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Integrated Artificial Neural Network Modeling and GIS for Identification of Important Factor on Groundwater Hydrochemistry (Fe^{-},Ca^{2+} and PO_4^{-3})

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A-B-S-T-R-A-C-T

Background & Aims of the Study: Groundwater resources are a crucial component of the ecosystem. Management and cleanup of contamination from groundwater resources requires a long term strategy and a huge amount of investments. Artificial neural networks (ANN) and Geographic Information System (GIS) can be useful in determining management strategies. To protect these valuable resources, groundwater hydrochemistry (Fe^{-}, Ca^{2+} and PO_4^{-3}) spatial distribution is evaluated; also, the important parameters that affect their rate and spatial distribution are identified.

Materials and Methods: This study employed GIS technique and Modeling technique based on artificial neural network for identification and investigation of important factor on groundwater hydrochemistry such as Fe^{-}, Ca^{2+} and PO_4^{-3}. The case study is Ghareh-su basin of Golestan province of Iran. The maps of land use, soil, geology, population density, digital elevation model, distance from built-up areas, roads and rivers, cultivated land density and water table are the parameters that used for running ANN model. Sensitivity analyses were also performed to identify the effective parameters of ground water hydrochemistry

Results: The results show that the concentration of the parameters around Gorgan and Kordkuy cities, and areas where the cultivated land is denser, is high.

Results indicated that the highest concentrations of these parameters were located around Gorgan and Kordkuy cities and where the cultivated lands have a high density. The present contribution confirms that a significant relation between the concentration of pollutants in groundwater resources and different land uses/land covers is found. Soil type, geological structure and high groundwater level in the north of Ghareh-su basin have a great impact on groundwater quality.

Conclusion: These techniques have successfully implemented in groundwater hydrochemistry mapping of Ghareh-su basin.

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Background

Groundwater conservation as a vital resource is very important (1). One of the threats that currently exist in many areas is increasing number of soluble chemicals from urban and industrial activities (2); also, from modern agricultural practices. Groundwater resources are a crucial component of the ecosystem. This water supply is essentially a renewable resource generated within the global water circulation system (3). In many cases, groundwater is polluted by industrial wastewater and sewage (4). In such cases, persons drinking contaminated water suffer from diseases (5). The life of many regions in the world is entirely depending on groundwater for the various uses. Groundwater contaminated with various pollutants may make it unsuitable for consumption and put human and animal life as well as the whole environment at great risk.

Artificial neural networks (ANN) model has become widely used in groundwater management in recent years. ANNs provide an innovative and appealing solution to issue of relating input and output variables in groundwater systems (6). Neural networks are powerful tools and attempt in simulation the brain that use a machine learning approach to quantify and model input and output response patterns and learn by example (7,8). In particular, neural networks are nonlinear and sophisticated modeling techniques capable of modeling complex functions (9). The neural network user gathers representative data, and then use training algorithms to automatically learn the structure of the data (10).

Ray and Klindworth (11) assessed nitrate pollution in rural groundwater with ANN. They used distance to cropland, water depth, geology, septic and disposal sites, topography, season and time of nitrate application for running ANN.

Lee et al (2) used GIS and statistical models for assessing groundwater nitrate's concentrations in the Seoul urban area. Babiker et al (12) assessed groundwater contamination by nitrate leaching from intensive vegetable cultivation, using geographical information system. Their study showed that the vegetable fields were considered the principal factor of nitrate pollution in the Kakamigahara. Sahoo et al (13) applied a feed-forward back-propagation neural network (BPNN) to predict pesticide concentrations in groundwater monitoring wells. The BPNN was applied to rank the input parameters cause to groundwater contamination, including two original and five ancillary parameters. The two original parameters are depth to aquifer material and pesticide leaching class. When these parameters were the only input to the BPNN, they were not able to predict contamination potential. Jiang et al (14) studied the relation between groundwater quality and land-use change in China. Their results indicated that fertilizers and cultivated land is the main cause of water pollution. Jalali (15) assessed the concentration of phosphor in ground waters of southern Malayer of Iran. Their results showed that the high consumption of P fertilizer, inefficient irrigation system and soil are the important variables that affect phosphor concentration in groundwater. Nas and Berktay (16) used the geostatistical methods of kriging and cokriging to assessing groundwater quality parameters in Turkey.

Management and cleanup of contamination from groundwater requires a long term strategy and a huge amount of investments. ANN and GIS can be helpful in determining management strategies.

