

## Case Study

# Piezometric depth modeling of groundwater using monthly variables of precipitation and water consumption (case study: Sarab Plain aquifer)

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## Abstract

The growth of the world population and the problem of food supply have led to the development of agricultural land, particularly in the Third World and in Iran, and thus to a sharp increase in water consumption regardless of the existing water resources. On the other hand, the ever-increasing growth of industries and factories, regardless of the impact on the environment, together with the increase in water consumption, has disturbed the balance of the environment and caused climate change with rising temperatures and increasing pollution. Unfortunately, the management of water resources and the environment is incompatible with the development of agricultural land and the development of industries, and therefore in most countries of the world a situation has arisen in which surface and groundwater resources are at risk. The two main variables, precipitation and water consumption, control groundwater levels. The area studied in this research is the Sarab Plain aquifer located in East Azerbaijan province, Iran. In the Sarab Plain and other plains of Iran, indiscriminate harvesting has led to a significant decline in the groundwater level (in other words, piezometric depth) and subsidence of the plain. The area under cultivation of various agricultural crops such as beans, cucumbers and alfalfa and gardens is about 38,176 ha, irrigated by 739 licensed wells. Agricultural uses on the one hand and industrial and animal uses on the other led to a progressive lowering of the piezometric level of the plain. The average water consumption from the table is currently 53 million cubic meters per year, while the amount of renewable water is 35.81 million cubic meters per year. The data used in the study are monthly precipitation from 19 rain gauge stations, monthly piezometric codes from 78 piezometers converted to piezometric depth, and monthly water consumption from 1886 consumable wells between 2007 and 2022. Individual regression relationships were created between the piezometric depth variable and consumption and precipitation variables. In the first step, a general hybrid exponential relationship between piezometric depth, consumption and precipitation was found. The correlation coefficient value between the calculated and observed piezometric depth was 0.69. Furthermore, the root mean square error and Kling-Gupta were 2 m and 0.57, respectively. In order to apply the hybrid exponential relationship to predict piezometric depth in the coming years, it was necessary to predict precipitation and consumption. To predict monthly precipitation based on its periodicity, the Thomas and Fiering (T&F) consumption forecasting method was used. 20% of the data was compared with calculated data. The result showed,  $R = 0.815$  and  $RMSE = 0.07$  mm between calculated and observed data. Additionally, to predict consumption in the coming years, a suitable regression relationship between consumption and time was constructed, showing a correlation of 0.97 and a root mean square error of 0.0008 mcm with observations. In the second step, precipitation and consumption were predicted for the next 3 years (2023–2025) and piezometric depth were determined for this period by applying them in the hybrid model. The forecast for the next three years shows that the upward trend

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of the piezometric level will continue. The application of the regression method resulted in a final equation, which is particularly important in view of the stabilization of the piezometric level of the reservoir. This method has no particular limitations and is an appropriate method when accurate consumption water and precipitation statistics are available. The only limitation that can be considered with this method is the movement around the average values and does not take into account the positional fluctuations. This work is new because it calculates groundwater simultaneously using two parameters: precipitation and water consumption. Other similar studies did not use groundwater consumption data.

**Keywords** Groundwater resources · Precipitation · Water consumption · Groundwater level · Piezometric depth · Piezometric code · Sarab Plain

## 1 Introduction

Water consumption per capita varies from community to community and is directly related to the culture and improving health levels of the community. The higher the level of culture and hygiene, the higher the need for water and its consumption. Therefore, raising people's awareness of optimal water consumption is one of the most important prerequisites for the correct use of water resources. Today's civilization has led to changes in water quality. While 70% of the Earth is covered in water, only 2.5% of the water on the planet is freshwater. This small amount of fresh water is used for various purposes; for example: agriculture, industry and finally for urban and domestic use. Therefore, there are several requirements for the available water [6, 16, 24]. Therefore, not only is there an urgent need to protect these resources (especially in highly polluted areas), but also to take the necessary measures for those resources that are not yet polluted.

According to Thesis [25] the rate of groundwater recharge depends on the rate at which water is added to the system and the rate at which the existing water penetrates into the depth and thus escapes before evaporation. Measures have been taken worldwide to compensate for the decline in groundwater. This includes increasing artificial feeding, such as importing surface water and absorbing rainwater. The recharge volume of an aquifer system alone does not reflect the proportion of the aquifer that is available for extraction. As stated by Asoka et al. [4] between 2002 and 2013, groundwater storage in northern India decreased by 2 cm annually. Accurate prediction of groundwater levels is one of the most important steps in the sustainable use of groundwater resources and helps engineers, planners and water managers make appropriate decisions to prevent or reduce adverse impacts such as well pumping losses, aquifer compaction and land subsidence. For this reason, numerous studies have been carried out in recent years on the connection between precipitation and groundwater [19] From the perspective of Thomas et al. [26] in the arid southwestern United States, precipitation demonstrated an important role in groundwater recharge in arid areas. Based on Asoka et al. [5] For more than 5800 groundwater data, it was shown that rainfall intensity is strongly related to groundwater recharge in India. Their results highlight the importance of rainfall intensity for groundwater recharge in the monsoon season in India. Numerous studies have been conducted to use ANN to predict groundwater levels [9, 12, 22, 23].

