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Artificial Intelligence Decision Support System for Groundwater Management under Climate Change: Application to Mornag Plain in Tunisia

Youssef TFIFHA[1], Manel ENNAHEDH[2], Nehla DEBBABI[1]

[1] ESPRIT School of Engineering, 2083 Tunis, Tunisia
[2] National Agronomic Institute of Tunisia, 1082 Tunis, Tunisia
nehla.debbabi@esprit.tn

Abstract. The purpose of this research is to investigate the influence of climate change on GroundWater Level (GWL) in Mornag plain in Tunisia. Indeed, due to the spatiotemporal variability of RainFall (RF) and temperature, aquifers all over the world have seen significant water level volatility in recent decades. Therefore, for a reliable GroundWater (GW) management under climate change context, it is essential to analyze and estimate the GWL variability. In this study, we focus on the plain of Mornag, located in the southeast of Tunisia, since it contributes with 33% in the national agricultural production. From this plain, we have collected historical piezometric and RF data covering the period 2005-2015. Knowing the RF data, our goal is to forecast the GWL one. This issue has already been studied using classical numerical GW modeling such as Modflow and Feflow. Unfortunately, these techniques are data and time consuming. To overcome all these drawbacks, we propose to use an Artificial Intelligence (AI) approach that has shown great performance in literature for recurrent data modeling and forecasting. This approach corresponds to the Long-Short Term Memory (LSTM) Neural Network. Compared with Modflow, LSTM has shown noticeable enhancement in terms of root mean squared error minimization, which confirms its adequacy for GWL forecasting. Using the proposed AI prediction model, the impact of climate change on Mornag GWL has been studied under two Representative Concentration Pathway (RCP) scenarios; RCP 4.5 and RCP 8.5 for three future periods: 2015-2040 (short term), 2041-2065 (medium term) and 2066-2100 (long term). As expected, results reveal a future decline of Mornag GWL. The performed study of future Mornag GWL behavior using LSTM could classify this AI approach as a good decision support system that could be used to optimize the management of our limited water resources in order to satisfy the population needs in terms of drinking water and agricultural production, as well as to prevent upcoming drought.

Keywords: Artificial Intelligence, Climate Change, Decision Support System, Forecasting, Groundwater Level, Representative Concentration Pathway

1. Introduction

GroundWater (GW) is one of the most important and significant sources of water in the world, as it affects many facets of human life, such as industrial growth, agricultural production, drinking water provision, etc [1]. Unfortunately, over recent decades, aquifers all over the world have experienced significant GroundWater Level (GWL) volatility that makes water resource management challenging [2]. Two key factors are behind this volatility; the increase in water consumption and climate change. Indeed, due to the fast urban growth, the consumption of water resources has been dramatically increased. As a consequence, the balance between human and ecosystem needs has become difficult to maintain. On the other hand, climate change has played a crucial role in GWL variability, with mainly the spatiotemporal unpredictable changes of RainFall (RF) and Temperature [3]. As a matter of fact, according to UNESCO, GW is the sole way for 2.5 billion people throughout the world to meet their daily water demands [4], however, climate change endangers these resources constantly. With full knowledge of the facts, a complete study of historical, current and future GWL variability is required for policymakers and practitioners to develop water resource planning and management strategies, as well as prevent drought for the upcoming years. Both research and public interest in the projected climatic consequences on GW have intensified in recent years. Indeed, GWL has long been anticipated using a variety of numerically based conceptual models, including Feflow and ModFlow [5]. These models, developed by the United States Geological Survey (USGS), are widely considered as a worldwide benchmark for predicting and forecasting GW. Though the non-linearity of these water systems and their response to climate conditions make modeling using numerical models difficult. In addition, these classical models are mostly data and time-consuming, hard to set up and maintain, and therefore expensive. In recent years, the limitations of traditional numerical models have been widely addressed through the application of Artificial Intelligence (AI) models since they offer high accuracy with relatively less parametriza- tion. Among these models, we find the Long Short-Term Memory (LSTM) neural network model [6] that has shown great performance in literature when handling recurrent data as for instance, for sign language translation [7], video prediction [8], or weather forecasting [9], to name a few. Since LSTM is well adapted to deal with sequential data, such as time series, we propose in this paper to use it to model GWL of the Mornag plain in Tunisia. Corresponding to our region of interest, the Mornag plain is one of the most important plains in Tunisia since it contributes with 33% in the

