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An artificial neural networks approach and hybrid method with wavelet transform to investigate the quality of Tallo River, Indonesia

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ABSTRACT
Water contamination has always been one of the greatest intense environmental issues. Rivers are more polluted than the other surface and underground water resources, since passing through different areas. The current study aimed to examine the exactitude of artificial neural networks (ANN) and wavelet-ANN (WANN) models in estimating the concentrations of pollutants including Cl, EC, Mg, and TDS by comparing the results of the observed data. Tallo River in Indonesia was selected as the case study. The concentrations of pollutant parameters Cl, EC, Mg, and TDS were available and used between 2010 and 2022. Then 70% (100 months) of the data were considered as training data, while 30% (44 months) were supposed to be the testing ones. ANN and WANN models were examined to evaluate and predict the concentrations of pollutants in river water. The results of each model were compared to the observed data, and the models' accuracy was assessed. The results demonstrated that applying wavelet transform improved the precision of simulation. All efficiency criteria associated with the WANN model yielded superior results compared to the ANN model. The findings indicated that using the hybrid method with wavelet transformation ameliorated the ANN model's exactitude by 10% during training and 16% during testing. Finally, the findings exhibited that the WANN method is better than ANN; consequently, the former has performed more exactitude modeling in the estimation of water quality.

Keywords: Water pollution, Tallo River, Artificial neural networks, Wavelet transform.
Article type: Research Article.

INTRODUCTION
Polluting elements enter the ecosystem as extremely stable pollutants that do not decompose (Parween *et al.* 2022; Abad *et al.* 2023). These contaminants enter the water ecosystem, contaminating water and disrupting the environment (Brontowiyono *et al.* 2022). In this situation, it appears necessary to regularly monitor changes in

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water quality, particularly river water (Montaseri *et al.* 2018; Aliasghar *et al.* 2022). The abundance, toxicity, and persistence of pollutants in aquatic ecosystems have attracted the attention of scientific communities worldwide (Fallah *et al.* 2021). Nowadays, these ecosystems are highly exposed to pollutants due to the development of areas and the concentration of industrial units near rivers (Saalidong *et al.* 2022). Pollutants in aquatic ecosystems have two sources: geology and anthropogenic (Banejad *et al.* 2013). The latter origin is caused by urban, industrial, and agricultural sewage discharge, mining waste discharge, urban runoff, etc. (Zhou *et al.* 2022). The qualitative and environmental review of water resources is being discussed now. It will be easier to find the critical points and the appropriate solution to fix them if it is possible to determine the issues of the river that are below the standard (Uddin *et al.* 2022; Javidan *et al.* 2022). Water scarcity, as well as a lack of space and time, has created numerous challenges (Yavari *et al.* 2022; Moore *et al.* 2023). Due to the increase in water demand, a detailed study of water resources and determining its pollutants, prevention, and control of pollution, and optimal use of available water resources are required (Zhu *et al.* 2022). Despite being the most accurate method for measuring the concentration of pollutants in water sources, measuring directly and through experimental methods can take time and effort. The artificial neural network (ANN) is a model for solving various problems based on simulating human brain function (Wu & Wang 2022). It consists of input, output, and intermediate neuron layers and weights related to input and bias values as well as stimulation operations (Kumar *et al.* 2022). Among the capabilities of an ANN, are the calculation of a known function, the approximation of an unknown mapping, the recognition of a signal processing pattern, and learning (Huang *et al.* 2018). One of the disadvantages of ANN methods is that they do not offer an explicitly usable function. Accurately estimating the value of pollutants lies in the optimal management of water resources, and decisions made based on these estimates (Heidari *et al.* 2022). Consequently, this issue has always constituted one of the most significant water resource management challenges (Jeihouni *et al.* 2019). Recently, the lack of freshwater resources has become a global problem due to the growth of the worldwide population and the increase in per capita water consumption. Due to the scarcity of water resources, proper and efficient management is one of the most crucial responsibilities of the water resources experts. The future quantity of water is the most essential pillars of water resources management (Heddam *et al.* 2022). Reasons that make the category of prediction and production of artificial statistics in catchment basins, include the recent establishment of the majority of hydrometric stations, deficiencies in the statistics of the majority of stations, the location of the majority of rivers in arid regions, the precarious situation of underground water harvesting, and the need to pay more attention to surface water. It imparts a more flawless appearance (Rajaee & Shahabi 2016; Khosravi *et al.* 2022). No one is unaware of the significance of fresh water and its impact on societies' industrial and agricultural development in the modern era (Farabi *et al.* 2022). Given the world's growing population, monitoring and controlling the quantity and quality of water resources can help these societies face the imminent water crisis that will occur to humanity (Ji & Lu 2018). The issue of environmental pollution has captured the attention of humanity more than any other category due to its accumulation and physiological effects at low concentrations on the activity of living organisms (Chen 2023). Multiple studies have demonstrated that deep learning techniques, such as ANN, are highly accurate at estimating the amount of water pollutants. In addition, researchers have attempted to utilize hybrid models, such as wavelet transformation, to better the precision and exactitude of the final model. Consequently, it is necessary to research hybrid methods. The present research aimed to examine the exactitude of ANN and WANN methods in estimating the concentrations of pollutants including Cl, EC, Mg, and TDS by comparing the results to observed data.

