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Monthly Prediction of Groundwater levels in a Coastal aquifer of Andhra Pradesh

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Abstract: India is mostly covered with arid and semi-arid area because of geographical features and climate conditions. In these areas, due to the lower degree of precipitation, the only way to gain potable water and agricultural water is restricted to groundwater resources which are done differently using aquifer derivation. Therefore any changes in these aquifers can influence the inhabitants' lives; or in cases that these changes are drastic, the people's lives might be endangered. For the effective management of groundwater, it is important to predict groundwater level (GWL) fluctuations. In this paper, Wavelet Neural Network (WNN) methodology is presented to predict monthly ground water levels in a coastal aquifer of Andhra Pradesh. Monthly rainfall and groundwater level data of three piezometers from different formations of the aquifer were used to predict the groundwater level in one-month advance. The WNN model is compared with the standard ANN. The predicted groundwater levels from the WNN model closely matched with the observed data in validation period. The WNN model predicted the groundwater levels to an acceptable accuracy. The benchmark results from WNN model applications showed that the model produced better results than ANN model.

Keywords: *Prediction, piezometer, Groundwater level, WNN*

1. Introduction

India is mostly covered with arid and semi-arid area because of geographical features and climate conditions. In these areas, due to the lower degree of precipitation, the only way to gain potable water and agricultural water is restricted to groundwater resources which are done differently using aquifer derivation. Therefore any changes in these aquifers can influence the inhabitants' lives; or in cases that these changes are drastic, the people's lives might be endangered. For the effective management of groundwater, it is important to predict groundwater level (GWL) fluctuations. Groundwater level forecasting is one of the most important requirements in hydrogeological studies.

Although white and gray box models (mathematical and conceptual models) are the main tools for representing hydrological variables and understanding the physical processes in a system, they have practical limitations of various hydrological and geological parameters and collection of input data, calibration and verification is difficult, time consuming and expensive [1]. When data is not sufficient and accurate prediction is more important than conceiving the physics, black box models can be a good option. Artificial neural network (ANN) models are such black box models with particular properties for modeling nonlinear systems. The ability to identify a relationship from given patterns makes it possible for ANNs to solve complex hydrologic problems. ANNs have the inherent property of nonlinearity since neurons activate a nonlinear filter called an activation function. ANN models have been used for rainfall–runoff modeling and precipitation forecasting and water quality modeling [2]. [3] Presented an ANN model to predict water levels in piezometers placed in the body of an earth fill dam in Poland considering upstream and downstream water levels of the dam as input data. In recent period, wavelet theory has been introduced in the field of water resources management replacing the Fourier analysis for signal decomposition. Wavelet analysis effectively decomposes the main signal and diagnoses its main frequency component and abstract local information. The combination of an ANN model with other mathematical tools, such as wavelet transform and fuzzy logic may be utilized for prediction of hydrogeological signals [4]. Wavelet analysis is a useful tool for non-stationary processes such as hydrological time series [5]. Wavelet transform, which is a pre-processing decomposed technique, showed successful performance in hydrological applications. [5] Applied wavelet combined with neuro-fuzzy and ANN for sediment load prediction, [6] developed a hybrid model for rainfall–runoff forecasting. [7] Developed different models as

Wavelet Neural Network (WNN) in combination with Discrete Wavelet Transform (DWT) and Levenberg-Marquardt based Feed Forward Neural Networks (FFNN) and Wavelet Multiple linear Regression (WREG) for monthly reservoir inflow forecasting. In this paper, Wavelet Neural Network (WNN) methodology is presented to predict monthly ground water levels in three piezometers in different formations in the coastal aquifer of Andhra Pradesh.

2. Study Area and Data

In the present study, monthly ground water levels were forecasted in one month advance in the coastal aquifer of East Godavari district of Andhra Pradesh. Three piezometers located at Prathipadu, Gandepalli and Alamuru were chosen in different formations of Khondalite, Tirupathi sandstone and alluvium respectively. These were selected in such a way that it represents upland area and delta area of East Godavari district. The location and details of these piezometres were given in Table 1. Monthly rainfall and groundwater level data of these piezometers wells were used from 2002-2011 (10 years) to forecast the groundwater levels in one-month advance. The model was calibrated using 7 years of data from 2002 to 2008 and validated by using the remaining 3 years of data from 2009 to 2011.