Aims of this study:

In this paper, multi–layer feed-forward networks (multilayer perceptrons or MLPs) was developed to assess the impact of land-use and land-cover on groundwater hydrochemistry.

Materials & Methods

Site characterization

The Gharehsu basin of Golestan province in Iran encompasses roughly1610 km^2. The basin includes Gorgan and Kordkuy cities, the south of Bandar Turkaman and AghGhala towns (17). (Figure1 and 2)

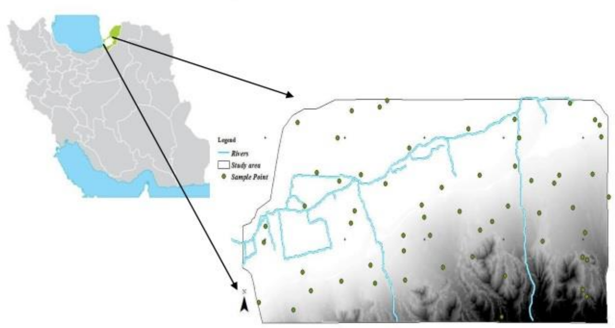


Figure 1) Location map of the study area

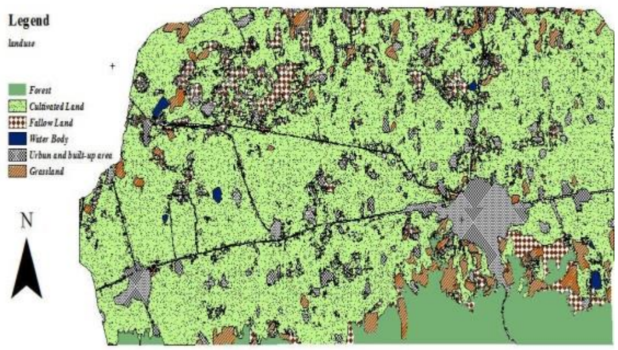


Figure 2) Land use/Landover maps for Ghara-Su River Basin

Data

The statistical summary (minimum, maximum, mean of values and standard deviation) of groundwater quality and their comparison with EPA and Iranian National Standards Organization, (2004) were shown in Table 1.

ANN modeling method and GIS technique were used to analyze and identification of important factor on groundwater hydrochemistry (Fe^-, Ca^{2+} and PO_4^{-3}). ANN model like as recreation analyze the relation between dependent and independent parameters. Input variables for running ANN model to analyze the impact of land-use/land-cover on groundwater hydrochemistry included: the maps of land-use (18) soil, geology, (DEM), distance from roads, built-up areas and rivers, cultivated land, population density and groundwater level as independent parameters (19) and groundwater hydrochemistry (Fe^-, Ca^{2+} and PO_4^{-3}) as dependent parameters.

The rock types identified in the Ghara-su basin included: clay (mainly clay, silt and sand), coastal sand, brown sand, thick–bedded to massive limestone, shale, quartzite, old alluvial terraces and young alluvial terraces, recent river deposits, loess, green schist, meta diabase, phyllite, slate and marble. Soil map was produced in seven classes.

The population data were prepared from Statistics Organization of Iran, the cultivated land area from Golestan Jihad-e-Agriculture Organization and water table data from Golestan Water and Waste-water organization.

To prepare population density map and those of cultivated-land and water level, the following procedures were applied.

The collected data on population and cultivated land were imported into the ArcMap GIS software and were pre-processed. This process included the conversion of all data to GIS layers. To produce population and cultivated-land density maps, the inverse distance weighted (IDW) interpolation method was used (20).

Water level map was produced, using the kriging method. Like IDW interpolation, in Kriging model, measured values were used to predict unknown points. The nearest measured points have the most effect (12). IDW uses a simple process based on distance, but kriging weights come from the spatial arrangement of the data as a semi vario gram (21).

The output parameter for modeling was the observed groundwater hydrochemistry in the sampled wells that included Fe^-, PO_4^{-3} and Ca^{2+} that their statistical summary and their comparison with Iranian National Standards Organization and EPA were presented in Table 1.

