VNU Journal of Science: Earth and Environmental Sciences, Vol. 41, No. 3 (2025) 108-115

VNU Journal of Science: Earth and Environmental Sciences

Journal homepage: https://js.vnu.edu.vn/EES

Original Article

Assess the Bottom Sediment Quality of the Saigon River and its Tributaries in Binh Duong Using an Artificial Neural Network

Nguyen Hien Than*, Tran Thi Anh Thu, Le Trong Dieu Hien

Thu Dau Mot University, 6 Tran Van On, Phu Loi, Ho Chi Minh City, Vietnam

Received 27th August 2024
Revised 05th April 2025; Accepted 30th July 2025

Abstract: Assessment of bottom sediment quality is vital in water resources management. The study collected sediment data at five monitoring stations in the Saigon River and its tributaries from 2013 to 2023. These monitoring data was used to construct our feedforward neutral network (FFNN) model. The model's accuracy is 95.5% in assessing sediment quality. The study also presents a speedy method for evaluating the quality of bottom sediments in Vietnam.

Keywords: Artificial neural network, Binh Duong, Classify, Saigon River, and Sediment.

1. Introduction

River sediment pollution is a growing concern in most parts of the world [1]. Sediments are an integral and dynamic part of river basins. In recent years, many studies evaluating bottom sediment quality have been published. Most studies apply indexes to assess sediment quality. Suresh, Sutharsan [2] used the pollutant load index and ecological risk to evaluate the sediment quality of Veer Anam Lake, India. Moreover, Zahra, Hashmi [3] applied enrichment factors, the geological accumulation index, and the metal pollution index to determine metal accumulation, distribution, and pollution status in Rawal Reservoir, Pakistan. Similarly, Zhou, Feng [4] applied the Nemerow pollution index, the geo-accumulation index, the risk index, and cluster analysis to evaluate the pollution level and ecological risk level of heavy metals in soil. Most previous research shows that the use of chemical parameters to evaluate sediment quality is widespread. In recent years, the fuzzy comprehensive evaluation method (FCE) has also been used to evaluate river sediment quality. Adebowale, Agunbiade and

* Corresponding author.
E-mail address: thannh@tdmu.edu.vn

https://doi.org/10.25073/2588-1094/vnuees.5232

Olu-Owolabi [5] exploited FCE to evaluate heavy metal pollution in surface water and sediments. The FCE method usually requires national standards or regulations divided into levels or different purposes of use. Not all bottom sediment quality standards meet this.

In recent years, artificial intelligence has been widely used in environmental assessment. An artificial intelligence network, also known as an artificial neural network, is understood as an information processing system built based on generalizing the mathematical model of biological neurons and adapting the working mechanism of biological neurons of the human brain [6]. Artificial neural networks are considered a valuable tool for determining water quality and understanding water pollution trends [7]. However, this tool has been narrowly used for sediment quality assessment. In 2008, Manuel A. and his associates indicated that the SOM model provided an useful classification tool for subsequent evaluation steps than multivariate analysis and hierarchical group analysis [8]. In 2013, Olawoyin R. et al. demonstrated the visualization capabilities of SOM, highlighted sensitive areas, and also provided a practical roadmap for decision-making and practical corrective actions [9].

Sediment quality monitoring has been carried out annually by many provinces and cities in Vietnam. In most reports assessing bottom sediment quality, the comparison method with standards is used in most reports. Phung Thai Duong and Huynh Thi Kieu Tram (2015) pointed out high levels of heavy metals in the Mekong estuary. This shows that the socio-economic activities of the people here also play a massive role in the accumulation of heavy metals in river bottom sediments [10]. Thai Thi Minh Trang et al., (2017) surveyed the status of organic pollution in bottom sediments in some areas of the Saigon River. Initial research on TOC content in sediments in the lower Saigon River in correlation with water environment indicators and suspended sediment components [11]. In another study, Le Thi Trinh assessed the accumulation and ecological risks of some heavy metals in Han River estuary sediments, Da Nang City. Geo-accumulation index (Igeo), pollution level (Cd value), and potential ecological risk are also proposed based on the environmental risk index (RI). The results of the potential ecological risk coefficient show that the risk of heavy metals is in descending order Cu> Pb> As> Cr> Cd> Zn [12].

