Prediction of groundwater drawdown using artificial neural networks

Vahid Gholami (Gholami.vahid@guilan.ac.ir)
University of Guilan
Hossein Sahour
The University of Texas at Austin Marine Science Institute

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Abstract

Groundwater drawdown is typically measured using pumping tests and field experiments; however, the traditional methods are time-consuming and costly when applied to extensive areas. In this research, a methodology is introduced based on artificial neural network (ANN)s and field measurements in an alluvial aquifer in the north of Iran. First, the annual drawdown as the output of the ANN models in 250 piezometric wells was measured, and the data were divided into three categories of training data, cross-validation data, and test data. Then, the effective factors in groundwater drawdown including groundwater depth, annual precipitation, annual evaporation, the transmissivity of the aquifer formation, elevation, distance from the sea, distance from water sources (recharge), population density, and groundwater extraction in the influence radius of each well (1000 m) were identified and used as the inputs of the ANN models. Several ANN methods were evaluated, and the predictions were compared with the observations. Results show that, the modular neural network (MNN) showed the highest performance in modeling groundwater drawdown (Training R-sqr = 0.96, test R-sqr = 0.81). The optimum network was fitted to available input data to map the annual drawdown across the entire aquifer. The accuracy assessment of the final map yielded favorable results (R-sqr = 0.8). The adopted methodology can be applied for the prediction of groundwater drawdown in the study site and similar settings elsewhere.

1. Introduction

Groundwater is the major water resource in arid and semi-arid areas of the world since these resources are less affected by evaporation and pollutants (Wada et al. 2010). Unfortunately, the increase in human population and agricultural and industrial developments have led to an increase in groundwater withdrawal, pollution, and depletion of these resources (Shivasorupy et al. 2012). Moreover, climate change and alteration of precipitation patterns have exerted extra pressure on groundwater resources in these regions making aquifers depletions a serious threat to human life (Abulibdeh et al. 2021). Therefore, access to groundwater fluctuations data and aquifer drawdown is essential for water resources management plans. Unfortunately, these data are often constrained by spatial and temporal gaps in many parts of the world. Even in areas with available groundwater observation networks, the estimation of groundwater drawdown is challenging when applied to a large domain. The use of artificial intelligence (AI) based models in groundwater studies has been growing in the past decade. Different methods of AI, including artificial neural networks (ANNs), fuzzy-neural networks, self-organized maps (SOM), and machine learning (ML), have been applied extensively in the groundwater modeling process. AI-based models have been used in groundwater quality studies (Chou 2006; Chou 2007; Han et al. 2011; Wang et al. 2014; Li et al. 2020; Maliqi et al. 2020; Pal and Chakrabarty 2020; Mosaffa et al. 2021), groundwater depth studies (Dixon 2004; Awasthi et al. 2005; Saemi and Ahmadi 2008; Shiri et al. 2013; Gong et al. 2018; Chen et al. 2020), and the other hydrological studies (Smith and Eli 1995; Dawson 1998; Cheng et al. 2002; Chau and Cheng 2002; Mehr et al. 2003; Wilby et al. 2003; Jain et al. 2004; Anctil and Rat 2005; Cheng et al. 2005; Peters et al. 2006; Demirel et al. 2009; Nourani et al. 2011; Can et al. 2012; Demirel et al. 2012; Kisi et al. 2013; Nourani et al. 2013; Kisi 2015; Taormina and Chau 2015; Nourani et al. 2017 & 2018; Nourani et al. 2019 a&b).

Ghose et al. (2010) used ANN for simulating water table in the region of Orissa and they found that the ANN is very efficient in water table simulation. Wang et al. (2013) used a numerical model for evaluating the dewatering-induced groundwater drawdown. They simulated the relationship between groundwater drawdown and stratum deformation. They indicated that groundwater extraction caused a notable drawdown in the pumping location. Pradhan et al. (2018) evaluated the groundwater extraction status and predicted groundwater level fluctuations using different AI methods such as radial basis function network (RBFN), neuro-fuzzy inference system, and fuzzy logic in an Indian inter-basin. Their results showed the higher performance of the fuzzy logic based model over the neuro-fuzzy and RBFN models in water table modeling. Combining AI-based models with GIS capabilities is a common exercize in groundwater modeling. Previous studies have shown the high performance of this exercize in modeling the quantity and quality of groundwater resources (Tweed et al. 2007; Ganapuram et al. 2009; Arslan 2012; Bradai et al. 2016; Haselbeck et al. 2019; Sahour et al. 2020; Abulibdeh et al. 2021).

The aquifer type and conditions, including the hydrodynamic characteristics of an aquifer, determine the natural recharge potential and fluctuations of the groundwater level (Rukundo and Dogan 2019; Abd-Elhamid et al. 2020; Hereher and Al-Awadhi 2020).

Distance from water resources (such as lakes and rivers), the location of groundwater withdrawal sites, and precipitation values affect the amount of groundwater recharge (Guevara-Ochoa et al. 2018; Shi et al. 2021). Numerous studies have been performed to simulate the fluctuations of groundwater depth; however, estimation of annual drawdown values is challenging because of the complexity of the controlling factors and the needs for various inputs in the modeling process. This study aims to evaluate several ANN methods to predict the spatial variation of the annual groundwater drawdown using its affecting factors in an alluvial aquifer (unconfined aquifer) on the southern coasts of the Caspian Sea.

