Prediction of groundwater suitability for irrigation using artificial neural network model: a case study of Nanded tehsil, Maharashtra, India

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Received: 22 October 2016 / Accepted: 31 October 2016 / Published online: 10 November 2016
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Abstract This study presents an artificial neural network (ANN) model predicting values of sodium adsorption ratio (SAR), residual sodium carbonate, magnesium adsorption ratio, Kellys ratio and percent sodium (%Na) in the groundwater of Nanded tehsil. The 50 groundwater samples were analyzed for different physicochemical parameters such as pH, EC, TDS, Ca, Mg, Na, K, Cl, CO₃, HCO₃, SO₄ and NO₃, for the pre monsoon season 2012. The ANN model is developed through R programming and compared with MS-Excel software. These parameters were used as input variables in the ANN based groundwater quality indices for irrigation suitability prediction. The best back propagation algorithm and neuron numbers were determined for optimization of the model architecture. The resilient backpropagation algorithm with weight back

tracking was used for optimization of seven neurons through sensitive analysis. It showed that a network with seven neurons was highly accurate in predicting the irrigation suitability indices. The relative mean squared error, coefficient of determination (R^2) and mean absolute relative error between experimental data and model outputs were calculated. It is observed that is a good agreement between actual data and ANN outputs of groundwater for irrigation suitability indices for training and testing datasets. The spatial distribution maps of measured and predicted values of irrigation indices were prepared using ArcGIS software. Hence, the result confirms that the ANN model is an applied tool to predict the groundwater suitability for irrigation purpose in Nanded tehsil.

Keywords Neural network · Backpropagation algorithm · Irrigation suitability · Nanded tehsil

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Introduction

Groundwater is an important natural resource for human survival system and one of the major sources of irrigation. The crop productivity and soil quality also depends on water used for irrigation. The poor quality water used for irrigation may reduce the crop yield and also affects soil quality (Ayers and Westcot 1994). In India, groundwater meets the 65% irrigation and 85% of drinking demand. However, surface water share has declined in irrigation from 60% in 1950 to 30% in the first decade of the twenty-first century (CGWB 2010). The groundwater quality is deteriorating day by day due to overexploitation of groundwater, surplus use of chemical fertilizers and pesticides which percolate into aquifer in many parts of the country (Goyal et al. 2010; Jangam et al. 2015).

Fig. 1 Study area with sample locations

The suitability of groundwater for irrigation is considerably based on the concentration of cations and anions present in the ground water. The sodium adsorption ratio (SAR), residual sodium carbonate (RSC), magnesium adsorption ratio (MAR), Kellys ratio (KR) and %Na plays a vital role to determine the suitability of groundwater for irrigation purpose (Richards 1954; Raghunath 1987; Kelley 1963; Doneen 1964). The investigation of water suitability for irrigation should focus on salt concentration, which increases soil salinity and affects soil fertility and crop productivity (Kirda 1997).

The artificial neural network is a system of processing elements called neurons, which are connected to each other by a set of weights. It takes number of inputs weight them, sums them up, adds a bias and uses a results as the argument for singular valued function, the transfer function, which results in the neurons output (Strik et al. 2005). In the ANN model three layers are used first one is input variables, then hidden neurons and the output. The input variables are processed with some weight and the predicted output is delivered. Neural networks have flexible nonlinear function mapping capability that can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical models do not have this property. Second, being nonparametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Also, high computation rate, learning ability through pattern presentation, prediction of unknown patterns, and flexibility affords for noisy patterns are other advantages of using ANNs.

The aim of the present study is to develop the optimized ANN model to determine the groundwater suitability for irrigation. The physicochemical analysis is carried out to measure the value of SAR, RSC, MAR, KR and %Na. The ANN resilient backpropagation algorithm is adopted to predict the values of the same. The different thematic maps prepared to identify the spatial variation among the measured and predicted values of these ratios. This study will be helpful to identify the irrigation water suitability particularly in arid and semi arid environment within short period of time.

