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Estimation of Water Quality of El- Timsah Lake Using Artificial Neural Networks (ANN) Model

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ABSTRACT

Ismailia City is located on El-TimsahLake. It is characterized by tourism, fishing activities, a significant source of food, and income generation for the local population. The aim of the present work is to assess the water quality of the lake using a numeric expression the Weighted Arithmetic Water Quality Index (WQI) and Prediction it using a newly developed Artificial Neural Network model. To develop the model, 22 x 3 data records of collected water samples from the three sites: the eastern, middle, and western of El-Timsah Lake. The data set includes the physicochemical properties of El-Timsah water such as temperature, DO, pH, Total alkalinity, EC, total hardness, Chloride, Magnesium, Calcium, sulphate, nutrients (NO_3, PO_4) Isotopic contents (D, ^{18}O) and trace elements concentrations (Cd, Mn, Fe, Ni, pb, Cu, Zn, V, and B).The collected data set of water samples were used to generate general regression neural networks (GRNN) as inputs which were divided into two subsets; training and testing based on a cross-validation approach, and the calculated quality index as target (output).The results of calculations and the developed Artificial Neural Networks (ANN) model indicated the suitability of the Lake for human activities although the middle part area of El-Timsah was the lowest water quality. GRNN has the ability to predict the winter water quality which represented that the pollution is increased.

Introduction

The coastal environment is mainly influenced by various physical, chemical, and biological processes. Water quality impacts both, directly and indirectly, the diversity and abundance of marine communities as well as the recreational use of the coast. El-Timsah Lake is considered one of the most important lakes in Egypt. Its basin represents the important natural ecosystem that supports various socio- economic activities in Ismailia city and its surroundings. The lake receives different water types as fresh water from the outlet of the Ismailia Canal and wastewater resulting from many activities of Ismailia city discharging into the El-Timsah lake (Donia, N. S. 2011). The discharge of wastes adds a large range of products such as nutrients, heavy metals, toxic organic, and others that may be toxic to both aquatic biota and humans. Pollutants follow a number of physical, chemical, and biological pathways, which are dependent to a large extent, on the chemical characteristics of the elements or the compounds.

The spatial distribution of the quality of EL-Timsah water Lake is influenced by seasonal changes and is primarily governed by the extent and composition of its dissolved solids (Diersing, N. 2009). The water quality index (WQI) is considered one of the simplest methods used in assessing the overall water quality (Mophin-Kania, K. and Murugesan,A.G. 2011). It is defined as a rating reflecting the composite effects of a number of parameters on the overall water quality. The WQI allows the reduction of vast amounts of data obtained from a range of physicochemical and biological parameters to a single number in a simple reproducible manner. Due to the numerous influencing factors affecting water quality changes, the water quality change process has the characteristics of non-linearity, time-varying parameters, and hysteresis. The existing traditional sensors cannot be used for effective, timely and rapid application and water quality prediction (WQS, 1986). With the development of modern mathematics and artificial intelligence technology as the user (ANN) model, the construction of water quality prediction models to realize the mining and analysis of existing monitoring data have become a hot spot in water quality prediction (Wechmongkhonkon, S. et al. 2012;Gazzaz.N. M. et al. 2012).

The present study was carried into two stages. The calculation of the Water Quality Index (WQI) was carried out in the first stage. The second stage was carried out to develop a new ANN model. In order to use this assessment to predict different inputs of water quality at different sites in the western (S1), middle (S2), and eastern (S3) of the El- Timsah lake.

Methodology

Study area

Lake Timsah lies between 30°33`and 30°35`N Latitude and 32°16` and 32°19`E Longitude in Egypt. The lake is small and shallow. It has a surface area of about 8 square kilometres with an average depth of only 10 meters (ICDE, 1998). The region is divided into three basins: Timsah Lake, the western lagoon and the Suez Canal pathway. The Lake receives high salinity water from the Suez Canal mainly from the South. It also receives fresh water from the outlet Ismailia Canal at its eastern side (S3), El-Forsan drains from the North middle (S2) and from drains via the western Lagoon (S1) as shown in Figure1 (EEAA, et al. 2011; El-Sherbiny M.M and, AL- Aidroos, A. G. 2011).

The marine construction and maintenance workshops located on the shores of Lake Timsah are discharging part of their wastewater directly into the lake. The studied area is located in an arid region with extremely hot weather in the summer. Rainfall in the study region usually occurred in the form of short showers. (Wali, M. A. A.1999).