national agricultural production. Knowing its importance in the whole bandwidth of GW dynamic flow in the country, it is essential to model well the Mornag GWL for better national water resources management. Indeed, available data from Mornag plain corresponds to RF and GWL observations measured over the period 2005-2015. Based on chronological RF data, we propose in this paper to apply a LSTM model to forecast GWL one. To ensure better results, we have used additional features that help to better describe RF dependencies. To highlight the performance of the proposed approach, for the same study period, we have compared the LSTM obtained results with those obtained using the Modflow model. The comparison has shown a huge enhancement in terms of minimization of the Root Mean Squared Error (RMSE). Once the model is validated, we have applied it to study the impact of climate change on GWL using two Representative Concentration Pathway (RCP) scenarios; RCP 4.5 and RCP 8.5 over the period 2015-2100, which are global reference data for short, medium, and long-term RF values [10]. As a result, we have depicted that more frequent, more intense, and longer drought seasons would have a particularly negative impact on the Morang plain. The performed study of future Mornag GWL behavior using LSTM could classify this AI approach as a good decision support system that could be used to optimize the management of our limited water resources in order to satisfy the population needs in terms of drinking water and agricultural production, as well as to prevent upcoming drought.
The remainder of this paper is structured as follows: In section 2, we describe the study area as well as the used dataset. The proposed model for GWL forecasting is detailed in section 3. Findings and outcomes are discussed in section 4. Finally, conclusions are drawn in section 5.

2. Materials and settings

2.1. Region of interest: the Mornag plain

This study focuses on the Mornag plain which is located in northern Tunisia, 20 kilometers southeast of the capital Tunis. The study area climate is considered arid to semi-arid with moderate temperature. The annual RF is approximately 526mm [11]. As illustrated in Fig. 1. This plain is drained by two major rivers (Meliane and El Hma). The surface area of the Mornag aquifer is about 200km². It stretches over 14 km from Tunis Gulf (Mediterranean Sea) in the North to the Khledia hills in the South. It is limited to the West by the Rades hills and its surroundings and to the East by the J. Rourouf mountain and its surroundings. Its hydraulic system consists of unconfined (GW lodged in recent Quaternary series) and confined aquifer (a deep aquifer which groups a series of 4 systems occured in ancient Quaternary, Oli- gocene, Miocene and Eocene sediments). The aquifer system of the Mornag plain is characterized by the presence of the most dense observation system of GWL in Tunisia [12]. In this study, we focus on the unconfined aquifer. Thus, it is more and more exploited: in 2015, the exploitation rate reached 195 % with a deficit equal to -6.62 mm3/year [13]. This massive exploitation created an important piezometric depression and consequently an increase in the salinity of the studied groundwater [11].

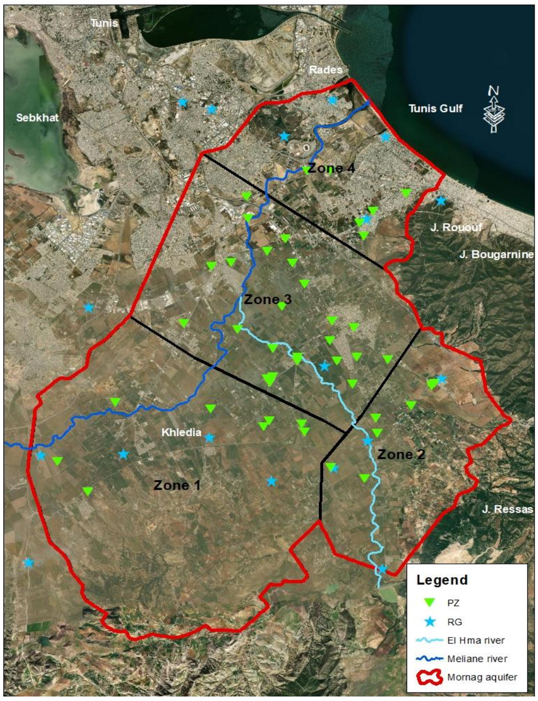

Fig. 1. The general location map for the Mornag plain

This aquifer is monitored by 44 piezometric stations and 18 pluviometric observation points, recording the GWL and RF, respectively, which allow hydrologists and researchers to better understand and investigate the Mornag aquifer system.