MATERIALS AND METHODS

Tallo River in Indonesia was selected as the case study, since the concentrations of pollutant parameters Cl, EC, Mg, and TDS were available and used between 2010 and 2022. The description of ANN and WANN models and the simulation process have been discussed in the following section.

Artificial neural networks (ANN)

Artificial neural networks (ANNs) are data analysis systems depended on the sequential analysis of processing units (neurons) with a brain-like architectural structure. It is possible to extract the appropriate answer for complex problems with errors in a short time using an ANN with a significant number of processing units called neurons and significant parallel connections between them (Wang *et al.* 2013; Nejatian *et al.* 2023). The nervous network is an organ system composed of neurons that coordinate organisms' actions and reactions and send signals to various body parts. In recent usage, this term also refers to an artificial neural network composed of artificial neurons. As a result, the term neural network refers to two distinct concepts: biological- and artificial- neural networks. ANN consists of a collection of nonlinearly interconnected processor elements. Individual processor elements with many inputs and outputs are linked in these networks. There are two stages of operation for the processor elements of artificial neural networks including the training and testing stages. During the training stage, the processor element learns to be activated and excited for a particular state or not to be excited for the same condition (Molajou *et al.* 2021). During the testing stage, the corresponding output is produced when a trained input pattern is detected. In artificial neural networks, each processing unit has input and output characteristics. Each unit's outcome is determined by its internal connection to other units and, if applicable, external inputs. The network's topology, aspects of individual neurons, learning method, and training data govern the overall operation of the artificial neural network.

Wavelet transform

One of the most effective signal-processing models is the wavelet transform. After analyzing the leading time series, each periodic period is examined separately to simplify the examination (Zubaidi *et al.* 2020). The discrete form of wavelet transform is used because of the discrete structure of hydrological time series. The transfer and scale parameters in the discrete wavelet transform are chosen discontinuously using the binary process (Nagaraju *et al.* 2023). The signal is decomposed into components, and approximation using discrete wavelet transform in each step (Zhang *et al.* 2018). In the current study, the ANN model, combined with the wavelet transformation, was investigated to increase simulation exactitude, and the results of both methods (ANN and WANN) were compared with each other and with observed data. The selection of the mother wavelet is essential to using wavelet transform. The Daubechies mother wavelet (DB) was used to analyze the signals in this study, since this type of mother wavelet is commonly used in hydrological studies.

Efficiency criteria

In this study, efficiency criteria such as the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), mean absolute error (MAE), and root mean squared error (RMSE) were utilized. The relations of the mentioned criteria are presented in relations 1 to 4. In the mentioned relations, Q_0, Qc, $\bar{Q}_0$, and $\bar{Q}_c$ represent the observation, simulation, mean observation, and mean simulation amount, respectively.

$$R^2 = \frac{[\sum_{i=1}^{N} ((Q_0)_i - \overline{Q_0})((Q_c)_i - \overline{Q_c})]^2}{\sum_{i=1}^{N} ((Q_0)_i - \overline{Q_0})^2 . \sum_{i=1}^{N} ((Q_c)_i - \overline{Q_c})^2} \quad \textbf{(1)}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N} [(Q_0)_i - (Q_c)_i]^2}{\sum_{i=1}^{N} [(Q_0)_i - \bar{Q}_0]^2} \quad \textbf{(2)}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |(Q_0)_i - (Q_c)_i|, \quad \textbf{(3)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} [(Q_0)_i - (Q_c)_i]^2}, \quad \textbf{(4)}$$

Simulation process

In the current study, the input variables of the ANN model include more than just pollutant data. In selecting the model's input variables, it is also necessary to identify relatively independent, effective, and accessible variables, such as the physical characteristics of the basin. This prevents the needless addition of inputs and the addition of complexity to the model, and as a result, a suitable model is constructed with the collected data. As the number of inputs increases, additional data should be managed. Regarding natural characteristics, model inputs can be divided into two categories. The first category consists of inputs intrinsic to the watershed and referred to as variables or fixed inputs. These variables include the area of the sub-basins, their average height above sea level, the length of the main waterway, and their slope. The second category consists of inputs that depend on climatic factors, called variables or dynamic inputs. These model variables include precipitation and discharge. In this study, 70% (100 months) of the data were supposed for the training stage, while 30% (44 months) to be testing stage. ANN and WANN models were examined to evaluate and predict the concentrations of pollutants in river water.