In addition, accurate determination of groundwater levels is necessary for effective and sustainable management of groundwater resources, as poor management can lead to deterioration of water quality, decline in groundwater levels and reduction in groundwater storage [11] a neural wavelet model (WNN) and a Thomas and Fiering model (T&F) were used to predict reservoir inflow for the years 1980–2005. The performance of the two models showed that the T&F model performed better in the rainy season at Danjiangkou Reservoir, an important water supply area of the South-North Water Transfer Project in China, and the WNN model performed better in the dry season. These two models were used to predict the total reservoir inflow in 2006 [7]. Additionally, direct and indirect impacts of climate change on the entire groundwater system were examined, which were assessed using groundwater climate and surface water models in groundwater hydrology to improve existing knowledge on climate change and groundwater interactions. The paper suggests two important considerations, First, the physical basis: the need for a deeper understanding of complex physical processes and feedback mechanisms using more sophisticated models, Second, there is a need to understand the socio-economic dimensions of climate-groundwater interaction through multidisciplinary synergies, leading to the development of better climate change and groundwater adaptation strategies and models [3]. Scientists have also carried out some research on the interactions between groundwater and climate. In particular, it has been shown that groundwater flows in arid regions react less strongly to climate fluctuations than in wet regions [8]. Likewise, a comparison between seven different models for predicting groundwater levels was examined. These include Random Tree (RT), Random Forest (RF), Decision Log, M5P, Support Vector Machine (SVM), Local Weighted Linear Regression (LWLR), and Reduce Error Pruning Tree (REP Tree). The entire dataset was divided into two parts, the training data set from 1981 to 2008, and the test dataset

from 2008 to 2017. The output of seven models was evaluated. The results of the study showed that the Bagging RT and Bagging RF models performed better than other ML models [18].

Moreover, precipitation (P), temperature (T), and evapotranspiration (ET) have been used for approaches such as: artificial neural network (ANN), fuzzy logic (FL), adaptive neuro-fuzzy inference system (ANFIS), group method of data handling (GMDH), and least-square support vector machine (LSSVM) for forecasting monthly groundwater levels. Based on different evaluation criteria, all models used could predict the ground water level with the desired accuracy and the results of LSSVM are the superior ones [21]. Furthermore, a comparison between the results of predictive models based on non-linear autoregressive with exogenous inputs (NARX) and extreme learning machine (ELM). The results showed that NARX models perform better than ELM models [17]. In addition, the performance of support vector regression (SVR) and SVR combined with metaheuristic algorithm of innovative gunner (AIG) in monthly groundwater level of Shabestar plain during 2001–2019 was studied. The results showed that the hybrid model (SVR-AIG) provides accurate estimates in hybrid patterns [20]. Furthermore, the combination of various metaheuristic algorithms, including the feed-forward artificial neural network (ANN), the algorithm of innovative gunners (AIG) and the black widow optimization (BWO) algorithm, was studied to calculate the groundwater level in the southwest of Iran during the period 2008–2018 on a monthly time scale. The results illustrated that all three hybrid models performed better on combinatorial patterns [10]. Additionally, a new groundwater level prediction method combining simulation, clustering and optimization tools was also used in northwestern Iran. This approach simulates the groundwater level (GWL) using the MODFLOW method, groups the studied aquifer into different clusters using the K-mean method, and predict regional GWL using the artificial neural network (ANN) and adaptive neuro-fuzzy inference system methods (ANFIS). In the predicting phase, the groundwater level of the previous month (determined with the MODFLOW method), sampling of aquifers, precipitation, temperature and evaporation were identified as the most influential variables for the groundwater level in different clusters [14].

There are very few studies examining changes in groundwater levels during consumption. Therefore, two main variables, precipitation and water consumption were used to predict groundwater levels. In other words: finding out a new formula between precipitation, water consumption and groundwater levels. Some regression relationships and the Thomas and Fiering (T&F) were used. Additionally, precipitation, water consumption and groundwater levels were predicted.

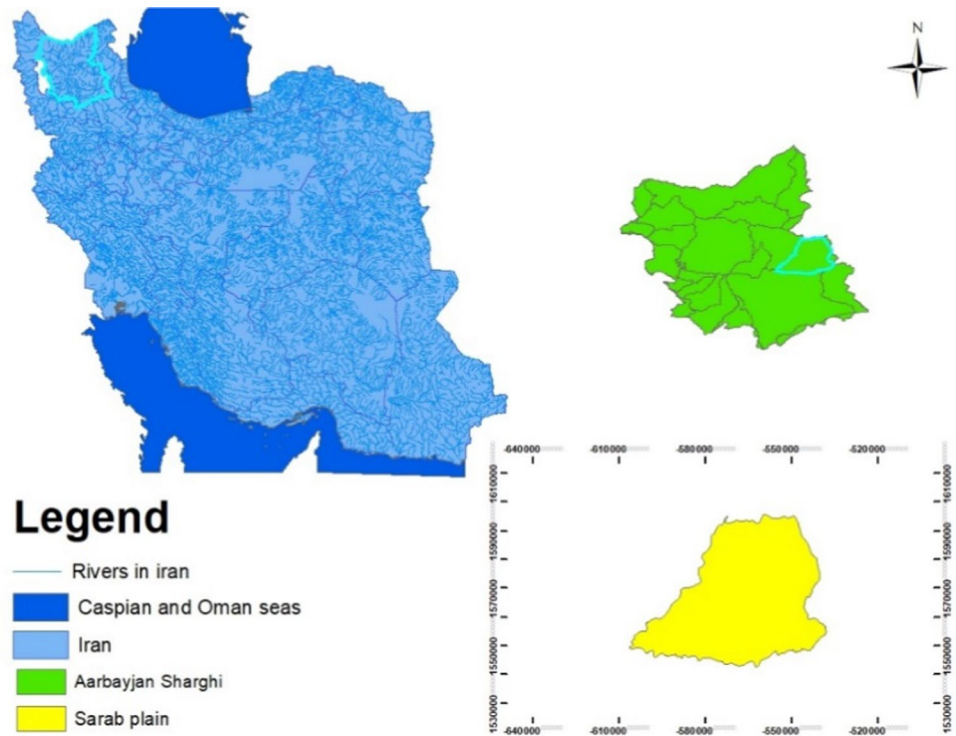
## 2 Study area and regional information