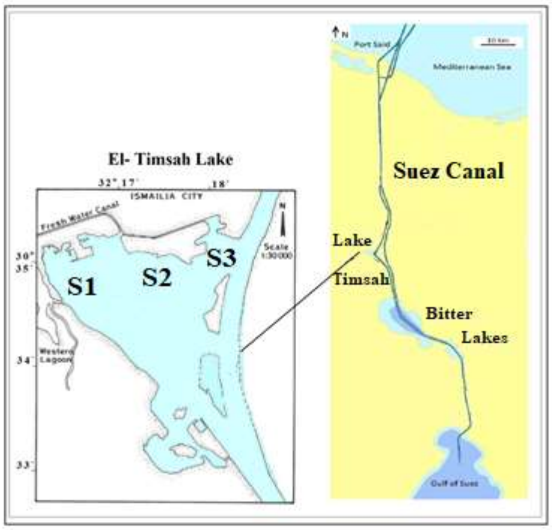

Fig. 1. The location of water samples in the studied area

The seasonal climatic changes particularly rainfall and solar heating, result in seasonal variations in water balance and water level.

ANN Model

One of the approaches conceivable in the evaluation of water quality is Artificial Neural Networks (ANN). ANN is a model that can be used to predict water quality indexes.

WQI Calculation

In the first stage of this study, Water Quality Index is calculated from Table 1 using a newly implemented MATLAB code, to determine the inputs and targets for the newly developed GRNN model that was developed in the second stage of the research.

Water Quality Indices are established from important physicochemical parameters to understand the water quality better for the general public using (WQI) in equation (1):

$$WQI = \frac{\sum_{i=1}^{n} Q_i W_i}{\sum_{i=1}^{n} W_i} (1)$$

Where: Qi = Quality rating Wi = Relative weight Water quality grads can be classified as excellent, good, poor, very poor and unsuitable with reference to the grads provide in Table 1(Khwakaram, A, I. 2015).

Table1: Grads of Water Quality Index (WQI) and status of Water Quality Rating

WQI	Category of Water Quality
<50	Excellent
50-100	Good
100-200	Poor
200-300	Very Poor
>300	Unsuitable

The New General Regression Neural Network (GRNN) Modeling

Artificial neural networks can transform low-dimensional nonlinear problems into high-dimensional linearly separable problems through a three-layer structure, so as to predict changes in water quality. In the second stage of this study, General Regression Neural Network (GRNN) was used as Artificial Neural Networks (ANNs) to predict water quality indexes.(Rumelhart, D. E. et al. 1986).

The generalized regression neural network (GRNN) as a type of ANNs was used in different applications related to modelling, system identification, prediction, and control of dynamic systems including: feedback linearization controller. GRNN is proposed by Donald Specht, falls into the category of probabilistic neural networks (Specht, D.F. 1991). GRNN is a single-pass neural network that uses a Gaussian activation function in the hidden layer as shown in Figure 2.