Study area

The present study area is located in the Nanded District of Maharashtra, which lies between latitudes $19^{\circ}03':19^{\circ}17'N$ and longitudes $77^{\circ}10':77^{\circ}25'E$ with total geographical area of 447.27 km^2 (Fig. 1). The Nanded tehsil receives an average rainfall of 767–1285 mm, out of which 89% rainfall is received during SW monsoon. The temperature ranges from 13 to $42^{\circ}C$ in the study area (CGWB 2013). The Godavari is the major River flowing in SW to SE direction in the study area. The area is irrigated by the Godavari and Asna River and also irrigated by the left bank canal from Siddheshwar dam of the Purna project in the Parbhani district. Geologically, the Nanded tehsil is part of South East part of Deccan Volcanic Province of Cretaceous-Eocene age (Krishnan 1982). The black cotton soil and loamy to sandy soil are the dominant soil types.

Table 1 Methodology/formulas adopted to analyze physicochemical parameters and Irrigation water suitability indices

Parameter	Methodology/formula adopted
pH	Multi-parameter PCS tester 35
EC	
TDS	
Ca	
Mg	
CO ₃	
HCO ₃	
Cl	
TH	
Na	
K	Flame photometer (Elico CL 361)
SO ₄	
NO ₃	UV spectrophotometer (Shimadzu UV-1800)
SAR	
RSC	
KR	
MAR	
%Na	

Materials and methods

Fifty representative groundwater samples were collected from different locations in rural and agricultural areas of Nanded tehsil during pre-monsoon season of 2012. A global positioning system (GPS) device used to record the location coordinates. The methodology adopted to calculate different physicochemical parameters and irrigation water suitability ratios are given in the Table 1. The ions were converted from milligram per liter (mg/L) to mill equivalents per liter (meq/L) to measure the different irrigation suitability ratios. The DOS based STIFF software used to compute the ionic balance errors ($\pm 10\%$). The R and MS-Excel software were employed for computing descriptive statistics and ANN analysis of the data. Finally, we will turn to an examination of the recommended model with the designed neural network to predict the ground water suitability based on analytical results. The spatial distribution maps of measured and predicted values are demonstrated for the better understanding by ArcGIS 10.2 software.

Selection of ANN model

Multilayer perceptron (MLP) with back propagation (BP) algorithm has been adopted in designing different

structures of the neural network (Sreekanth et al. 2009). In the multilayer neural network, depending on the pattern of relation between the materials, input is put in first layer and the output in the last layer by means of neurons weights, bias and the activity algorithm in the middle layer(s). In each structure, the input information, after processing, is put through to the next layer(s) through the output of the first layer neurons and finally, provided that it is acceptable, to the network output. The explicit expression for an output value of a three layered MLP is given by (Nourani et al. 2013) Eq. (1).

$$y_k = f \circ \left[\sum_{i=1}^{M_N} W_{kj} \cdot f_h \left(\sum_{i=1}^{N_N} W_{ji} X_i + W_{j0} \right) + W_{k0} \right], \quad (1)$$

where, W_{ji} is a weight in the hidden layer connecting the i th neuron in the input layer and the j th neuron in the hidden layer, W_{j0} is the bias for the j th hidden neuron, f_h is the activation function of the hidden neuron, W_{kj} is a weight in the output layer connecting the j th neuron in the hidden layer and the k th neuron in the output layer, W_{k0} is the bias for the k th output neuron, f_o is the activation function for the output neuron, X_i is i th input variable for input layer and y_j is computed output variable, N_N and M_N are the number of the neurons in the input and hidden layers.

The weights are different in the hidden and output layers, and their values can be changed during the network training process. Every neuron in each layer is connected to a neuron of an adjacent layer having different weights. Each neuron receives signals from the neurons of the previous layer weighted by the weighted connections between neurons except in the input layer. Neurons then produce an output signal by passing the summed signal through an activation function (Maqsood et al. 2005; Ghavidel and Montaseri 2014). The gradient descent, conjugate gradient, Levenberg–Marquardt, and etc. Learning algorithms can be used for training the MLP model (Kisi et al. 2015).

