Identifying most influencing input parameters for predicting chloride concentration in groundwater using an ANN approach

Youssef Kassem[1,2] · **Hüseyin Gökçekuş**[1] · **Mahmoud R. M. Maliha**[1]

Abstract

Assessment of groundwater quality at a specific location is an important step to provide adequate information about water management and sustainable development. Several variables affect groundwater salinity, expressed by chloride concentration, prediction; therefore, identification of the most significant parameters for accurate prediction is an important research area. In the present study, artificial neural network (ANN) models with various combinations of input parameters were developed to determine the most significant parameters that influence chloride concentration prediction. To achieve this, the variables affecting chloride concentration (recharge rate (RR), abstraction (A), abstraction average rate (AVR), lifetime (LT), groundwater level (GWL), aquifer thickness (AT), depth from the surface to well screen (DSWS), distance from sea shoreline (DSSL)) and climate parameters (total rainfall (R), relative humidity (RH), minimum temperature (Tmin), maximum temperature (Tmax), average temperature (Tavg), average wind speed (W), minimum wind speed (Wmin), and maximum wind speed (Wmax)), in addition to initial chloride concentration (ICC), were considered as input variables. The output variable was the final chloride concentration (FCC). 17 ANN models were developed by varying the identified input parameters. Additionally, the coefficient of determination (R^2) and root mean squared error (RMSE) were used to select the best predictive model. The results demonstrate that the ANN 5 model with the combinations of [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, W] produced excellent estimation in predicting the value of final chloride concentration with reported values of 0.977 and 0.022 for R^2 and RMSE respectively. The proposed approach illustrates how the ANN modeling technique can be used to identify the key variables required for the most significant parameters affecting chloride concentration.

Keywords Chloride concentration · Gaza Strip · Groundwater salinity prediction · Neural network models · Palestine

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✉ Youssef Kassem
  yousseuf.kassem@neu.edu.tr;
  youssef.kassem1986@hotmail.com

  Hüseyin Gökçekuş
  huseyin.gokcekus@neu.edu.tr

  Mahmoud R. M. Maliha
  engmahmoudrafiq@gmail.com

1 Department of Mechanical Engineering, Engineering Faculty, Near East University, (via Mersin 10, Turkey), 99138 Nicosia, Cyprus

2 Department of Civil Engineering, Civil and Environmental Engineering Faculty, Near East University, (via Mersin 10, Turkey), 99138 Nicosia, Cyprus

Introduction

Water scarcity has led to the wide use of reclaimed water for irrigation worldwide, which may threaten groundwater quality. Additionally, the scarcity and pollution of groundwater are still one of the most important topics nowadays (Clemens et al. 2020; Rezaei et al. 2019; Jia et al. 2018). Additionally, the growth of population, urbanization, industrialization, and climate change have led to reducing the availability of groundwater resources. According to Döll et al. (2012), groundwater source is one-third of all freshwater withdrawals used for supplying 36% for domestic, 42% for agricultural, and 27% for industrial purposes.

Furthermore, scientific researchers worldwide have studied the effect of climate parameters such as rainfall under various conditions on the groundwater level, groundwater availability, and physic-chemical properties of groundwater (Nazarenko 2006; Jan et al. 2007; Hong and Wan 2010;

Abdullahi et al. 2015; Abdullahi and Garba 2015; Hsieh et al. 2015; Tashie et al. 2016; Cai and Ofterdinger 2016; Kotchoni et al. 2018; Rahman et al. 2018; Mohan et al. 2018; Li et al. 2019; Rajendiran et al. 2019; Nemaxwi et al. 2019; Patil et al. 2020; Dey et al. 2020; Akbari et al. 2020). For instance, Hsieh et al. (2015) studied the variation characteristics of the groundwater level using an analytical solution generated by linearizing the one-dimensional non-linear Boussinesq equation. The authors concluded that large rainfall intensity with tidal waves had a significant effect on the fluctuation of the grown water level. Rahman et al. (2018) investigated the impact of temperature and rainfall changes on agriculture and groundwater resources in Bangladesh. The results showed that the moisture content of the soil and recharging of the groundwater were influenced by the amount of rainfall. Li et al. (2019) explored the impact of rainfall infiltration in rain gardens on groundwater level and water quality using Visual MODFLOW. The results showed that the centralized infiltration of rainwater gardens was not affected by the safety of groundwater at a specific scale, and it is conducive to the conservation of groundwater sources. Rajendiran et al. (2019) analyzed the hydro-geochemistry properties of coastal groundwater related to variation in water level in response to the rainfall pattern. The authors concluded that the rainfall and water level gave a significant variation in the geochemical process of groundwater in the coastal aquifer system. Akbari et al. (2020) investigated the effects of temperature, precipitation, and groundwater salinity changes on farmer's income risk, water shadow price, and economic, social, and environmental indicators in the Qazvin region. The results showed that climate change and groundwater salinity increasing have negatively affected income risk and water shadow prices. Dey et al. (2020) examined the relationship between the long-term rainfall and the corresponding water table variation over the Varanasi district in Uttar Pradesh, India. The results showed that rainfall variations were found to be one of the major causes behind the fluctuation of the water table in the selected area.

Moreover, in recent years, empirical approaches like machine learning models and mathematical models have been used as powerful modeling tools in the estimation of physicochemical properties of groundwater (Abuamra et al. 2020; Hasda et al. 2020; Sahour et al. 2020; Poursaeid et al. 2020; Wagh et al. 2018; Nozari and Azadi 2017; Alagha et al. 2017; Barzegar and Moghaddam 2016; Nasr and Zahran 2014; Banerjee et al. 2011). For example, Hasda et al. (2020) predicted the weekly level of groundwater using a non-linear autoregressive model with exogenous inputs (NARX) of artificial neural network (ANN) in the drought-prone Barind Tract, Bangladesh. The results demonstrated that rainfall is one of the potential input parameters influencing the weekly level of groundwater in the area. Sahour et al. (2020) investigated the relationship between groundwater

salinity and its controlling factor (aquifer transmissivity, distance from the sea, the mean annual precipitation, the mean annual evaporation, elevation, and the depth to the water table) using extreme gradient boosting, deep neural network and multiple linear regression methods. The results showed that extreme gradient boosting gave the highest performance compared to the other methods. Wagh et al. (2018) developed an Artificial Neural Network (ANN) model to predict the nitrate concentration in groundwater of Kadava River basin, India using input variables such as EC, TDS, TH, Mg, Na, Cl, HCO3, and SO4 as an input variable. The authors concluded that the proposed model may helpful for similar studies in other areas to estimate the water contamination problems. Barzegar and Moghaddam (2016) evaluated the accuracy of different neural computing in the prediction of groundwater salinity expressed by electrical conductivity using Ca^{2+}, Mg^{2+}, Na^+, SO_4^{2-} and Cl^- as input variables. The results showed that the committee neural network gave the highest performance compared to other proposed models for predicting groundwater salinity. Nasr and Zahran (2014) artificial neural network (ANN) with a feed-forward back-propagation to estimate the groundwater salinity using pH value as an input variable for the proposed model. The results found that the R-squared value was 0.64, 0.67, and 0.9 for training, validation, and test, respectively.

