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Modeling of daily groundwater level using deep learning neural networks

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Abstract

Groundwater is an essential water source, becoming more vital due to shortages in available surface water resources. Hence, monitoring groundwater levels can show the amount of water available to extract and use for various purposes. However, the groundwater system is naturally complex, and we need models to simulate it. Therefore, we employed a deep learning model called CNN-biLSTM neural networks for modeling groundwater, and the data was obtained from USGS. The data included daily groundwater levels from 2002 to 2021, and the data was divided into 95% for training and 5% for testing. Besides, three deep CNN-biLSTM models were employed using three different algorithms (SGDM, ADAM, and RMSprop). Also, Bayesian optimization was used to optimize parameters such as the number of biLSTM layers and the number of biLSTM units. The model's performance was based on Spearman's Rank-Order Correlation (r), and the model with SGDM showed the best results compared to other models in this study. Finally, the CNN model with LSTM can simulate time series data effectively.

1. Introduction

Groundwater refers to the gravitational water in the more subordinate soil layer [1]. It is an essential provider of freshwater that can assist in solving problems related to the shortages in freshwater supplies. Therefore, frequent groundwater level monitoring is necessary for practical groundwater resource management [2] because precise and trustworthy groundwater level (GWL) predictions give fundamental details on groundwater availability [3]. Besides, the plunge in water levels implies that the resources are consumed significantly in some areas [4]. Thus, assessing the known groundwater resource in a more practical technique is required and developing the best consumption objectives [5].

The GWL is part of the natural groundwater system, which is exceptionally complicated. Therefore, there is a necessity for simplification in managing groundwater resources. A model, such as the groundwater model, is an approach that can be used to simulate and understand the natural groundwater system. Besides, modeling groundwater is meant to imitate the aquifer's physical variables [5]. Thangarajan [5] showed that the groundwater models could be classified into physical, analog, and mathematical Models. Physical models were employed from the 1930s to the 1950s to analyze groundwater problems; for instance, the physical groundwater model called the sand tank model, a basic laboratory-scale standard with proper aquifer features, is scaled down to simulate the field conditions [5]. The mathematical model includes the exact details of the conceptual model but is described as controllable equations with analytical and numerical explanations [6-9]. The analog model considers a similarity between 1D groundwater steady flow expressed by Darcy's law and the constant flow of electrical waves by Ohm's law [9]. It is essential to mention that the details of these models are out of the scope of this study.

Various studies were employed broadly to study GWL using the literature mentioned above models (physical, analog, and mathematical models). Faulkner et al. [10] used a laboratory analog model to imitate groundwater flow and solute transport in an aquifer and showed that the analog model could provide the hydraulic head distribution. Gholami et al. [11]

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constructed a laboratory approach to investigate the influence of the GWL change on internal air pressure. Boyraz et al. [12] performed analytical, experimental, and numerical solutions to describe the GWL distribution. Lee et al. [13] employed numerical and sandy tank models to study the increase of GWL due to underground obstructions in the coastal aquifer. They showed that the sandy tank experiment offered details of the hydraulic features of groundwater systems such as GWL in the coastal aquifer with an obstacle like a seawall. Xu et al. [14] conducted a sequence of laboratory experiments to examine the differences in GWL during dewatering. Kagabu et al. [15] designed a three-stage tank model to imitate GWL changes before the earthquake and then apply it to the same case for the post-earthquake duration. They showed that their model could represent GWL differences due to earthquake events. Ansarifar et al. [16] employed MODFLOW mathematical approach to simulate the groundwater level in a coastal aquifer. Akter and Ahmed [17] used MODFLOW 2005 mathematical model to study water level drawdown and groundwater modeling. They showed that mathematical models could show pertinent details and save money and time. Armanuos et al. [18] used MODFLOW to study the effects of the rising pumping on the GWL in the aquifer. Yang et al. [19] employed an analytical model to study the GWL over height varying with multi-tidal circumstances.