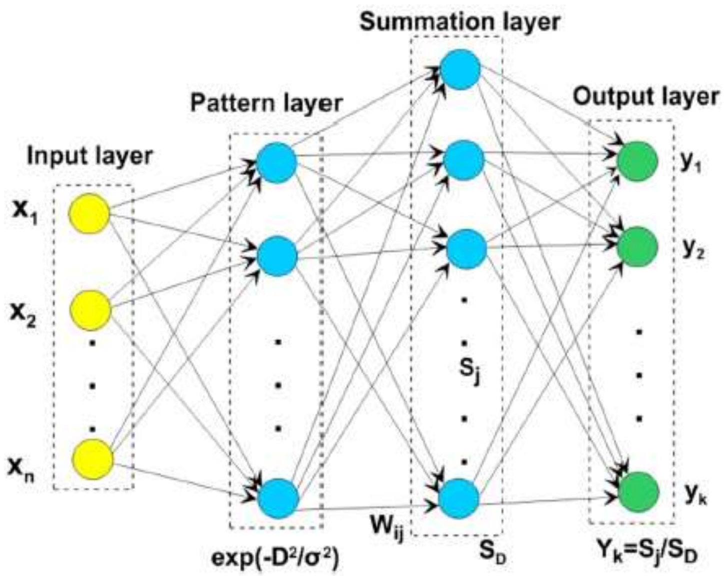

Fig.2 Schematic diagram of a generalized regression neural network Model

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The combination of gray theory and artificial neural network can combine the advantages of the two to predict changes in water quality as shown in Figure2. It has very important practical significance to improve the accuracy of water environment monitoring. The GRNN consists of four layers: the input layer, pattern layer, summation layer and output layer (Patterson, D.W.1996). The first layer is fully connected to the second pattern layer through the weights of the pattern layer, where each unit represents a training input pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected with the weights of the summation layer to the two neurons in the summation layer: S-summation neuron and D-summation neuron. The S-summation neuron computes the sum of the weighted outputs of the pattern layer while the D-summation neuron calculates the unweighted outputs of the pattern neurons. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value to an unknown input vector x as:

$$y = \frac{\sum_{i=1}^{n} W_i \ \exp[-D(x, x_i)]}{\sum_{i=1}^{n} W_i \ \exp[-D(x, x_i)]} \quad (2)$$

Where: x is the input vector, x_i is the i^{th} case vector, x_j is the j^{th} input variable. W_i is the weight connecting the i^{th} neuron in the pattern layer to the summation layer. n and p denote the number of training pattern and elements of an input vector, respectively. D is the Gaussian function of the following form:

$$D(x, x_i) = \sum_{j=1}^{p} \left(\frac{x_j - x_{ij}}{\sigma_j}\right)^2 (3)$$

During the training process, the error is measured by the means of square error (MSE). The training process would be repeated several/numerous times with different smoothing factors until the network is optimized according to the minimum amount of MSE or a pre-defined threshold value (Kisi, O. et al., 2013). ANNs use a trial-and-error method implementation, to optimize the weights of between input and outputs in the training process. So that, t*he new* GRNN *developed model structure determination is a* fixed network structure on trial-and-error approach to determine the model structure through determining the number of neurons of the hidden layer, input layer, and output layer as shown in Figure 3 (Du, Z. et al. 2021).

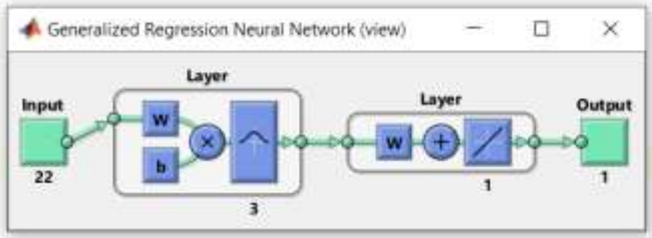

Fig. 3. New GRNN developed model structure determination

Data Processing

The newly developed GRNN model for the estimation of different water quality parameters of the sites (S1, S2 and S3) was done. To develop the model, 22 x 3 data records of canal water samples were collected from El-Timsah water into three sites (Abd El Samie,G. et al. 2008;Hassan, H. B. et al. 2020; Abd El-Azim, H, et al. 2018). The data set includes DO, pH, Total alkalinity, EC, total hardness, Chloride, Mg,Ca,SO_4, nutrients (NO_3, PO_4) Isotopic contents (D, O-18) trace elements concentrations (Cd, Mn, Fe, Ni, pb, Cu, Zn, V, and B) are recorded in Table 2 as the inputs and quality index that calculated is used as targets as shown in Table 2.

Input data are divided into two subsets; training and testing based on cross- validation approach. After the training and testing the model, the performance of the model was evaluated using Mean Square Errors (MSE). In training process, the input weights are the training inputs transposed, and the output weights are training targets. Since GRNN is an associative memory, after training, the number of hidden neurons is equal to the number of training samples. The Calculated WQI index for the input data of the three sites is used as the target (outputs) (Minasny, B and McBratney, A. B. 2002, Dennis, J.E. et al.1981).