The study area is the Sarab Plain in the Iranian province of East Azerbaijan. Based on the division of structural zones of Iran according to the prophetic division, the studied area is part of the Alborz zone of Azerbaijan, according to the Ashtoklein division it is in the Central Iranian zone and according to the latest division related to it, the area is in the zone of the Middle Iran [2]. According to the studies conducted in the Sarab region, the oldest rocks in the region date back to the Cambrian period. These stones were uncovered in the southeast of the Bezgosh Mountains at the Balkhali Pass and northeast of the village of Fundhalo. The main geological units include Eocene volcanic rocks, pyroclastic sediments and Miocene sedimentary deposits, Quaternary units and current age sediments. The Sarab region's water resources come from atmospheric precipitation, which flows either in the form of surface runoff through canals and rivers or by penetrating the soil and accumulating in alluvial deposits and formations of the earth, thus forming groundwater [15].

This plain has one of the most important rich sources of ground water reserves and is of particular importance, provides an important part of the region's agricultural, drinking and industrial needs. An important part of the flowing water comes from the surrounding mountains and feeds the aquifer as this water flows from the foothills toward the middle of the plain. Several rivers named Wang Chai, Buyuk Chai, Pislir Chai, Tajyar Chai etc. The rivers originating from the surrounding heights join near Andarab village and are then called Aji Chai (Bitter River). They flow from east to west in the northwest of the plain. After crossing the Sarab Plain, it flows west north of Tabriz, passes Azarshahr and flows into Lake Urmia [13]. The study region has an area of 2242 square kilometers, of which 1147 square kilometers are mountain areas and 1095 square kilometers are related to the plains of the Sarab region. The Sarab plain is located on the southern slope of the Sablan volcanic massif and on the northern slope of the Bezgosh Mountains with the geographical coordinates 37° 44'–38° 12' north latitude and 47° 15'–47° 54' east longitude. Figure 1 shows the geographical location of the Sarab plain.

The average long-term annual precipitation in the Sarab Plain is 332 mm, and the climate of the plain is estimated to be cold and semi-arid based on the Amberg climate classification.

**Fig. 1** Geographical location of the Sarab Plain



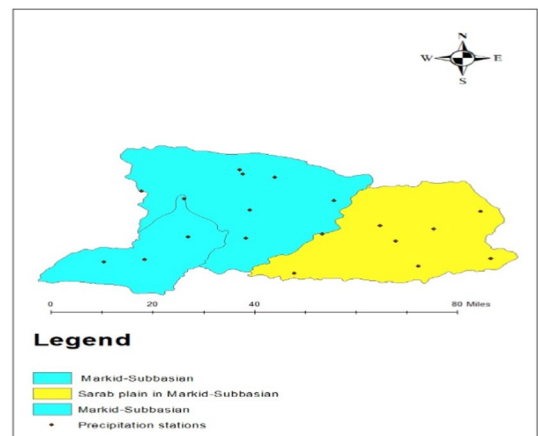
### 3 Data collection

#### 3.1 Monthly precipitation

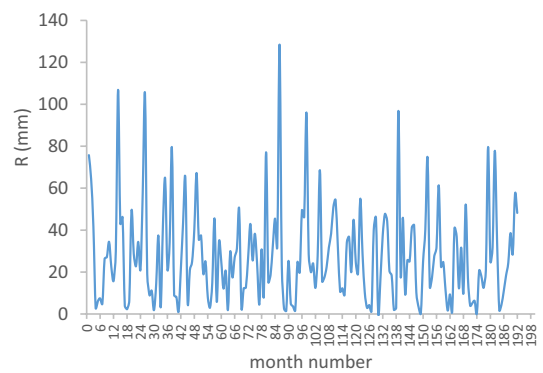
To determine the regionalized monthly precipitation in the Markid sub-basin, including the Sarab Plain, the monthly precipitation from 19 precipitation measurement stations above the Markid hydrometric station co in the following figures showing time relationships, months are written from number 1 to 192 to obtain correct time relationships. Therefore, the numbers of months 1 to 192 represent the months of the years 2007 to 2022, respectively, in other words, the month numbers 1–12 of the year 2007, 13–24 of the years 2008, etc. for other years The data collected in the statistical period from 2007 to 2022 was taken into account by Thiessen-Polygon.