In this context, this study's goal was to identify the most relevant parameters for predicting the groundwater salinity expressed by chloride concentration. To achieve this aim, an artificial neural network (ANN) with feed-forward back-propagation models were developed to find the most influencing input parameter for accurate prediction of chloride concentration in groundwater of the Gaza Strip. To this aim, the variables affecting chloride concentration (recharge rate, abstraction, abstraction average rate, lifetime, groundwater level, aquifer thickness, depth from the surface to well screen, and distance from sea shoreline) and climate parameters (total rainfall, relative humidity, minimum temperature, maximum temperature, average temperature, average wind speed, minimum wind speed, and maximum wind speed) were considered as input parameters. To check the prediction accuracy, 17 ANN models were developed by varying the identified input parameters. The coefficient of determination (R^2) and root mean squared error (RMSE) were used to select the best predictive model.

To the best of our knowledge, there are no studies in the Gaza Strip about evaluating the accuracy of chloride concentration prediction using the ANN model with different combinations of input parameters. At last, this work introduces another contribution: the application of ANN to identify the most relevant parameters for chloride concentration prediction in groundwater of Gaza Strip, Palestine. A flowchart given in Fig. 1 illustrates the analysis procedure of this study.
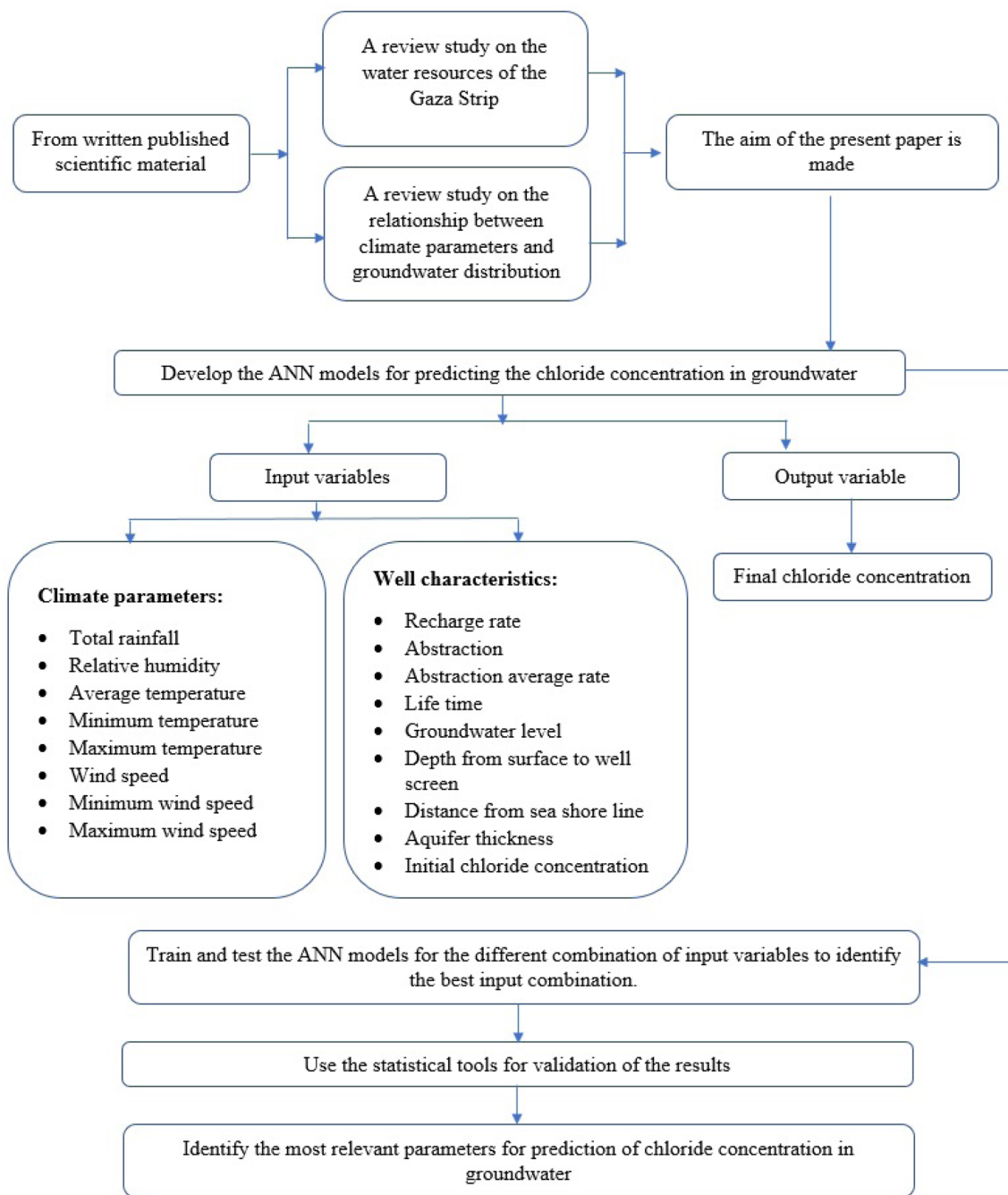
Fig. 1 Schematic description for the proposed methodology

Material and methodology

Study area and data sets

The Gaza Strip is located on the southwestern side of the State of Palestine, where it overlooks the Mediterranean Sea from the west and from the south to Egypt, where the Sinai desert is located as shown in Fig. 2. The geographical location of the Gaza Strip with coordination of Latitude N 31° 26′ 25″ and Longitude E 34° 23′ 34″ and the area of the Gaza strip is 365 km^2. It also consists of five provinces Northern, Gaza, Middle, Khan Yunis, and Rafah. Due to the tremendous population, the water demand in the Gaza strip is sharply increased (Gampe et al. 2016). The main water source is groundwater and its source is from the coastal reservoir only (Jabal et al. 2014). Coastal reservoir layers mainly consist of sandy sediments, gravel, and sandstone, with overlays of mud and baskets
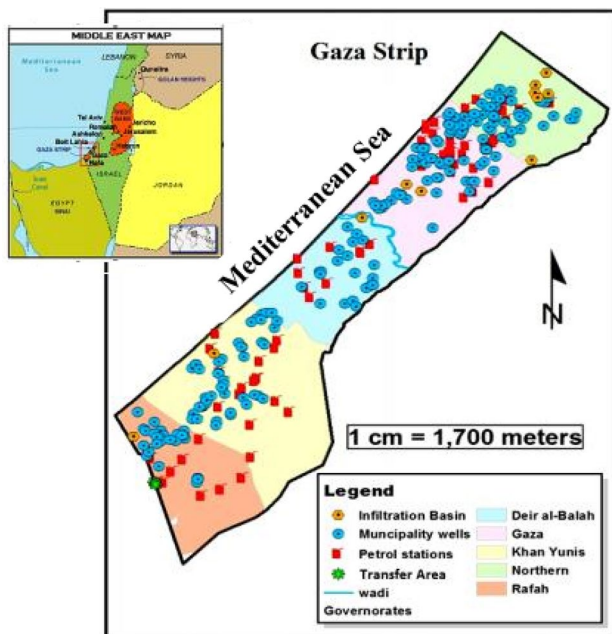
Fig. 2 Gaza Strip map (Ghabayen et al. 2013)