2.2. Data understanding and preprocessing

This section aims to describe the Mornag plain dataset as well as the added features that will be used to enhance the GWL forecast. Originally, our dataset is composed of 285480 rows with 4 features; daily RF (RFd), Rain Gauge (RG), GWL, and PieZometer (PZ). Indeed, since 1971, using the 44 PZs, GWL data has been gathered twice a year, and from 2005 up to the present, RF has been measured daily using RGs. The collected dataset contains some missing values (8,8% for RFd and 4% for GWL), to manage them we have used a mean interpolation . As the GWL of the Mornag aquifer changes both geographically (by location and depth) and temporally (hourly, daily, seasonally, inter-annually, and at longer time scales), it will be helpful to use all of these factors to add new features for better understanding of the GWL behavior. As a matter of fact, observing the GWL over the time, we have distinguished 4 different delimited zones (shown in Fig. 1.); each one clusters PZs with similar variability. Hence, the first added feature is named Zone which indicates the piezometric site. Moreover, because of the strong association between GWL and both long-term and short-term RF levels [14], we have included the data seasonal influences such as; monthly RF (RFm), trimestrial RF (RFt), semestrial RF (RFm) and yearly RF (RFy). While seasonal climatic fluctuations are the most important driver of GWL variations, nearby surface water bodies, such as rivers, can also have an impact on groundwater levels. Therefore, investigating the Standardized Precipitation Index (SPI) will yield important information about wetness and dryness Category described by the feature SPI-C [15]. Finally, we consider as well Month and Year as two features since the chronological dependencies. As a summary, the new dataset is composed of 13 features with 4 categorical features; RG, PZ, SPI-C, Zone and 9 continuous features; RFd, RFm, RFt, RFs, RFy, SPI, Month, Year, GWL.

3. Artificial intelligence for groundwater level modeling

Long Short-Term Memory (LSTM) networks are an improved version of the traditional Recurrent Neural Networks (RNNs) [16] that are frequently used to handle sequential data, such as time series. As stated in the literature, RNNs suffer from the vanishing gradient problem during backpropagation, where the gradient gets less and less with every layer, during the network training, until it is too small to reach the deepest levels. This drawback makes basic RNN memory unable to learn past information [6]. Alternatively, LSTMs came to recall long-term dependencies since they were specifically developed to address this issue. With LSTM, training errors retain their values, which overcomes the vanishing gradient problem and allows learning from sequences hundreds of timesteps long [6]. The initial LSTM model consists of a single hidden LSTM layer that could be composed of several Memory Blocks (MBs). A MB like depicted in Fig. 2. (B), which is composed of 3 sigmoid (σ) seperate network layers and one hyperbolic tangent (Tanh) one, corresponds to the key contribution of the LSTM neural network, since the decision to consider or throw away information is taken inside. Indeed, the LSTM MB has three gates to govern the information flow; for a given time t, coupling the input x_t and the output of the previous hidden state h_{t-1}, the forget gate f_t regulates which and how much cell information is forgotten, the input gate i_t controls which inputs are used to update the old cell state (convoying important information) c_{t-1}, into the new cell state c_t and as for the output gate o_t it defines which cell memory elements are used to update the hidden state h_t of the LSTM cell [16].

