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Groundwater Modeling - Review

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Abstract
A number of attempts had been made by researchers to investigate the availability of groundwater in an area and to quantitatively assess its potential. Estimation of water balance volumes consists of estimation of two basic components of groundwater balance namely recharge and discharge. For solving the problems of groundwater system, soft computing techniques are commonly used, which are capable of simulating the real world condition. A number of computing techniques with possible solution has been put forward in soft computing by different researchers. These techniques are very effective in dealing with dynamic, noisy and nonlinear data, particularly when underlying physical relationships are not completely understood. The main intention of the paper is to present a comprehensive review ground water management and development. Specific methodologies for regional groundwater flow modeling are descried.

Introduction

Groundwater is a highly valuable resource. Groundwater has agricultural, domestic, and industrial uses and is acquired by constructing and operating extraction wells. Measurement and analysis ofgroundwater level is needed for maintaining groundwater availability. Groundwater is an important resource so it must be used wisely. However, there are so many difficulties associated with understanding a groundwater system. Firstly, since groundwater by its very nature is underground, it can not be directly observed, except via intrusive investigations, such as boreholes, or where it outcrops at a spring or wetland. Secondly, natural systems, especially the ground beneath our feet, are very diverse. This makes it extremely difficult to accurately characterize the media in which the groundwater is stored. one way of improving understanding of these highly difficult systems is to build and investigate with models which replicate them.

1.1 Groundwater Modeling

The developed groundwater models could be used extensively to understand the mechanisms which comprise groundwater resources and to predict what would happen under possible future conditions. Numerical simulation predict the groundwater levels for many years. The powerof these models is to capture high spatial and temporal variability of aquifer's properties and conditions inherent to natural hydrogeologic systems. However this capability makes numerical models to be data intensive. To achieve acceptable simulation and estimation performance, the properties and conditions of the groundwater system must be accurately represented within the model's space and time domains. The unavoidable discrepancies between the model and the real world system inevitably produce simulation and prediction error. Because the properties and conditions of the groundwater system can never be ascertained with absolute accuracy, empirical models may provide a suitable alternative method and can provide useful results without costly calibration time.

Groundwater level modeling is important for environmental protection: maintaining the groundwater equilibrium system, controlling groundwater level fluctuation, and protecting against severe land subsidence. Groundwater management approaches based on a variety of simulation and prediction techniques and control measures have been proposed and adopted by researchers and relevant authorities to address the problem of providing long-term countermeasures against land subsidence and protection of groundwater resources.

The groundwater models are needed to understand the behavior of groundwater system and to estimate the response of aquifer to any external changes like recharge, discharge etc. The groundwater models can be classified into following two categories:

1. Material Model
   a) Physical Model
   b) Analog Model
2. Mathematical Model
   a) Empirical Model
   b) Theoretical Model

Recently, groundwater level fluctuation (GLF) analysised by means of forecasting or prediction has increased. This paper presents an overview of groundwater flow modeling.

Litrature Review

James et al., (1981) stated that Groundwater modeling is a tool that can help analyze many groundwater problems. Models are useful for reconnaissance studies preceding field investigations, for interpretive studies following the field program and also to estimate future field behavior. In addition to these applications, models are useful for studying various types of flowbehavior by examining hypothetical aquifer problems. Before attempting such studies, however, one must be familiar with ground water modeling concepts, model usage and modeling limitations.

Huston (1993) studied the well field, Kabwe, Zambia and reported that the responseof water level fluctuations were dependent upon pumping rates and prior rainfall and can be simulated by a simple linear regressionmodel. The rate of dewatering of mine was shown to be dependent upon mine size and antecedent rainfall, and could also be simulated by a multiple linear regression model. Such models can be used for forecasting and control of groundwater systems, where more costly and complex methods cannot be used. He also cautioned about the principal limitation of multiple linear regression models that it needs data collected over a reasonable time span for producing meaningful results.

El-Kadi *et al.* (1994) reported that the groundwater modeling is generally hindered by the lack of information about the groundwater system for data preparation and result analysis. Such a lack of information usually demands for use of a tedious iterative methodology within a sensitivity analysis scheme. These kindsof situations were managed by using GIS. They integrated the modeling environment with the GIS as an item in the main menu. The formulation of the groundwater modeling environment necessitated creation of a spatial mesh with parameter values that were assigned to each element or node of the mesh. They also reported that the aquifer parameters were usually known at a some degree of number of sampling points. The values assigned to the elements were estimated by interpolation. They also stated that the integrated system that they used was suitable for extracting and interpolating from the point measurements from the maps. Through this, the data can be import and export to or from the cells.