RESULTS AND DISCUSSION

Results of ANN model

The results of the ANN method are presented in this section. Table 1 displays the efficiency criterion amounts for all pollutants. Table 1 indicate that the training stage findings are more accurate than the test stage.

Table 1. The values obtained from the ANN model for efficiency criteria of the desired pollutants

Pollutant	NSE		MAE		RMSE		R^2	
	Train	Test	Train	Test	Train	Test	Train	Test
Cl	0.81	0.67	0.76	0.91	0.18	0.23	0.76	0.69
EC	0.73	0.59	0.53	0.89	0.16	0.22	0.88	0.76
Mg	0.74	0.66	0.71	0.97	0.13	0.19	0.80	0.74
TDS	0.86	0.78	0.62	0.83	0.11	0.16	0.87	0.75

Figs. 1 to 4 show the graphs related to the time series of the observation data and the simulation results using the ANN method for all pollutants and different stages. According to the presented data, it is evident that 100 months of observational data (2010-2018) served as the training stage, while 44 months (2018-2022) as the testing stage. In addition, scatter plot diagrams are displayed in Figures 1 to 4 to facilitate comparison and evaluation of the results. The results demonstrated that the training stage produced more accurate estimations than the testing stage. The time series graphs and scatter plots in Figs. 1 to 4 indicate that the ANN model needs to be more exactitude at estimating extreme points, since the exactitude of the ANN method is highly dependent on the number of input data.

Results of WANN model

The desired pollutant-related data sets were discretized in various parameters using the wavelet transform method to obtain more precise results. Table 2 demonstrates that the WANN model yields more exact results for the train and test stages than the ANN method; consequently, using the wavelet has bettered the quality of the findings (Alizadeh & Kavianpour, 2015). In the WANN model, it is essential to note that the results of the training stage are more accurate than the results of the testing stage.

