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EXTENDED ABSTRACT

Modeling of Groundwater Salinity Using Artificial Neural Network (ANN) and Geographic Information System (GIS) on the Caspian Southern Coasts

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Introduction

Groundwater is one of the most important water resources on earth, and water salinity studies are very important for the protection and planning of water resources, especially in arid and semiarid areas such as Iran. Groundwater currently accounts for more than 90 percent of Iran's total drinking water consumption. This water resource is less susceptible to bacterial pollution and evaporation than surface water, and hence it is more important than surface water.

Materials and Methods

An ANN includes three layers, namely, input layer, hidden layer and output layer. A network can have more than one hidden layer. In this study, multi-layer perceptron (MLP) was applied to simulate groundwater salinity. MLP is generated through adding one or more hidden layers to one-layer perceptron and can solve complex problems. The feed-forward neural network was the first and simplest type of artificial neural network devised. In a feed-forward network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. In the first stage of simulation, all data were normalized and divided into three classes: training data (65% of all data), test data (25% of all data) and cross validation data (10 % of all data). The different transfer functions such as hyperbolic tangent and sigmoid transfer functions were evaluated. Based on the results of this study (through trial-and-error method), the hyperbolic tangent transfer function was the best transfer function. Artificial neural network (ANN) is an efficient tool in hydrologic studies. In this study, an integration of ANN and GIS (the geographic information system) was applied to simulate groundwater salinity. ANN and GIS were, indeed, used for simulation purposes and as a pre-processing and post-processing system of the applied data, respectively. Thus, GIS was applied as an efficient tool to provide the base maps and to estimate the model's quantitative parameters. Different digital/base maps were provided in GIS environment including DEM, transmissivity of aquifer formations, water table depth, precipitation values and distance from Caspian Sea and water resources using topographic maps of the region and EC values using water salinity secondary data. Different piezometric wells were selected to simulate groundwater salinity (EC). In GIS pre-processing stage, raster layers of the input factors were provided and combined using overlay analysis with a pixel size 1×1 km. Therefore, the surface of study plain was separated to more than 10000 geo-referenced pixels (1×1km). These pixels had values of model inputs or groundwater salinity factors (transmissivity of aquifer formation, water table depth and the distance from water resource). We inserted the site coordinate for every pixel automatically in the GIS medium.

Pixels data (networks inputs and coordinate) were exported from GIS and then imported to NeuroSolutions software. In ANN medium, groundwater salinity (EC) was simulated using the validated optimum network for all of the 10000 pixels (the whole study plain).

Results and Discussion

Groundwater salinity was estimated for the studied plain based on the secondary data, observational wells and a validated MLP network. We estimated significant factors on water salinity including aquifer formations transmissivity, water table depth, site elevation, and distance from water resource. A number of the estimated significant factors on water salinity and EC are presented in Table (1). These data were imported in ANN medium for simulating the groundwater salinity. In the training stage, the changes in input data pattern and sensitivity analysis showed that three factors constituted the best inputs for simulating groundwater salinity. These three factors are transmissivity of aquifer formation, groundwater depth and distance from water resources (Gholami et al., 2010). Digital maps of these three factors were generated in GIS, shows the results of ANN simulation in the training stage for ground water salinity simulation, and as can be seen, Rsqr= 0.78. The results of network evaluation are presented in Tables (2) and (3) showing error values in the training stage. Accordingly, acceptable results were observed in the training stage. The optimum network structure in groundwater salinity simulation included an MLP with three inputs, tangent hyperbolic transfer function, LM (Levenberg- Marquart) training technique and one neuron. Tangent hyperbolic transfer function and LM training technique are some of the best selections in modeling hydrologic parameters which were applied in different studies as a prior selection in the world. Finally, the optimized network was validated in the test stage (R^2=0.78). Moreover, the validated network and GIS were applied to simulate and map the groundwater salinity on the Caspian southern coasts.

Table 1- factors of groundwater salinity (EC) values and model inputs for a number of wells

Salinity (µ mho/cm)	Transmissivity (m2/day)	Water table Depth (m)	Elevation (m)	Annual evaporation (Mm)	Annual evaporation (Mm)
6400	175	1.54	7227	1000	630
6200	100	2	3266	1000	650
5400	175	2.25	7159	1000	650
5200	100	3	2463	1000	650
5000	175	0.88	7651	1000	750
4800	175	2.25	9737	1000	650
4400	375	3	1271	1000	700
4200	100	1.73	1894	1000	620
4020	100	0.9	4276	1000	700
2900	175	2.24	6657	1000	700
3750	100	3	9567	1000	650
3600	100	2	1358	1000	670

Table 2-The results of network training for simulating EC

All runs	Training minimum	Training standard deviation	Cross validation minimum	Cross validation standard deviation
(Average of minimum MSEs)	0.02	0.0003	0.02	0.0006
(Average of final MSEs)	0.02	0.003	0.02	0.0006
The square of the mean squared error	0.009	0.009	0.16	0.16

Table 3- The results of network training and optimum network selection

(Best network)	validation	Training	Test
(Run)	1	2	-
(Epoch)	337	1000	-
(Average of minimum MSEs)	0.025	0.02	0.8
(Average of final MSEs)	0.025	0.02	0.9
The square of the mean squared error	0.16	0.09	0.112
R^2	-	-	0.78

Conclusions

Different model structures were developed to evaluate the probability impacts of enabling/disabling transmissivity of aquifer formation, water table depth, the distance from water resources as inputs. Results showed that three factors, namely, transmissivity of aquifer formation, water table depth, and the distance from water resources are the most important factors and the best inputs for groundwater salinity modeling (Gholami et al., 2010). Artificial neural network is an efficient tool in modeling, but it cannot preset its results in the forms of maps and geo-referenced data. We applied ANN to simulate the groundwater salinity and GIS as a pre-processing and post-processing tools in monitoring and mapping the results. Further, GIS resulted in an increasing modeling accuracy and modeling velocity. An MLP network with the tangent hyperbolic transfer function and LM training technique was the best network structure in the groundwater salinity simulation. Previous studies reported that an ANN with LM technique was an efficient structure in the hydrological parameters simulation (Chen and Adams, 2006).

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