2. Materials And Method

2.1. Study area

The study area includes a plain with an area of 10000 square kilometers in the north of Iran.

This plain is located on the southern coasts of the Caspian Sea, extending from 50°34' E to 54°10' E and 35°47' N to 37° N (Fig. 1).

The mean annual precipitation of the study area varies from 1300 mm in the west to 600 mm in the east. Rainfall is a common type of precipitation in the Mazandaran plain, and snowfall is rare.

The major types of land uses of the plain are agricultural lands (rice fields and gardens), residential areas (cities and villages) and water bodies (rivers and wetlands), forests, and industrial lands. Geologically, the plain is composed of Quaternary alluvial sediments, and there is an unconfined aquifer in an alluvial aquifer with shallow groundwater. Groundwater depth varies between 1 to 30 meters. The agricultural section is the main consumer of water in the study area, and the main consumption is related to rice fields. The need for groundwater in the agricultural, residential, and industrial sectors in the region is very high.

Due to the existence of more than 300,000 hectares of agricultural lands, the uncontrolled development of tourism and construction, and population growth, this region has faced an increase in water demand and groundwater exploitation. This has led the groundwater resources to experience a significant drawdown and decline in water table across the region (Gholami et al. 2015).

2.2. Measurement of annual groundwater drawdown

To measure the values of groundwater drawdown, 250 piezometric wells in the plain were selected. The location of piezometric wells is shown in Figure (1). The secondary data of monthly groundwater levels in those wells in a period of 5 years (2015 to 2020) were obtained from Mazandaran Regional Water Company (MRWC 2020) and the Water Resources Research Organization of Iran (TAMAB 2020). The difference between groundwater level at its maximum (early spring) and minimum (early autumn) was determined as the values of the annual drawdown. At the beginning of spring, the water table is at its highest due to precipitation and pausing on agricultural activities during the cold seasons. The groundwater in the region is recharged during the six rainy months (Shiri et al. 2013). During the warm seasons (late summer and early fall), low precipitation rates and high agricultural activities, and extraction of groundwater leads to a decline in the water table (Yan et al. 2015). The study period was normal in terms of precipitation and climate without any drought period.

The drawdown values of the examined wells have changed during the 5 years due to changes in precipitation values and agricultural lands as well as the development of residential areas.

Therefore, the mean annual drawdown in this five-year period was determined as the groundwater drawdown values at the location of each well, and the effective factors in groundwater drawdown were quantitatively estimated.

2.3. Factors affecting groundwater drawdown

In this study, the factors affecting groundwater drawdown including extraction values, the transmissivity of aquifer formation, depth to the water table, topography (slope and elevation), location in the watershed, distance from water resources (groundwater recharge), annual precipitation, annual evaporation, and distance from industries and residential centers were used as the inputs of the modeling process (Awasthi et al. 2005; Shiri et al. 2013; Gong et al. 2018; Guevara-Ochoa et al. 2018, Pradhan et al. 2018; Abd-Elhamid et al. 2020; Shi et al. 2021). Examples of inputs are shown in Table (1).

2.3.1. Groundwater level

Groundwater level is one of the main factors affecting the groundwater extraction values (Adamowski and Chan 2011).

Based on the secondary data of the observed groundwater level (water table) in the examined wells, the mean groundwater levels were determined.

Then, using the interpolation of the mean values at each point and the interpolation capabilities of the GIS, the spatial distribution of annual groundwater depth in the Mazandaran plain was estimated.

2.3.2. Transmissivity of aquifer formations

Transmissivity of aquifer formations affects the permeability and the influence radius of the wells (Shie et al. 2016; Gholami et al. 2020).

The aquifer transmissivity in each well was determined using pumping tests conducted by MRWC.

Then, the mean transmissivity map of the entire aquifer was provided using the values of each well and determination of homogeneous areas of transmissivity using geological and hydrogeological maps. The homogeneous areas of transmissivity were prepared and confirmed by MRWC.

2.3.3. Groundwater withdrawal

Determining groundwater extraction is one of the most challenging inputs.

Access to accurate data on exploitation, especially in the case of agricultural wells in the region, was difficult due to the lack of automatic gauges.

For this purpose, data of all rural and urban drinking water wells as well as industrial wells were provided, and their annual extraction values were determined. Further, an accurate digital cadastral map was prepared in the study plain (accuracy 1 meter), which identified all land uses, especially rice fields and gardens.

The maximum influence radius of the wells is considered to be 1000 meters (Shi et al. 2016). Finally, the summation of the groundwater withdrawal was considered as the annual extraction values.

It is noteworthy that according to studies, the water need for one hectare of rice field and one hectare of the garden is about 11,000 and 5,000 m^3/year, respectively (MRWC).

As noted above, measuring groundwater withdrawal is very difficult and requires extensive data. In this study, extensive groundwater extraction data from drinking, agricultural, and industrial water wells within the influence radius of the wells were provided.

To prepare a map of groundwater withdrawal within the influence radius of the well, digital layers of agricultural land (rice lands and gardens) and the location and rates of wells were provided in GIS. Since the maximum influence radius of the wells is 1000 meters, therefore, for a 2000 m pixel (sides 1000 meters), the area of agricultural lands was multiplied by their water consumption.