Figures 2 and 3 show the polygonised map of rain gauges and the temporal variation of regional precipitation according to the month number, respectively.

**Fig. 2** Thiessen polygons of precipitation stations in the Markid-Subbasian



**Fig. 3** monthly variation of regional precipitation in the Markid-Subbasian



### 3.2 Monthly piezometric depth

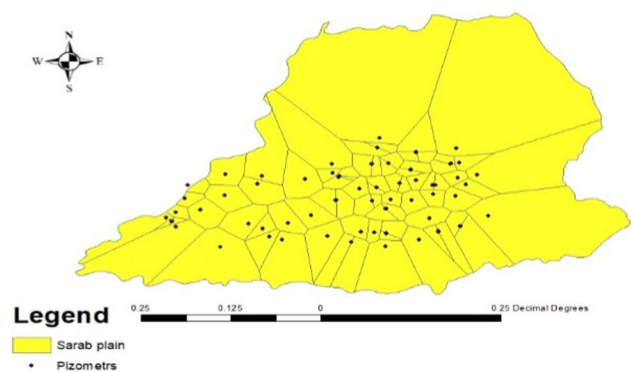
The data from 78 piezometers in the Sarab plain were considered to extract regionalized monthly piezometric depth data using Thiessen's polygonization method. Figures 4 and 5 show the polygon map of the placement of piezometers in the Sarab plain and the temporal variation of the regional piezometric depth according to the month number, respectively.

### 3.3 Monthly water consumption volume

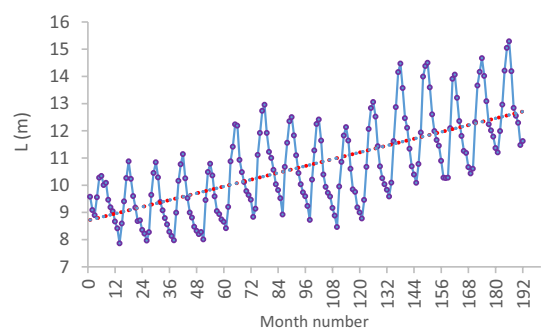
The monthly water consumption volume was extracted from 1886 operational wells in the Sarab Plain which provide the industrial, agricultural and drinking needs of the Sarab region. Figures 6 and 7 show the deployment map of the consumption wells and their polygonization and temporal variation of regional water consumption according to month number, respectively. As Fig. 7 shows, there is a good temporal relationship between monthly water consumption and time as follows:

$$Cns = \frac{4.073}{(1 + e^{6.342 - 0.0516t})^{0.121}}, \tag{1}$$

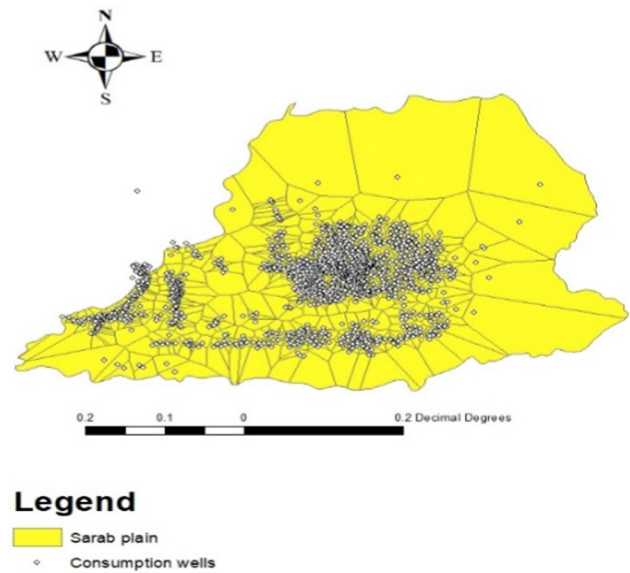
**Fig. 4** Thiessen polygon of Sarab plain piezometers



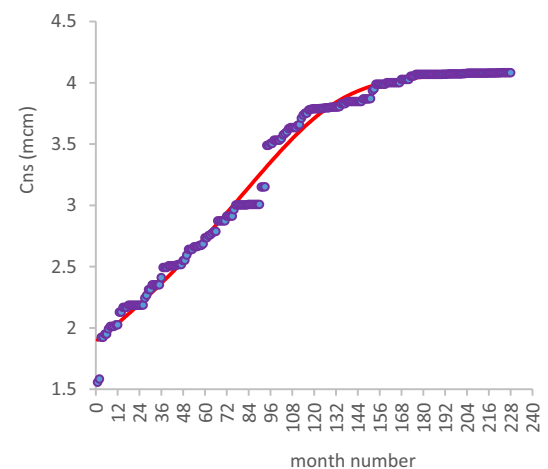
**Fig. 5** Temporal variation of the regional piezometric depth according to the number of months



**Fig.6** Thiessen polygon of the Sarab plain extraction well



**Fig. 7** Monthly changes in water consumption in the Sarab plain



Cns (mcm) and  $t$  are the monthly water consumption and the month number, respectively. Likewise, it can be seen that water consumption remains stable after a few years. The formula showed correlation of 0.97 and a root mean square error of 0.0008 mcm with observed data.