Normalized information was used as the network input, in which the software normalizes information. In this study, several training algorithms and functions performed using neuralnet and nnet tool of R software were adapted. Normalization of data ensures fast processing and convergence during training and minimizes prediction error (Rojas 1996). The input and output data (raw data) were normalized before subjecting to training and testing by transforming the data to the range of 0–1 using the Eq. (2):

$$\hat{X} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}. \quad (2)$$

When the neural networks training completed, the value of the networks output is normalized and it needs de-

normalization transforming into the actual value. The equation is defined as follows (Eq. 3):

$$X = \hat{X} \times (X_{\max} - X_{\min}) + X_{\min}, \quad (3)$$

where, X is original value, $X_{\min}$ and $X_{\max}$ are minimum and maximum values in the series, $\hat{X}$ is the normalized data.

The training/testing data split can have a significant impact on the results of the model. The cross-validation technique (Chang et al. 2013; Fijani et al. 2013) is used to divide the data sets. Based on this approach, 50 data points were divided in two sets; training 70% (35 samples) and testing 30% (15 samples).

The neuralnet function is used in R programming for the development of ANN model. A vector is specified by number of hidden layers and hidden neurons in each layer. The resilient backpropagation algorithm with weight back tracking was used through sensitive analysis for 1–30 hidden neurons. Through the sensitivity analysis it is found that the seven neurons show the optimum R^2 , relative mean squared error (RMSE) and mean absolute relative error (MARE) for all the indices. So, further investigation the vector (13, 7, 5) induces a neural network with specified number of neurons is used. The resilient back propagation with weight backtracking algorithm with cross entropy differentiable error function is considered and logistic function is used as an activation function with the assumption that logically output is not linear.

Act criteria

The adequacy of the ANN is evaluated by considering the R^2 defined on the basis SAR, RSC, MAR, KR and %Na

estimation errors, also the values RMSE and MARE are used as the index to check the knack of model. The acceptance criterion rests on the quantitative error passing into the calculations and observations, including maximum R^2 , minimum RMSE and MARE value of error, being less than 1 and the relative error is computed.

The act of the simulation of training and testing sets was evaluated by following measures of goodness of fit: R^2 , RMSE and MARE shown in Eqs. 4, 5 and 6, respectively. The R^2 express the degree of the relation when two variables are linearly related. If R^2 is close to 1, there is good correlation between the dependent and independent variables.

$$R^2 = \left[\sum_{i=1}^N (P_i - \bar{P})(O_i - \bar{O}) \right]^2 \left[\sum_{i=1}^N (P_i - \bar{P})^2 (O_i - \bar{O})^2 \right]^{-1}, \quad (4)$$

$$RMSE = \left[N^{-1} \sum_{i=1}^N (P_i - O_i)^2 \right]^{0.5}, \quad (5)$$

$$MARE = \frac{1}{N} \sum_{i=1}^N \frac{|O_i - P_i|}{O_i} \times 100, \quad (6)$$

where, N is the number of observations, P_i is the predicted values, O_i is the observed data, $\bar{P}$ and $\bar{O}$ are the mean values for P_i and O_i , respectively.

Results and Discussion

The Descriptive statistics of physicochemical parameters are computed and represented in Table 2.