Then, the map of annual groundwater withdrawal within the influence radius was provided as the total consumption rate of agricultural lands.

2.3.4. Annual precipitation and evaporation

Precipitation and evaporation are two affecting factors in groundwater recharge (Guevara-Ochoa et al. 2018).

To estimate the spatial distribution of precipitation and evaporation in the study area, the field-based precipitation and evaporation data were interpolated in the GIS environment to provide the raster layers of annual mean precipitation and evaporation rates.

2.3.5. Topography

Slope affects the hydrogeological conditions in a coatal aquifer (Abd-Elhamid et al. 2020). A 10 m digital elevation model (DEM) was generated using 10 meter counter lines within the GIS. Then, a slope map was provided using DEM and GIS. Further, the spatial location of the wells in the watershed was defined based on the distance from the Caspian Sea or the watershed outlet.

2.3.6. Distance from water sources

All rivers, wetlands, and lakes of the study site were surveyed based on topographic maps and satellite images, and a distance from the water resources map was prepared in the GIS environment. The distance from water resources can be effective in groundwater recharge and depletion (Awasthi et al. 2005).

2.3.7. Distance from industries and residential centers

A database of the plain's industries has been prepared and checked on satellite images.

Residential areas were prepared based on remote sensing and topographic maps with a scale of 25,000. Then, distance from industries and residential areas were prepared in the GIS environment. The wells near industrial and residential areas have a high pumping discharge and can affect the groundwater level (Gholami et al. 2015).

2.4. Prediction of groundwater drawdown by using ANN

The first step is to normalize the data and were randomly divided into three classes: training class (65 percent of the data), cross-validation class (10 percent of the data), and test class (25 percent of the data). Correlation analysis between groundwater drawdown and its affecting factors was conducted to evaluate the network inputs and determine the main factors of groundwater drawdown. NeuroSolutions software was used for the modeling process with different ANNs. In the neural network environment, different structures of inputs were used using the trial-error method and evaluation of network performance. Moreover, the trial-error method was used to determine the optimal architecture of the selected networks, including optimal transfer function, learning technique, neurons number, and number of training epochs. Sensitivity analysis was performed to evaluate the optimal inputs. The goal was to achieve a network that has the highest performance and minimum error in the modeling process. Evaluation criteria of the network performance were the correlation between the predicted and the measured values as well as the error indices such as the coefficient of determination (R-sqr) and the mean squared error (MSE).

Different structure of ANNs including multilayer perceptron (MLP), Jordan and Elman Network (JEN), generalized feed-forward (GFF), radial basis function (RFB), time-lagged recurrent (TLRN), principal component analysis (PCA), and modular neural network (MNN) were used for modeling groundwater drawdown. The multilayer perceptron network typically relies on the back propagation algorithm. The main problems of MLP network are low training speed and need to a large number of training data (Gholami et al. 2020). The JE network develops the MLP with processing elements (PEs). PEs create a network with the ability to extract temporal data from the input data (Mohamed and Atta 2010). The GFF network has a similar structure to the MLP network how connections can go through one or more layers. In fact, the ability of the MLP network to solve problems is not the secret of the GFF network. But, GFF is often much more efficient in solving problems (Beghdad 2008). An MNN is an ANN specialized through a series of independent ANNs moderated by a number of intermediaries.

The intermediaries take the module output and processes them to create an output of the ANN as a whole. Further, the intermediaries only receive the outputs of the modules and does not respond to the modules that do not interact with each other (Bart and Jacob 1994).

The RBF includes a nonlinear hybrid network that is typically comprised of a single hidden layer of the PEs. One of the advantages of this network is its faster processing compared to the MLP network. The TLRN network includes an algorithm with short memory. The TLRN network is developed in nonlinear time series predicting, temporal pattern classification, and identification systems (Sattari et al. 2011). Supervised and unsupervised learning techniques are integrated in the same topology in a PCA network. In fact, the PCA finds a series of uncorrelated features among the inputs and that is an unsupervised linear procedure (Beghdad 2008).

2.5. Performance evaluation of the models

Statistical indices such as the coefficient of determination (R-sqr), the mean absolute error (MAE), the mean squared error (MSE), the Nash–Sutcliffe efficiency (NSE), and matching and correlation between the measured and predicted rates in modeling stages have been used to evaluate the performance of the used networks. Moreover, the observed and predicted values of groundwater drawdown layers were displayed in GIS for comparison and visual evaluation.

3. Results

The mean annual drawdown rates of groundwater in the study region according to the statistics of groundwater depth fluctuations in 250 piezometric wells was between 0.15 to 4.37 meters per year.

The average drawdown in these wells was 1.75 meters per year. A drawdown of about seven meters in a particular year has been observed in some wells. The elevation of the Mazandaran plain varies between − 27 to 30 meters with an average slope of less than 5 percent.

The model inputs such as distance from water resources, distance from industrial centers and population centers vary from zero to several kilometers. Further, the mean annual depth to the water table in the studied plain varies from 0.5 to 40 meters (Fig. 2). The shallow groundwater is observed on the coasts of the Caspian Sea or the outlet of watersheds, and the deepest groundwater is observed in the southern border of Mazandaran plain. The mean annual precipitation and evaporation vary between 600 to 1300 mm and 875 to 1000 mm, respectively.