Sharma (1998) developed the following multiple curvilinear regression models to predict the depth to water table below ground level, Y, for Jamrani Dam Command:

Model 1: $Y = a + a_1.X_1 + a_2.X_2 + a_3.X_3 + a_4.X_4$

Model 2: $Y = b + b_1.R + b_2.D$

Model 3: $Y = c + c_1.R + c_2.D + c_3.R^2 + c_4.D^2$

Model 4: $Y = d + d_1.R + d_2.D + d_3.R^2 + d_4.D^2 + d_5.R^3 + d_6.D^3$

Model 5: $Y = e + e_1.R + e_2.D + e_3.R^2 + e_4.D^2 + e_5.R^3 + e_6.D^3 + e_7.\ln(R) + e_8.\ln(D)$

Where, R and D were groundwater recharge and groundwater discharge, respectively. It was observed that Model 5 gave the highest correlation coefficient values at all the nodes, therefore, was treated as the best fit model for the Jamrani Dam Command.

Affandi and Watanabe (2007) predicted daily groundwater level fluctuations (GLF) to monitor pattern of groundwater level fluctuation. Two observation wells in Saitama City, Japan were analyzed. Models were developed based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) and two artificial neural networks (ANN) algorithms *i.e.* radial basis function (RBF) and Levenberg-Marquardt (LM). This study was conduct in two scenarios. The first scenario was to analyze the effect of a number of time lags as inputs for one-day-ahead prediction using the ANFIS algorithm. It was observed that three input nodes with three time-lag of studied well gave satisfactory forecast results. In the second scenario, three soft computing techniques were applied to predict the groundwater level fluctuation one to seven day-ahead using three input nodes. The results showed that with an increase in time-lag ahead the performance of models were decreased and the prediction of groundwater level fluctuation by three algorithms had no significant difference. It was also suggested from this study that daily groundwater level fluctuation monitoring can be conducted by a forecasting model considering time-lag as an input.

Mohammadi (2008) simulated groundwater flow via MoDFLoW and then used data sets generated by MoDFLoW for training of the ANN and found that ANN models could have accurate GWL predictions.

Adamowski and Sun (2010) proposed a method, which was based on coupling the Discrete Wavelet Transforms (DWT) and the Artificial Neural Networks (ANN) for flow estimation in non-perennial rivers in semi-arid watersheds. The wavelet coefficients were used as inputs into Levenberg Marquardt Artificial Neural Network models to estimate the flow. The results of the coupled Wavelet Neural network models (WA–ANN) and regular Artificial Neural Network (ANN) models were compared for the flow estimation at lead times of 1 and 3 days for two different rivers in Cyprus. The analysis was performed on 6 years of peak weekly water demand data and meteorological variables *i.e.* maximum weekly temperature and total weekly rainfall. It was concluded that the peak weekly water demand corresponded with the rainfall occurrence rather than the amount of rainfall itself for both the rivers, and the Levenberg-Marquardt ANN method gave a more accurate forecast of peak weekly water demand than the other two types of ANNs.

Mayilvaganan and Naidu (2011) developed and compared Adaptive Neuro Fuzzy Systems and feed-forward Neural Network System for the estimation of a groundwater level of a Thurijapuram watershed situated in Thiruvannamalai district of Tamil Nadu, India. The results concluded that ANFIS method showed a good potential to model complex, nonlinear and multivariate problems. Considering the complication of the relationship between the input and the output, results obtained were quite accurate and encouraging. The less RMSE value obtained by the ANFIS method suggested its good generalization potential.

Adamowski and Chan (2011) proposed a method for groundwater level estimation based on coupling the Discrete Wavelet Transforms (WA) & Artificial Neural Networks (ANN). Relative performance, of proposed coupled Wavelet Neural network models (WA-ANN), regular Artificial Neural Network (ANN) models & Autoregressive Integrated Moving Average (ARIMA) models, was compared with the estimated monthly groundwater levels. Monthly total precipitation, average temperature and average groundwater level data recorded at two sites in Chateauguay watershed in Quebec, Canada were used as variables to develop and validate the models. Input nodes were tested, which consisted of various combinations of variables from current month, 1 month, 2 months, 3 months and 4 months before. For both the study sites, the best WA-ANN models were found to provide more accurate groundwater level estimates than both the best ANN models and the ARIMA models for 1 month lead-time estimation. For both the study sites, the best WA-ANN models were a function of total precipitation from current, previous and 2 months before and the average groundwater level from the current and previous month.

Australia, National Water Commission (2012) gave the guidelines for groundwater modeling, which involves the following steps:

- Planning
- Conceptualization
- Model design
- Calibration
- Uncertainty analysis
- Presentation of results

Series of decisions were involved in the design and construction of model to implement the conceptualization in a mathematical and numerical modeling environment. Selection of numerical method and modeling software, an appropriate model dimension, definition of a model domain and the spatial and temporal discretization to be used in the model were included in the decisions required.

Sahoo and Jha (2013) compared MLR and ANN in GWL prediction while consider all the significant inputs that affect GWL. They concluded that ANN models were superior; however, taking into consideration of practical advantages of the MLR technique, it was suggested as a cost-effective GWL modeling tool.