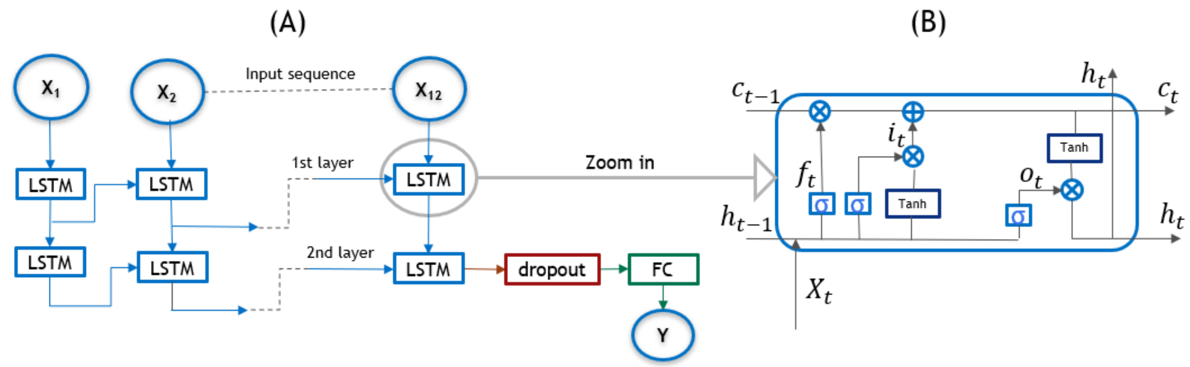

Fig. 2. Illustration of the proposed LSTM Neural Network architecture for GWL forecasting.

Using a unique LSTM model as initially developed, the past information stored inside a sequence is barely captured [6]. Alternatively, one could use the stacked LSTM which is a model expansion that involves several hidden LSTM layers, with many MBs for each of them, enhancing the ability to capture more complicated associations in the dataset.

Based on experimentation, in this paper, we propose the stacked LSTM architecture illustrated in Fig. 2. (A) for which two LSTM layers are used, each one consists of 50 MBs. As input, our stacked LSTM model uses 30 timesteps of the encoded sequence X_1 to X_{12} corresponding to our 12 features. The stacked LSTM is followed by a dropout layer in order to reduce overfitting while improving model performance. Finally, we add a Fully-Connected (FC) layer giving rise to the output layer, denoted by Y and corresponding to the GWL in our study.

4. Results and discussion

To train the proposed stacked LSTM model, we have used 70% of our dataset corresponding to the period from 04-2005 to 04-2011 and have kept 30% of data for the test phase, corresponding to the period from 05-2011 to 08-2015. As a result of hyperparameter tuning, we have used the "Adam" optimizer which is a stochastic gradient descent technique that has shown great efficacy and resilience in modeling hyperparameters. We have set the corresponding batch size to 512 and have considered 8 epochs. For the dropout layer, we have considered a rate of 0.2 and as a loss function we have used the RMSE. Once trained, we have used the proposed stacked LSTM model to predict GWL using test data. In Fig. 4, we illustrate training and testing losses (in a log-scale) using RMSE. Both loss curves are decreasing and reaching a low point with a small gap of order 10^{-2}which underlines a good fit quality. Moreover, for each PZ, we represent the obtained RMSEs in Fig. 3.; results depict very acceptable values. Based on identical conditions and data, and over all PZs, we have in addition compared forecasting results using the proposed stacked LSTM and the Modflow one; with an RMSE of **0.85m**, LSTM highly outperforms the Modflow, which has an RMSE of **6.9m** [17]. The findings of this study highlights the use of AI techniques for Mornag GWL forecasting, which makes it a good decision support system for water resources management.

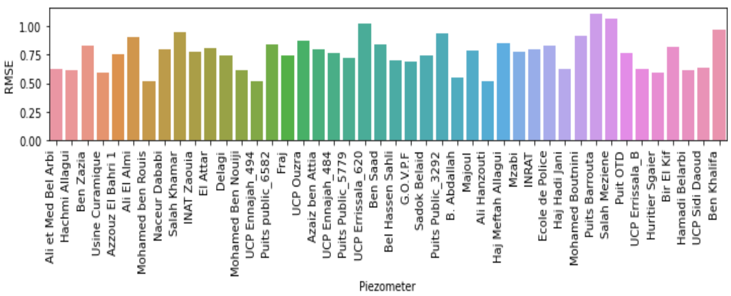

Fig. 3. RMSE of all piezometric stations using data from 2013 to 2015.