Previous research indicates that there has been a significant focus on assessing sediment quality. Research directions mainly focus on pollution spread and ecological risks from bottom sediment pollution. In this study, research methods are standard comparison, dynamic models, and risk indexes. The FFNN network model is limitedly used to evaluate bottom sediment quality. This study will build a FFNN model to evaluate bottom sediment quality. The research results are expected to provide a functional neural network model for bottom sediment quality in Binh Duong.

2. Data and Methods

2.1. Research Data

Table 1. Bottom sediment sampling locations

No.	**Symbol**	**Coordinates**		**Location**
		Latitude	Longitude	
1	SG1	$11^0$17’17,34’’	$106^0$21’14,88’’	Distance to the Dau Tieng dam about 2km
2	SG2	$10^0$58’54,78’’	$106^0$38’35,58’’	At the water pump station of the Thu Dau Mot wastewater treatment plant
3	SG3	$10^0$52’0,9’’	$106^0$42’47,7’’	Distance fork at the Vinh Binh Canal, Sai Gon River, about 50 m in the direction downstream area
4	RSG3	$10^0$59’3,18’’	$106^0$39’9,18’’	At the bridge Ong Danh Canal
5	RSG6	$10^0$52’8,04’’	$106^0$42’47,7’’	Dinh Ky restaurant at Vinh Binh Canal

Bottom sediment monitoring data was collected from 2013 - 2023 at Saigon River and its tributaries (Table 1). The study data is collected from the Center for Technical Monitoring of Natural Resources and Environment (https://moitruongbinhduong.gov.vn/). The province monitors the frequency of bottom sediments twice a year. The type of data used in the study is manual monitoring data. Monitoring will be performed every two months.

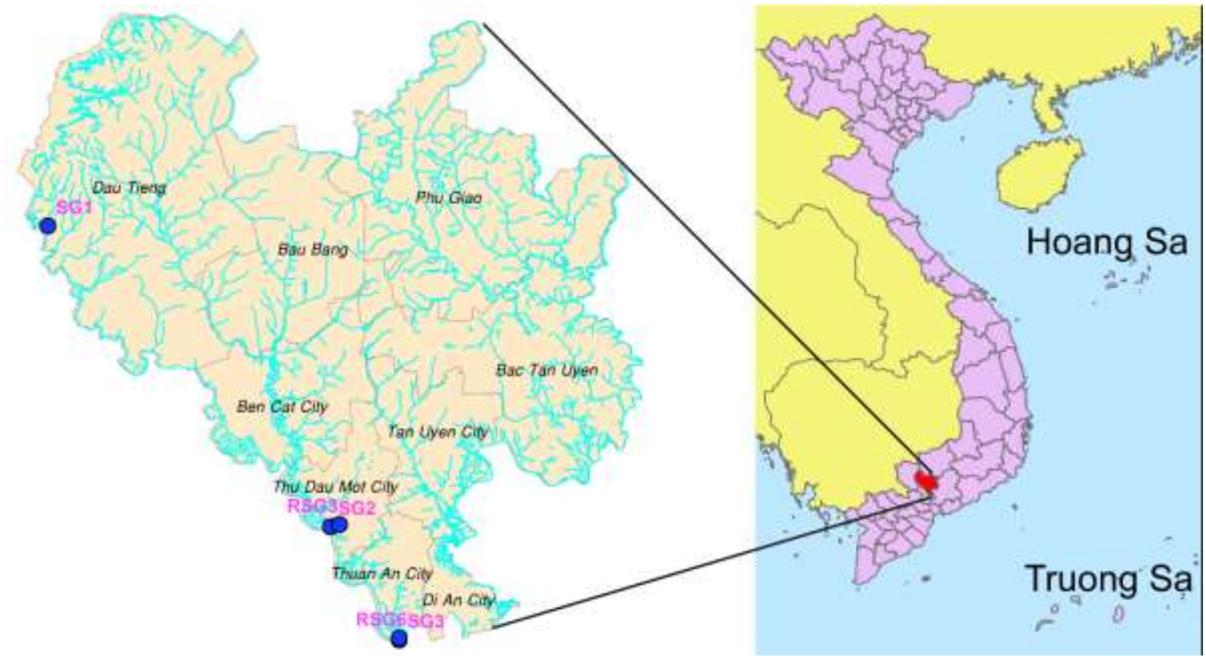

Figure 1. Locations of sediment monitoring.