Table 1*Details of Piezometers*

Name of Piezometer	Formation	Latitude	Longitude	MSL	Groundwater level (bgl)	
					Minimum	Maximum
Prathipadu	Khondalite	17.23	82.19	39.789	0.34	16.66
Gandepalli	T. Sandstone	17.14	81.96	63.260	36.52	60.33
Alamuru	Alluvium	16.79	81.88	10.425	0.00	8.46

3. Methodology

3.1. Wavelet Analysis

The wavelet transform is the tool of choice when signals are characterized by localized high frequency events or when signals are characterized by a large numbers of scale-variable processes. Because of its localization properties in both time and scale, the wavelet transform allows for tracking the time evolution processes at different scales in the signal. The continuous wavelet transform of a time series f (t) is defined as

$$f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt \qquad (1)$$

Where $\psi(t)$ is the basic wavelet with effective length (t) that is usually much shorter than the target time series f (t). The variables are *a* and *b*, where *a* is the scale or dilation factor that determines the characteristic frequency so that its variation gives rise to a `spectrum'; and *b* is the translation in time so that its variation represents the `sliding' of the wavelet over *f(t)*. The wavelet spectrum is thus customarily displayed in time-frequency domain. For low scales i.e. when |a| << 1, the wavelet function is highly concentrated (shrunken compressed) with frequency contents mostly in the higher frequency bands. Inversely, when |a| >> 1, the wavelet is stretched and contains mostly low frequencies. For small scales, thus a more detailed view of the signal (known also as a "higher resolution") whereas for larger scales a more general view of the signal structure can be expected. However, in practical the hydrologic time series does not have a continuous – time signal process but rather a discrete – time signal. The Discrete Wavelet Transform (DWT) is to calculate the wavelet coefficients on discrete dyadic scales and positions in time. Discrete wavelet functions have the form by choosing $a = a_0^m$ and $b = nb_0a_0^m$ in equation (1). The Eq. (1) has taken the form

$$g_{m,n}(t) = \frac{1}{\sqrt{a_o^m}} g\left(\frac{t - n b_o a_o^m}{a_o^m}\right) \qquad (2)$$

Where *m* and *n* are integers that control the wavelet dilation and translation respectively; a_0 is a specified fined dilation step greater than 1; and b_0 is the location parameter and must be greater than zero. The appropriate choices for a_0 and b_0 depend on the wavelet function. A common choice for them is a_0=2, b_0=1.

The original signal X(n) passes through two complementary filters (low pass and high pass filters) and emerges as two signals as Approximations (A) and Details (D). The approximations are part of low pass filter, high-scale and low frequency components of the signal. The details are part of high pass filter, low-scale, and high frequency components. Normally, the low frequency content of the signal (approximation, A) is the most important part. It demonstrates the signal identity. The high-frequency component (detail, D) is nuance. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components (Figure 1). Thus, DWT allows one to study different investigating behaviours in different time scales independently [5]. Decomposition level is generally based on signal characteristics and experiences to selection. [8] used int[lg$n$] as resolution level number, where n is the length of daily stream flow sequences and lg denotes the logarithm to base 10. The P may be selected from the range of 2 and int[lg$n$], that is, $2 \leq P \leq$ int[lg$n$]. Based on this concept, three decomposition levels were used in this study. In this study, wavelet function derived from the family of Daubechies wavelets with order 5 (db5) used for the selection of best architectures of ANN.

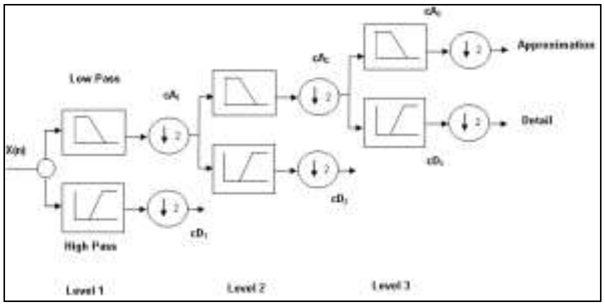

***Figure 1**. Diagram of multiresolution analysis of signal*

Based on the physical knowledge of the problem and statistical analysis, different combinations of antecedent values of the groundwater levels and rainfall time series were considered as input nodes. The output node is the groundwater level to be predicted in one step ahead. The time series data of all variables was standardized for zero mean and unit variation, and then normalized into 0 to 1. The activation function used for the hidden and output layer was logarithmic sigmoidal and pure linear function respectively. For deciding the optimal hidden neurons, a trial and error procedure started with two hidden neurons initially, and the number of hidden neurons was increased up to 10 with a step size of 1 in each trial.