The improvement of soft computing applications such as artificial intelligence (AI) has recently encouraged researchers to adopt it to study various engineering problems [20-27]. One of the AI applications is deep learning (DL), as shown in Figure (1) [27], and is established on the algorithms created and inspired by the biological neuron system of humans to calculate or approximate functions by solving many inputs into a target output [28]. Besides, DL boosts computer technology to create outcomes established on the earlier known data [29-30]. DL has changed conventional industries and is increasingly employed in many scientific fields [31] and water resource engineering. For example, AI models were used to show the potential to handle investigations on relations between input and important system variables [32].

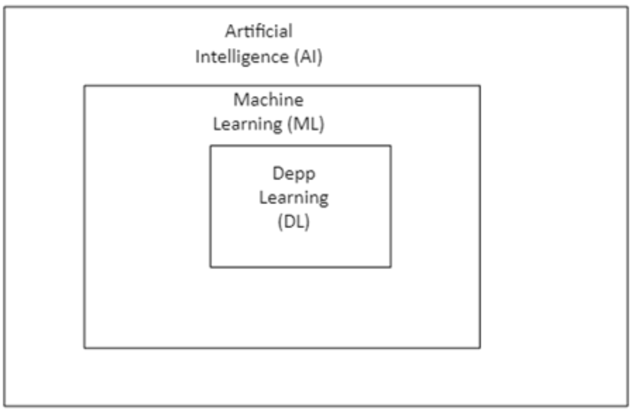

Figure 1. Artificial Intelligence models [27]

Moreover, Rajaee et al. [33] reviewed 67 papers for applications of machine learning approaches such as artificial neural networks, adaptive neuro-fuzzy inference systems, genetic programming, and support vector machine in GWL modeling from 2001 to 2018. They showed that artificial intelligence techniques could be employed to forecast the GWL time series in various aquifers. Nevertheless, the deep learning approaches grew slowly initially [31] but are to succeed in water resources engineering [32]. It is recommended to read published studies in the literature for more details on DL models, which can be found in [34-36].

Long short-term memory (LSTM) neural network is one of the deep learning applications, and it has been applied in various studies [37-40], and the employment of LSTM in GWL modeling is also increasing. Zhang et al. [41] created a two-layer LSTM model for forecasting GWL and trained the LSTM model with monthly water diversion, evaporation, precipitation, temperature, and time as input parameters. They showed that The LSTM offers a good performance for GWL simulating. Huang et al. [42] applied the LSTM model to estimate groundwater recharge according to GWL change. They compared the performance of the LSTM model with multi-layer perception (MLP) and linear regression models and found that LSTM demonstrated better results than the two models. Shin et al. [43] employed LSTM to forecast the GWL due to pumping wells in the locations close to observing wells. They showed that the GWL forecast by the LSTM model was extremely high. Vu et al. [44] used the LSTM model to rebuild GWL missed data of piezometers employed to observe water changes in a regional karstic aquifer. They showed that LSTM is proper for rebuilding the GWL changes with acceptable precision. Solgi et al. [45] employed LSTM to forecast GWL for short and long periods compared to a simple neural network. They showed that the LSTM exceeded the accurate GW level prediction of the simple neural network. Yokoo et al. [46] employed the LSTM model for GWL modeling and demonstrated that the model could simulate GWL in acceptable agreement with the measured data. Besides, a convolutional neural network (CNN) is another deep learning model used for various problems in civil engineerings, such as groundwater problems. Ali et al. [47] one of few studies that used groundwater level as the only input for training the AI model, used a hybrid CNN-BI LSTM neural network to model hourly groundwater levels. They showed that CNN-biLSTM could handle modeling hourly groundwater levels, and this model can be used for time series data.

AI techniques have been utilized to emulate GWL by engaging data like rainfall, temperature, humidity, evaporation, and extraction rates. Nonetheless, few pieces of research were used to predict the groundwater level based on the measured groundwater level as the only input to the AI model [45]. Hence, this study aims to employ daily groundwater level data to train CNN-bi LSTM models with Bayesian optimization to simulate GWL using only the GWL time series data as input to the models. The first section of the article contains a brief introduction to recent studies of GWL using various modeling approaches. The second section shows the study area and the deep learning models. The third section illustrates the results. Finally, the discussion with recommendations for further study.