Table 2: Average Data of Results of physicochemical analysis

Parameters	**Standards**	**Statistics**	**S1 (Western)**	**S2 (Middle)**	**S3 (Eastern)**
Temperature ^oC	27.49	Min	25.5	25.8	25.8
		Max	28	29	29
		Mean	26.4	27.2	27.3
DO (mg/L)	5.0	Min	6.1	6.0	6.2
		Max	6.5	6.4	7.0
		Mean	6.4	6.3	6.8
pH	7.7	Min	7.8	7.9	8.0
		Max	8.1	8.1	8.2
		Mean	8.0	8.0	8.1
Total alkalinity (mg/L)	98	Min	150	160	190
		Max	180	190	230
		Mean	169.7	179.7	220.3
EC (ms/cm)	60.3	Min	46	43	13.5
		Max	60.8	52.8	47.5
		Mean	53.0	34.0	26.1
Total hardness (mg/L)	8375	Min	6486	5500	4126
		Max	8980	8377	6938
		Mean	8405.	6031.5	4611
Cl (mg/L)	23607	Min	20045	18000	7400
		Max	22010	20060	21833
		Mean	20506	15671	12000
Mg (mg/L)	1570	Min	1240	1028	900
		Max	1702	1494	1148
		Mean	1611.3	1190.625	910
Ca (mg/L)	721	Min	561	401	300
		Max	801	761	501
		Mean	720.0	461	352
SO_4 (mg/L)	1260	Min	2559	2144	800
		Max	3818	2900	2133
		Mean	3840.0	2463	1882
NO_3(mg/L)	12.4	Min	3.0	0.5	2.0

		Max	10.0	4.0	6.0
		Mean	7.0	2.1	4.1
PO_4 (mg/L)	0.5	Min	0.2	0.4	0.3
		Max	0.8	1.2	1.3
		Mean	0.6	1	1.1
^{18}O	1.98	Min	1.7	1.5	2.3
		Max	2.1	2.3	2.9
		Mean	1.9	2.1	2.7
D ‰	13.8	Min	13.2	14.0	17.0
		Max	15.5	19.0	18.7
		Mean	14.8	18.6	18.9
Cd (mg/L)	0.0006	Min	DL	DL	DL
		Max	0.00005	0.0006	0.02
		Mean	0.00002	0.0003	0.0001
Mn (mg/L)	0.003	Min	0.0004	DL	DL
		Max	0.03	0.08	0.03
		Mean	0.001	0.005	0.006
Fe (mg/L)	0.02	Min	0.12	DL	0.002
		Max	0.16	0.6	1.0
		Mean	0.015	0.16	0.1
Ni (mg/L)	0.003	Min	DL	DL	DL
		Max	0.0023	0.02	0.003
		Mean	0.002	0.004	0.0001
pb (mg/L)	0.006	Min	DL	DL	DL
		Max	0.002	0.05	0.4
		Mean	0.0014	0.024	0.035
Cu (mg/L)	0.009	Min	DL	DL	DL
		Max	0.008	0.01	0.006
		Mean	0.0013	0.006	0.000001
Zn (mg/L)	0.0006	Min	0.0005	DL	DL
		Max	0.0026	0.006	0.014
		Mean	0.0011	0.0006	0.000001
V(mg/L)	0.01	Min	0.007	DL	0.006
		Max	0.01	0.008	0.015
		Mean	0.01	0.004	0.01
B (mg/L)	1.2	Min	0.08	0.05	0.03
		Max	3.6	2.5	1.7
		Mean	3	2	0.08

Results and discussion

The calculated water indexes of the three sites (S1, S2 and S3) and the average data of analysis results in Table 2 showed that El- Timsah Lake may be suffering from increasing pollution levels which are essentially caused by industrial wastewater in addition to drainage water from the outflow of Ismailia cannel. The effect of wastewater discharge in the lake was illustrated in the fluctuation of DO between 6.3 and 6.8mg/l. The lowest DO was in the middle of Lake S2 because the area is subjected to the dumping of industrial wastes. The DO standard of marine water is 5.0 mg/l and not less than 3.5 mg/l at any time of the year for the protection of aquatic lives (MPCA, 2019).

TDS values of Timsah Lake water samples differ from 26 to 53 g/L where the lowest TSD values of 26g/l appear in site S3 near the discharge point of freshwater of El- Ismailia Canal. The maximum TDS value reached 53.0 g/L as and chloride 20506 mg/L at site S1were within the safe limits according to the specification of the Red Sea water(Abdel-Aal E.A. et al.,2015).

The PH values of El-Timsah ranged from 8.0 to 8.2 thus, the data were reflective of the slight alkalinity conditions of the Lake. Total alkalinity ranged between 169- 220 mg/L. The largest value of total alkalinity was near the S3 side due to outfall of discharge of fresh Ismailia cannel water. Total hardness (TH) was varied from 4611 to 8377 based on the concentration of $CaCO_3$ (150-300 mg/l). The pH specification of the Red Sea water tended to be alkaline (Abdel-AalE.A. et al.,2015).