Table 2 Descriptive statistics of the physicochemical parameters

Variable	Mean	Minimum	Maximum	Standard deviation	Standard error	Kurtosis	Skewness	Range
pH	7.48	7.10	7.80	0.17	0.02	−0.74	−0.08	0.70
EC	4889.58	843.00	64,963.00	13,201.70	1867.00	14.80	3.97	64,120.0
Ca	44.70	11.17	101.20	20.96	2.96	1.10	0.99	90.03
Mg	32.34	9.10	61.51	11.83	1.67	−0.01	0.08	52.41
Na	110.68	29.10	315.90	71.90	10.17	0.56	1.09	286.80
K	2.72	1.37	3.90	0.63	0.09	−0.58	−0.09	2.53
CO ₃	17.80	0.00	60.00	12.50	1.77	1.54	0.89	60.00
HCO ₃	186.60	80.00	470.00	77.92	11.02	5.03	1.96	390.00
Cl	169.49	59.70	495.10	81.66	11.55	5.17	1.96	435.40
NO ₃	3.36	0.11	7.11	1.72	0.24	−0.73	−0.15	7.00
SO ₄	13.00	3.13	37.06	7.56	1.07	0.50	0.83	33.93
TDS	580.69	337.74	1208.28	186.58	26.39	3.04	1.68	870.54
TH	244.63	98.53	425.09	71.66	10.13	0.07	0.00	326.56

All values expressed in mg/L except pH and EC

Fig. 2 Optimized ANN model

These all parameters are used as input layers with 7 hidden neurons to evaluate the groundwater suitability for the irrigation purpose.

The ANN plot shows the value of the function, in terms of training the iteration number (Fig. 2).

The applicability of ANN was investigated to predict the groundwater suitability for irrigation. The 50 observation wells in Nanded tehsil are studied. In ANN predicting model the selection of input variables is significant step, as it affects the model performance. In this context, selected all the physicochemical parameters such as pH, EC, TDS, Ca, Mg, Na, K, Cl, CO_3 , HCO_3 , SO_4 and NO_3 were used as input variables for the prediction of different indices which represents the suitability of groundwater for irrigation purpose.

The accuracy of MLP is employed and the results of the ANN model are summarized in Table 3. The RMSE, R^2 and MARE values of the predicted SAR model in training step were 0.17, 0.997 and 13.14%, respectively.

Table 3 Accuracy of developed ANN model for the prediction of different irrigation water suitability indices in training steps

Output result	R^2	RMSE	MARE (%)
SAR	0.997	0.17	13.14
RSC	0.997	0.15	9.501
MAR	0.997	0.19	14.66
KR	0.997	0.2	13.58
%Na	0.997	0.11	9.626

The RMSE, R^2 and MARE values of the predicted RSC model in training step were 0.15, 0.997 and 9.50%, respectively. The RMSE, R^2 and MARE values of the predicted MAR model in training step were 0.19, 0.997 and 14.66%, respectively. The RMSE, R^2 and MARE values of the predicted KR model in training step were 0.2, 0.997 and 13.58%, respectively. The RMSE, R^2 and MARE values of the predicted %Na model in training step were 0.11, 0.997 and 9.62%, respectively.

The Table 3 confirms that the MLP performance is in general, accurate and reliable. The high accuracy of the developed model is due to the high coefficient of determination. The sensitivity of different neurons in predicting the neural network of the model was carried out. It is observed that the seven neurons showing the less error for prediction of the groundwater irrigation suitability indices.

Figure 3a–e represents the different plots through MS-Excel of measured and predicted indices of different groundwater irrigation suitability. It can be seen that, from these figures for the testing phase model is closer to exact fit line. The results of the model computed through MS-Excel are given in Table 4. The RMSE, R^2 and MARE values of the predicted SAR model in training step were 0.22, 0.97 and 30.34%, respectively. The RMSE, R^2 and MARE values of the predicted RSC model in training step were 0.00, 1.00 and 0.28%, respectively. The RMSE, R^2 and MARE values of the predicted MAR model in training step were 21.81, 0.96 and 5.38%, respectively. The RMSE, R^2 and MARE values of the predicted KR model in training step were 0.16, 0.95 and 36.31%, respectively. The RMSE, R^2 and MARE values of the predicted %Na model in training step were 10.34, 0.99 and 5.84%, respectively. The association between SAR, RSC, MAR, KR and %Na ratios measured and observed values in the form of linearity and coefficient of determination indicates the reliability of the evaluated model.