(Ubeid 2011; Elmanama et al. 2016; Alastal et al. 2015). It also consists of sand, gravel, mud, and sandstone (Ubeid 2011; Elmanama et al. 2016; Alastal et al. 2015). Generally, rainfall is the main source for the groundwater, and accordingly, the increase and distribution of rain will have a positive impact on the groundwater, whether in terms of quantity or quality (Şen 2015). It is located in an arid and semi-arid zone with an annual precipitation range between 230 to 410 mm and the rainfall occurs during the period between October and April (Abuzerr et al. 2019a, b). The quantities of water fed to the underground reservoir in the Gaza Strip are estimated at 76 million cubic meters, which constitutes 138% of the general average feeding rate of about 55 million cubic meters annually (Efron et al. 2018). Additionally, the annual recharge of 60 MCM and a deficit of approximately 55 MCM/year have led to reducing in the available quantities of groundwater as well as degradation of water quality (Abd-Elaty et al. 2020; Shatat et al. 2018). Additionally, Shomar et al. (2010) found that the concentration of chloride element as an indicator of salinity ranges horizontally over a sector area between less than 100 mg/l in the western regions of the Gaza Strip. Furthermore, according to the Palestinian Water Authority (2018), most of the freshwater with little salinity is largely concentrated in the strange areas of the governorates of Gaza (Camp Beach) and the North Governorate (west of Jabalia and Beit Lahia) as well as in the western areas of Khan Yunis Governorate (Al-Amal and Al-Mawasi neighborhood). Additionally, in the central region of the Gaza Strip, the nature of the underground reservoir is semi-salty,

where the concentration of chloride in general ranges between 1000–3000 mg/l, as the nature of the aquifers has little permeability with a slow flow of groundwater and reaches the degree of stagnation in the western side of Deir al-Balah is high, bringing the concentration of chloride to more than 1000 mg/l (Palestinian Water Authority 2018). In addition, based on the previous scientific studies related to Gaza Strip (Al-Ghuraiz and Enshassi 2005; Yassin et al. 2006; Aish 2014; Zaqoot et al. 2016; Mattar 2018; Abu-Alnaeem et al. 2018; Abuzerr et al. 2019a, b; Alnaeem et al. 2019; Baba et al. 2020; Abuzerr et al. 2020; Seyam et al. 2020; Fathi Ubeid and Al-Agha 2020; Qrenawi and Shomar 2020; Ziara 2020; Ricolfi et al. 2020), it was found that seawater intrusion along the coastline, and saltwater up-coning inland highly influenced the groundwater salinity of areas. In addition, the highest and the lowest levels of salinization and the highest level of nitrate pollution were recorded in the northern area.

For this research work, the variables affecting the chloride concentration including recharge rate, abstraction, abstraction average rate, lifetime, groundwater level, aquifer thickness, depth from the surface to well screen (the depth from the surface to well screen was estimated by subtracting the level of well screen from top screen level of study well), and distance from sea shoreline were collected from 56 wells distributed over Gaza Strip. Table 1 shows the characteristics of the selected well. It should be noted that the chloride concentration was measured in two phases (A and B). Phase A called a dry season, which starts from April to September and Phase B called the wet season, which starts from October to March. Additionally, the climate parameters in terms of total rainfall, relative humidity, minimum temperature, maximum temperature, average temperature, average wind speed, minimum wind speed, and maximum wind speed are adopted for identifying the most influenced parameter that affects the chloride concentration in the groundwater. The study data covers a period from 2009–2015.

Correlation analysis

In the current study, Pearson product-moment (Javari 2017) correlation is used to investigate the relationship between final chloride concentrations (CC), variables affecting the chloride concentration, and climate parameters (see Table 2) followed by a parametric method for normal distribution. Additionally, in spatial correlation, meteorological parameters are utilized for correlation with the final chloride concentrations data followed by a non-parametric method for non-normal distribution series (Spearman correlation coefficient) to test the spatial statistical significance of the results (Javari 2017). Correlation coefficients and *P*-values are calculated using Minitab 17 software.

Table 1 Well characteristics used in this study

Well number	Year operation	Distance from sea shoreline [m]	Depth from the surface to well [m]	Aquifer thickness [m]	Sub-aquifer
D/67	1987	2.4	79	80	C
A/180	1983	3.1	82	90	C
D/73	1996	2.1	79	53	A
D/72	1998	2.9	46	41	A
E/61	1974	1.3	43	40	A
A/185	1987	3.6	80	95	C
D/71	1998	2.7	50	43	A
C/127	1987	5.6	75	115	A
D/74	1997	2	81.4	50	B2
D/70	1996	3	42	40	A
D/69	1993	2.7	40	58	A
E/6	1971	4.6	31	100	C
E/142	1998	2.1	36.6	52	A
D/68	1988	2.6	72	58	A
D/60	1993	3.3	45	43	A
C/79	1970	6.4	63.6	90	A
E/4	1960	4.7	34	124	A
E/154	1975	1.7	92	50	B2
C/128	1984	7.7	110	86	A
E/157	1988	2.6	38	58	A
E/156	1987	4.2	70	80	C
E/90	1987	3.6	70	50	A
R/162B	1971	1.7	70	30	B1
C/76	1972	6.5	38	90	A
R/162L	1985	1.7	110	45	B2
R/162LA	1986	1.6	55.9	30	A
R/162G	1973	2.3	90	70	A
R/162HA	1990	2.4	85	69	A
R/162H	1987	2.4	90	69	A
Q68	1999	5	73	104	A
R/112	1965	0.6	36	30	A
R/25A	1950	4.4	85	109	A
R25B	1950	4.5	52	109	A
R/113	1965	0.8	32	40	A+B
R/25D	1972	4.5	50	109	A
R/25C	1957	4.5	45	109	A
R/254	1984	1.4	46	36	A
R/265	1995	1	39	40	B1
R/74	1993	5	45	100	A
R/75	1988	5	62	100	A
S/69	1989	5.1	72.7	71	A
J/146	1987	4.8	62	78	A
L/179	1987	3	86	35	C
L/159A	1998	2.5	62	30	B2
L/159	1974	2.4	42	40	B1+B2
L/87	1970	3.4	82	45	C
L127	1987	3.4	60	30	A
L/43	1971	3.9	79	69	A
L/176	1988	3.4	110	50	C
L/41	1971	5.1	54	60	A

Table 1 (continued)

Well number	Year operation	Distance from sea shoreline [m]	Depth from the surface to well [m]	Aquifer thickness [m]	Sub-aquifer
P/139	1998	0.8	30	30	C
P/144	1993	2.8	80	30	C
P/145	1996	4	75	40	C
P/138	1995	3.6	67	33	B1
P/124	1987	3.1	48	42	A
P/15	1987	3.6	18	34	A