The effect of wastewater discharge in the lake is clear in a variation of El-Timsah Lake isotopic contents. The isotopic contents $\delta^{18}O$ and δD in the lake varied from 1.9 to 2.7‰ and 14.2 to 18.9‰ respectively. The highest δD and $\delta^{18}O$ isotopic contents are observed in site S3 and reached to 2.7 and 18.9‰. This value is nearest to the outflow and drainage of Ismailia Canal water which has an isotopic content ($\delta^{18}O$ = +2.8 ‰ and δD= +24.8 ‰) and represents the source of fresh water discharge into the Lake (Craige, H. 1966a). The isotopic contents δD and $\delta^{18}O$ in S2 location were 2.1 ‰ and 18.6 ‰ wherever in site S1 were 1.9‰ and 14.8 ‰ respectively which these isotopic values close to the Red Seawater ($\delta^{18}O$ = 1.98 ‰ and δD = 13.8 ‰) (Abd El- Samie. S.G. et al. 2012). Moreover, the results of trace elements show that high concentrations of Cd, Fe, Ni, and Pb were at the middle edges S2 of the lake. These concentrations were close to a source of industrial wastewater which may be reached the lake. (Bayati, K. . 2005).

The Results of the New GRNN Developed Model

The ANN model for the estimation of different water quality parameters of the sites (S1, S2 and S3) was done. To develop the model, 22 x 3 data records of water samples were collected from El-Timsah water into three sites. The data set includes DO, pH, Total alkalinity, EC, total hardness, Chloride, Mg,Ca,SO_4, nutrients (NO_3,PO_4) Isotopic contents (D,^{18}O) trace element concentrations (Cd, Mn, Fe, Ni, pb, Cu, Zn, V and B) as the inputs and quality index that calculated using : (method) as an output as shown in Table 2. Input data were divided into two subsets; training and testing based on cross-validation approach. After training and testing the model, the performance of the model was evaluated using root mean square errors (RMSE).

In this study the new model is developed using GRNN algorithm-based on WQI calculations to help in predict it; in different seasons such as winter using different temperatures of the water surface as dependent variables and the 23 input variables as the independent variables. Fig.4 illustrates the one-by-one relationship between the predicted and calculated WQI. Mean Square Error (MSE) was employed to evaluate the new model's performance which has a general formula and mathematically indicates in Equation (4) as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_o)^2 \qquad (4)$$

where :y_i is the output calculated by the model, and y_0 is the target output

A generalized regression neural network (GRNN) is a variation of the radial basis neural networks, which is based on kernel regression networks (Celikoglu, H.B. and Cigizoglu H.K. 2007). In GRNN model, the key parameter, including the spread factor, plays a crucial role in establishing a good ANN regression model with high prediction accuracy and stability. Different spread factor values between 0.1 and 1.5 were tried for the GRNN model and the optimal one that gave the minimum MSE in the validation period were selected.

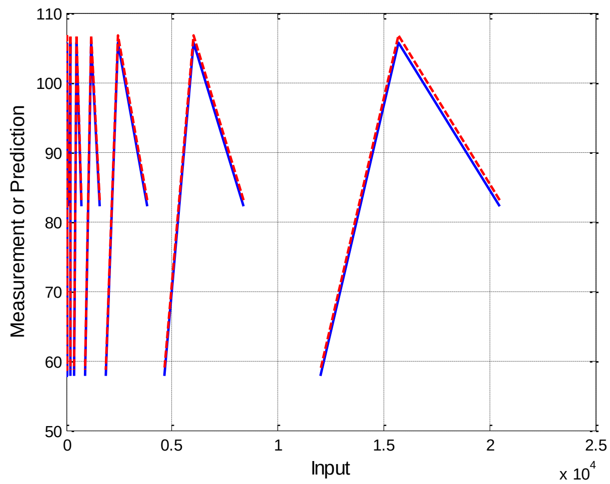

Fig.4. Schematic diagram of comparison between measurements and the developed GRNN Prediction

The performance of the newly developed GRNN model for the estimation of different Water Quality Indexes (WQI) of El-Timsah Lake sites (S1, S2 and S3) in the summer season in Table3.