2.2. Methods

2.2.1. Feedforward Neural Network.

A feedforward neural network (FFNN) is a simple artificial intelligence network. In the FFNN, input information is transmitted in only one direction (direct transmission) from the input layer, through the hidden layer, and to the output layer. There is no repetition in the network [13].

The network training process is illustrated in Figure 2. Input data are parameters: As, Cu, Zn, Pb, Cd, Cr and Hg. The output data represents the quality level of the bottom sediment, calculated using the Nemerow index. Details of

2.2.2. *Nemerow* Index

Applying the Nemerow index [1, 14, 15] to evaluate the quality of sediments in the Saigon River and its tributaries. The sediment quality level obtained was used to set up the output layer in the FFNN model.

the index calculation method are presented in the study [16, 17]. The bottom sediment quality scale is divided into five levels: Perfect $P < 1$ (I), Good $1 < P < 2$ (II), average $2 < P < 3$ (III), Poor $3 < P < 5$ (IV), Poor $P > 5$ (V).

Research data is divided into three main groups: 70% training, 15% evaluation, and 15% validation. The ANN model is evaluated through model errors. The smaller the model's error, the better the model. The process of assessing bottom sediment quality using the ANN network is summarized as follows:

Statistical method: RMSE [18] and the correlation coefficient R^2 is used to evaluate the model.

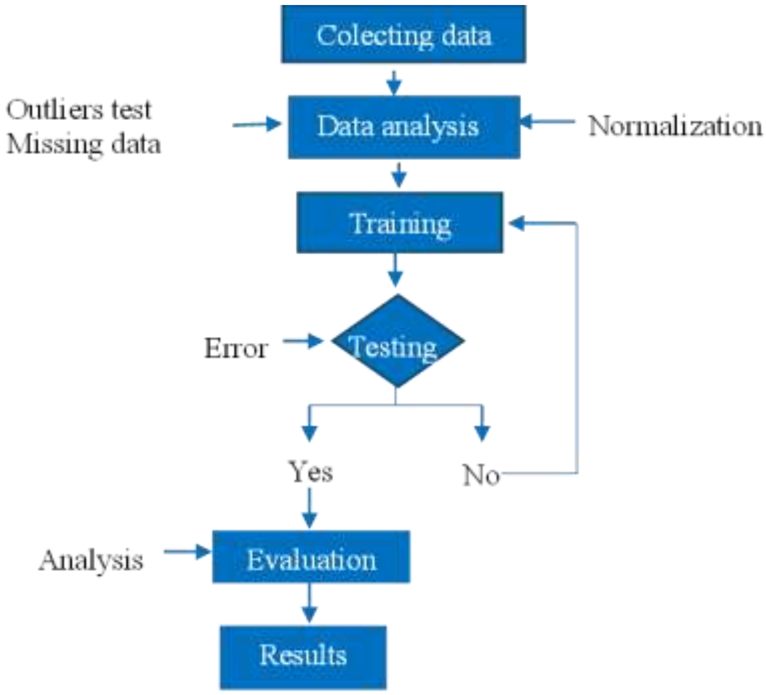

Figure 2. Procedure for determining bottom sediment quality.

3. Develop a Sediment Quality Classification Model Using the FFNN

3.1. Data Preprocessing

Bottom sediment monitoring data are often affected by natural and artificial factors affecting research results. Therefore, the study conducted data preprocessing through statistical methods to check missing data.

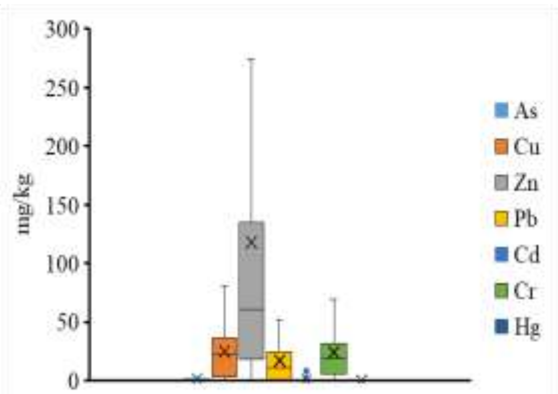

Figure 3. Sediment quality at the bottom of the Saigon River and its tributaries.

The heavy metal monitoring data showed the presence of outliers (Figure 3). These outliers were screened using non-parametric methods. The extreme values were removed and restored through imputation analysis using SPSS version 26.