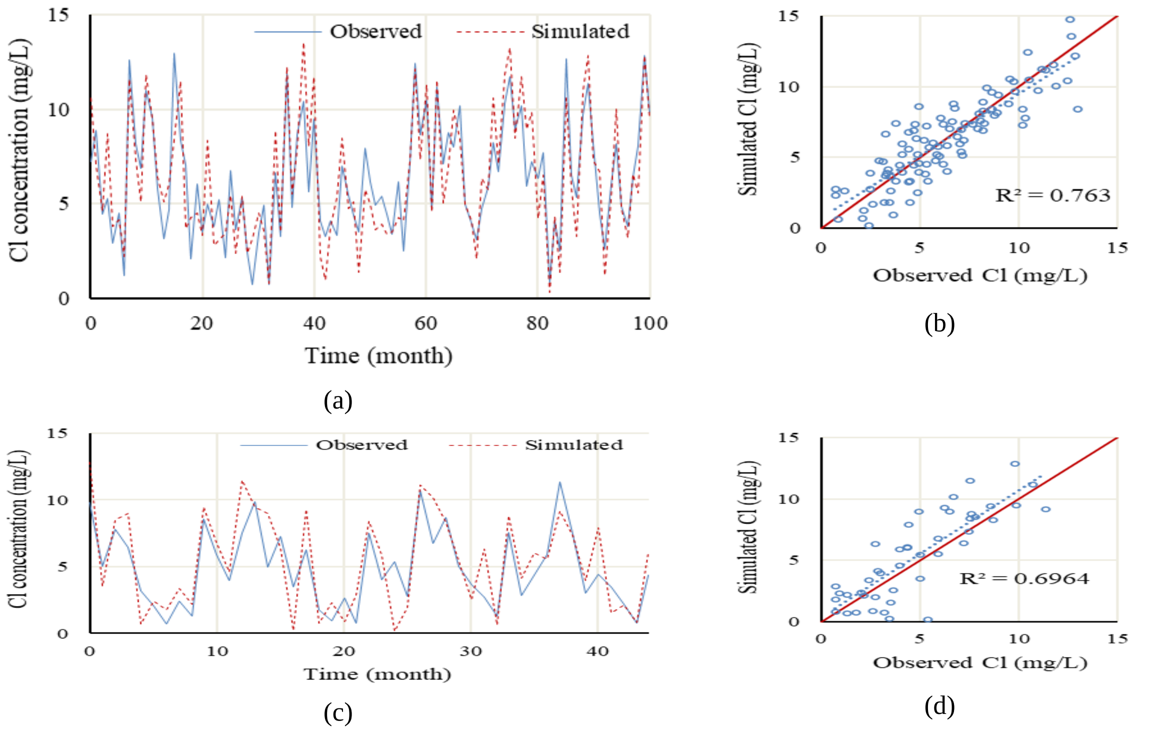

Fig. 1. Findings of Cl by the ANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

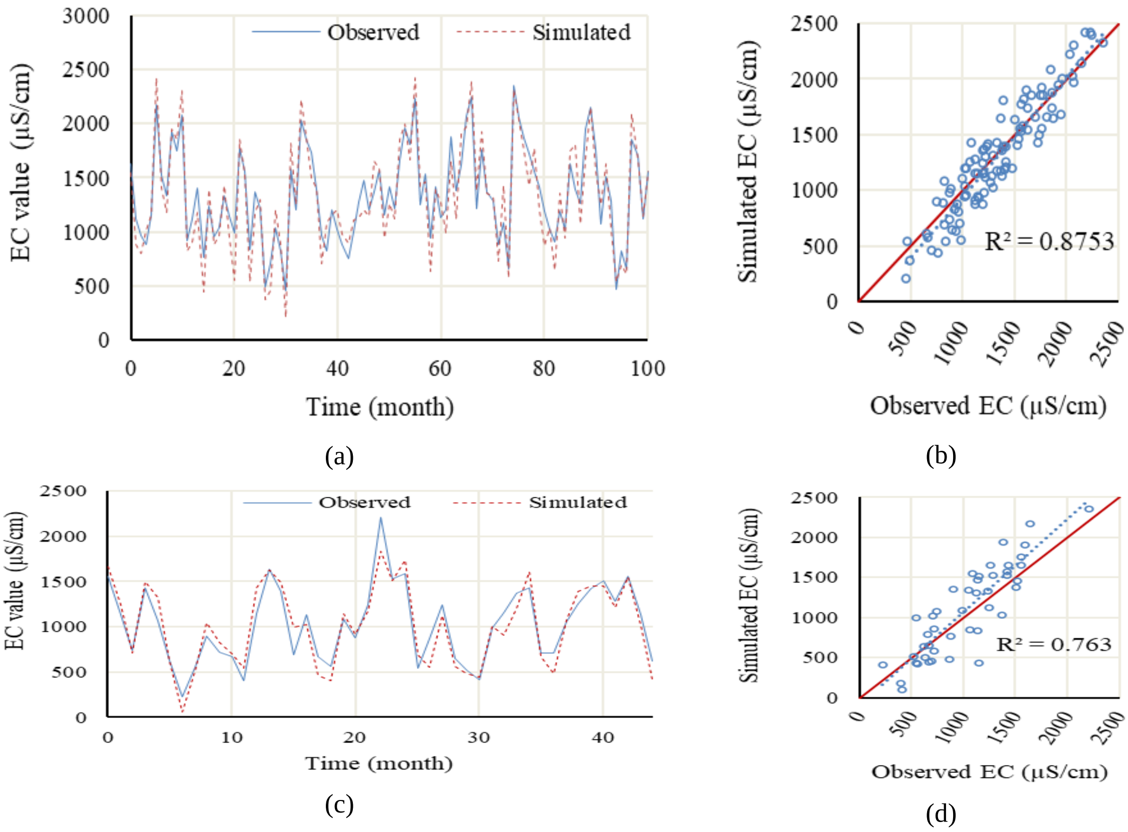

Fig. 2. Findings of EC by the ANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