The annual groundwater extraction within the influence radius of the sampling wells was estimated between 0.1 to 3.66 million m^3/year (average 2 million m^3/year). The maximum extraction values occur around rice lands and drinking water supply wells (Fig. 2). An example of the estimated data on the inputs and output of neural networks is presented in Table (1). Correlation analysis between inputs and network output was used to find the optimal inputs and the main factors of groundwater drawdown in the region (Table 2).

According to Table 2, factors such as groundwater extraction values, depth to groundwater, and transmissivity of aquifer formations have the highest correlation coefficients.

Therefore, these three factors will be the most important factors in the drawdown of groundwater depth (Pradhan et al. 2018; Abd-Elhamid et al. 2020; Shi et al. 2021)

The results also indicated that the hyperbolic tangent transfer function or sigmoid function and LM learning technique are the best selections for the optimal network structure, which in previous studies were also among the optimum options (Gholami et al. 2021). Different results were obtained during the trial-error procedure with different neural network structures, transfer functions, learning techniques, and the number of neurons. Neural network training in two stages of cross-validation and training yielded favorable results (Table 3). According to the results, all tested neural networks showed acceptable performance in simulating groundwater drawdown. However, the MNN and MLP networks have the highest correlation between the measured and predicted values and the lowest error in the predicted values. Results of the evaluation on the test stage are presented in Table (4).

According to the statistical criteria in Table 4, the MNN network is the most efficient network among the tested networks in predicting the water table drawdown.

The comparison between the predicted and the observed values of groundwater drawdown in the test stage in different structures of the neural network is presented in Figure (3). As can be seen, the MNN network has the highest correlation between the predicted and the observed values. As we mentioned before, the raster layers of optimal network inputs (depth to groundwater, transmissivity, and annual extraction values) were prepared in the GIS environment. The values were converted to numerical format to predict the groundwater drawdown values across the entire studied plain. Finally, the predicted values were converted back to raster format in GIS. The predicted values were presented as a map of the annual groundwater drawdown values (Fig. 4).

The comparison of the predicted and observed groundwater drawdown values (Fig. 4) indicates the accuracy of the results and the performance of the used methodology.

Based on the results, the MNN network has the highest performance and the lowest error in the modeling process (training and testing stages).

4. Discussion

The measured values of groundwater in the wells showed a decline of more than 1.7 m in most parts of the area of the study.

The maximum groundwater drawdown values occur in places with high groundwater depth, high transmissivity (coarse texture), and high groundwater extraction.

According to Table (1), depth to groundwater, extraction values, the transmissivity of aquifer formations, annual precipitation, and evaporation, location elevation, distance from industries and residential centers have a significant relationship with drawdown. The three factors of transmissivity of aquifer formations, exploitation values , and groundwater depth with correlation coefficients of 0.8, 0.7, and 0.6, respectively, were the most effective controlling factors in groundwater drawdown in the study area. The higher the transmissivity or permeability of the aquifer, the higher the possibility of extraction with higher pumping discharge, and as a result, we will see a higher decline in the water table (Pradhan et al. 2018). In fact, high transmissivity leads to a larger influence radius in a well. Therefore, groundwater extraction, even at a further distance, affects the water table in adjacent areas. According to the results, the amount of groundwater withdrawal is also directly related to the decline of the groundwater table (Awasthi et al. 2005; Saemi et al. 2008; Gong et al. 2018).

Precipitation is one of the main factors of the natural recharge of groundwater. A significant and inverse relationship between precipitation and groundwater drawdown values was reported in previous studies (Shiri et al. 2013). However, this relationship was not meaningful in the study area since there is no significant variation in precipitation to be correlated with the change in water table.

Evaporation can affect near surface groundwater or in the areas where groundwater meet surface water such as wettlands. However, evaporation is not correlated with groundwater drawdown in the studied plain. The elevation is an effective factor in the water table in unconfined aquifers. Low lands have more water recharge capacity, and the water table is higher in them causing lower decline in water table. The precipitation in these area are high and the gentle topography cause water to have enough time to recharge the groundwater. Also, the areas closer to the Caspian Sea coasts are affected by surface water discharges.

Distance from industries and residential centers are two factors that have a significant relationship.

Because these areas are the place of drilling wells and they reflect the density of withdrawal sites and the extraction values of groundwater (Gholami et al. 2015). The presence of surface water can reduce the reliance and pressure on groundwater resources. Therefore, distance from water resources (rivers, wetlands, freshwater lakes) can play an important role in water table fluctuations.

However, no significant relationship between this parameter and groundwater drawdown values were observed in the studied plain.

The process of predicting groundwater drawdown was performed using different neural networks in which most of them showed an acceptable performance. Previous studies have also indicated the performance of the ANNs in modeling the groundwater depth)Coulibaly et al. 2001; Daliakopoulos et al. 2005; Lallahem et al. 2005; Nayak et al. 2006; Krishna et al. 2008; Yoon et al. 20011; Li et al. 2012; Mohanty et al. 2013; Alshehri et al. 2020). Among the various neural network structures used, the MNN network showed the highest efficiency, and the TLRN network had the lowest performance in predicting groundwater drawdown. According to Table (3), there was not much difference between the performance of the tested networks. Correct prediction of the maximum drawdown values is important in water resources management planning. The adopted methodology showed high accuracy in predicting maximum drawdown values.