3.2. Build a Model to Classify Bottom Sediment Quality

3.2.1. Model Training

The initial setup includes 6 input neurons, two hidden layers, and one output neuron to train the network to evaluate sediment quality. The input neurons are pollution parameters in the bottom sediments: As, Cu, Zn, Pb, Cd, Cr, and Hg. The Levenberg-Marquardt algorithm is used to train the network. The network training model is implemented by adjusting the number of neurons in the hidden layer. Neurons start running from 2 or more until the model's statistical parameters reach an optimal. The Gradient reduction algorithm is set to 0.0554 when the number of epoch threshold iterations reaches 11, *Mu* is recorded as 0.01, and the value used for model evaluation is 6.

3.2.2. Model Evaluation

The network training process is performed multiple times, as described above. The running models are run many times to find the dark model based on two parameters: MSE and correlation coefficient. The model operates stably when the number of neurons in the hidden layer reaches 5. The model does not obtain the optimal parameters when the number of neurons in the hidden layer is increased. Therefore, the FFNN model with the structure *O(7) - H(5) - I(1)* is a suitable network structure to evaluate bottom sediment quality.

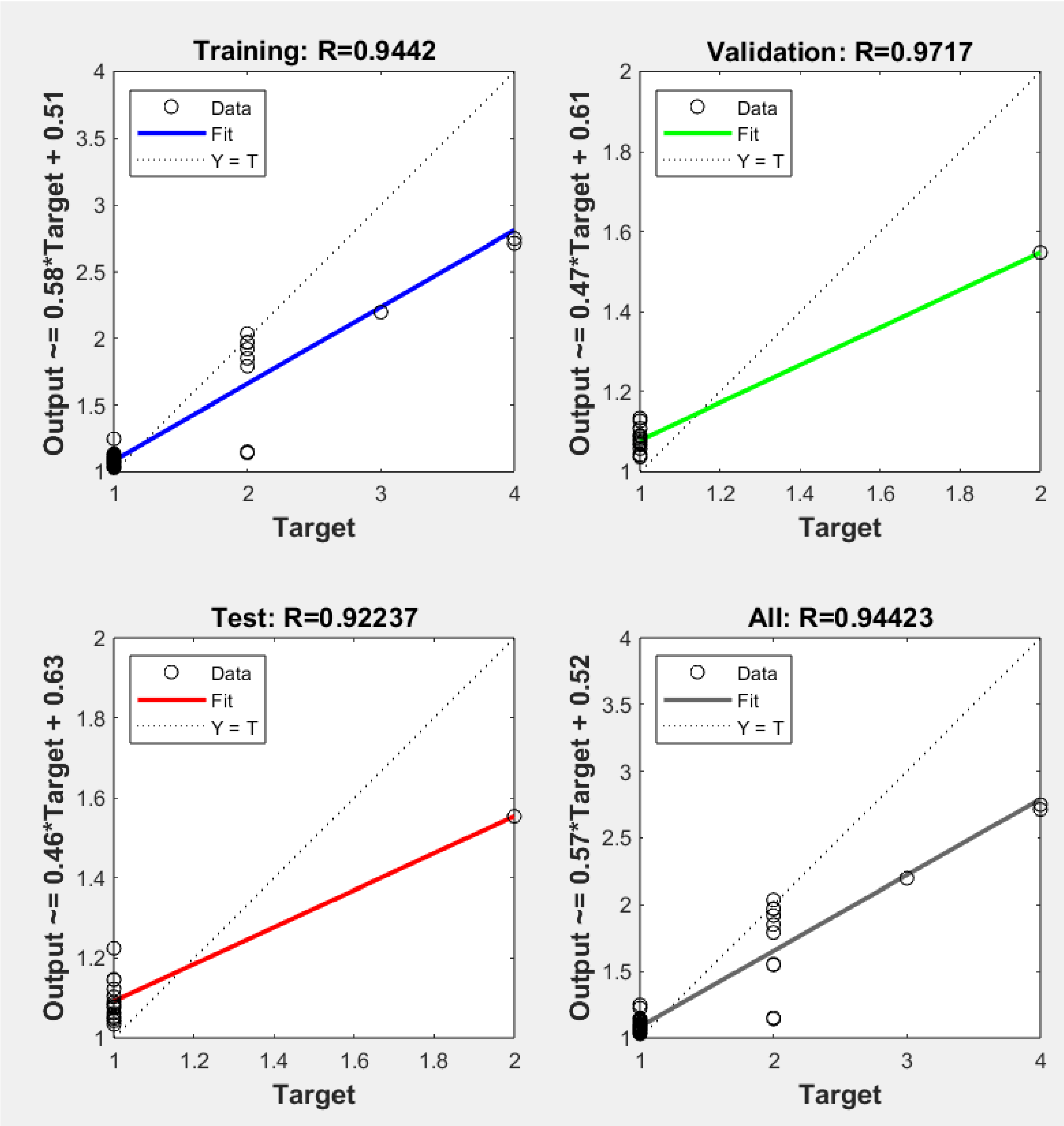

Figure 4. Correlation coefficient in the FFNN model *O(7) - H(5) - I(1).*

The network structure model *O(7) - H(5) - I(1)* obtained error values of 0.0773, 0.01854, and 0.002176 for the training set, evaluation set, and testing set, respectively. The model's correlation coefficient reached a statistical value higher than 0.9 in the three data sets in Figure 4.

Comparing sediment quality at the bottom of the Saigon River and its tributaries using the Nemerow method and the FFNN model shows a high level of similarity, as shown in Figure 4. Correlation analysis of the results of assessing the quality of Saigon River bottom sediment using the Nemerow and FFNN methods shows that the correlation coefficient $R^2 = 0.879$ and adjusted $R^{2\,=}$ 0.878. This gives me two highly related methods. The obtained P-value shows that the correlation between the two methods is very statistically significant. Numerous studies have demonstrated the effectiveness of these models in accurately evaluating and forecasting the amount of sediment carried by rivers. A study comparing FFNN and ANFIS models for modeling suspended sediment concentrations reported high accuracy for both, with R^2 values ranging from 0.77 to 0.98, and FFNN showing a slight advantage [19].