No comparable studies have been conducted in the region. In addition, a study was conducted in Ajabshir, Azerbaijan Province, Iran [1]. The data used for the study were the amount of precipitation, water table elevation and water consumption on a monthly time scale for the period between 2001 and 2011. The cross-correlation analysis showed that the one delayed monthly precipitation and the two delayed monthly consumption values had the greatest impact on the height of the groundwater table. The general relationship of these three variables was obtained with  $R^2 = 0.87$  and  $RMSE = 0.35$  through multivariate nonlinear regression analysis. To predict the water table elevation in the coming years, predictions were made by ANN and Thomas–Firing, respectively. So, the outcome of putting them into regression equation gave the water table elevation. On the other hand, the artificial neural network was used to predict the water table elevation, for which, the resulted values of  $R^2$  and  $RMSE$  were 0.82 and 0.39 m, respectively. The comparison of two methods showed that the multivariate nonlinear regression model represented more accurate results in predicting the elevation of the water table.

## 4 Materials and method

In this research, there are no predetermined empirical relationships, but based on the data structure, the necessary equations were extracted by the software. The general form of the relationship between water consumption and time is as follows:

$$y = \frac{\alpha}{(1 + e^{\beta + \gamma x})^\delta} \quad (2)$$

where  $y$  is used as the variable of the volume of water consumed and  $x$  as the variable of time.  $\alpha$ ,  $\beta$ ,  $\gamma$  and  $\delta$  are the coefficients of the equation determined by the data. The general form of the equation for the relationship between piezometric depth and water consumption and between piezometric depth and precipitation is as follows:

$$y = \alpha + \beta e^{\gamma x^\delta}, \quad (3)$$

where  $y$  is used as the piezometric depth and  $x$  is used as water consumption and precipitation.  $\alpha$ ,  $\beta$ ,  $\gamma$  and  $\delta$  are coefficients of the equation that are determined for the piezometric depth—water consumption and piezometric depth—precipitation relationships separately from the relevant data.

According to the above exponential equations, the following combined equation was used to relate the piezometric depth with the variables of water consumption and precipitation:

$$y = \alpha + \beta e^{\gamma \frac{x_1^\delta}{x_2^\theta}} \quad (4)$$

In this relationship,  $y$  was used as the piezometric depth,  $x_1$  as the water consumption variable and  $x_2$  as the precipitation variable.  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$  and  $\theta$  are coefficients of the equation obtained by the data.

### 4.1 Thomas and Firings method (T&F)

The T&F model method is a regression method and is suitable for creating periodic data. The T&F model can be written as follows:

$$x_{i(j+1)} = \bar{x}_{(j+1)} + \beta_j (x_{ij} - \bar{x}_j) + z_{j+1} \sqrt{1 - R_j^2}. \quad (5)$$

Regarding the monthly time step used in this study,  $i$  is the annual index and  $j$  is the monthly index.  $x$  is a periodic variable and  $\beta_j$  is the linear regression coefficient of a pair of consecutive months. It means  $j$  and  $j + 1$ , with the following regression equation.

$$Q_{i(j+1)} = \alpha_j + \beta_j Q_{ij}. \quad (6)$$

$S_{j+1}$  is the standard deviation of the variable in month  $j + 1$ .

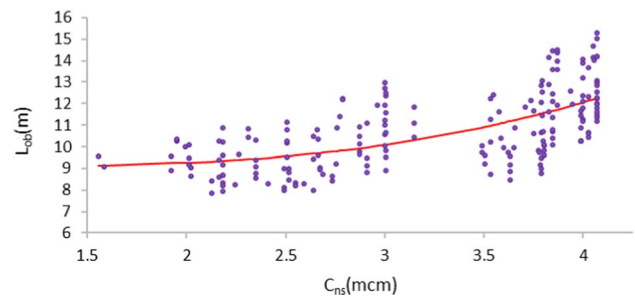
## 5 Result and discussion

The shortcoming of this research is that the water consumption was determined based on the maximum permissible flow indicated for each well, and this data was obtained from the country's authorized organizations. But if the relevant organizations can install a water meter on each well so that the actual consumption of each well can be seen. More precise relationships are obtained.

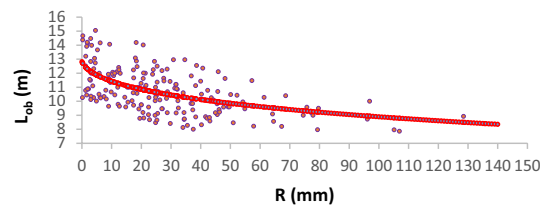
### 5.1 Creating regression relationships

In the first step of the modeling, the regression relationship between the piezometric depth and the precipitation and consumption was developed individually. The purpose of developing these individual models is to identify the form of the

**Fig. 8** Variation of piezometric depth with monthly water consumption



**Fig. 9** Variation of piezometric depth with precipitation



relationship between the piezometric depth and each of the variables involved in the water table so that a multivariate regression relationship can be constructed based on the non-linear effect of the variables on the piezometric depth. Figure 8 shows the variation of the observed regionalized piezometric ( $L_{ob}$ ) depth and the observed water consumption volume ( $C_{ns}$ ). It is worth noting that the piezometric level has been converted to the piezometric depth based on the land surface benchmark code and the water level code. In this figure, the purple dots represent the observed piezometric depth and water consumption data. Additionally, the red line shows the calculated piezometric depth value and water consumption.