The study also showed that using only three main inputs (transmissivity, depth to the water table, and extraction rate) and an efficient neural network structure, groundwater drawdown can be predicted with acceptable accuracy. Providing a reliable groundwater drawdown map can help water resource managers adopting strategies to mitigate the impacts of groundwater depletion.

Further, the inputs of groundwater depth and groundwater exploitation values will change over time. The adopted methodology can be used for investigating different scenarios of groundwater withdrawal and climate variability.

5. Conclusion

Assessment of groundwater drawdown is complex and challenging task due to the presence of various climatic and anthropogenic factors. Traditional field-based measurement of groundwater drawdown requires a dense network of observational wells, which is not available in many countries. We adopted a feasible conventional methodology to map a large scale prediction of groundwater drawdown in an alluvial and coastal aquifer. The relationship between groundwater withdrawal and its affecting factors in 250 wells was established using ANN-based models. Using available input data in the study area, the spatial changes of the annual groundwater drawdown was mapped across the entire study area.

In the modeling process, different neural network structures with different inputs can be used. However, the most challenging step is to quantify the parameters that explain the groundwater drawdown in an aquifer in order to train an ANN. The advantages of using artificial intelligence in predicting the groundwater drawdown are speed of operation, high performance, low cost, and connectivity with other systems such as GIS. The adopted methodology can be used to predict changes in groundwater drawdown in the study area and in similar settings elsewhere. This can be performed under different scenarios of climate and groundwater withdrawal. To complete future studies we suggest using other methods of artificial intelligence and machine learning, as well as different input parameters for the prediction of drawdown values.

Declarations

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Tables

Table (1). A number of the network inputs and output for predicting the groundwater drawdown.

ID well	Drawdown (m)	Groundwater depth (m)	Transmissivity (m^2/day)	Exploitation (10^6 m^3)	Elevation (m)	Evaporation (mm)	L_{sea} (m)	Precipitation (mm)	Population (people)	$L_{settleme}$ (m)	L_{indus} (m)
1	2.12	18.17	1500	2.5	89	953	20428	806	174	378	343
2	2.87	2.57	1250	2.66	-5	960	10279	594	2568	20	500
4	1.05	3.49	300	0.3	-24	747	854	1480	5730	30	40
5	1.60	6.67	375	1.98	-8	995	7083	620	1955	12	640
7	1.24	1.98	150	1.95	-5	1006	18626	753	323	7	226
8	0.24	0.42	75	0.3	20	1024	26288	833	1358	30	1080
9	3.09	37.13	2750	3.04	82	998	20728	818	676	0	780
15	1.79	9.02	1250	1.8	40	1021	33425	1036	582	70	377
16	1.33	3.75	750	1.9	-5	961	10734	822	205	10	590
17	1.26	7.80	175	2.24	-9	1023	10288	539	394	22	570
19	0.78	2.14	375	2.21	-21	892	2214	1029	1966	15	693
20	3.00	34.70	2580	3.17	108	1015	26681	909	1506	0	405
21	1.58	0.77	400	2.41	0	1023	13945	584	1215	10	890
27	1.25	1.65	500	2.89	3	1029	20436	643	967	12	1270
28	2.93	3.93	2000	2.85	29	1024	29427	889	360	15	600
31	1.09	1.75	175	2.76	-20	1008	854	985	212	35	1588
32	1.72	2.13	375	2.76	-8	1020	10139	588	837	2	910
35	0.24	0.82	75	2.6	-23	953	1000	1163	1036	3	864
42	1.41	2.36	100	2.85	-25	1010	922	923	2950	10	1393
49	0.77	3.43	1000	1.15	31	958	14277	791	308	50	86
50	2.68	7.86	2000	1.55	38	1021	33741	1045	961	0	1250
52	0.53	1.80	750	1.13	-23	875	1746	1006	185	17	979
53	3.25	5.03	2500	3.4	-7	972	10412	745	2850	30	240
55	1.68	1.17	500	2.43	-25	939	5000	697	1124	10	1510
57	2.41	1.75	1500	2.32	155	1001	1273	503	600	630	610
58	2.37	2.36	2000	1.9	-15	994	583	462	910	102	188
60	1.72	1.93	300	2.56	-26	944	8233	656	1525	660	236
61	1.55	0.75	125	2.06	-26	934	5728	638	332	4300	217
63	2.10	21.08	2000	2.13	178	1189	6768	565	506	1750	292
65	2.90	11.96	2000	3.27	37	1127	7710	512	638	2300	370
69	4.37	36.02	3000	2.78	34	993	10100	737	1528	10	48
70	3.58	9.58	2500	3.38	20	996	8698	688	1044	10	366
77	4.08	26.28	2750	2.84	24	970	12816	740	2930	318	279
78	2.99	3.33	2500	2.03	-2	982	4600	556	1269	378	170
79	0.88	2.61	500	1.98	-19	990	1118	478	1100	621	510
80	2.70	2.52	1500	2.6	1	1023	5412	529	389	1440	209
84	3.97	26.54	3000	2.78	13	973	16754	747	2760	15	310
102	2.05	1.60	2000	1.64	-13	710	1600	1298	814	90	480
103	3.40	8.00	2750	1.55	36	745	3900	1342	1003	78	336
122	4.08	23.20	3000	2.96	30	981	4880	1210	450	48	350
152	1.13	1.65	175	2.27	-6	1001	9610	611	725	200	474
169	3.36	7.76	2500	2.77	12	971	16274	602	199	27	740

218	2.72	27.19	2200	3.05	144	1006	24490	851	1374	100	5
222	0.20	0.48	50	0.1	-3	862	2961	903	2183	3600	1560
232	0.34	1.12	125	1.12	-23	849	632	1004	2151	9	1190
236	0.71	2.84	100	0.62	-12	701	500	1081	490	15	700
240	0.53	1.52	750	2.4	17	891	11669	879	386	5	405

Table (2). Correlation matrix of the input variables and the groundwater drawdown.