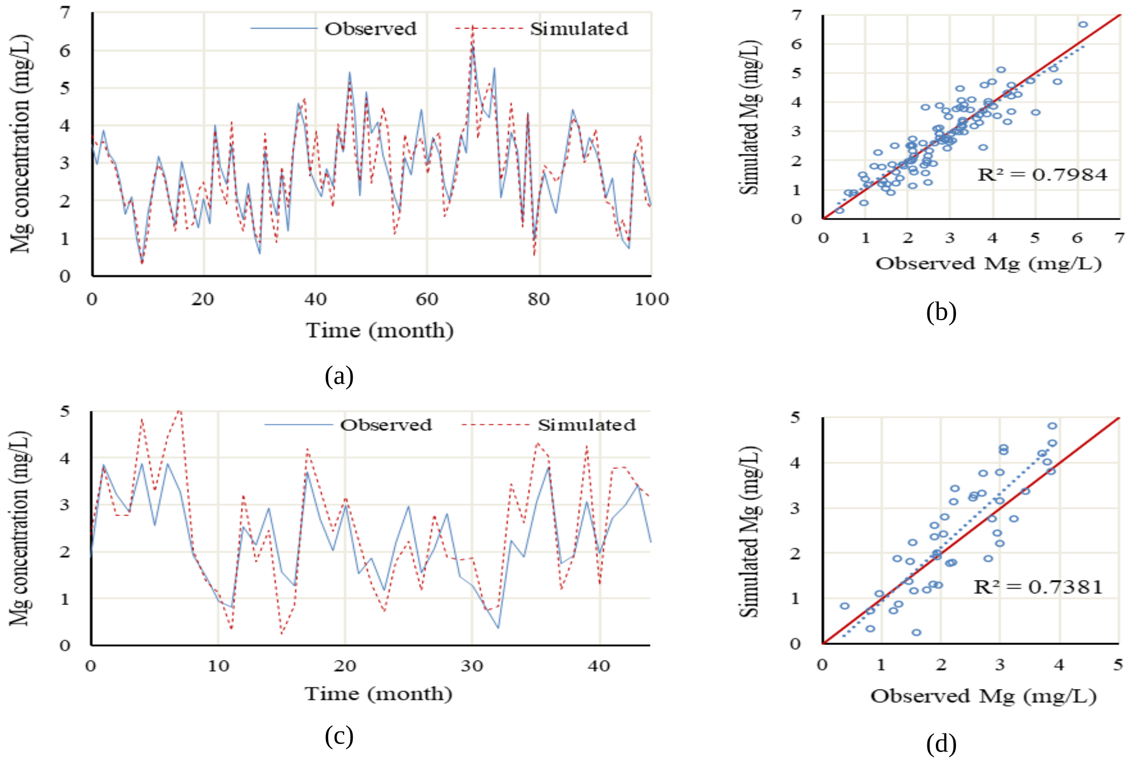

Fig. 3. Findings of Mg by the ANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

The evaluation of the observation and simulation graphs with the WANN method for all pollutant and simulation stage is depicted in Figs. 4 - 8. The figures demonstrate that the WANN method is rather better at simulating the location of points. Consequently, using wavelet transform has enhanced the ANN model's precision. Significantly during the testing stage, the WANN model's quality improved significantly (Ahmadianfar *et al.* 2020).