2. Method

2.1. Study Area

The daily groundwater data were collected from The United States Geological Survey (USGS) for a city called Camdenton, a municipality in the middle of Camden County, Missouri, USA. The data consist of groundwater daily measurements from Jan 2002 – Oct 2021, as shown in Figure 2. The total number of measures was 7242; 0.95% of data was selected for training the AI model, and 0.5% for testing the AI model.

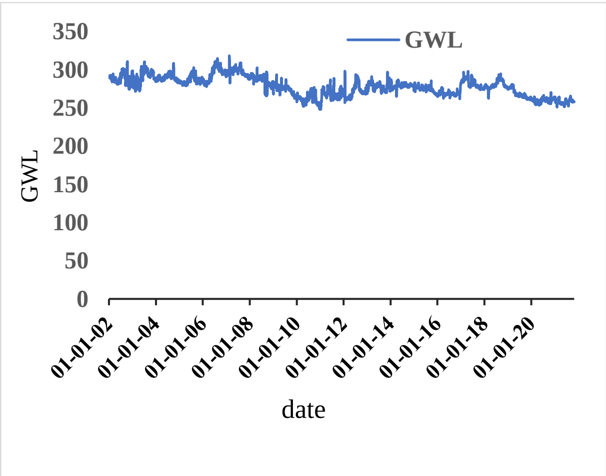

Figure 2. Daily groundwater measurements

2.2. CNN-biLSTM Model

Bidirectional -LSTM (BiLSTM) is a distinct network of the traditional long-term short-memory neural network (LSTM), which includes forward and backward LSTM, supplying entry to the long-range context in both directions. Furthermore, LSTM is developed to fix the vanishing gradients problem using a unique gating process [48]. Besides, biLSTMs improve the quantity of data attainable to the AI model (Chiu and Nichols, 2016). Thus, the biLSTM permits for incorporation of the prior and following data [49]. The traditional LSTM contains multiple memory cells or blocks. Memory blocks include many memory units and three gates. The first one, the input gate, seeks to determine the required latest data and convert it to the cell form. The second one, called forget gate, manages to extract the details that are not important anymore. In contrast, the output gate determines what type of essential details in the cell should be considered as the outcome [49].

As biLSTM is a particular type of recurrent neural network (RNN), it converts the different activations into dependent activations procedures by delivering all the neural network layers with the same weights and biases and specifying earlier outcomes to give the subsequent hidden layer as input. For illustration, in a precise RNN method, per iteration, t, the hidden layer endures a hidden form, ht, updates and accelerates it based on the layer input, xt, and earlier hidden form, h_{t-1}, employing the Equation 1 [50].

$$h_t = \sigma_h(Wx_t + Vh_t - 1 - b_h) \tag{1}$$

W is the weight matrix delivered via the input to the hidden layer, V is the weight matrix between two hidden serial states (ht−1 and ht), $b_h$is the bias vector for the hidden layer, and σh is the activation function to generate the hidden structure. The model result can represent as Equation 2 [50]:

$$y_t = \sigma_y(Uh_t + b_y) \tag{2}$$

U is the weight matrix from the hidden converted to the output layer, and σy is the activation function of the result layer. Finally, the hidden layer supplies the outcome yt. The LSTM layers procedure series data uni-directionally and modify it to capture the randomness. Nonetheless, a backward LSTM layer can deliver bi-directionally into the model. Thus, developing a Bi LSTM layer, including a forward LSTM layer and a backward LSTM layer, processes series data with two particular hidden layers and merges them into the same result layer [51].

