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Artificial neural network modeling of the water quality index for Kinta River (Malaysia) using water quality variables as predictors

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A B S T R A C T

This article describes design and application of feed-forward, fully-connected, three-layer perceptron neural network model for computing the water quality index (WQI)[1] for Kinta River (Malaysia). The modeling efforts showed that the optimal network architecture was 23-34-1 and that the best WQI predictions were associated with the quick propagation (QP) training algorithm; a learning rate of 0.06; and a QP coefficient of 1.75. The WQI predictions of this model had significant, positive, very high correlation ($r = 0.977$, $p < 0.01$) with the measured WQI values, implying that the model predictions explain around 95.4% of the variation in the measured WQI values.

The approach presented in this article offers useful and powerful alternative to WQI computation and prediction, especially in the case of WQI calculation methods which involve lengthy computations and use of various sub-index formulae for each value, or range of values, of the constituent water quality variables.

1. Introduction

Water quality (WQ) is a description of biological, chemical, and physical characteristics of water in connection with intended use(s) and a set of standards (Boyacioglu, 2007; Khalil et al., 2011; Liou et al., 2004). Hence, water quality assessment can be defined as the evaluation of the biological, chemical, and physical properties of water in reference to natural quality, human health effects, and intended uses (Fernández et al., 2004; Pesce and Wunderlin, 2000). Nonetheless, the WQ can be evaluated by a single parameter for certain objective or by a number of critical parameters selected carefully to represent the pollution level of the water body of concern and reflect its overall WQ status. However, since no individual parameter can express the WQ sufficiently, the WQ is normally assessed by measuring a broad range of parameters (e.g., temperature; pH; electric conductivity (EC); turbidity; and the concentrations of a variety of pollutants, including pathogens, nutrients, organics, and metals). In consequence, a large amount of data is generated by the monitoring programs and these data require integration if the monitoring results are to be presented in a meaningful way to local planners and decision makers, watershed managers, and the general public. In view of this, water quality indices have been developed to integrate measurements of a set of parameters into a single index (Zandbergen and Hall, 1998). A quality index is a unitless number that assigns a quality value to an aggregate set of measured parameters (Pesce and Wunderlin, 2000). So, the water quality index (WQI) may be defined as a single numeric score that describes the WQ condition at a particular location in a specific time (Kaurish and Younos, 2007).

The WQIs have been designed to evaluate suitability of water for certain uses. The main idea of these indices is comparison of some water quality variables (WQVs) with WQ standards so that the indices will reveal the variable(s) exceeding the standards as well as the frequency and extent of exceedance. These indices offer several advantages including representation of measurements on many variables varying in measurement units in one metric, thus establishing a criterion for tracking changes in WQ over time and space and simplifying communication of the monitoring results (Fernández et al., 2004). Besides, when pollution is identified and remedial action is taken, the WQI can be used to track and follow-up any incremental WQ improvement trends to determine effectiveness of stream restoration efforts (Kaurish and Younos, 2007).

In 1974, the Department of Environment of Malaysia recommended adoption of WQ indexing to evaluate and rank the levels of pollution of the Malaysian rivers. Then, this department adopted

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[1] *Abbreviations:* AAE, average absolute error; ANN, artificial neural network; FA, factor analysis; MAE, mean absolute error; MSE, mean squared error; N_h, number of hidden neurons; PFA, principal factor analysis; QP, quick propagation (Quickprop); r, correlation coefficient; R^2, coefficient of determination; SEM, standard error of the mean; SSE, sum of squared errors; WQ, water quality; WQI, water quality index; WQV, water quality variable.

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