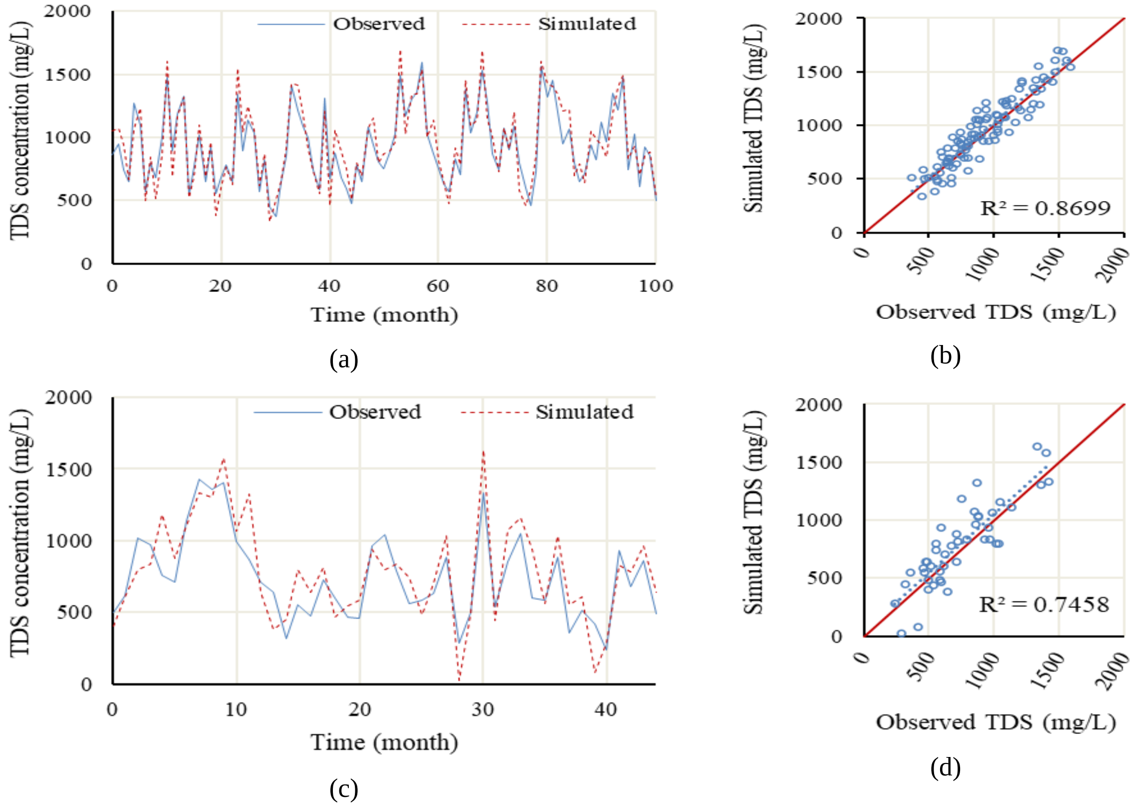

Fig. 4. Findings of TDS by the ANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

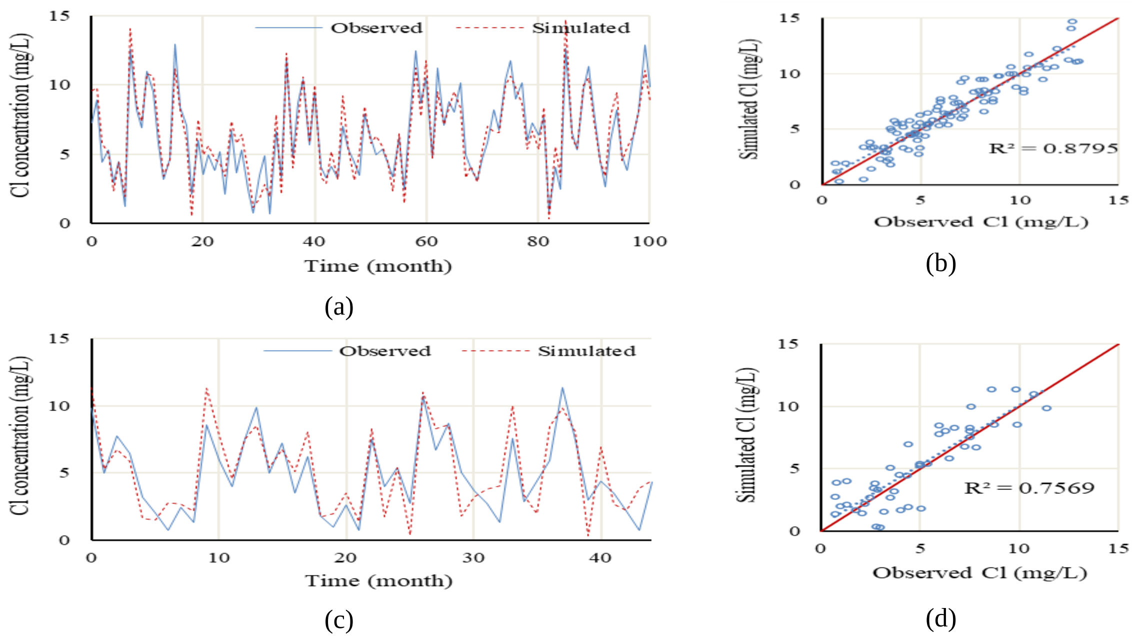

Fig. 5. Findings of Cl by the WANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

Table 2. The values obtained from the WANN model for efficiency criteria of the desired pollutants

Pollutant	NSE		MAE		RMSE		R^2	
	Train	Test	Train	Test	Train	Test	Train	Test
Cl	0.83	0.74	0.34	0.79	0.09	0.16	0.88	0.76
EC	0.86	0.79	0.27	0.58	0.06	0.11	0.93	0.88
Mg	0.85	0.76	0.17	0.26	0.08	0.12	0.92	0.81
TDS	0.89	0.84	0.23	0.49	0.04	0.07	0.96	0.89