Use the confusion matrix (Table 2) to evaluate the accuracy of the FFNN model *O(7) - H(5) - I(1)*. The results obtained Kappa coefficient = 0.77 and P-value = 0. This indicates that the FFNN model accurately classifies sediment quality. The accuracy rate of the model compared to the actual value (105/110) ×100 = 95.5%. The Kappa coefficient of the two results is 0.771. A P-value of the Chi-square test obtained 0. This indicates that the FFNN model exhibits good performance. B. Joshi et al., also demonstrate that the FFNN model has low error and high model efficiency [20]. These performance metrics are consistent with the high accuracy and substantial agreement often reported for FFNN and other ANN models in environmental classification tasks worldwide [5]. This reinforces the potential of machine learning models for providing reliable assessments of sediment quality [19].

Table 2. Confusion matrix between actual values and the FFNN model

Matrix		FFNN			Total
	Level	1	2	3	
Actual	I	97	0	0	97
	II	2	8	0	10
	III	0	1	0	1
	IV	0	0	2	2
Total		99	9	2	110

Both the Nemerow index and FFNN models have their inherent strengths and limitations. The Nemerow index is easy to calculate and interpret, making it a practical tool for initial assessments and for highlighting severe pollution [21]. However, its sensitivity to extreme values and dependence on predefined standards can be limited. FFNN models, on the other hand, can model complex relationships and achieve high accuracy, but they require sufficient data for training and can be less transparent in their decision-making process. The strong correlation observed in the Saigon River study suggests that, in this context, the FFNN model may effectively mirror the assessment provided by a more interpretable index.

4. Classification of Sediment Quality of Saigon River and its Tributaries

Using the FFNN model with structure *O(7) - H(5) - I(1)* to evaluate the quality of the bottom sediment of the Saigon River and its tributaries shows that the bottom sediment quality has been excellent in recent years. The evolution of bottom sediment quality can be divided into two periods, starting from when the bottom sediment quality monitoring begins (Table 3).

- Phase 1 from 2013 - 2016: the quiet quality had slight fluctuations during this period. In 2013, bottom sediment quality ranged from average (>2) to excellent (<1). In 2014 - 2016, the bottom sediment quality improved, ranging from level 1-2 (excellent level - good level), as shown in Table 3.

- Phase 2 from 2017 - 2023: The bottom sediment quality was stable and good during this period.

Nguyen Xuan Tong et al., found that sediment quality was more strongly affected by trace metals than surface water [22]. The study also noted a decreasing trend of trace metal concentrations in sediments over the survey period 4 which could indicate improving sediment quality in some areas of HCMC, similar to the trend observed in the Saigon River between 2013 and 2016.