3.2. Method of combining wavelet analysis with ANN

The decomposed details (D) and approximation (A) were taken as inputs to neural network structure as shown in Figure 2.

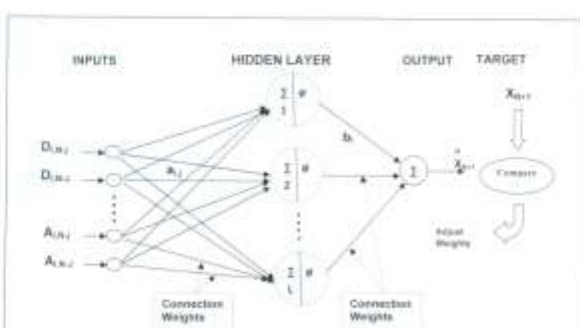

***Figure 2.** Wavelet based multilayer perceptron (MLP) neural network*

To obtain the optimal weights (parameters) of the neural network structure, Levenberg–Marquardt (LM) back-propagation algorithm has been used to train the network. A standard MLP with a logarithmic sigmoidal transfer function for the hidden layer and linear transfer function for the output layer were used in the analysis. The number of hidden nodes was determined by trial and error procedure. The output node will be the original value at one step ahead.

3.3. Performance Criteria

To find out the optimal model developed in the prediction of groundwater level, different statistical indices were used. The indices employed are the coefficient of correlation (R), Root Mean Square Error (RMSE) between the observed and forecasted values and the coefficient of efficiency (Nash-Sutcliffe) (COE).

4. Results and Discussion

In this study, groundwater levels and rainfall data is divided into training and testing data sets. First 7 years of data from 2002 to 2008 are used for training and the remaining 3 years data from 2009 to 2011 are used for testing. The wavelet decomposed standardized data of antecedent values groundwater level and rainfall data was taken as input to ANN which makes the WNN. ANN was trained using backpropagation (BP) with Levenberg-Marquardt algorithm (LM) neural network algorithms. The number of inputs in each model was shown in Table 2. The optimal number of hidden neurons was determined by trial and error procedure. The output node is the original groundwater level in one month advance. Table 3 shows the performance of WNN and ANN models for different model inputs in calibration and validation periods for three piezometers.

***Table 2** Model Inputs*

Model I	gw (t)= f [gw (t-1)]
Model II	gw (t)=f [gw (t-1), gw(t-2)]
Model III	gw (t)=f [gw (t-1), gw(t-2), R(t-1)]
Model IV	gw (t)=f [gw (t-1), gw (t-2), R (t-1), R(t-2)]

It was observed from Table 3 that WNN predicted groundwater level above an accuracy of 87.03%, whereas ANN predicted above an accuracy of 55.23% in validation period. The WNN model II for Prathipadu, Model II for Gandepalli and model III for Alamuru predicted an accuracy of 94.49%, 87.13% and 87.03% respectively in validation period. It was noted that model performance was better in Khondalite than that of Sandstone and alluvium formations. It may be due to the variation in nature and response of the groundwater level in these formations.

Figure 3, shows the observed and modeled well hydrographs and scatter plots for three piezometres for

WNN and ANN models during validation period. It was observed from the well hydrographs that values modeled from WNN model properly matched with the observed values, whereas ANN model underestimated the observed values. From figure 3 of scatter plot between the observed and modeled groundwater levels observed that the groundwater levels predicted by WNN models were very much close to the 45 degrees line. From this analysis, it is evident that the performance of WNN was much better than ANN model in the prediction of groundwater levels.