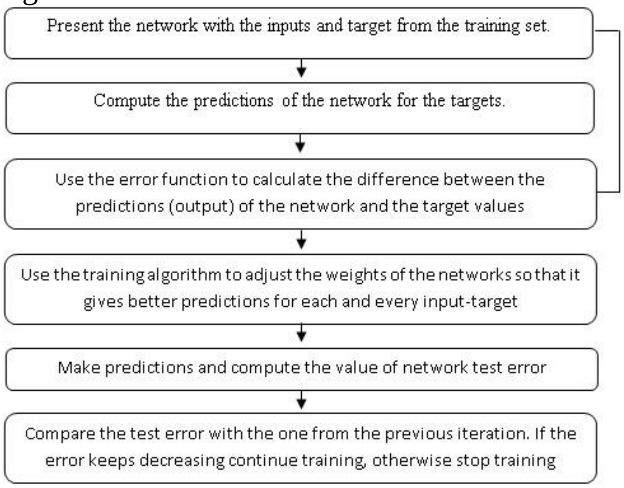
Artificial Neural Network (ANN)

Multilayer perceptrons or MLPs included an input layer, hidden layers and an output layer (4,13). Optimum network structure is selected by error and trial; there isn't standard rule to define the structure of network.

The general steps followed to validate and identify the ANN model:

Training algorithms: At first units and layers' number in each layer has been selected, the network's weights and thresholds to reduce the prediction error must be set (22). There was only one output which is the groundwater hydrochemistry properties in wells. 60% of sample set was selected randomly for calibration of model (training), 20% for testing and 20% for model validation. Training is performed until the mean square error of the training patterns reaches a minimum (4).

This technique slightly modifies the training algorithm to:



Validation: This step was done, using the validation data set. The validation phase assesses the ability of the model to provide correct responses to unknown input data sets. Then, the ANN runs for all pixels in Ghareh-su basin with the model that was selected in training phase. The same phases for each ground hydrochemistry in the sampled wells were repeated that included Fe^{-}, PO_4^{-3} and Ca^{2+} produced one prediction map for each ground water parameter was produced that relevant to the above ground land-cover/land-use properties through the model. Sensitivity analysis was also performed, which estimates the importance of independent variables with respect to dependent variable (23). To do this, the ANN model was run several times, each time dropping one variable with recording the validation statistic. The importance of the dropped variable is shown by the change in statistics.

Results

The statistical summary of groundwater quality and their comparison with Iranian National Standards Organization and EPA (2004) were shown in Table 1.

The results of ANN were shown as a prediction map for each ground water parameters that was indicated the impact of land-cover/ land-use on groundwater hydrochemistry (Figure 3–5).

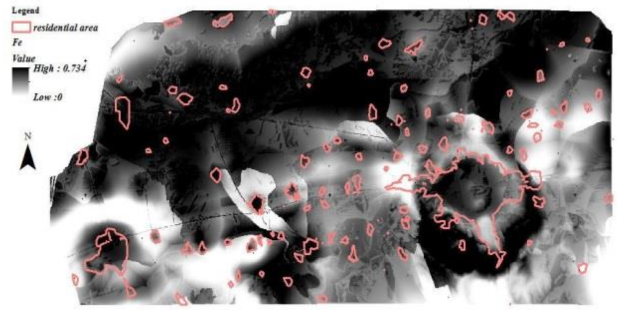


Figure 3) Effect of land use/land cover on Fe^{-} (mg/l) dispersion

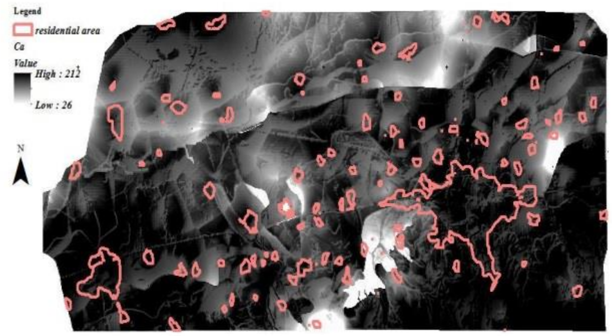


Figure 4) Effect of land use/land covers on Ca^{+2} (mg/l) dispersion

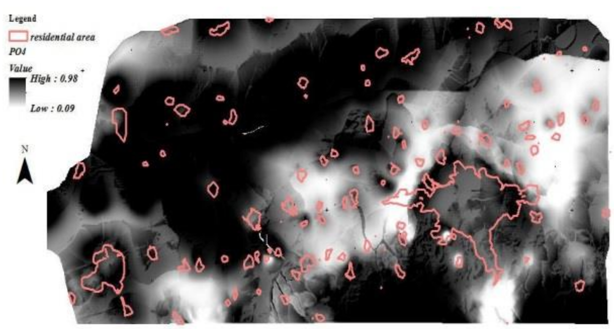


Figure 5) Effect of land use/land cover on Po_4^{-3} (mg/l) dispersion

The sensitivity analysis figures to identify the important parameters that affected the groundwater hydrochemistry were represented in Figures 6– 8. The sensitivity analysis showed that the soil type and geology have large impact on groundwater quality.