A unconfined aquifer, *B1, B2, C* confined towards the sea

Table 2 Parameter descriptions and units

Number	Variables	Parameter	Parameter description	Unit
1	–	ICC	Initial chloride concentration	mg/l
2	Well characteristics	RR	Recharge rate	mm/m^2/month
3		A	Abstraction	m^3/h
4		AVR	Abstraction average rate	mm/m^2/month
5		LT	Lifetime	year
6		GWL	Groundwater level	m
7		DSWS	Depth from the surface to the well screen	m
8		AT	Aquifer thickness	m
9		DSSL	Distance from the sea shoreline	km
10	–	FCC	Final chloride concentration	mg/l
11	Climate parameters	R	Total rainfall	mm
12		RH	Relative humidity	%
13		Tavg	Average temperature	°C
14		Tmin	Minimum temperature	°C
15		Tmax	Maximum temperature	°C
16		W	Average wind speed	m/s
17		Wmin	Minimum wind speed	m/s
18		Wmax	Maximum wind speed	m/s

Simulation using the ANN model

The ANN is a powerful mathematical modeling tool especially for complex systems (Kassem et al. 2019a, b). ANNs have long been used as an alternative methodology in different areas such as function approximation and so on. Many types of ANNs have been developed by scientific researchers of which the Multilayer feed-forward neural network (MFFNN) is one of the most popular ANNs. The node numbers in the input and output layers are estimated by the nature of the problem.

Multilayer feed-forward neural network (MFFNN)

In general, MFFNN consists of an input layer, one or two hidden layers, and an output layer. In the present study, the input layer is composed of initial chloride concentration (ICC), recharge rate (RR), abstraction (A), abstraction average rate (AVR), lifetime (LT), groundwater level (GWL), aquifer thickness (AT), depth from the surface to well screen (DSWS), distance from sea shoreline (DSSL) total rainfall (R), relative humidity (RH), minimum temperature (Tmin), maximum temperature (Tmax), average temperature (Tavg), average wind speed (W), minimum wind speed (Wmin), and maximum wind speed (Wmax). The output layer has one node, which is the final chloride concentration (FCC). To determine the optimum number of the node in the hidden layer, the trial and error approach is used.

Moreover, the structure of ANN, which has been used in this paper, is shown in Fig. 3. In this study, the number of epochs and performance goal were 100,000 and 0.001, respectively. Besides, the number of the hidden layers varied between 1 and 10, while the number of neurons varied between 5 and 50 neurons.
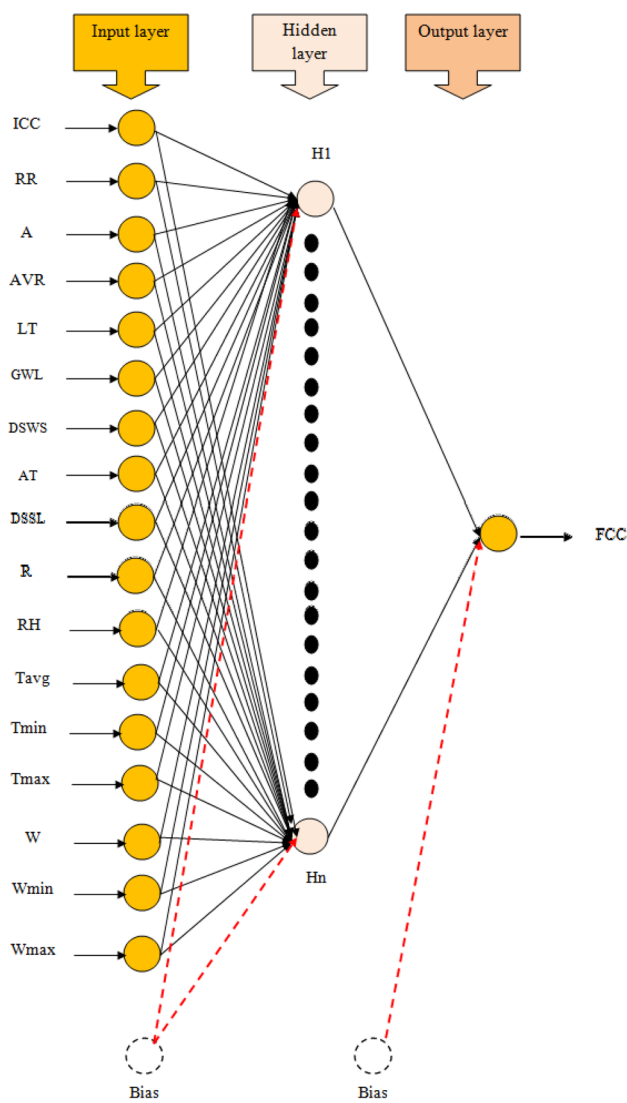
Fig. 3 Structure of ANN used for modeling of FCC

Training and testing

In this work, TRAINLM is used as a training function that updates the weight and bias values of the neuron connections according to Levenberg–Marquardt (LM) optimization. The backpropagation algorithm is used as a learning algorithm and it is a gradient descent algorithm. The logistic-sigmoid (*logsig*) and tangent-sigmoid (*tansig*) are used as activation functions whose outputs lie between 0 and 1 and are defined as

$$logsig = \frac{1}{1 + e^{-x}} \tag{1}$$

$$tansig = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

The key step for developing an ANN is the training procedure, where the weights and biases are adjusted to minimize the difference between the output of the ANN and the actual value. To find the best performance for the ANN trained model, the mean squared error (MSE) is used.

Equation (3) is used to normalize the data in the range of 0–1 and Eq. (4) is used to return the data to the original values after the simulation.

$$x_n = \frac{x_{actual} - x_{min}}{x_{max} - x_{min}} \tag{3}$$

$$x_{actual} = x_n(x_{max} - x_{min}) + x_{min} \tag{4}$$

Final chloride concentration prediction with selected inputs

The methodology used in this study (see Fig. 4) is divided into three stages: (1) collect the database; (2) Develop ANN models able to estimate the FCC; (3) Implement a comparative study between the simulated and actual database. The Matlab software was used for the application of the artificial neural network. By trial and error, the optimum number of nodes in the hidden layers, the most suitable transfer function, and the number of neurons are determined. To obtain the best performance results, various ANN models are designed.

In this research, a conventional data division technique was used to divide the data, whereby the sets were divided on an arbitrary basis and the statistical properties of the respective data sets were not considered. Approximately 80% of the data was used for training, while the remaining 20% was reserved for testing. The training data was used to train the ANN models with the LM algorithm. The testing data do not affect training and provide an independent measure of network performance during and after training. Moreover, Eq. (3) was used to normalize the data for improving the performance of the ANN model. Table 3 lists the number of inputs used to develop the ANN models.

Appraisal of the developed models

In general, the performance measures are utilized to select the "better" predictive model. The following statistical indicators are widely used to assess the predictive power of ANN.

