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GROUND WATER LEVEL MONITORING SYSTEM USING MACHINE LEARNING

Rajendrakumar
Asst Professor,
Department of Computer Science,
Government First Grade College, Sedam.

Abstract

Developing accurate soft computing methods for groundwater level (GWL) forecasting is essential for enhancing the planning and management of water resources. Over the past two decades, significant progress has been made in GWL prediction using machine learning (ML) models. Several review articles have been published, reporting the advances in this field up to 2018. Understanding of the state-of-the-art ML models implemented for GWL modeling and the milestones achieved in this domain. Furthermore, recommendations for possible future research directions to improve the accuracy of GWL prediction models and enhance the related knowledge are outlined.

Keywords

State-of-the-art, Machine learning, Groundwater level, Input parameters, Prediction performance Catchment sustainability.

I. Introduction

Groundwater resources, as one of the most valuable and important sources of water in the world, play a direct and crucial role in various aspects of human lives, such as agriculture, industrial development, and potable water supply. In addition, the indirect effects of groundwater resources on the environment and communities are undeniable. The groundwater level is a direct and simple measure of groundwater availability and accessibility. Having a proper understanding of the past, current, and future situations of GWL can provide policy-makers and practitioners in water sectors with better insight and perception to develop strategies for the planning and management of water resources, to ensure sustainable socioeconomic development. However, GWL consists of an integrated response to several climatic, topographic, and hydro geological factors and their interactions, which makes the simulation of GWL a challenging task.

Groundwater is the largest global reservoir of liquid freshwater, which is under increasing stress due to overdraft. Groundwater is "the water stored beneath earth's surface in soil and porous rock aquifers", and plays a principal role in sustaining ecosystems and producing food in a vast area of arid and semi-arid land globally. Groundwater accounts for around 33% of total worldwide water withdrawals, and over two billion people rely on groundwater as their main water source. Over-drafting is causing groundwater levels to drop continuously and dramatically in many regions, leading to a global groundwater crisis.

The complexity of this system of systems makes accurate physical process simulations challenging due to the large agricultural and hydro geological data requirements for model development and calibration. Thus, it is appealing to consider data-driven and machine learning methods based on nonlinear interdependencies that may be able to predict groundwater level change without deep knowledge of the underlying physical parameters. Machine learning methods recognize patterns hidden in historical data and then apply those patterns to predict future scenarios.

Even though these classical models are robust and reliable, the precision and accuracy of numerical models are confined by several factors, such as their high dependency on large volumes of data related to aquifer properties, the geology of the porous media, and basement topography. In last two decades, artificial intelligence (AI) models have been widely used to overcome the drawbacks of conventional numerical models for simulation. Presents the goal map, depicting the two major pieces of information, one being the most studied geographical locations and other those which have not yet been studied. The usability and reliability of AI models in dealing with complex and high-dimensional engineering problems have been proven in the last few decades. AI consists of multidimensional systems

Combining various mathematical and statistical components and arithmetic and heuristic algorithms. AI has been extensively employed in different fields of science, engineering design, energy, robotics, and economics. It has also been intensively used for solving various civil and environmental engineering problems. Some examples include soft computing techniques, Machine Learning (ML) methods, probabilistic analysis, and Fuzzy-based systems. In recent years, more attention has been paid to the successful use of AI in different hydrological fields, including water resources, surface and groundwater hydrology, sediment contamination, and hydraulics.

Discussion

Research objectives

The present paper deals with performance evaluation of application of three machine learning algorithms such as Deep neural network (DNN), Gradient boosting machine (GBM) and Extreme gradient boosting (XGBoost) to evaluate the ground water indices over a study area of Haryana state (India).

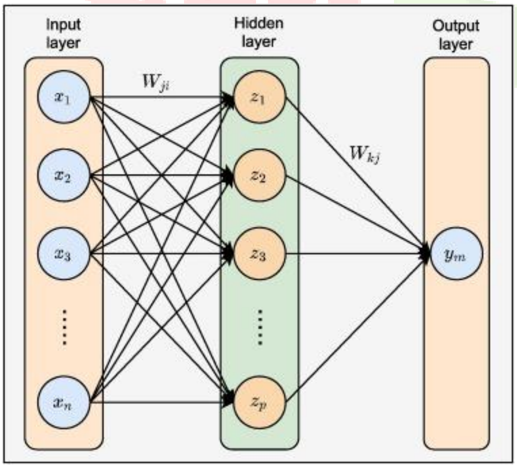
It is quite understandable that many hydrologists and hydro geologists have recognized the potential capability of ML models, in particular, for their use in GWL simulation. Even though there have been a few comprehensive review studies published on the subject of GWL modelling using ML models, Furthermore, the focus of the present article is the recent developments, progresses, restrictions, and shortcomings of advanced AI

Methods in dealing with GWL. The models each have one hidden layer, but the number of hidden neurons varies across each study area. The optimal number of hidden neurons, the associated weights, and model performance indicators were all derived for each well individually.

Application of artificial neural network models

An ANN is a computer system designed to mimic the manner in which information is processed and analyzed by the human brain. It is a major sort of AI applications, which is capable of handling complex issues which are difficult, according to statistical and human standards. Furthermore, ANNs have efficient abilities to approximate functions that are commonly unknown or to predict future values based on potentially noisy time-series data. The structure of an ANN is comprised of several simple elements working in parallel. The hidden layer is an important component of an ANN, due to its location between the input layer and output layer, where the neurons receive a set of weighted inputs and, hence, generate an output by applying a certain activation function. The information transfers from one layer to another through neurons. An activation function is always used, regardless of using an ANN with a single or several hidden layers. Feed-forward neural networks (FFNNs), which are often called multilayer perceptions (MLPs) are one of the most famous and powerful types of ANN and have been widely used for solving hydrological issues. In a traditional FFNN, three parameters need to be considered, in order to accomplish more accurate

Predictions: (1) The number of hidden nodes and transfer functions; (2) the initial weight and bias values; and (3) choosing a sufficient number of epochs.