5. Conclusions

In this study, a hybrid model called wavelet neural network model used for the prediction of groundwater levels of three piezometers located in different formations in a coastal aquifer of East Godavari district of Andhra Pradesh. Monthly rainfall and groundwater levels were used for a period of 10 years from 2002 to 2011. The proposed model is a combination of wavelet analysis and artificial neural network (WNN). Wavelet decomposes the time series into multilevels of details and it can adopt multi-resolution analysis and effectively diagnose the main frequency component of the signal and abstract local information of the time series. Monthly time series data of rainfall and groundwater levels was decomposed into sub series by DWT. Each of the sub-series plays distinct role in original time series. The results from WNN model were compared with the standard ANN. In this study WNN model predicted groundwater level up to an accuracy of 94%. In the analysis, original signals are represented in different resolutions by discrete wavelet transformation; therefore, the WNN forecasts are more accurate than standard ANN model.

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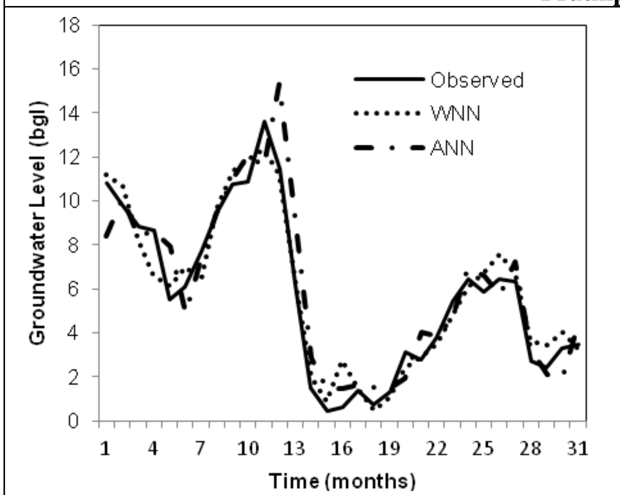
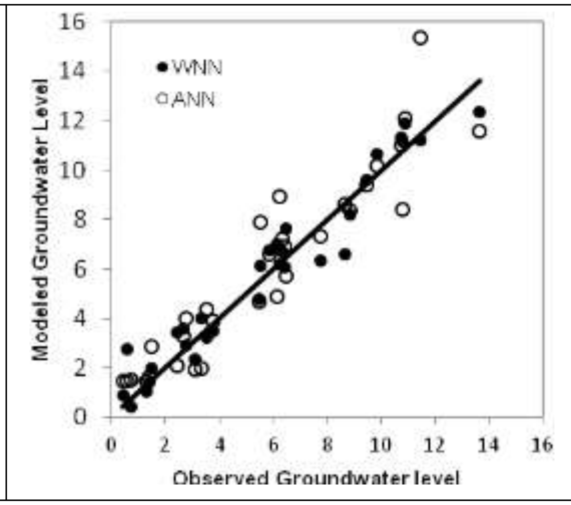
Table 3 *The performance statistics for the calibration and validation period*

Calibration					Validation		
Prathipadu							
WNN							
Model	**Neurons**	**RMSE**	**R**	**CE (%)**	**RMSE**	**R**	**CE (%)**
I	5	1.11	0.972	94.53	2.03	0.853	69.04
II	3	0.53	0.994	98.75	0.86	0.973	94.49
III	3	0.38	0.997	99.35	1.32	0.940	86.99
IV	6	0.18	0.999	99.86	1.96	0.872	71.28
ANN							
I	4	2.03	0.904	81.72	1.85	0.872	74.43
II	5	1.80	0.925	85.58	1.69	0.894	78.67
III	3	1.64	0.939	88.08	1.33	0.938	86.72
IV	3	1.65	0.937	87.83	1.41	0.930	85.16
Gandepalli							