Coefficient of determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (a_{a,i} - a_{p,i})^2}{\sum_{i=1}^{n} (a_{p,i} - a_{a,ave})^2} \tag{5}$$

Mean squared error (MSE)

Fig. 4 The flowchart of the ANN-based method prediction procedure
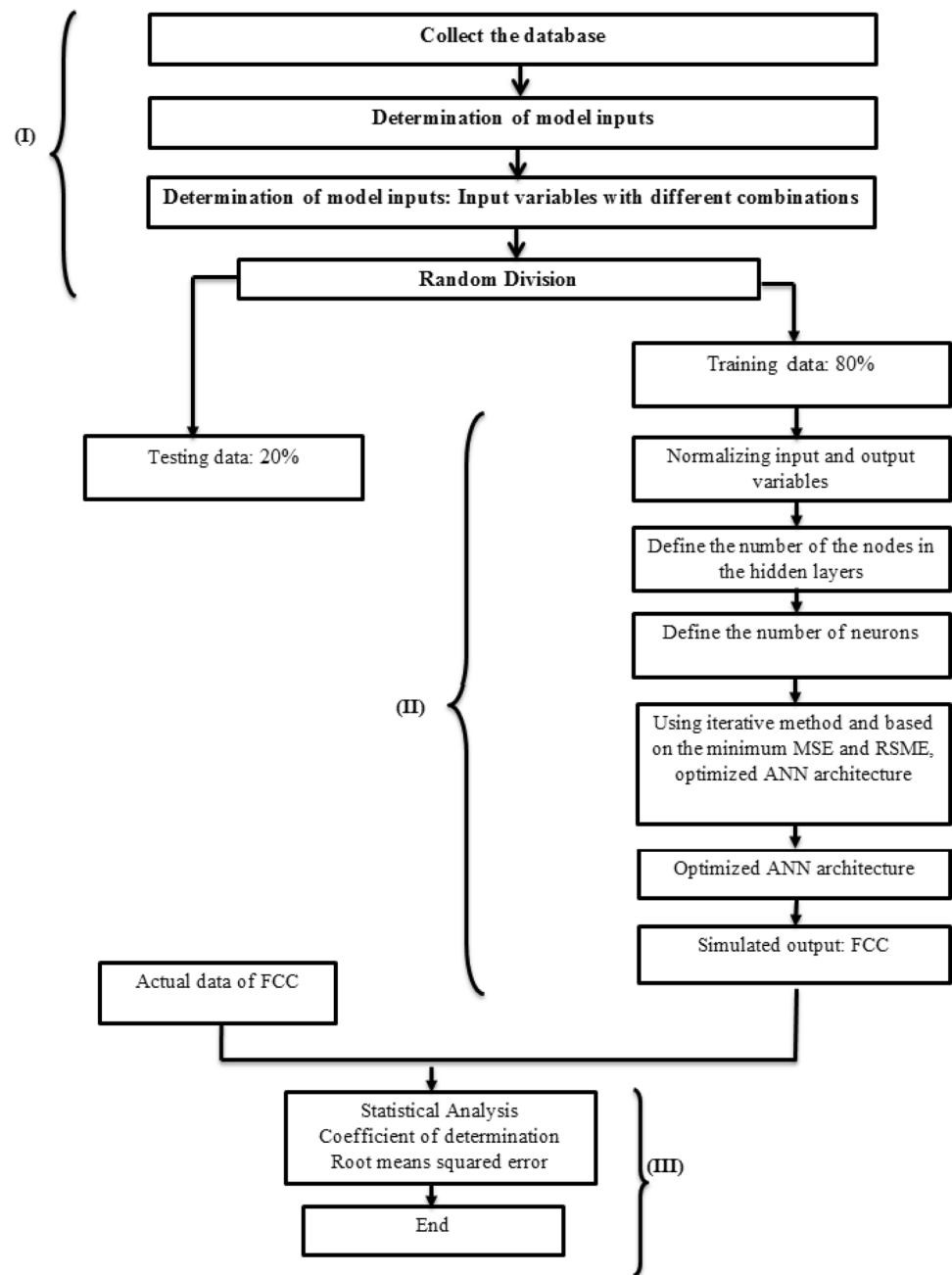
$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(a_{a,i} - a_{p,i}\right)^2 \tag{6}$$

Root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(a_{a,i} - a_{p,i}\right)^2} \tag{7}$$

where n is the number of data, $a_{p,i}$ is the predicted values, $a_{a,i}$ is the actual values, $a_{a,ave}$ is the average actual values and i is the number of input variables.

Results and discussions

Descriptive statistics of collected data

As mentioned previously, the Gaza Strip has very limited water resources. As well, rainfall is the main source of the groundwater, and accordingly, the increase and distribution of rain will have a positive impact on the groundwater, whether in terms of quantity or quality. Thus, the monthly rainfall (R) data are analyzed statistically in this section. The statistical characteristics including arithmetic mean (Mean) standard deviation (SD), coefficient of variation

Table 3 ANN models developed in this study for predicting FCC

Model	Input
ANN 1.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL
ANN 2.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R
ANN 3.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, RH
ANN 4.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, Tavg
ANN 5.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, W
ANN 6.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, RH
ANN 7.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, Tavg
ANN 8.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, W
ANN 9.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, RH, Tavg
ANN 10.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, RH, W
ANN 11.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, Tavg, W
ANN 12.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, RH, Tavg
ANN 13.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, RH, W
ANN 14.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, Tavg, W
ANN 15.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, RH, Tavg, W
ANN 16.	ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, RH, Tavg, Tmin, Tmax, W, Wmin, Wmax
ANN 17.	R, RH, Tavg, Tmin, Tmax, W, Wmin, Wmax

in percent (CV), sum, minimum (Min.), the first and third quartiles (Q1 and Q3), median and maximum (Max.) of monthly rainfall for the selected region are summarized in Table 4. It is found that the mean values of monthly rainfall are within the range of 6.4–19.71 mm. The maximum value of monthly rainfall occurred in December 2012 with a value of 76. 74 mm and the minimum value of 0 mm is recorded in summer seasons (June, July, and August) as shown in Fig. 5. Moreover, the annual variation of the meteorological parameters including mean temperature (Tavg), maximum temperature (Tmax), minimum temperature (Tmin), mean wind speed (W), minimum wind speed (Wmin), maximum wind speed (Wmax), and relative humidity (RH) are shown in Fig. 6. It is found that the mean temperature values are varied from 19.77 to 20.63 °C. Also, it is noticed that the annual maximum temperature is recorded in 2013 with a value of 25.93 °C, while the minimum temperature of 15.87 °C is obtained

in 2009 and 2014. Also, it is found that the selected region has low wind speeds, which are varied from 1.6 to 5.82 m/s.

Moreover, as mentioned previously, the study data covers a period from 2009–2015 in the selected region. The reason for choosing this period is due to the complete numeric values for all parameters considered in this study. The descriptive statistics of seasonal time series data of selected parameters (recharge rate (RR), abstraction (A), abstraction average rate (AVR), lifetime (LT), groundwater level (GWL), aquifer thickness (AT), depth from the surface to well screen (DSWS), distance from sea shoreline (DSSL), initial chloride concentration (ICC) and final chloride concentration (FCC)) are listed in Table 5. It is observed that ICC and FCC values are within the range of 56–1295 mg/l and 55–1505 mg/l, respectively. The mean and standard deviation values suggest that there is good consistency in the time series data behavior.