Spatial distribution of indices

SAR is an important ratio to determine the water suitability for irrigation. It measures the sodium concentration over calcium and magnesium content in water. The excess sodium is hazardous to the crop due to its cementing effect which affects soil permeability and structure. From Table 5 it is confirmed that the predicted and measured values are nearly similar. The values are below ten and hence suitable for irrigation (Richards 1954). The spatial distribution map (Fig. 4a) of predicted

Fig. 3 Measured and Predicted values of **a** SAR, **b** RSC, **c** MAR, **d** KR and **e** %Na

and measured values of SAR represents the similar distribution. The soil permeability is assessed by the concentration of carbonate and bicarbonate over calcium and magnesium ions by RSC ratio. The carbonate and bicarbonate ion precipitates the calcium and magnesium. Positive RSC value indicates that sodium built is

possible which affects soil permeability (Eaton 1950). The ANN model is best fitted for RSC as it predicts the exact value as shown in Table 5 and spatial distribution map (Fig. 4b).

The present ANN model is best fit for % sodium and MAR ratio. It is observed that predicted and measured

Fig. 3 continued

Table 4 Evaluation results of prediction different ratios (using MS-Excel)

Output ratio	R^2	RMSE	MARE (%)
SAR	0.97	0.22	30.34
RSC	1.00	0.00	0.28
MAR	0.92	21.81	5.38
KR	0.90	0.16	36.31
%Na	0.98	10.34	5.84

values of % sodium and MAR are almost same. The spatial distribution of these two indices is quite similar as represented in Fig. 4c and e, respectively.

Kelly ratio is used to measure sodium contents against calcium and magnesium. The high contents of sodium can cause undesirable effects on soil properties. From Table 5 it is confirmed that measured and predicted average KR values are similar but there is a variation in spatial distribution and it is clearly observed in Fig. 4d.

Table 5 Descriptive statistics of measured and predicted values of irrigation water suitability indices

Parameter	Measured					Predicted				
	SAR	RSC	KR	MAR	%Na	SAR	RSC	KR	MAR	%Na
Min	0.67	-4.97	0.17	20.09	15.07	0.07	-4.97	-0.32	18.10	11.36
Max	9.64	4.70	4.64	78.76	82.36	8.99	4.70	3.81	77.71	84.54
Average	3.30	-1.28	1.18	55.00	46.42	3.30	-1.28	1.18	55.00	46.42
SD	2.43	2.02	1.08	14.35	18.00	2.39	2.02	1.03	13.78	17.79

Fig. 4 Spatial distribution of measured and predicted ratio **a** SAR, **b** RSC, **c** MAR, **d** KR and **e** %Na

Conclusion

The study demonstrated that, ANN provides vigorous tool for predicting SAR, RSC, MAR, KR and %Na values in 50 observation wells of Nanded tehsil. A neural network model consisting 13 input neurons, 7 hidden neurons and 5 output variables were used for computing ground water suitability for irrigation in study area. The SAR, MAR and KR values increases due to excessive use of chemical fertilizers. The RSC and %Na were found to be more precise as compared to SAR,

MAR, and KR values as per RMSE, R^2 and MARE values of the predicted values. EC was most significant parameter within input parameters used in the modeling. The proposed model gave satisfactory fit to the experimentally obtained dataset in 50 observation wells. A comparison between different irrigation indices computed through ANN model and MS-Excel indicates that, it is capable of improving the accuracy to determine the suitability of ground water irrigation purpose. The spatial distribution map represents the accuracy of measured and predicted values. Hence, the proposed ANN model is

Fig. 4 continued

applicable to measure the ground water suitability for irrigation in easier way. This model can be considered by local development authorities for better management of groundwater resources.

Acknowledgements This research work was funded under minor research project scheme by Swami Ramanand Teerth Marathwada University, Nanded. The authors wish to thank The Director, School of Earth Sciences, for provided necessary facilities during the research work.

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