The relationship between the water consumption and the piezometric depth is non-linear as follows:

$$L = 19.68 - 10.61e^{-0.001C_{ns}^{4.142}}, \quad (7)$$

where  $L$  and  $C_{ns}$  are the piezometric depth and consumption, respectively. According to Eq. (7), as the consumption increases, the dropping of depth becomes faster; i.e., the distance of the piezometer surface from the land (piezometric depth) increases faster. The reason for this probably lies in the decrement of storage coefficient subject to depth increment as well as conical or bowl-shaped shape of the aquifer. According to the Eq. (7), the non-linear correlation coefficient between the calculated piezometric depth from Eq. (7) and the observed piezometric depth is 0.64 and  $RMSE = 1.3$  m. On the other hand, the monthly precipitation shows a significant correlation with the piezometric depth according to Fig. 9. The most appropriate equation was obtained as follows:

$$L = 12.856 - 93.053e^{-5.5202R^{-0.1215}}, \quad (8)$$

where  $L$  is the piezometric depth in meters and  $R$  is the precipitation in millimeters. Figure 9 shows the fitted curve. In this figure, the purple dots represent the observation piezometric depth and precipitation data. Additionally, the red line shows the calculated piezometric depth value and precipitation.

According to the Fig. 9, the piezometric depth decreases as the precipitation increases. The value of the nonlinear correlation between precipitation and piezometric depth is equal to 0.54 and  $RMSE = 1.3$  m.

## 5.2 General modeling

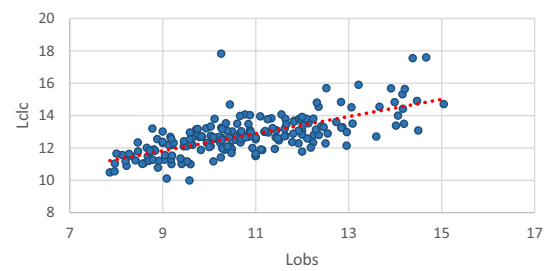
According to the general form of the individual relationship of the piezometric depth ( $L$ ) with the monthly water consumption ( $C_{ns}$ ) and the monthly precipitation ( $R$ ), the following combined relationship was proposed.

$$L = 1.07e^{2.239\frac{C_{ns}^{0.1158}}{R^{0.028}}} + 1.36. \quad (9)$$

The plot of the observed piezometric depth ( $L_{ob}$ ) versus the calculated piezometric depth ( $L_{ca}$ ). Figure 10 shows the distribution of the data around the bisector, indicating the accuracy of Eq. (9) with  $R = 0.69$ ,  $RMSE = 2$  m and Kling-Gupta = 0.57.



**Fig.10** Distribution of the  $L_{ob}$  versus  $L_{ca}$  around the bisector



### 5.3 Prediction procedure

Equation (9) can be used to predict piezometric depth in the coming years. Therefore, it is necessary to predict precipitation and consumption. Since monthly precipitation is periodic, the Thomas and Firings method (T&F) is appropriate for forecasting.

In order to predict the amount of precipitation for the coming years, it is necessary to validate the T & F model. For validation, the last 20% of the precipitation data were considered and predicted using this model. Figure 11 shows the changes in observed and calculated precipitation over time in the validation section; the similarity of the changes and the correlation coefficient of 0.815 ( $R=0.815$ ), the error of 0.07 m ( $RMSE=0.07$  m) indicate an acceptable accuracy of the T and F model.

## 6 Results

To predict water consumption in the coming years, Eq. (1) can be used, which is accurate enough. Likewise, it can be seen that the water consumption in Fig. 7 reaches a fixed value and, in principle, the amount of water considered for consumption should be determined and water resource management should be able to easily allocate this amount to different consumption levels.

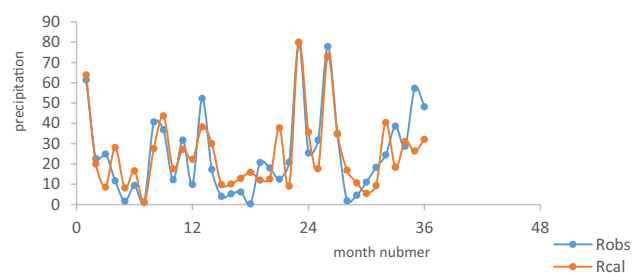
In addition, as shown in Fig. 11, precipitation can be predicted with high accuracy using the T&F model. The Table 1 illustrates information about the R and RMSE values of the regression model for the available data based on Formula (9).

R, RMSE and Kling-Gupta are the correlation coefficient, the root mean squared errors and the Kling-Gupta coefficient, respectively, between the observed and calculated piezometric depths resulting from the Eq. (9) over the statistical period.

Table 2 shows information about the T&F model for precipitation predicting.  $R_{T\&F}$  and  $RMSE_{T\&F}$  are the correlation coefficient and root mean square, respectively, between the observed and calculated precipitation by the T&F model for the last 20% of the data.

Table 3 shows information for predicting water consumption.  $R_{cns}$  and  $RMSE_{cns}$  are the correlation coefficient and the root mean, respectively, between the observed and calculated consumption water by Eq. (1) model for data.