Table 4 Statistical estimators of the mean monthly rainfall for the period 1997–2003

Year	Mean	SD	CV	Sum	Minimum	Q1	Median	Q3	Maximum
2009	19.71	20.56	104.32	236.47	0	0.53	17.55	32.23	61.12
2010	6.66	8.91	133.81	79.91	0	0	1.85	13.9	27.1
2011	6.4	8.05	125.78	76.78	0	0	3	15.25	20.07
2012	16.43	27.34	166.37	197.19	0	0	2.89	22.32	76.74
2013	10.35	11.95	115.43	124.24	0	0	5.32	16.7	36.3
2014	19.71	20.56	104.32	236.47	0	0.53	17.55	32.23	61.12
2015	9.51	13.57	142.71	114.12	0	0	2.52	18.12	41.97
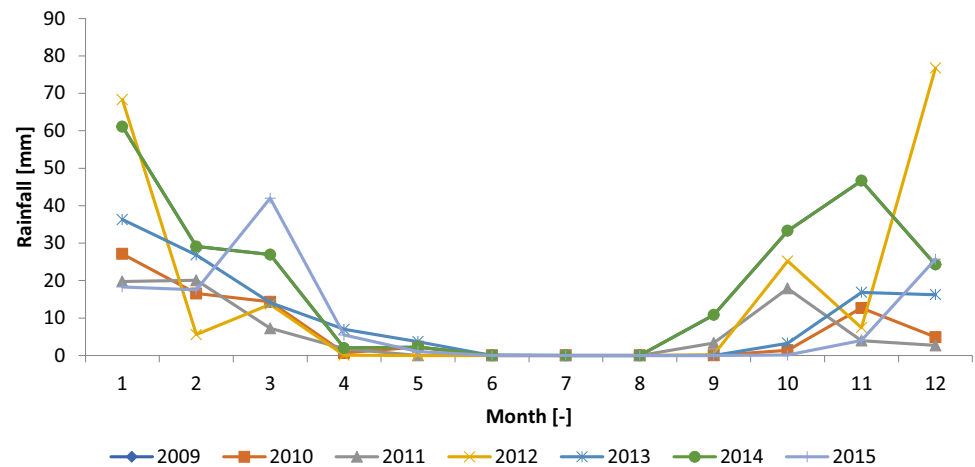
Correlation analysis

According to the data characteristics, the temporal correlation and spatial correlation coefficient between the FCC and other variables (ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, RH, Tavg, Tmin, Tmax, W, Wmin, Wmax) are computed and tabulated in Tables S1 and S2. According to Tables S1 and S2, there are considerably associated with well characteristics (ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL) and FCC because the *P*-value is less than 0.05. Furthermore, it is noticed that *P*-value is greater than 0.05, which indicated that there is no relationship between climate parameters and FCC for both temporal and spatial correlation. The authors concluded that well characteristics (ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL) are considered as the most important parameters that have a greater impact on the estimated FCC. Additionally, it is found that climate parameters have a minimum effect on FCC.

Prediction

Based on Section "Simulation using the ANN model" (correlation analysis), this section aims to determine the optimal combination set of the input parameters for predicting FCC. In the present study, 17 ANN models with a different combination of input are evaluated in this work for the FCC prediction. All the models are validated against the actual data of the FCC based on statistical measures such as RMSE, MSE, and *R*-squared. For higher modeling accuracy RMSE indices should be closer to zero but the *R*-squared value should be closer to 1. MATLAB 2015 was used to train and test the developed ANN models. To select the best architecture of the developed ANN model, the numbers of hidden layers and neurons were varied. The network with minimum MSE invalidation is called the trained ANN model. Table 6 shows the best number of hidden layers and neurons and the activation function that was chosen for each ANN model.
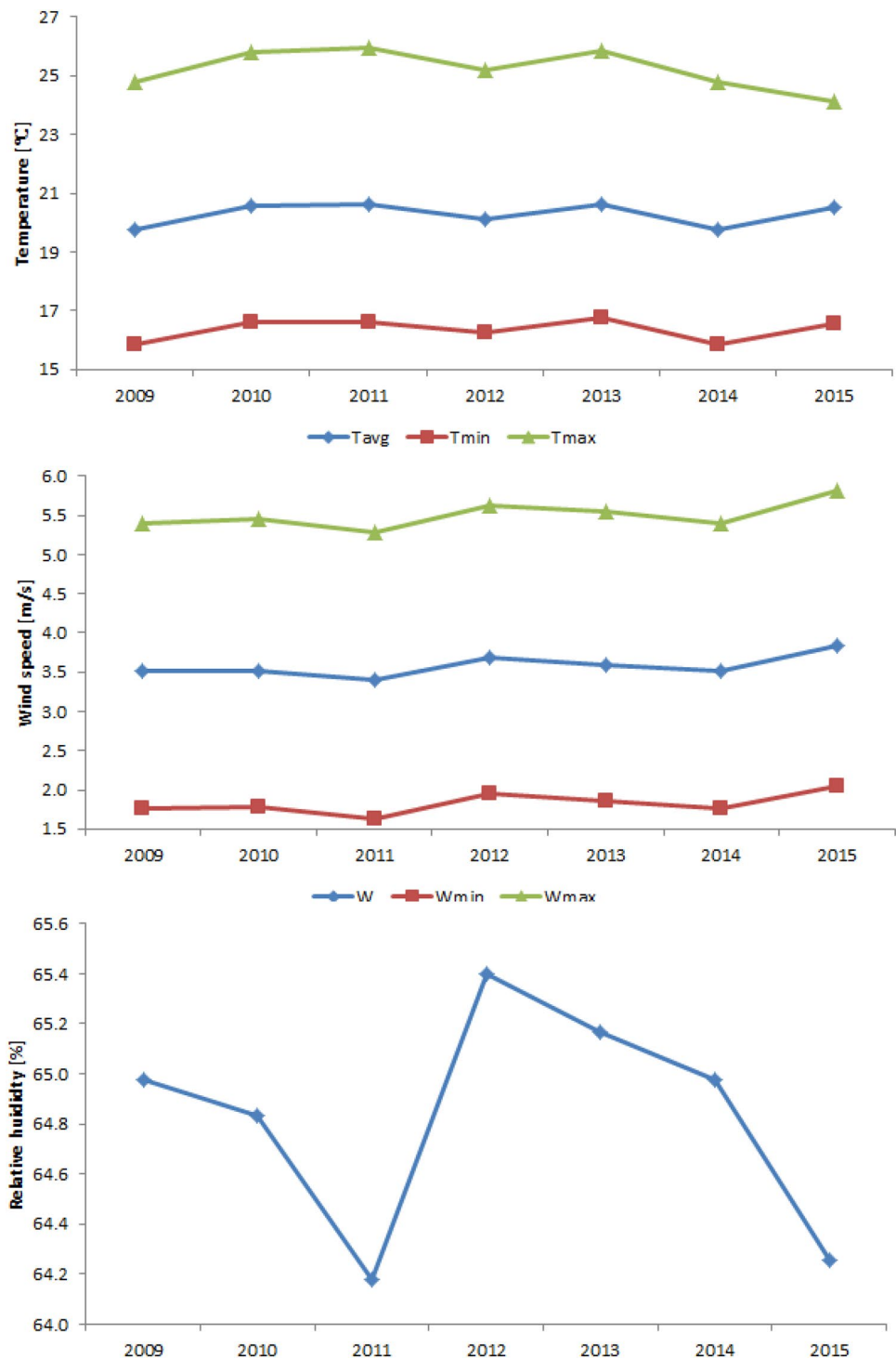
Case 1: well characteristics and no climate parameter

This section aims to evaluate individually the performance of groundwater salinity parameters as input parameters for the ANN model. The best performance of the network was obtained by training the developed ANN architecture several times until the MSE showed the minimum value. The same-trained network was tested with the new datasets to check the performance of the network. The best number of the hidden layer (HL) and neurons (NN) in the proposed model are one hidden layer and 8 neurons, respectively. Furthermore, the results show that the ANN model with *logsig* was the most successful learning algorithm for the estimation of the FCC. It is found that the values of R^2 in the training and testing processes are 0.9753 and 0.9523, respectively.