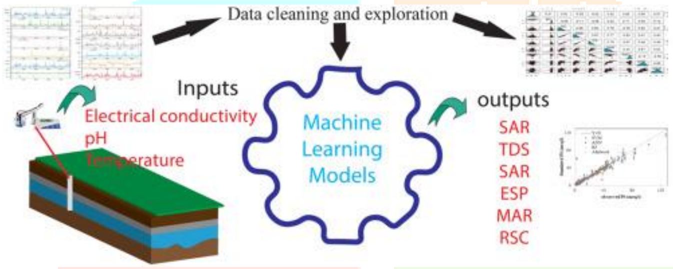


A large volume of literature is available on the application of ANN models to forecast GWL in different regions. The predictive models were constructed using only four meteorological factors as predictors: Rainfall (Raf), potential Evapotranspiration (EVP), Temperature (T), and Humidity (H %). Moreover, the Levenberg–Marquardt (LM) algorithm was applied to train several ANN model structures, in order to optimally choose the weight and bais values. Another study in India used an ANN approach to estimate the monthly GWL at four sites located in south-east Punjab for the period of 2006 to 2013, where Raf and preceding GWL were used as inputs. The results showed that the use of an ANN using the LM back-propagation algorithm provides more accurate predictions, compared to other algorithms.

LM back-propagation was used as a learning algorithm. The study revealed that the proposed model was able to estimate GWL more accurately, in terms of different statistical criteria.

Furthermore, the results revealed that the tangent sigmoid transfer function was most efficient and the data division with 80% for training, 10% for validation, and 10% for testing was more effective and optimistic, compared to other data divisions.

The process of understanding and predicting the fluctuations of GWL is usually very complex, as several parameters play significant roles in determining the storage capacity of water in a certain aquifer. To achieve better estimation performance, different ANN structures were chosen, based on different input parameters including meteorological and hydrological factors. It is important to mention that the LM algorithm was utilized to train the predictive models. The outcomes of the study exhibited the robustness of multiple linear regressions (MLR) in forecasting the GWL, based on several statistical criteria. Additionally, the study presented a good relationship between the hydrological parameters and GWL.



The extreme learning machine, an advanced version of an ANN, was invented in 2006 and has gained good popularity, in recent years, in solving water resource issues and groundwater estimation tasks. The main structure of the classical ELM model is about the same as a single-layer FFANN model. However, the input weights and biases in the ELM algorithm are always assigned randomly and the output weights are calculated using

The singular value decomposition (SVD) method. ELM models have many advanced aspects, which make them superior to traditional ANN models in solving complex engineering problems. Moreover, the proposed model showed better performance in predicting multi-month GWL than the other employed models.

Hybrid ML models applications

Despite significant advancement in recent years, in terms of handling non-stationary, dynamic, and non-linear time-series data using ML models-particularly applied in hydro-environmental and water resource management-there are still some weakness associated to such approaches. A variety of problems in hydrological simulation research related to a single AI-/machine learning-based modelling has been addressed, regardless of their promising performances demonstrated in various studies. According to, hybrid models have proved not only their merit and superiority to the use of a single model, but can also address a variety of different problems associated with the use of single techniques.

The concept of Hybrid methods implies the combination of one or more AI-based models, computing machine learning models, and/or classical regression models for improving the performance accuracy or to obtain optimal outcomes. Hybrid methods could be utilized in the prediction or optimization stages, based on their specific purposes. Hence, it can be justified that hybrid methods comprise several combined single techniques and/or optimization algorithms, which have been proved to be more reliable and capable

of outperforming single models, with regards to modelling accuracy.

Literature review

In the literature, many successful applications of statistical models, including logistic regression, k-NN, linear discriminate analysis, quadratic discriminate analysis, multivariate adaptive regression spline (MARS), and regression trees, in hydrology have been reported. However, time-series models such as autoregressive, Moving average, autoregressive moving average, autoregressive integrated moving average, and seasonal autoregressive integrated moving averages have been extensively applied to predict the present and to forecast future values in

The monthly GWL from 1990 to 2004 were first clustered using the Vard algorithm of the hierarchy method to classify the true groups of piezometric wells into five groups, according to their similarities to each other. The performance of the five models was investigated through 11 different structures, according to the lag time and differencing processes. They concluded that time-series models are one of the appropriate methods which could be of use to forecast the GWL. The AR with 2-lag showed the best forecasting of GWL for 60 months ahead for the five clusters.

Conclusion and future work

We propose an automated hybrid artificial neural network (HANN) model with a new input data processing method for simulating groundwater level change. We apply, evaluate, and discuss the model capability for predicting seasonal groundwater level change at 1124 wells across two major agricultural regions of the US: the HPA and MRVA. In both regions, groundwater pumping has produced groundwater level declines across large areas and is a growing concern for water resource managers. We elected to test the HANN model on these two well-studied aquifers to allow for model output comparison. Ultimately, the HANN model may be most useful in regions lacking known hydro geologic subsurface parameters.

The occurrence and movement of groundwater are subjected to various factors such as its geology, hydrology, land planes, etc. Thus, it requires carrying out different types of studies to identify the potential zones of groundwater. The modern tools and techniques are helpful in groundwater exploration to satisfy the need for drinking water and other human requirements.

The ensemble method is a Machine Learning technique that combines several base learners' decisions to produce a more precise prediction than what can be achieved with having each base

Learner's decision. This method has also gained wide attention among researchers recently.

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