Table 3. Average bottom sediment quality in the period 2013 - 2023

STT	Monitoring point	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	RSG3	2	2	1	1	1	1	1	1	1	1	1
2	RSG6	**3**	2	1	2	1	1	1	1	1	1	1
3	SG1	1	2	1	1	1	1	1	1	1	1	1
4	SG2	1	2	1	2	1	1	1	1	1	1	1
5	SG3	2	1	1	2	1	1	1	1	1	1	1

5. Conclusion

The research was conducted to build a model to evaluate sediment quality at the bottom of the Saigon River and its tributaries. The study has successfully built a model to assess bottom sediment quality using the FFNN model. The network structure *O(7) - H(5) - I(1)* is the optimal model to evaluate water quality-sediment quality at the bottom of the Saigon River and its tributaries. Bottom sediment quality is divided into 2013 -2016 and 2017 - 2023. In particular, 2013 - 2016 was recorded to have lower bottom sediment quality than 2017 - 2023. The FFNN model is a simple and easy-to-implement neural network model. Therefore, this model is easy to use to evaluate the bottom sediment quality. The research results provide a valuable tool for assessing bottom sediment quality, which is currently limited by the assessment methods used in Vietnam.

References

[1] J. P. Brady, G. A. Ayoko, W. N. Martens, A. Goonetilleke, Development of a Hybrid Pollution Index for Heavy Metals in Marine and Estuarine Sediments, Environmental Monitoring and Assessment, Vol. 187, No. 306, 2015, pp. 1-28, https://doi.org/10.1007/s10661-015-4563-x.

[2] G. Suresh, P. Sutharsan, V. Ramasamy, R. Venkatachalapathy, Assessment of Spatial Distribution and Potential Ecological Risk of the Heavy Metals in Relation to Granulometric Contents of Veeranam Lake Sediments, India, Ecotoxicology and Environmental Safety, Vol. 84, 2012, pp. 117-124, https://doi.org/10.1016/j.ecoenv.2012.06.027.

[3] A. Zahra, M. Z. Hashmi, R. N. Malik, Z. Ahmed, Enrichment and Geo-Accumulation of Heavy Metals and Risk Assessment of Sediments of the Kurang Nallah-Feeding Tributary of the Rawal Lake Reservoir, Pakistan, Science of the Total Environment, Vol. 470-471, 2014, pp. 925-933, https://doi.org/10.1016/j.scitotenv.2013.10.017.

[4] J. Zhou, K. Feng, Z. Pei, M. Lu, Pollution Assessment and Spatial Variation of Soil Heavy Metals in Lixia River Region of Eastern China, Journal Soils Sediments, Vol. 16, 2016, pp. 748-755, https://doi.org/10.1007/s11368-015-1289-x.

[5] K. O. Adebowale, F. O. Agunbiade, B. O. Owolabi, Fuzzy Comprehensive Assessment of Metal Contamination of Water and Sediments in Ondo Estuary, Nigeria, Chemistry Ecology, Vol. 24, No. 4, 2008, pp. 269-283.

[6] S. A. Rounds, Development of a Neural Network Model for Dissolved Oxygen in the Tualatin River, Oregon, Second Federal Interagency Hydrologic Modeling Conference, Hydrology of the Interagency Advisory Committeeon Water Information, Las Vegas, Nevada, 2002.

[7] P. S. Rosman, Water Quality Assessment of Muar River Using Environmetric Techniques and Artificial Neural Networks, ARPN Journal of

Engineering and Applied Sciences, Vol. 11, No. 11, 2016, pp. 7298-7303.

[8] M. A. Guerra, C. G. Piñuela, A. Andrés, B. Galán, J. R. Viguri, Assessment of Self-Organizing Map Artificial Neural Networks for the Classification of Sediment Quality, Environment International, Vol. 34, 2008, pp. 782-790, https://doi.org/10.1016/j.envint.2008.01.006.

[9] R. Olawoyin, A. Nieto, R. L. Grayson, F. Hardisty, S. Oyewole, Application of Artificial Neural Network (ANN) - Self-Organizing Map (SOM) for the Categorization of Water, Soil and Sediment Quality in Petrochemical Regions. Expert Systems with Applications, Vol. 40, No. 9, 2013, pp. 3634-3648, https://doi.org/10.1016/j.eswa.2012.12.069.