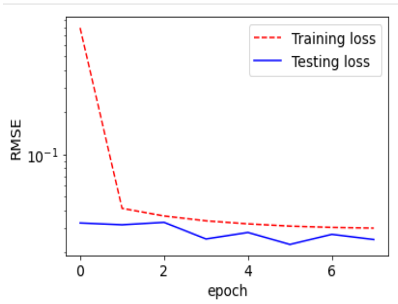

Fig. 4. Validation and train losses.

The forecasting will be performed using both the Representative Concentration Pathway RCP 4.5 and 8.5, which are two of the Intergovernmental Panel on Climate Change (IPCC) scenarios of radiative forcing trajectories to the year 2100. Because of constraints such as the selection of future virtual situations, an imprecise physical understanding of various self-connections, and computational capabilities, these scenarios are unexpected. As a result, they were readily rectified by utilizing the mean values of the various models constituting these scenarios. The predicted results of the piezometric station "Ben Saad" are presented in Fig. 5.

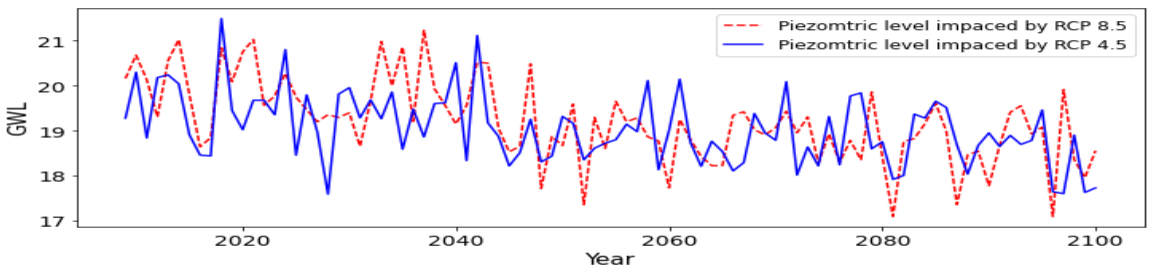

Fig. 5. A sample of the forecasting results under RCP 4.5 and 8.5 of "Ben Saad" piezometric station

For our simulated results up to 2100, GW resources in the Mornag aquifer were affected by climate change due to a decline in natural recharge from reduced precipitation (the mean will be 19.42% less at the end of the century for RCP 4.5;and 44.86% less for RCP 8.5). As Fig. 5. shows, the absolute variations in GWL under RCP 4.5 and RCP 8.5 may seem small (between 1 and 5 m), but the fact that we are investigating a shallow aquifer (thickness between 30 and 50m) reinforces the importance of results in terms of water availability for vegetation and agriculture. A drop of tens of centimeters (depending on the thickness of the aquifer) can be vital for plants during hot and dry periods, if therefore GW is no longer accessible [18].

This decrease in GWL presents a great concern for the future of irrigated agriculture in the study area as some farms would be abandoned due to GW unavailability. Nevertheless, there is an urgent need for adaptation measures that take into account these impacts of climate change on GW resources, in particular to improve productivity in the agriculture sector, such as an extensive reconversion of gravity irrigation to drip irrigation and adapted crops that are water efficient and more resilient to climate change.

5. Concluding remarks

The Mornag plain has already faced water scarcity due to anthropogenic activities such as over-pumping and climate change conditions as, during the last few decades, an increasing number of drought years has been observed. Therefore, the present study focuses on the assessment of the pressure that climate change will impose on GWL in the future. However, an Artificial Intelligence Decision Support System was conducted, while the Standardized Precipitation Index SPI was adopted, for the first time in Mornag plain, in order to identify climate change impacts on groundwater resources, at the same time, explore the use of SPI as an indicator to predict GW responses to climate conditions and the use of the AI modeling techniques in designing and planning GW management. The elaborated intelligent model LSTM has shown significant results in GWL prediction with an RMSE below 1m. In addition, the main finding of the assessment of climate change impacts indicates that the predicted hydrological drought events will affect the water table fluctuation in the medium and long term with a drawdown up to 5m. Thus, these results are of great importance as key information for decision-makers regarding the future of the sustainable exploitation of groundwater resources in the aquifer.

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