Case 2: well characteristics and one climate parameter

In this case, the climate parameters including total rainfall, relative humidity, wind speed, and temperature are added to groundwater salinity parameters and used as input variables for ANN models. Four possible combinations were considered and analyzed to find the best integration of parameters (ANN 2–ANN 5). The obtained values of the statistical parameters for both training and testing phases of ANN models with groundwater salinity parameters and one climate parameter for prediction FCC are tabulated in Table 6. It is found that the highest *R*-squared for training model is recorded for the combinations of ANN 3 [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, RH] and the lowest RMSE for testing is obtained from the combinations of ANN 5 [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, W] for predicting FCC. Moreover, out of all the formed combinations, the ANN with the combination of ANN 5 [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, W] produced the highest R^2 and lowest RMSE in estimating the seasonal FCC.

Fig. 6 Annual variation of meteorological parameters including relative humidity, temperature, and wind speed during the investigation period

Case 3: well characteristics and two climate parameters

In this case, groundwater salinity parameters and two climate parameters are considered as input. For this purpose, the ANN models (ANN 6–ANN 11) are developed to evaluate the importance of each input variable and identify the most relevant input. Table 6 presents an evaluation of the

six ANN models with different combinations of inputs and the statistical tools' performance of these models. The ANN 8 with a combination of [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, W] produces the highest *R-squared* of 0.9688 and lowest RMSE of 0.0247 for predicting FCC. Additionally, it is found that the highest RMSE is recorded for the combinations of ANN 12 [PD, AL] and the lowest

Table 5 Descriptive statistics of selected data series (2009–2015)

Parameter	Mean	SD	CV	Minimum	Maximum
ICC	345.7	280.3	81.08	56	1295
RR	1.226	0.715	58.28	0.23	2.14
A	110.4	57.3	51.89	0	198.4
AVR	19.16	5.64	29.42	12.16	28.48
LT	21.29	10.94	51.37	0	47
GWL	− 1.226	1.146	− 93.51	− 4	1
DSWS	68.23	21.12	30.95	18	110
AT	61.94	28.22	45.56	30	124
DSSL	3.474	1.477	42.52	1.3	7.7
FCC	373.2	305.7	81.9	55	1505

RMSE of 0.0298 is obtained from the combinations of ANN 9 [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL,RH, Tavg] for estimating FCC.

Case 4: well characteristics and three climate parameters

In this case, the test was performed to select the most important sets combined of groundwater salinity parameters and three climate parameters as input parameters. To achieve this, three different combinations of inputs were considered to determine and introduce the most significant one for the prediction of the FCC. It is observed that the best combination for predicting FCC is ANN 14 [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, Tavg, W] with R-squared equal to 0.9697and 0.0245 for RMSE as shown in Table 6. Also, it is found that the maximum RMSE is recorded for ANN 13 with a combination of [ICC, RR, A, AVR, LT, GWL,

DSWS, AT, DSSL, R, RH, W] for estimating FCC as shown in Table 6.

Case 5: well characteristics and four climate parameters

Table 6 presents an evaluation of the ANN model with groundwater salinity parameters and four climate parameters (ANN 15) and the statistical tools' performance of this model. The ANN 15 has shown good prediction accuracy with an R^2 value of 0.9605 and RMSE of 0.0287 for estimating FCC.

Case 6: well characteristics and eight climate parameters

All eight climate variables and groundwater salinity parameters are applied to train and test the developed ANN, named ANN 16. The statistical tools' performance during training and testing is shown in Table 6. The ANN 16 has produced high R-squared with a value of 0.9569.

Case 7: climate parameters

In this case, climate parameters are used as the input parameter for the ANN model. It is observed that ANN 17 produces the lowest value of R-squared and the high value of RMSE compared to other models. The R-squared value is approximately zero, which indicated that the model explains none of the variability of the response data around its mean. This result has been proven by the correlation analysis.

Moreover, Table 6 presents the ranking of the ANN models for predicting FCC based on the RMSE. Hence, based on the RMSE, ANN 5 has the lowest value, which is considered

Table 6 Evaluation of the networks and Statistical tools' performance of the ANN model with different combinations

Cases	Model	HL	NN	TF	MSE	R^2-training	R^2-testing	RMSE-testing	Rank
Case 1	ANN 1	1	8	*logsig*	0.000450	0.9753	0.9523	0.0315	13
Case 2	ANN 2	1	5	*logsig*	0.000999	0.9789	0.9648	0.0266	5
	ANN 3	2	8	*logsig*	0.000584	0.9851	0.9445	0.0366	15
	ANN 4	1	8	*logsig*	0.000523	0.9820	0.9531	0.0348	14
	ANN 5	1	5	*logsig*	0.001042	0.9796	0.9770	0.0222	1
Case 3	ANN 6	2	8	*logsig*	0.001065	0.9719	0.9577	0.0288	9
	ANN 7	1	5	*tansig*	0.000529	0.9754	0.9649	0.0264	4
	ANN 8	1	8	*logsig*	0.000662	0.9768	0.9688	0.0247	3
	ANN 9	1	8	*logsig*	0.000458	0.9847	0.9581	0.0298	12
	ANN 10	2	5	*logsig*	0.000499	0.9691	0.9568	0.0292	11
	ANN 11	1	10	*tansig*	0.001644	0.9718	0.9589	0.0284	7
Case 4	ANN 12	2	5	*tansig*	0.000854	0.9748	0.9598	0.0283	6
	ANN 13	1	10	*logsig*	0.000583	0.9720	0.9300	0.0398	16
	ANN 14	1	5	*tansig*	0.000964	0.9780	0.9697	0.0245	2
Case 5	ANN 15	1	5	*logsig*	0.00058	0.9728	0.9605	0.0287	8
Case 6	ANN 16	1	5	*logsig*	0.001914	0.9721	0.9569	0.0291	10
Case 7	ANN 17	2	20	*logsig*	0.01977	0.0004	0.0066	0.1500	17

as the best model to predict the FCC of 56 well in the Gaza Strip.