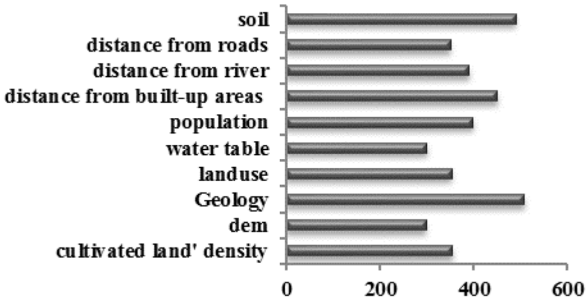


Figure 6) ANN sensitivity analysis for Fe^-

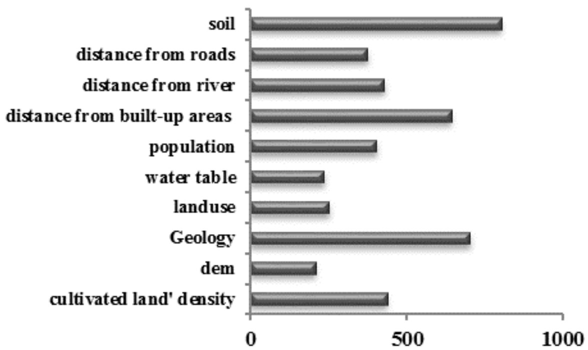


Figure7) ANN sensitivity analysis for Ca^{+2}

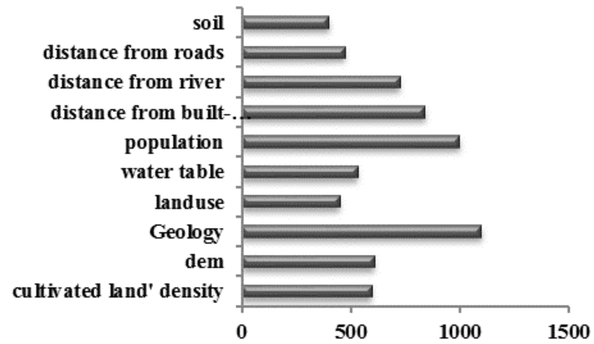


Figure 8) ANN sensitivity analysis for Po_4^{-3}

Model's results (Output layers and activation Function type for hidden, Correlation Coefficient, Performance of test, activation and training, Networks type) were presented in Table 2.

Table 1) The statistical summary (minimum, maximum, mean, and standard deviation) of groundwater quality (mg/l)

Groundwater quality	Max.	Min	Mean	STd	EPA	(INSO)
Ca_2^+	212	26.4	77.35	27	-	75
PO_4^{-3}	31	0	0.43	0.8	0.1	0.1
Fe^-	3.78	0	0.14	0.2	0.3	0.3

Table2) Results of ANN model

Network type	Training Performance	Validation Performance	Test Performance	Correlation Coefficient	Activation Function type (Hidden)	Activation Function type (Output)	Ground water quality
MLP 10-9-1	0.9821	0.9887	0.9855	0.9895	Logistic	Tanh	Fe^-
MLP 10-10-11-1	0.9912	0.9904	0.9911	0.9901	Exponential	Logistic	Ca^{+2}
MLP 10-8-1	0.9842	0.9932	0.9862	0.9874	Tanh	Exponential	Po_4^{-3}

Discussion

In surface waters, phosphate is a limiting plant nutrient. The recommend maximum concentration in streams and rivers is 0.1mg/L of total phosphate. Also, there isn't specific recommendation for calcium, but high calcium causes hardness, suspended solids and aesthetic problems.

Groundwater hydrochemistry is a measure of its suitability for human consumption, irrigation and industries. The results revealed a significant relation between the concentrate of pollutants in groundwater resources and different land-uses/land- covers.

Iron is a chief component of the earth's crust. It occurs in groundwater due to dissolved iron from the rock formations and soil as rainwater seeps (24). Anthropogenic sources of this component could be due to landfill leakages, acid-mine drainage, industrial effluents, well casing, piping and storage tank.