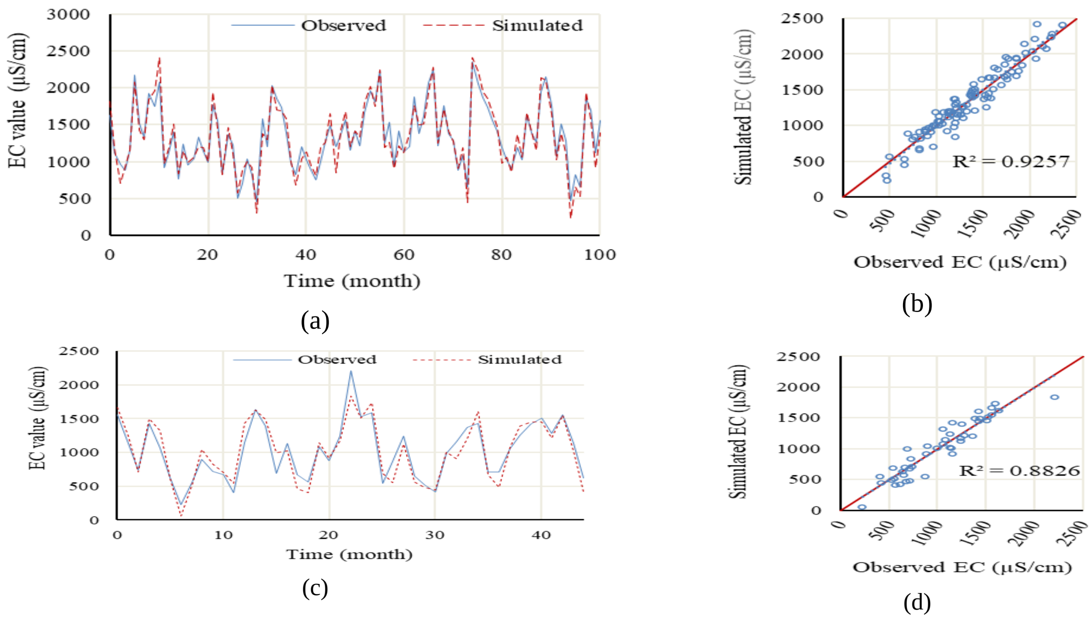

Fig. 6. Findings of EC by the WANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

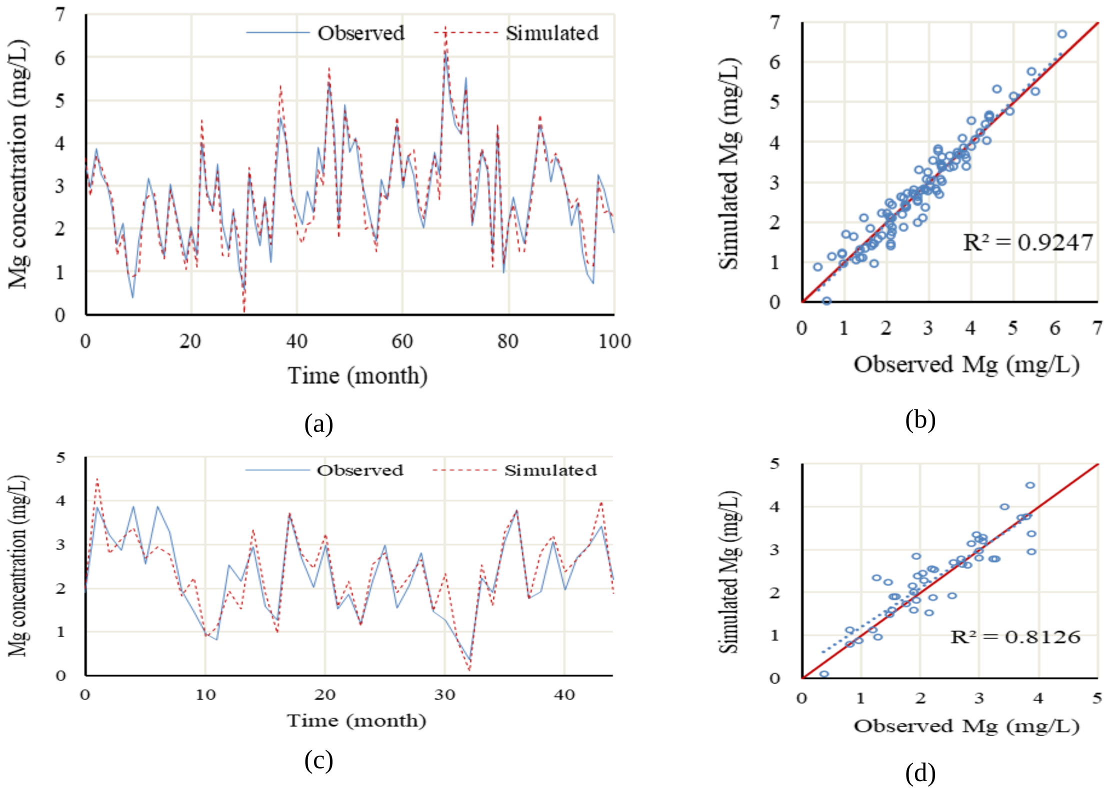

Fig. 7. Findings of Mg by the WANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