Convolutional Neural Network (CNN) is a multi-layer artificial intelligence model founded on convolution calculation. CNN model has been widely used in numerous areas. It is presented by Y. LeCun et al. [52] and is a feed-forward neural network. CNN's local perception and weight sharing can remarkably reduce the parameters; thus, models can be executed to foretell time-series data. Besides, the typical CNN model provides a standard network configuration for the CNNs, primarily including convolutional layers, pooling layers, and fully connected layers, as shown in Figure 2. The mechanism of CNN is that each layer retains a majority of convolution kernels and pulls the data characteristic. Its calculation is as Equation (3):

$$l_t = \tanh{(x_t * k_t + b_t)} \tag{3}$$

Where l_t is the result value after convolution, tanh is the activation function, xt is the input vector, kt is the weight of the convolution kernel, and bt is the bias of the convolution kernel [53].

A CNN-biLSTM standard model, as illustrated in Figure 3, incorporates CNN layers that carry the characteristic from input data and biLSTMs layers to deliver sequel projections. It is employed for activity recognition. Their specific attributes utilize optical time series projection problems [54]. biLSTM with CNN layers has been used for encoding spatiotemporal elements for varied objectives, like precipitation estimation [55]. Still, the applications of CNN-biLSTM approaches in hydrology have not been exploited to unravel problems [56]. The component for both CNN and Bi LSTM models is presented in the publications extensively.

In this study, three CNN-biLSTM models were developed to model the daily groundwater level, and these models were optimized with Bayesian optimization to determine the best performance. Table 1 shows the hyperparameters parameters for the three models. The three models were trained with 350 epochs, 60 iterations, 32 batch sizes, and a factor for dropping rate equal to 0.5. Moreover, each model was trained with three different algorithms to update the weights, as shown in Table 2. The first model was trained with stochastic gradient descent with momentum (SGDM), the second one with RMSprop, and the last one with root mean squared propagation (ADAM).

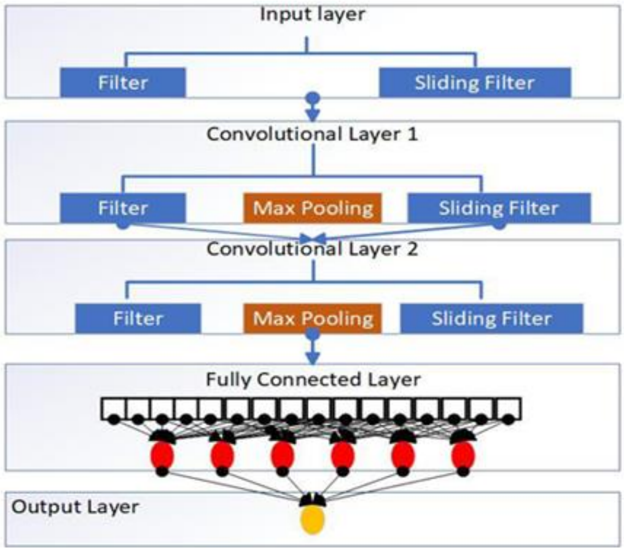

Figure 3. CNN model [57]

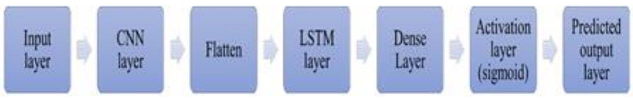

Figure 4. CNN-biLSTM model [57]

Besides, the performance of models was assessed based on Spearman's Rank-Order Correlation:

$$\rho = 1 - \frac{6\sum {d_i}^2}{n(n^2-1)} \tag{4}$$

Where ρ is Spearman's rank correlation coefficient, is the distinction between the two classes per observation, and n is the number of data.

Table 1. Hyperparameters parameters

Number of LSTM Layer	**1 to 4**
Number of BI-LSTM Units	75 to 200
Learning Rate	0.001 to 1
L2Regularization Rate	0.00000000001 to 0.001

Table 2. CNN-biLSTM models

Model	**Training algorithm**
Model 1	SGDM
Model 2	RMSprop
Model 3	ADAM

3. Results

The results showed that the first model is the best among CNN-biLSTM models developed for modeling daily groundwater levels. Model 1 showed a high correlation coefficient (R) equal to 0.9896 for training and 0.9633 for the testing stage, as illustrated in Figures 5 and 6. Furthermore, Bessie, Bayesian optimization showed the best parameters for training model 1, as shown in Table 3.