Table3: Prediction of WQI in the three sites

Site	Measurements	GRNN Predictions	Mean Square Error (MSE)
1	82.19278	81.1917	1.1996e-05
2	105.7721	105.7715	-5.4875e-06
3	57.79828	57.7965	3.0797e-05

The Water Quality Index (WQI) calculations used in GRNN model based on the standards exhibited different water quality in the El-Timsah sites. The (WQI) results at eastern, western and middle lake sites were approximated to 58, 106 and 82 (WHO, 2011). It shows that the overall (good) water quality is located in the western and eastern of the lake. The less quality was in the middle of the lake near the industrial wastewater drains.

The Prediction of Water Quality in winter

The developed ANN model was used to predict the water quality parameters at o El Timsah Lake in winter. The input values were the temperature ^oC (18.5, 18.2, 18.0) of surface water at the three sites S1, S2 and S3 in winter. The testing of the GRNN was run as input data. The results of winter testing data are recorded in Table 4. It showed that the water quality in winter was less than in summer.

Table 4. The GRNN Summer& Winter Prediction Values

Site	GRNN summer Predictions	GRNN winter Predictions
1	82.19278	96.1357
2	105.7721	111.8729
3	57.79828	79.9892

Comparison of the results of the Prediction Values between the GRNN developed model in Summer &Winter (the time of collecting samples and required predictions) are shown in Fig.5.The calculated water quality of El-Timsah water decreased in winter due to the seasonal effect on the change in surface water temperature as shown in Figure 5.

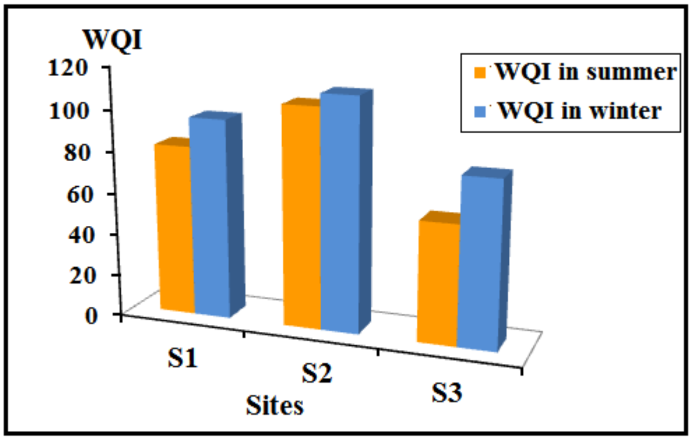

Fig 5. Comparison the results of the prediction values between the developed GRNN model in Summer &Winter

Conclusion

El-Timsah Lake is considered one of the most important lakes in Egypt. So, it is very important to calculate and predict the water quality for it. Thus, in this study WQI is calculated in the first stage and in the second stage. It is predicted using a newly developed GRNN model as ANNs. The calculated values of the (WQI) and the predicted outputs of the developed GRNN model of the El-Timsah Lake three sites (S1, S2 and S3) showed that the most water in El- Timsah Lake is good except for the middle part area S2 of the lake was the lowest water quality. Moreover, the results indicated that the newly developed GRNN model has been able to predict water quality indexes in others input times as winter. Particularly, the developed GRNN has the ability to predict the summer and winter water quality indexes which represent that the pollution increases due to seasonal effects on the change in surface water temperature.

References

Abd El Samie G., Hamza M.S., and Hassan H.B. (2008) Estimation of the Pollution Level in El Timsah Lake, Egypt. ESENSA-08 9th International Conference of Nuclear Sciences and Applications, Sharm El-Shiekh, Egypt

Abd El- Samie S. G., Ahmed, M. A., Hassan, H. B. (2012) Environment assessment of pollution of Pollution hazards- Suez Canal waterway. Journal of Nuclear Science and Applications.

Abd El-Azim, H., Belal, A. A., Abd El-Salam, E. T., Mourad, F. A. and Abo Elwafa, S. Y. (2018) Water Pollution by Heavy Metals in The Western Lagoon and its Effect on Timsah Lake and Consequently on Suez Canal, CATRINA17 (1): 71-76.

Abdel-Aal, E.A., Farid, M.E., Hassan, F.S.M. and Mohamed, A. E. (2015) Desalination of Red Sea water using both electrodialysis and reverse osmosis as complementary methods. Egy. J. Petrol., 24: 71.

Bayati, K. (2005) Environmental geochemistry of heavy metals in a sediment core off Bushehr, Persian Gulf, Iran. J. Environ. Health Sci. Eng. 2 255–260.