Parameter N=250	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Groundwater drawdown	1.00												
2. Depth to water table	0.60	1.00											
3. Transmissivity of aquifer formation	0.81	0.63	1.00										
4. Elevation	0.28	0.51	0.34	1.00									
5. Slope	0.09	0.06	0.139	0.06	1.00								
6. Annual evaporation	0.26	0.18	0.12	0.23	-0.03	1.00							
7.Distance from water resources	-0.01	-0.11	-0.02	-0.17	0.01	-0.006	1.00						
8. Distance from sea	0.23	0.33	0.25	0.37	-0.13	0.45	0.00	1.00					
9. Annual precipitation	-0.18	-0.005	-0.02	-0.11	0.02	-0.63	0.10	-0.26	1.00				
10. Population	0.20	0.16	0.15	-0.06	-0.03	0.02	0.10	0.06	-0.052	1.00			
11. Distance from residential areas	0.05	0.01	0.01	0.08	0.04	0.12	0.00	-0.15	-0.171	-0.006	1.00		
12. Distance from industries	-0.27	-0.19	-0.20	-0.14	-0.05	-0.12	-0.05	-0.17	0.08	-0.18	0.00	1.00	
13. Goundwater extraction	0.69	0.43	0.47	0.28	0.009	0.39	-0.03	0.233	-0.37	0.17	0.07	-0.22	1.00

Table (3). Evaluating the performance of the used ANN methods in the training and cross-validation phase for predicting the groundwater drawdown.

R-sqr	NSE	Final MSE	The minimum MSE	Prediction stage	ANN network
	0.89	0.001	0.006	Training	GFF
0.88		0.0001	0.005	Cross-validation	
	0.96	0.0001	0.004	Training	MLP
0.95		0.0002	0.004	Cross-validation	
	0.88	0.0000	0.004	Training	JEN
0.87		0.0001	0.005	Cross-validation	
	0.9	0.0000	0.004	Training	RFB
0.88		0.0000	0.005	Cross-validation	
	0.97	0.0001	0.001	Training	MNN
0.96		0.0002	0.004	Cross-validation	
	0.85	0.0000	0.004	Training	PCA
0.86		0.0002	0.005	Cross-validation	
	0.76	0.001	0.02	Training	TLRN
0.75		0.002	0.03	Cross-validation	

Table (4) Evaluating the performance of the used ANN methods in the testing or validation stage for predicting the groundwater drawdown.

R-sqr	NSE	ME	MSE	ANN
0.79	0.78	0.34	0.18	GFF
0.8	0.8	0.34	0.18	MLP
0.77	0.79	0.35	0.19	JEN
0.77	0.73	0.38	0.21	RFB
0.81	0.81	0.32	0.17	MNN
0.78	0.78	0.35	0.19	PCA
0.66	0.65	0.41	0.31	TLRN