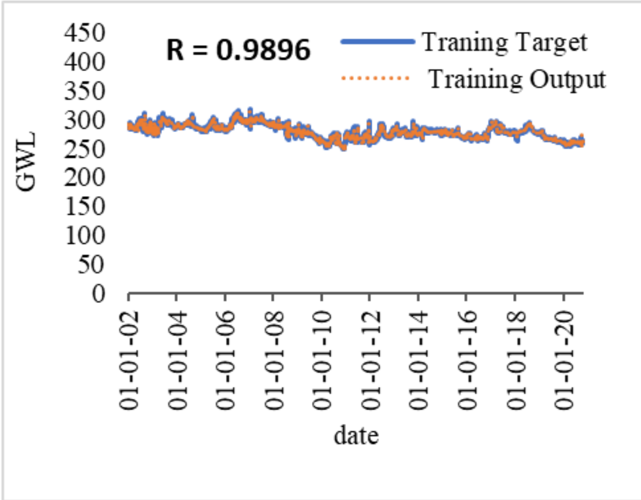

Figure 5. Training stage for model 1

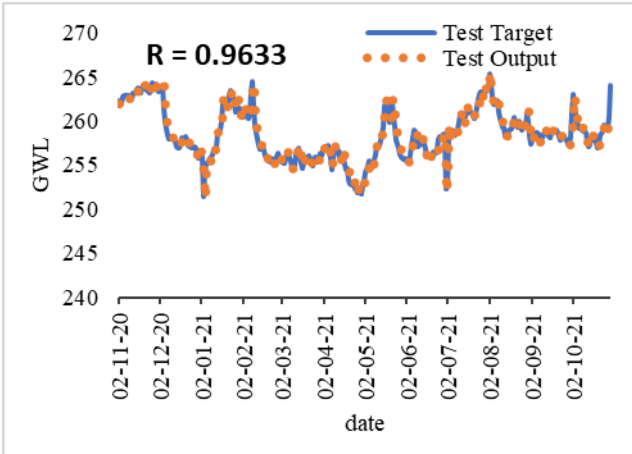

Figure 6. Testing stage for model 1

Table 3. Optimized parameters for model1

Number of BI-LSTM Layer	**1**
Number of BI-LSTM Units	171
Initial Learning Rate	0.021642
L2Regularization Rate	$2.8\times e^{-10}$

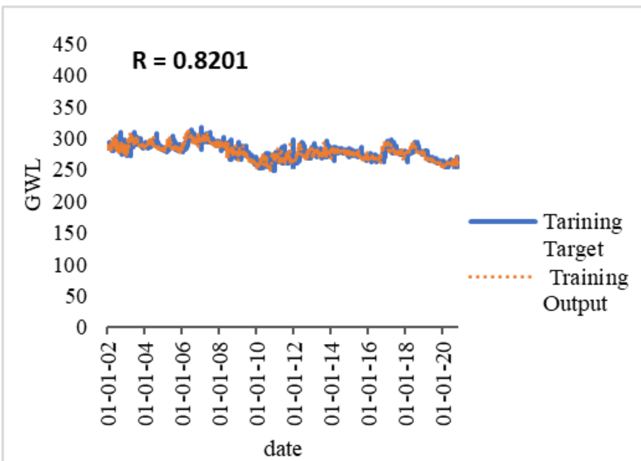

Figure 7. Training stage for model 2

Meanwhile, the second model showed a good correlation coefficient (R) equal to 0.8201 in the training stage but a better correlation in the testing stage equal to 0.9027, as shown in Figures 7 and 8. Besides, Table 4 shows the optimized parameter for model 2.

Finally, the last model, model 3, showed the worse performance, with a correlation coefficient (R) equal to 0.8128 in training and 0.8811 in testing stages, as shown in Figures 9 and 10, respectively. Besides, Table 5 shows the optimized parameter for model 3.