Celikoglu, H. B. and Cigizoglu, H.K. (**2007**) Public transportation tripflow modeling with generalized regression neural networks. Advances in Engineering Software, 38(2): 71–79.

Craige, H. (1966a) Isotopic composition and origin of the Red Sea and Salton Sea brines, Science, (154): 1544- 1547.

Dennis, J.E., Gay, D.M., and Welsch, R.E. (1981) NL2SOL – An adaptive nonlinear least squares algorithm. ACM Transactions on Mathematical software, (7): 369-383.

Diersing N. (2009) Water Quality: Frequently Asked Questions Florida Brook, Keyss National Marine Sanctuary Key West, FL.

Donia, N. S. (2011) Water quality management of lake Temsah, Egypt using geographical information system (GIS).International Journal of Environmental Science and Engineering (IJESE) 2: 1-8.

Du, Z., Qi, J., Wu, S., Zhang, F. and Liu, R. A (2021) Spatially Weighted Neural Network Based Water Quality Assessment Method for Large-Scale Coastal Areas. Environ. Sci. Technol., 55: 2553–2563.

Egyptian Environmental Affairs Agency (EEAA) (2011) Annual Report for the Survey Program of the Egyptian Lakes Lake El-Temsah, pp: 1-10.

EL-Sherbiny, M.M., AL-Aidroos, A. G.(2011) Seasonal composition and population density of zooplankton in Lake Timsah, Suez Canal, Egypt**.** OCEANOLOGIA 53 (3)**:** 837–859.

Gazzaz, N. M., MohdKamil, Y., Ahmad Z. A., Hafizan, J. and Mohammad, F. R. (2012) ArtificialneuralnetworkModelling of the water quality index for Kinta River (Malaysia) using water qualityvariables as predictors.Marine Pollution Bulletin64**:**2409-2420.

Hassan, H.B., Rayan R.A., and Hussien R.A. (2020) Surface-Groundwater Interaction in the Area between El-Timsah Lake and Ismailia Canal Using Hydrochemical and Isotopic Techniques. Arab J. Nucl. Sci. Appl., 3 (53): 276-290.

International Center for Environment and Development (ICDE) (1998) Environmental Profile of LakeTimsah Area.Technical Report No.1.

Khwakaram, A, I., Majid, S. N., Ahmed, Z. H., and Hama N. Y. (2015) Application of water quality index (WQI) as a possible indicator foragriculture purpose and assessing the ability of self purification process by Qalyasan stream in Sulaimani city/Iraqi Kurdistan Region (IKR). International Journal of Plant, Animal and Environmental Sciences, 1(5): 162-173.

Kisi,O. Shiri, J.andTombul, M. (2013) Modelling rainfall-runoff process using soft computing technique. Computers & Geoscience, 51: 108-177.

Minasny, B. and McBratney, A. B. (2002) Theneuro-m method for fitting neural network parametric pedotransfer functions. Soil Science Society of America Journal, (66): 352-361.

Minnesota Pollution Control Agency (MPCA) (2019)Statement of need and reasonableness, Proposed Amendments to Rules Governing Water Quality Standards – Class 2 and Class 7 Use Designations, *Minn. R. ch*. 7050; Revisor's ID No. 4561.

Mophin-Kania, K. and Murugesan, A.G. (2011) Evaluation and Classification of Water Quality of Perennial River Tamirabarani through Aggregation of Water Quality Index. International Journal of Environmental Protection, 1(5): 24-33.

Patterson, D. W. (1996) Artificial Neural Networks Theory and Applications. Prentice Hall International Editions, Korea, p 477

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986) Learning representations by back-propagating errors. Nature, (323): 533–536.

Specht, D.F. (1991) A General Regression Neural Network. IEEE Transactions Neural Network, (2):568-576.

Wali, M.A A., (1991) Carbonates and evaporates. 2 (6) p.225-238.

Water Quality Standards for Coastal Waters Marine Outfalls.SW-II Standard (1998) Central Pollution Control Board.NewDelhi. Source:EPA1986.

Wechmongkhonkon, S., Poomtong, N. and Areerachakul, S.(2012) Application of Artificial NeuralNetwork to Classification Surface Water Quality.World Academy of Science, Engineering andTechnology6**:**199-203.

WHO (2011)Guidelines for Drinking-water Qualit. Gutenberg, 4th ed, pp: 541.