[10] P. T. Duong, H. T. K. Tram, Study and Assessment of the Concentration of some Heavy Metals in Bottom Sediments of the Mekong River Estuary, Ho Chi Minh City University of Education Journal of Science, Vol. 9, No. 75, 2015, pp. 119-129, https://doi.org/10.54607/hcmue.js.0.9(75).702(2015) (in Vietnamese).

[11] T. T. M. Trang, N. T. M. Yen, N. X. Quang, Organic Pollution in Sediments at Selected Areas of the Saigon River, 7th National Scientific Conference on Ecology and Biological Resources, Hanoi, 2017, pp. 1970-1978 (in Vietnamese).

[12] L. T. Trinh, Assessment of the Accumulation and Ecological Risk of Some Heavy Metals in Sediments of the Han River Estuary, Da Nang City, VNU Journal of Science: Natural Sciences and Technology, Vol. 33, No. 3, 2017, pp. 112-119 (in Vietnamese).

[13] G. Steyl, Application of Artificial Neural Networks in the Field of Geohydrology, Master Science Degree, Natural and Agricultural Sciences, Institute of Groundwater Studies, Faculty of Natural and Agricultural Sciences University of the Free State, 2009.

[14] Y. Ju, C. Chen, Y. C. Lim, C. Tsai, C. Chen, C. Dong, Developing Ecological Risk Assessment of Metals Released from Sediment based on Sediment Quality Guidelines Linking with the Properties: a Case Study for Kaohsiung Harbor, Science of the Total Environment, Vol. 852, No. 158407, 2022, pp. 1-11, https://doi.org/10.1016/j.scitotenv.2022.158407.

[15] K. Su, Q. Wang, L. Li, R. Cao, Y. Xi, Water Quality Assessment of Lugu Lake Based on Nemerow Pollution Index Method, Scientific Reports, Vol. 12, No. 13613, 2022, https://doi.org/10.1038/s41598-022-17874-w.

[16] Q. Zhang, M. Feng, X. Hao, Application of Nemerow Index Method and Integrated Water Quality Index Method in Water Quality Assessment of Zhangze Reservoir, Earth and Environmental Science, Vol. 128, 2018, pp. 1-6.

[17] T. Tang, Y. Zhai, K. Huang, Water Quality Analysis and Recommendations through Comprehensive Pollution Index Method, Management Science and Engineering, Vol. 5, No. 2, 2011, pp. 95-100, http://dx.doi.org/10.3968/j.mse.1913035X20110502.011.

[18] H. Banejad, E. Olyaie, Application of an Artificial Neural Network Model to Rivers Water Quality Indexes Prediction – a Case Study, Computer Science, Engineering, Environmental Science, Vol. 7, No. 1, 2011, pp. 60-65, https://api.semanticscholar.org/CorpusID:8993366.

[19] T. Zeyneb, M. Nadir, R. Boualem, Modeling of Suspended Sediment Concentrations by Artificial Neural Network and Adaptive Neuro Fuzzy Interference System Method - Study of Five Largest Basins in Eastern Algeria, Water Practice & Technology, Vol. 17, No. 5, 2022, pp. 1058-1081, https://doi.org/10.2166/wpt.2022.050.

[20] B. Joshi, V. K. Singh, D. K. Vishwakarma, M. A. Ghorbani, S. Kim, S. Gupta, V. K. Chandola, J. Rajput, I. Chung, K. K. Yadav, E. Mirzania, N. Al-Ansari, M. A. Mattar, A Comparative Survey between Cascade Correlation Neural Network (CCNN) and Feedforward Neural Network (FFNN) Machine Learning Models for Forecasting Suspended Sediment Concentration, Scientific Reports, 2024, Vol. 14, No. 10638, 2024, https://doi.org/10.1038/s41598-024-61339-1.

[21] K. Su, Q. Wang, L. Li, R. Cao, Y. Xi, G. Li, Water Quality Assessment Based on Nemerow Pollution Index Method: a Case Study of Heilongtan Reservoir in Central Sichuan Province, China, PLoS ONE, Vol. 17, No. 8, 2022, https://doi.org/10.1371/journal.pone.0273305.

[22] N. X. Tong, N.T . T. Thao, L. H. Anh, Assessment of Water Quality, Heavy Metal Pollution and Human Health Risks in the Canal System of Ho Chi Minh City, Vietnam, Environmental Research Communications, Vol. 6, No. 7, 2024, https://doi.org/10.1088/2515-7620/ad5ad7.