Figures

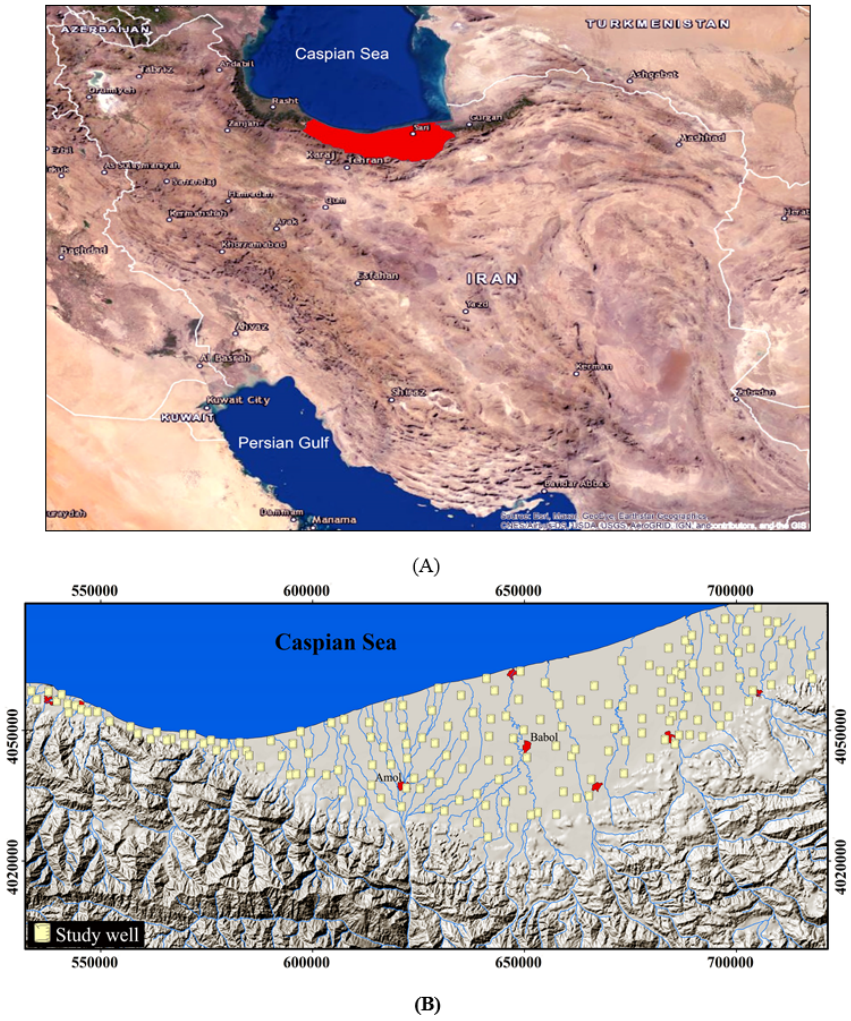

Figure 1

Geographical location of the study plain (A), and the studied wells on the southern coasts of Caspian Sea (B). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

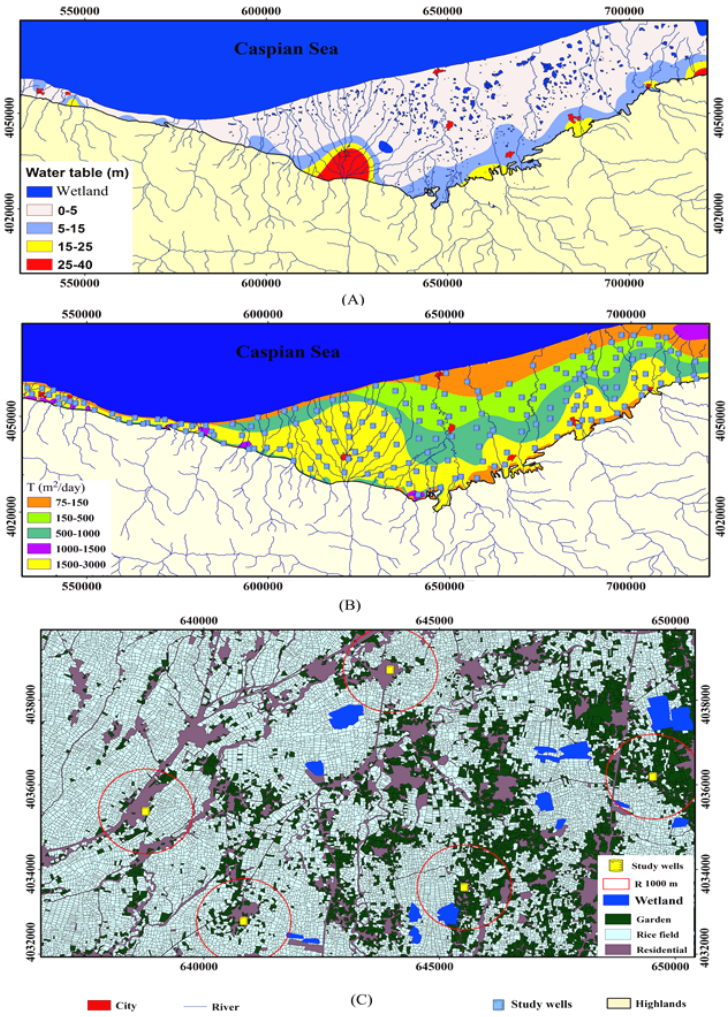

Figure 2

(A) The mean depth to water table (m); (B) The spatial variation of the mean transmissivity of aquifer formation (m2/day); (C) A view of the study area showing the location of sampling wells and different types of land uses (groundwater exploitation estimation). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

