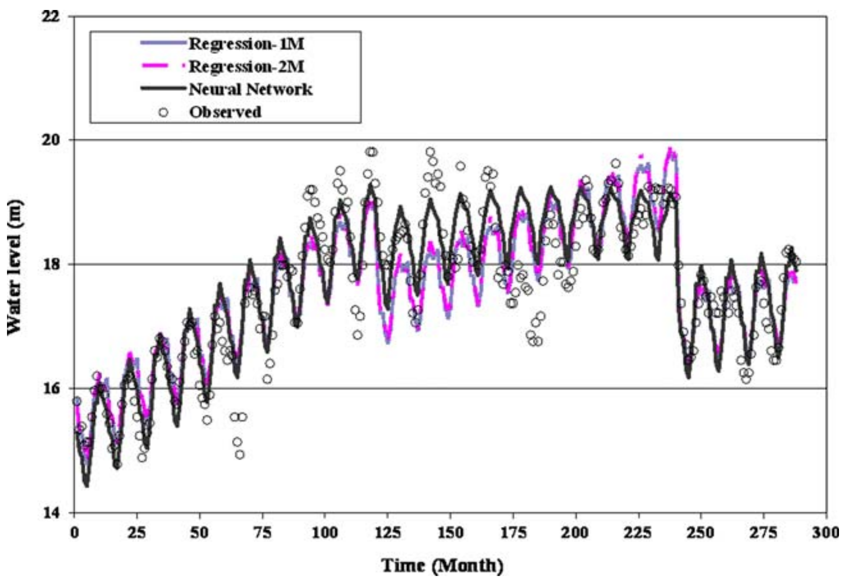

Fig. 10 Visual comparison of the abilities of regression and neural network models to predict monthly water levels at the well

Summary and conclusions

The capabilities of ANN and regression schemes to predict water levels were evaluated in this study using historical time-series measurements on monthly and quarterly scales at a well that taps into the deeper sections of the Evangeline formation of the Gulf coast aquifer. As the water levels in this well were not influenced by hydro-climatic factors like temperature and precipitation, an alternative modeling strategy was required to generate forecasts. An endogenous model using time as the independent variable was therefore adopted in this study. The short-term (monthly or quarterly) variations in the water levels were modeled using a dummy variable that altered the intercept. The decadal shifts in water levels caused due to climatic, land use and land cover characteristics were modeled using dummy variables that altered the coefficient of time (slope). Linear regression models were developed with different amounts of data. All the developed models were significant and explained a reasonable amount of variance. In general, the model developed with a larger dataset had more statistically significant coefficients, but explained lesser variability. Residual analysis and statistical tests indicated that the models did not violate the underlying assumptions of the regression significantly. However, the lack-of-fit test alluded to possible curvature in time and certain dummy variables.

Nonlinear feed-forward ANN models were constructed and solved using back percolation algorithm. A compact configuration with one hidden layer and two or three hidden nodes resulted in optimal networks. The predictive capabilities of the neural network models were superior to that of their regression counterparts as assessed using RMSE, MAD and correlation coefficient. However, the neural network model constructed using quarterly data likely suffered from over-fitting phenomenon, which was not observed in monthly dataset. The developed monthly models had difficulties predicting dry and wet periods of the 1980s. The neural network models were seen to be better in capturing drought conditions, while the regression model predictions were closer to water levels obtained during wet periods.

The endogenous modeling of water levels using time and dummy variables is a viable strategy for forecasting water levels in deep aquifers when the hydro-climatic influences on the well response are not strong.

Acknowledgments Financial support for the National Oceanic and Atmospheric Administration (NOAA) through a cooperative agreement to Texas A&M University-Kingsville is greatly appreciated.

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