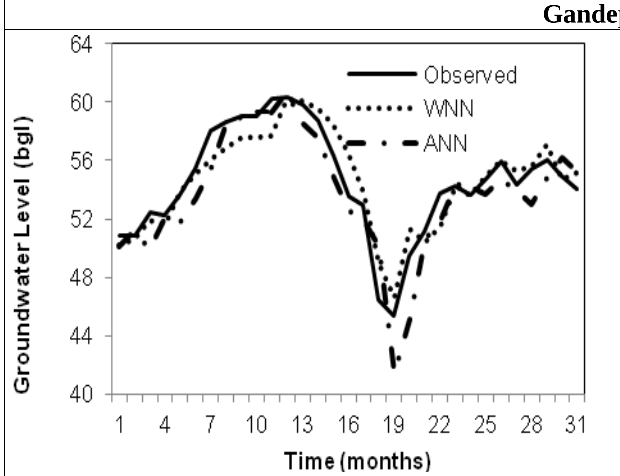
WNN							
I	5	1.160	0.949	90.10	1.963	0.904	71.38
II	3	0.619	0.986	97.18	1.317	0.934	87.13
III	3	0.376	0.995	98.96	2.179	0.897	64.72
IV	6	0.008	1.000	100.00	2.846	0.919	39.86
ANN							
I	3	1.942	0.850	72.25	2.502	0.811	53.51
II	3	1.432	0.921	84.90	2.058	0.871	68.53
III	3	1.442	0.920	84.69	1.733	0.928	77.70
IV	3	1.212	0.944	89.18	2.262	0.878	61.99
Alamuru							
WNN							
I	3	0.441	0.866	89.23	1.022	0.945	71.15
II	3	0.254	0.912	96.44	0.791	0.982	82.70
III	3	0.236	0.933	96.93	0.685	0.985	87.03
IV	3	0.136	0.902	98.97	0.833	0.995	80.85
ANN							
I	3	0.892	0.748	55.98	1.566	0.585	32.26
II	4	0.779	0.815	66.43	1.433	0.666	43.33
III	3	0.638	0.880	77.48	1.273	0.813	55.23
IV	3	0.563	0.908	82.47	1.310	0.734	52.60

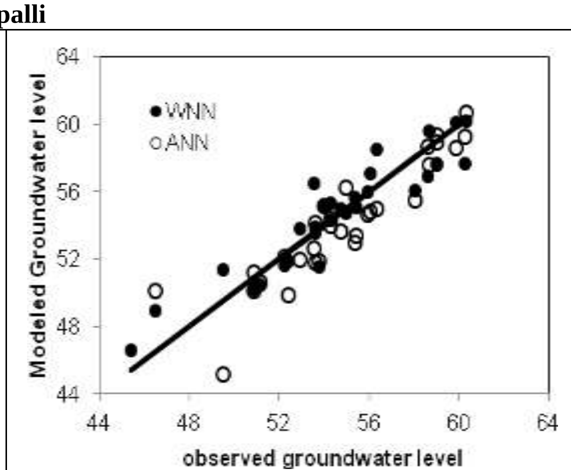
Prathipadu



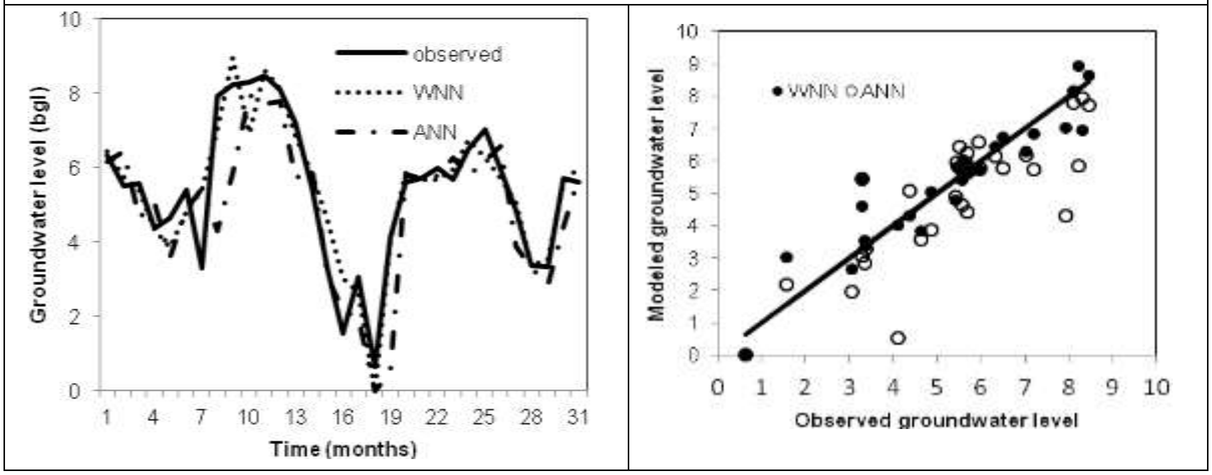


Gandepalli





Alamuru


observed
WNN
ANN
Groundwater level (bgl)
Time (months)
WNN ANN
Modeled groundwater level
Observed groundwater level