Iron at very low concentrations caused the problems in water consumption that included unpleasant taste to drinking water, laundering, problems in manufactured products and distribution systems by growthing of iron bacteria. For these reasons, recommended limit in public water supplies by U.S. Public Health Service is 0.3 mg/L.

As shown in figure 3, the high iron concentration in around of Gorgan and Kordkuy city and the MCL of iron (0.3mg/L) was exceeded in some wells and reached to 0.73 Mg/L. This proves that anthropogenic factors are the main cause of high iron concentrations.

The sensitivity analysis indicated that the geology and soil type of the region have large impact on groundwater quality. Hence, the origin of iron is due to dissolved iron from the rock formations and soil as rainwater seeps, percolates and drains down the soil and rocks. Industrial effluent, acid-mine drainage, sewage and landfill leachate may contribute iron to local ground water. These results were in line with findings of Raju (2006) that proved the high iron concentrations can be due to the seepage of domestic sewage effluents, smelting processes and the dissolution of rocks and ferruginous minerals (25).

Assessing of the sensitivity analysis show that the soil type and geological structure have a great impact on groundwater hydrochemistry . Residential and agricultural areas and limestone-dominated aquifers were the area that Ca^{2+} had a high concentration.

Carbonate rock's dissolution was the main cause of Ca^{2+} in groundwater; also, anthropogenic parameter was an effective factor;the application of calcium phosphate fertilizer, concrete structures and the wastewater discharges (26-28).

As indicated by figure 5, the high Ca^{2+} concentration, around the Gorgan city, was exceeded in some wells and reached to 212mg/l.

As indicated by figure 5, phosphate concentration reaches 0.98 mg/l.

The sensitivity analysis is used to identify the important parameters that affect PO_4^{-3} concentration.

Geological structure, distance from built up area and rivers and population density are the most important factors that affect PO_4^{-3} distribution. This showed that the urban area has an obvious effect on PO_4^{-3} in groundwater. Also, it's concentration in cultivated lands was obvious which were in line with Jalali (15). Fertilizers from non-point sources may cause high PO_4^{-3} concentration. In residential area, pollution problems involved detergents that have phosphate in their composition (29). Assessing of the sensitivity analysis indicated that cultivated lands and population are important variables that affect ground water quality properties.

The observed high phosphate retention in the soil applies only to non-point source phosphate (e.g., fertilizers) and from point sources (e.g., sewerage treatment plants with overloading the soil zone) can directly recharge into groundwater and cause elevated phosphate loads

This study indicated that there is high correlation (more than 90%) between land-cover/land-use and groundwater quality. Assessing the sensitivity analysis indicated that the soil type and geological structure of the region have a great impact on the groundwater hydrochemistry. The sensivity analysis showed the level of water in the north of Ghareh-su basin had high impact on groundwater hydrochemistry. Groundwater hydrochemistry in Ghareh-su basin is determined by both natural activities such as recharge water quality, lithology, interaction with water aquifers and also anthropogenic activities.

The results of ANNs (Activation Function type for hidden and output layers, Correlation Coefficient, Performance of test, activation and training, Networks type) were presented in Table 2 that indicated ANNs can be an effective and reliable tool for assessment of groundwater hydrochemistry.

Conclusion

Assessing of regional vulnerability of groundwater pollution for measures management is an effective and reliable way in order to supply high groundwater hydrochemistry for future generations (12). The primary objective of this paper was the assessment of the groundwater hydrochemistry in Ghareh-su basin of Golestan province in the north east of Iran. Spatial distribution of groundwater hydrochemistry was performed through GIS and ANNs. These ways have successfully represented their capability in groundwater hydrochemistry mapping of Ghare-su basin. This study showed that ANNs are useful and credible algorithms which able to performing functional input/output mappings. The present contribution confirms that there was a significant variation between the concentration of pollutants in groundwater resources and different land uses/land covers. Soil type, geological structure and high level of water table in the north of the region have a great impact on groundwater quality.

The final maps demonstrated that the high pollution concentrations were located around Gorgan and Kordkuy city and where the cultivated lands are dense.

Monitoring of groundwater hydrochemistry's trend with regards to changes in urbanization and farming systems are important tasks which cause sustainability in water management. This approach that integrates RS, GIS with ANN can be useful tools to quantify and evaluate the impacts of land-cover/land-use on ground water hydrochemistry. Mapping of groundwater hydrochemistry demarcate their spatial distribution and can be useful in groundwater management and its pollution control ways

Footnotes

Conflict of Interest:

The Authors have no conflict of interest.

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