The predictions of the seasonal FCC values using the best-input combination of all the ANN models, which were chosen based on the highest value of RMSE is compared with the actual values and are shown in Fig. 7. It is observed that the predicted values are mostly close to the actual values. Out of the 17 ANN models, ANN 5, ANN 14, and ANN 8 have given the best prediction with the combinations of [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, W], [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, Tavg, W] and [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, R, W], respectively. From the developed ANN models, it can be observed that the combinations consisting of wind speed and rainfall outperformed the other combinations. It can be concluded that total rainfall and wind speed are the only parameters considered in all the ANN models and this confirms that the total rainfall and wind speed of a particular location are important factors that affect the prediction of FCC.

In general, the groundwater aquifers are recharged mainly by rainfall in the Gaza Strip, thus, the rate and duration of rainfall are essential factors that affect the amount of recharge. Besides, the rain is the most important means for the replenishment of moisture in the soil water system and recharge to groundwater (Jiang and Weng 2017). Hence, the impact of climate parameters on soil moisture contents has been investigated by several scientific studies. For instance, Husain et al.

(2014) investigated the relationship between wind speed, air temperature, and soil moisture. The results indicated that the colder near-surface temperature and lower near-surface wind speed lead to an increase in the soil moisture, while lower soil moisture was associated with warmer near-surface temperature and higher near-surface wind speed. Also, Jacobson (1999) found that the lower wind speeds led to an increase in the high soil moisture contents, which decreasing average pollutant concentrations in the area. Moreover, there is a strong relationship between the evaporation rate and soil moisture contents (Li et al. 2018). According to Harris et al. (1916) wind speed is one of the most important factors that affect the evaporation rate, i.e. the increase in the wind speed leads to an increase in the rate of evaporation, which reduces the soil moisture contents. Furthermore, Back, and Bretherton (2005) found that there was a significant positive relationship between the wind speed and precipitation in moist conditions and the increases in precipitation are much greater than evaporation changes associated with the increased wind speed. Moreover, several scientific researchers concluded that climate change including rainfall and evaporation is one of the important factors to change the groundwater level (Taylor et al. 2013; Qi et al. 2018; Li et al. 2018). Hence, the salinity including chloride concentration and groundwater level is generally associated with climate parameters. Yan et al. (2015) and Li et al. (2018) concluded that precipitation and evaporation led to the fluctuation of groundwater levels and salinity during dry and
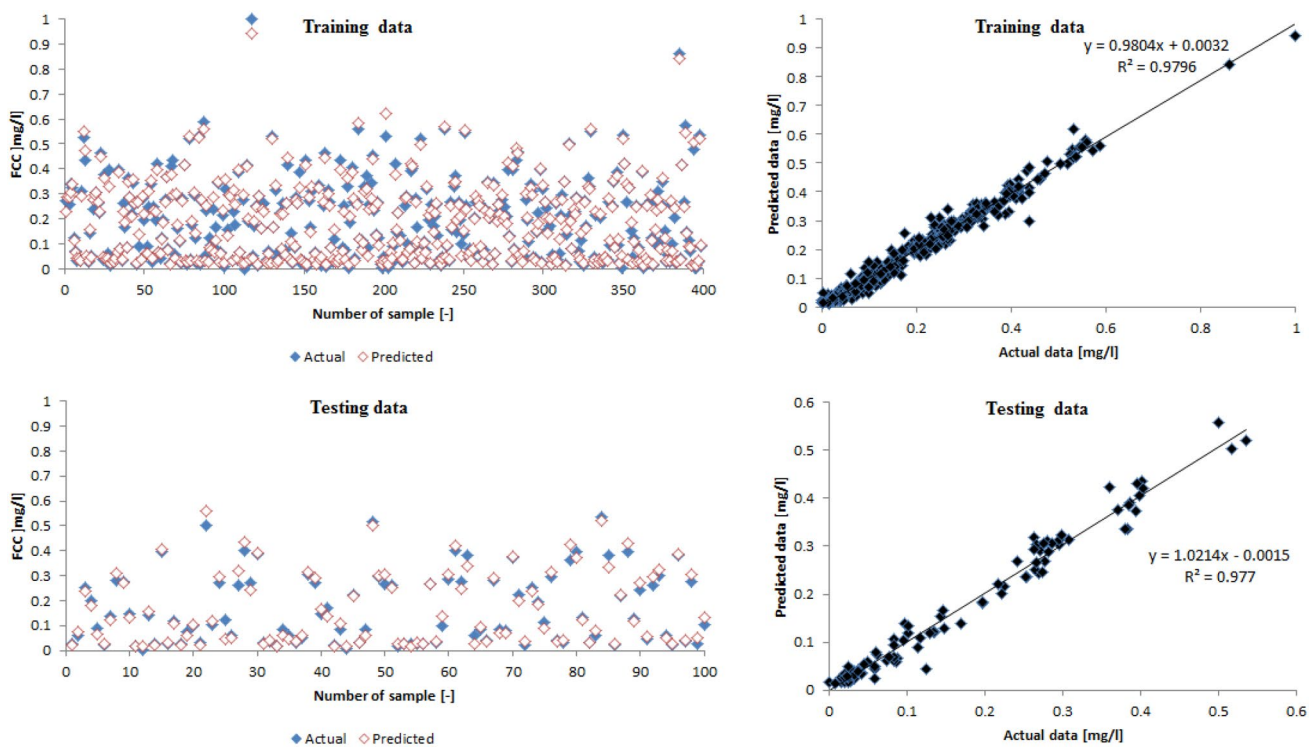

Fig. 7 Comparison between actual and predicted values obtained by ANN 5

wet seasons. Consequently, this behavior can be considered a complex phenomenon. This phenomenon should be further investigated in detail.

Conclusions and future works

The salinization of groundwater may be caused and influenced by many variables. Therefore, in the present study, the groundwater salinity of the Gaza Strip (i.e. in terms of chloride concentration) based on the climate parameters and the variables affecting chloride concentration (recharge rate (RR), abstraction (A), abstraction average rate (AVR), lifetime (LT), groundwater level (GWL), aquifer thickness (AT), depth from the surface to well screen (DSWS), distance from sea shoreline (DSSL)) was predicted by using ANN model. 17 ANN models were developed with different input combinations. The present study has shown the powerful artificial neural network tool to identify the most influencing input parameters in the prediction of chloride concentration. The results demonstrated that the most relevant input variables for estimating the FCC are ANN 5 model with the combinations of [ICC, RR, A, AVR, LT, GWL, DSWS, AT, DSSL, W]. In addition, it is found that climate parameters (ANN 17 model) have a minimum effect on the FCC prediction.

Moreover, in the present paper, Pearson product-moment and spatial correlation were applied to measure the relationship between chloride concentration data and other parameters for the selected region. The results showed that RR, A, AVR, LT, GWL, DSWS, AT, DSSL have a greater impact on the estimated value of chloride concentration (CC), while climate parameters have a minimum effect on CC. The sensitivity and uncertainty analysis approach such as GIS multicriteria decision analysis and Analytic Network Process (ANP) model can be a useful approach to study the groundwater potential (Feizizadeh et al. 2014; Feizizadeh and Blaschke 2014; Valverde et al. 2016). Therefore, future research should focus on the predicting of future groundwater salinization using GIS multicriteria decision analysis.

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