**Fig. 11** Comparison plot of calculated precipitation using the T & F method and observations in the Validation Data section



**Table 1** Information about the regression model

$R_4$	$RMSE_4$	Kling-Gupta <sub>4</sub>
0.69	2 (m)	0.57

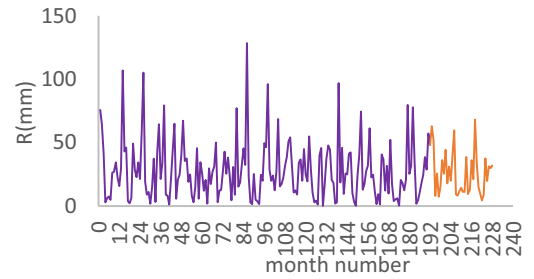
**Table 2** information about T&F model to predict precipitation

$R_{T\&F}$	$RMSE_{T\&F}$
0.815	0.07 (m)

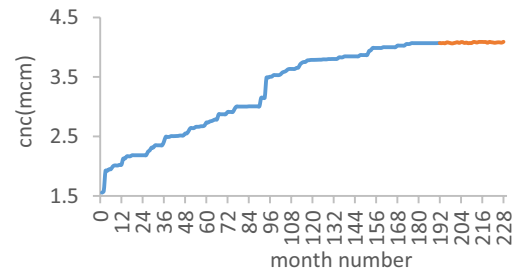
**Table 3** Information about predicting water consumption

$R_{cns}$	$RMSE_{cns}$
0.97	0.0008 (mcm)

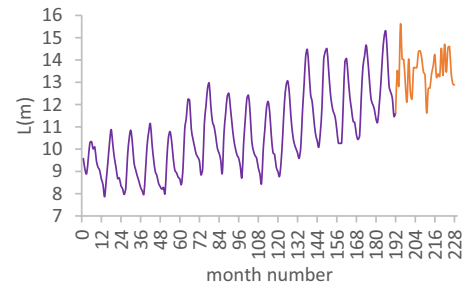
**Fig. 12** Predicted monthly precipitation



**Fig. 13** Predicted monthly consumption



**Fig. 14** Predicted monthly piezometric depth



The precipitation and the water consumption values for the next 3 years from 2023 to 2025 were predicted using the T&F method and Eq. (1), respectively. Figures 12 and 13 show the predicted sections. In addition, Fig. 14 shows the predicted section of the piezometric depths according to Eq. (9) with the application of predicted precipitation and the predicted consumption.

As mentioned earlier, the formulas require us to start the time scale at 0. In other words, the months between 0 and 192 correspond to the years between 2007 and 2022. In addition, the months between 192 and 228 correspond to the years between 2023 and 2025.

## 7 Conclusion

Developing of a model that takes into account the variables involved in groundwater level variability plays a fundamental role in providing an important tool for groundwater resource management. The most important variables in creating this model for an aquifer are mainly precipitation, river discharge and water consumption from aquifer. However, if the river feeds the aquifer, it means that the table water level is lower than the riverbed code. When the aquifer feeds a river, there is usually a significant relationship between the water level and the river's discharge. However, when the water table is lower than the river bottom, the river feeds the groundwater. In such a case, due to the width spread of the aquifer, the fluctuation of water level in the river dose not significantly effect on ground water table on the monthly time scale. The discharge therefore does not show significant relation with groundwater level, as it was not shown in this research too even by time delay. Therefore, the infiltration of river water into groundwater will have an almost constant value, which is hidden in the observed pizometric depth data. However, on the annual time scale, due to the accumulation of changes in the river's water level, there is a significant correlation between the annual runoff and the piezometric groundwater depth (correlation coefficient of  $-0.64$ ). Because of the work on the monthly scale, the annual scale was not our goal in this study.

Therefore, the variables monthly precipitation and monthly consumption were used as the main variables for the model development. According to the accuracy measurement of models, these variables also turned out to be the most important variables in controlling the water table. In order to measure the time responses of the variables, the required time lags were applied to them, but due to the monthly nature of the variables, the greatest association was observed with parallel times. Monthly precipitation and consumption are usually predictable variables; so, with the aim of developing the application of multiple regression model it was necessary to predict monthly precipitation using the T&F model and predict consumption using Eq. (1) to propose the prediction of piezometric depths. In this study, water consumption is accounted for using the authorization issued by the provincial regional water organization.

## 8 Suggestions

1. It is recommended that water-related organizations should control consumption and measure it monthly in order to conserve resources, reduce consumption and achieve the standard of 40% renewable water consumption.
2. It is proposed that through the intelligent design of consumption wells, consumption will be provided in real terms and not based on the flow specified in the well license.

**Author contributions** Sepideh Khosravi wrote the main manuscript text and prepared figures. Ahmad Fakheri Fard checked whole manuscript. Yaghob Din Pashoh reviewed the manuscript.

**Data availability** For data availability inquiries, you can contact [sepideh.khosravi1996@gmail.com](mailto:sepideh.khosravi1996@gmail.com). All data used for this research will be made available to the journal as an Excel file upon request.