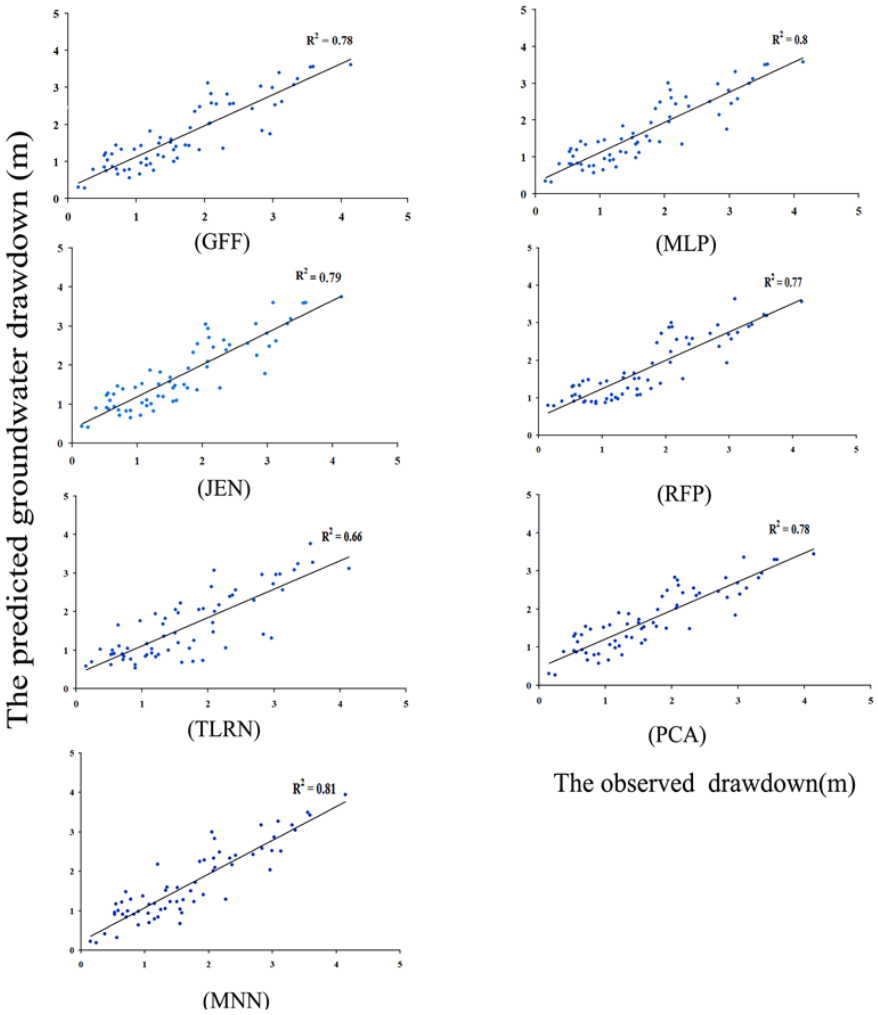

Figure 3

Comparison of the measured and predicted annual groundwater drawdown in the test stages of the different used ANNs.

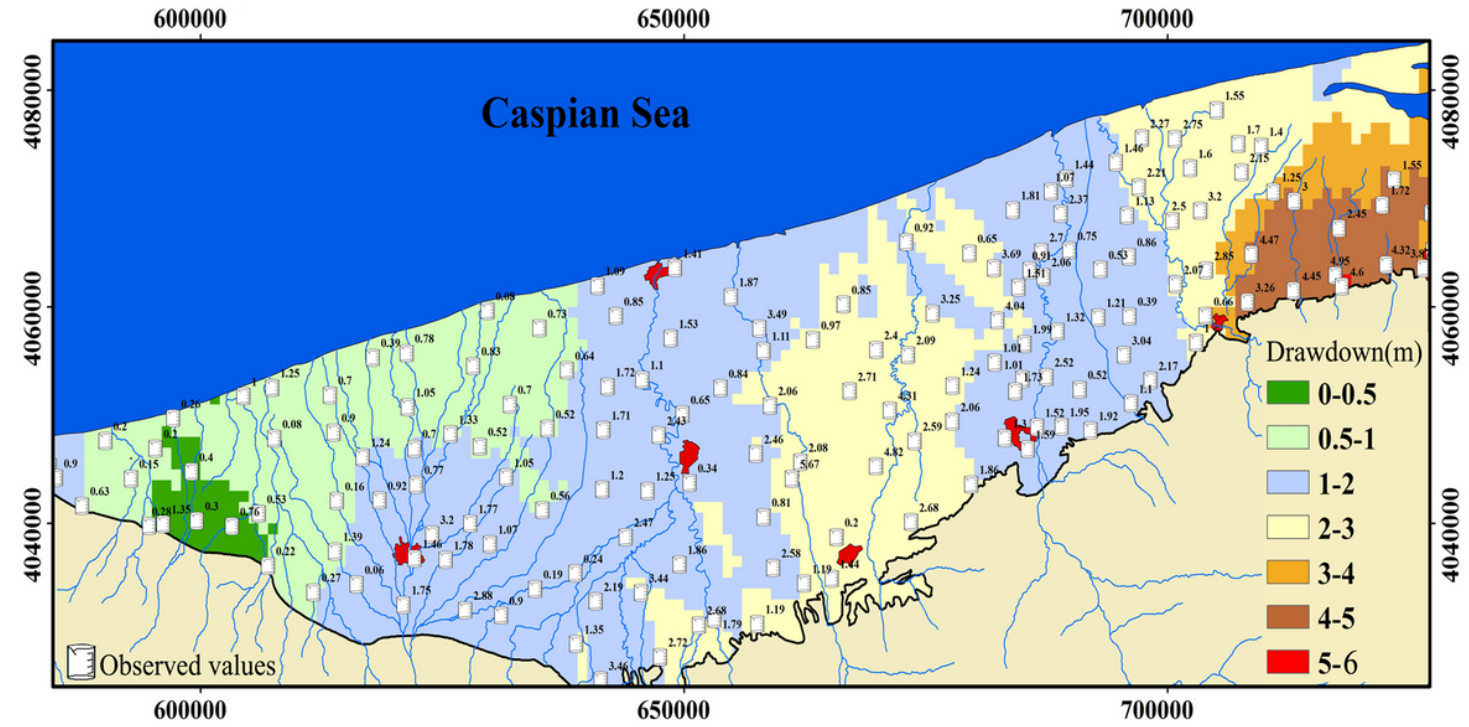

Figure 4

Map of the annual groundwater drawdown (m) in the study region. The observed values in the wells are also shown to assess the accuracy of the final map (R-sqr=0.8). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.