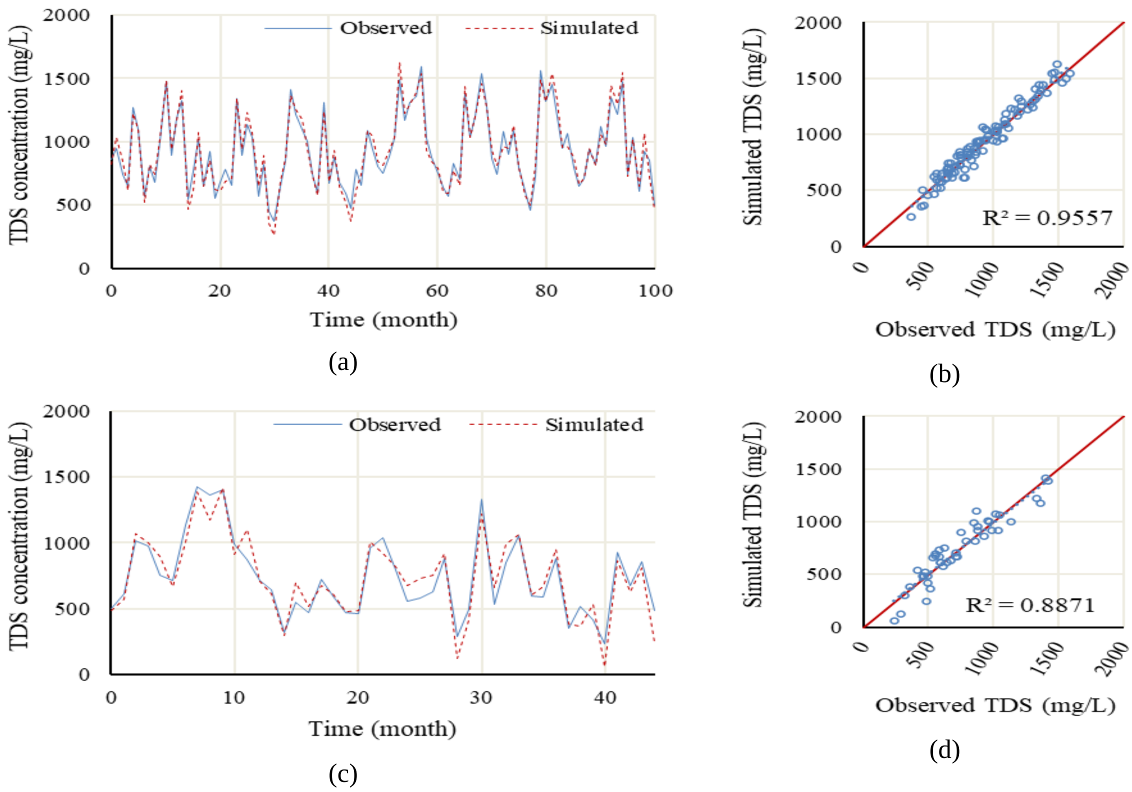

Fig. 8. Findings of TDS by the WANN method, (a) diagram of training stage, (b) scatterplot of training stage, (c) diagram of testing stage, and (d) scatterplot of testing stage.

The results demonstrated that applying wavelet transformation increased the precision of simulation. All efficiency criteria associated with the WANN model yielded superior results compared to the ANN method (Shi *et al.* 2018). Consequently, the WANN method produces excellent results. Examining only four pollutants, including Cl, EC, Mg, and TDS, is one of the limitations of the present study. For future studies, additional machine learning- and experimental- methods are suggested to be used to estimate pollutants and compare the findings. It is also recommended that a similar study be conducted in additional periods and on other rivers.

CONCLUSION

Nowadays, human activities have increased the pollution of water resources, making it essential to assess their quality. The study has demonstrated that using deep learning models, like artificial neural networks, is a suitable method for determining the concentration of pollutants in water sources. Therefore, the current study used ANN and WANN models to evaluate and simulate pollutants, including Cl, EC, Mg, and TDS. Thus, the simulation was conducted using the ANN model, which was then combined with the wavelet transformation to better the precision of the results. Consequently, the WANN method has performed more accurate simulating in the estimation of water quality.

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