Moosavi *et al.* (2013) compared Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Wavelet-ANN and Wavelet-ANFIS to forecast monthly groundwater level for different prediction period (1, 2, 3 and 4 months ahead) under two case studies in two sub-basin of Mashhad plain, Iran. It was found that forecasting of groundwater level by wavelet transformation can increase the accuracy and Wavelet-ANFIS hybrid model had the best performance compared to other models. It was also suggested from the study that the best number of neurons in the hidden layer can not always be calculated by the specific formula but it should be determined using trial and error method. The forecast of groundwater level for these models was more satisfactory for 1 and 2 months ahead [R^2 = 0.99 and RMSE = 0.12 for Wavelet-ANFIS model for 1 month ahead] than for 3 and 4 months ahead [R^2 = 0.91 and RMSE = 2.07 for Wavelet-ANFIS model for 4 months ahead].

Mehdipour *et al.* (2014) employed an Adaptive Neuro Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA) as Artificial Intelligence tools to obtain governing groundwater flow equations in Ghaen and Karaj aquifers in Iran. Input output data sets, for both the training and the testing data sets of both the aquifers, were determined by the use of numerical simulation model, Iterative Alternating Direction Implicit Method (IADIM). The water table elevation at each cell in the model was function of the aquifer recharge and discharge at the current period and water table elevation at the previous period. Application of ANFIS and Genetic Algorithm (GA) in these studies showed the superior flexibility of GA over ANFIS in time series modeling. It was observed that GA provided water table elevation results with smaller root mean squared error (RMSE) as the error criterion, especially in the testing data set.

Sharma *et al.* (2014) proposed a data driven ANFIS model and a physically based watershed model LSPC in Chickasow Creek Watershed, which was situated in South Alabama. Since suitable rain gauge stations were not available near the watershed proximity, and also the study area was affected with the EI Nino Southern Oscillation (ENSO); the sea surface temperature (SST) and sea level pressure (SLP) were also integrated in ANFIS based model. Models were evolved for same periods of datasets and model performance was checked through comprehensive model comparison in several ways, including statistical analysis for various seasons and periods over 50 years of simulation period. It was concluded from the research that the performance of ANFIS based model was fairly comparable to a physically based Watershed model Loading Simulation Program C^{++} (LSPC); especially when raingauge stations were not available. Additionally, the research concluded that ANFIS based model's performance was also fairly comparable to that of LSPC no matter whether SST and SLP in ANFIS input vector was included or not.

Mirzavand *et al.* (2015) estimated groundwater fluctuation by two different methods, Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Regression (SVR) in the Kashan plain, Isfahan province, Iran. The rainfall, evaporation, stream flow, spring discharge, and aquifer discharge data were used as an input. Radial Basis Function (RBF) and polynomial function were used as the kernel function of the SVR. These models were evaluated on the basis of correlation coefficient (R) and root mean squared error (RMSE) statistics. SVR with kernel of Radial Basis Function (RBF) was found better than polynomial function. During testing of models the results confirmed that ANFIS model with RMSE = 3.6 and R = 0.985 was more accurate then SVR using RBF kernel function with RMSE = 13 and R = 0.821

Alam (2016) developed the groundwater models using MoDFLoW, Artificial Neural Network (ANN) and Multi Linear Regression (MLR) method for the prediction of groundwater table depth in Bellan Canal Command, located in Allahabad district of Uttar Pradesh. It was concluded that ANN based model showed closer relationship between observed and predicted depths to water table followed by MoDFLoW and MLR. The performance of MLR based models was not found satisfactory in the Bellan Canal Command.

Yan *et al.* (2016) propoosed a 'Wavelet Adaptive Neuro Fuzzy Inference System conjunction model' for monthly groundwater level fore casting, for two observation wells in the city of Xi'an, China. The comparison was made on the performance of groundwater level estimation for the proposed model (WANFIS) and the performance of regular Auto regressive Integrated Moving Average (ARIMA) based model and Adaptive Neuro Fuzzy Inference System (ANFIS) based model. Average temperature, maximum temperature, total precipitation and average groundwater level of every-month of the period 1998-2010 was used to develop and validate the models. The data of the first eleven years was used for training the applied models and the data of last two years was used for the testing. The results showed that, both during the training and testing period, the WANFIS based model provided more precise monthly groundwater level predictions compared to that of the ARIMA and ANFIS based model.

Fereydooni and Tajbakhsh (2017) compared efficiency of Support Vector Machine (SVM) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) in predicting the groundwater level. The data of rainfall and the groundwater level were used as an input of the models. The data for the period of 19 years (1994 - 2013) of the Neyriz plain was used. Different patterns were considered to achieve input of models. The performance of models were evaluated on the basis of different performance indicators such as correlation coefficient (R) and mean square error (MSE). on the basis of the study it was concluded that both the models were able to give the accurate results and there was no significant difference in the performance of two models.

Conclusion

It was observed from above review of literature that any groundwater models can be developed by Genetic Algorithm (GA), Adaptive Neuro Fuzzy Inference System (ANFIS) based model, Wavelet Neural network models (WA-ANN), Wavelet Adaptive Neuro Fuzzy Inference System (WANFIS) and Support Vector Regression (SVR) based model for the prediction of groundwater table depth in the different part of any region. Keeping it in view, any model can be used to study groundwater behavior and to develop the groundwater models for the prediction of depth to water table as well as to suggest preventive measures in identified problematic regions of the study area.

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