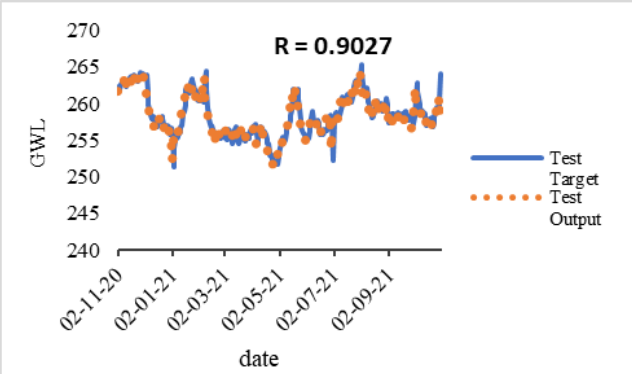

Figure 8. Testing stage for model 2

Table 4. Optimized parameters for model 2

Number of BI-LSTM Layer	**2**
Number of BI-LSTM Units	94
Initial Learning Rate	0.010901
L2Regularization Rate	$1.7 \times e^{-5}$

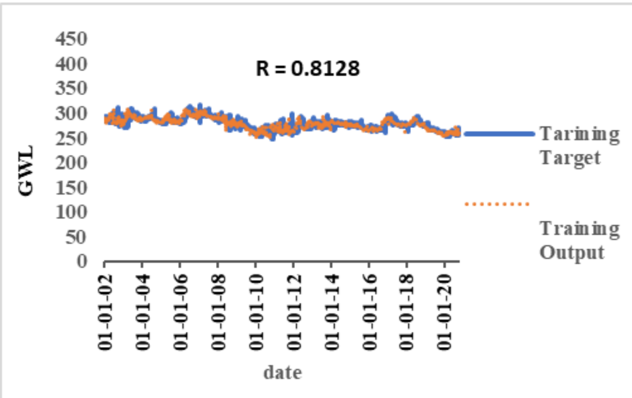

Figure 9. Training stage for model 3

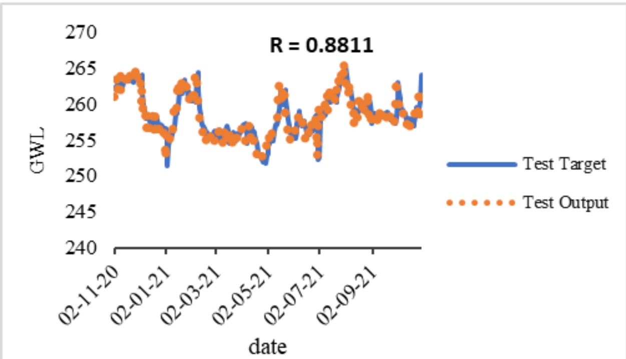

Figure 10. Testing stage for model 3

Table 5. Optimized parameters for model 3

Number of BI-LSTM Layer	2
Number of BI-LSTM Units	84
Initial Learning Rate	0.010009
L2Regularization Rate	0.00015

4. Conclusion

The groundwater level is a vital detail that can be influenced due to environmental divergence. For instance, an investigation of climate deviation shows that decreasing rainfalls and temperature growths lead to problems such as finding available water resources [50-60]. Besides, research on the groundwater level is critical for providing details on the availability of groundwater resources. Thus, a hybrid CNN-biLSTM was utilized, which integrates CNN and biLSTM networks. The results showed that the three models showed good outcomes based on the coefficient correlation (R), especially the model trained with the SGDM training algorithm. Besides, the CNN-bi LSTM showed it could handle time series data related to hydrology problems like modeling daily groundwater data. Finally, Bayesian optimization was employed to locate the most acceptable hyperparameter parameters, including the number of LSTM layers, the number of LSTM units, the learning rate, and the L2regularization rate. The limitation of the current study is that the model is trained with only daily groundwater level, and it is recommended that the model trained with monthly groundwater level to show the ability of model for simulating various time steps.

Conflicts of interest

The authors declare no conflicts of interest.

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