## Declarations

**Consent for publication** Informed consent was obtained from all individual participants included in the study.

**Competing interests** The authors declare no competing interests.

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## References

1. Abdolazadeh M, Fakherifard A, Asadi E, Nazemi A. Modeling the effects of consumption and precipitation on the watertable oscillations (case study: Ajabshir aquifer). *Water Soil Sci.* 2016;26(1):83–97.
2. Aghanabati A. Stratigraphic culture of Iran. (Precambrian-Silurian) 2007.
3. Amanambu AC, Obarein OA, Mossa J, Li L, Ayeni SS, Balogun O, Oyebamiji A, Ochege FU. groundwater system and climate change: present status and future considerations. *J Hydrol Hydrol.* 2020;125163:589.
4. Asoka A, Gleeson T, Wada Y, Mishra V. Relative contribution of monsoon precipitation and pumping to changes in groundwater storage in India. *Nat Geosci.* 2017;10(2):109–17.
5. Asoka A, Wada Y, Fishman R, Mishra V. Strong linkage between precipitation intensity and monsoon season groundwater recharge in India. *Geophys Res Lett.* 2018;45(11):5536–44.
6. Bricker SH, Banks VJ, Galik G, Tapete D, Jones R. Accounting for groundwater in future city visions. *Land Use Policy.* 2017;69:618–30.
7. Cui Q, Wang X, Li C, Cai Y, Liang P. Improved ThomaseFiering and wavelet neural network models for cumulative errors reduction in reservoir inflow forecast. *J Hydro-Environ Res.* 2016;13:134–43.
8. Cuthbert MO, Gleeson T, Moosdorf N, Befus KM, Schneider A, Hartmann J, Lehner B. Global patterns and dynamics of climate–groundwater interactions. *Nat Clim Change.* 2019;9(2):137–41.
9. Daliakopoulos IN, Coulibaly P, Tsanis IK. Groundwater level forecasting using artificial neural networks. *J Hydrol.* 2005;309:229–40.
10. Dehghani R, TorabiPoudeh H. Application of novel hybrid artificial intelligence algorithmsto groundwater simulation. *Int J Environ Sci Technol.* 2022;19:4351–68.
11. Famiglietti JS. The global groundwater crisis. *Nat Clim Chang.* 2014;4(11):945–8.
12. Iqbal M, Naeem UA, Ahmad A, Rehman HU, Ghani U, Farid T. Relating groundwater levels with meteorological parameters using ANN technique. *Measurement.* 2020;166: 108163.
13. Karami F, Rostamzadeh H. An analysis of the contribution of morphogenetic factors in salinity of lands in Sarab Plain. *Iran J Natural Res.* 2006; 59.
14. Kayhomayoon Z, Ghordoyee-Milan S, Jaafari A, Arya-Azar N, Melesse AM, Moghaddam HK. How does a combination of numerical modeling, clustering, artificial intelligence, and evolutionary algorithms perform to predict regional groundwater levels? *Comput Electron Agric.* 2022;203: 107482.
15. Khaleghi F. Environmental survey of drinking water sources in Sarab with emphasis on marginalization effects. *Environ Geol Sci Res Quart.* 2021;56.
16. Nayak PC, Rao YRS, Sudheer KP. Groundwater level forecasting in a shallow aquifer using artificial neural network approach. *Water Resour Manage.* 2006;20:77–99.
17. Fabio DN, Abba SI, Pham BQ, Islam ARMT, Talukdar S, Francesco G. Groundwater level forecasting in Northern Bangladesh using nonlinear autoregressive exogenous (NARX) and extreme learning machine (ELM) neural networks. *Arab J Geosci.* 2022;15:647.
18. Pham QB, Kumar M, Nunno FD, Elbeltagi A, Granata F, Islam ARMT, Talukdar S, Nguyen XC, Ahmed AN, Anh DT. Groundwater level prediction using machine learning algorithms in a drought-prone area. *Neural Comput Appl.* 2022;34:10751–73.
19. Prinos ST, Lietz AC, Irvin RB. Design of a real-time ground-water level monitoring network and portrayal of hydrologic data in southern Florida (Water-Resources Investigations Report, issue). 2002.
20. Roshni T, Mirzania E, Kashani MH, Bui Q-AT, Shamshirband S. Hybrid support vector regression models with algorithm of innovative gunner for the simulation of groundwater level. *Acta Geophys.* 2022;70:1885–98.
21. Samani S, Vadiati M, Azizi F, Zamani E, Kisi O. Groundwater level simulation using soft computing methods with emphasis on major meteorological components. *Water Resour Manage.* 2022;36:3627–47.
22. Sanghoon L, Kang-Kun L, Heesung Y. Using artificial neural network models for groundwater level forecasting and assessment of the relative impacts of influencing factors. *Hydrogeol J.* 2019;27(2):567–79.
23. Sreekanth PD, Geethanjali N, Sreedevi PD, Ahmed S, Kumar NR, Jayanthi PDK. Forecasting groundwater level using artificial neural networks. *Curr Sci.* 2009;96(7):933–9.
24. Sreekanth PD, Sreedevi PD, Ahmed S, Geethanjali N. Comparison of FFNN and ANFIS models for estimating groundwater level. *Environ Earth Sci.* 2011;62:1301–10.
25. Thesis CV. The source of water derived from wells. United states department of interior geological survey water resources division ground water branch. American Society of Civil Engineering. vol. 34. 1940.
26. Thomas BF, Behrangi A, Famiglietti JS. Precipitation intensity effects on groundwater recharge in the Southwestern United States. *Water.* 2016;8(3):90.

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