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Predicting Phytoplankton Biomass in RanuGrati using Hybrid Neural Fuzzy Inference System (HyFIS)

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ABSTRACT: Phytoplankton are ultimate aquatic biota that serves food for other organisms in water. The growth of phytoplankton heavily depended on nutrient availability. Nutrient can be enriched in waters as the organic matter being piled up. This will create algae bloom or eutrophication. This phenomenon may put aquatic organisms in danger. Specifically, freshwater ecosystem like RanuGrati is prone to this issue as it located in land and adjacent to anthropogenic activities. For this reason, it is important to build statistical/mathematical model to predict phytoplankton biomass to prevent eutrophication. Furthermore, standard model that has been commonly used (linear regression) is not satisfactory for this modelling. The objective of this study was to estimate phytoplankton biomass in RanuGrati using hybrid neural fuzzy inference system (HyFIS) approach. The result showed that this method performed quite well with high accuracy in predicting phytoplankton biomass in RanuGrati. Furthermore, model that only included nutrient concentration (eutrophication model) was preferable than model that incorporated many water quality parameters.

Keywords: eutrophication, fuzzy logic, neural network, nutrient enrichment, phytoplankton, prediction model, water quality.

I. INTRODUCTION

Phytoplankton are the ultimate microscopic aquatic biota, serving as the base of the aquatic food chain [1]. This is because phytoplankton are able to carry out photosynthesis, changing sunlight energy into inorganic material or food [19]. The growth rate of phytoplankton is determined by the availability of nutrients such as nitrate and phosphate [12]. The sustainability of an aquatic system is heavily dependent on its phytoplankton abundance [15]; however, excessive phytoplankton biomass will lead to water pollution instead [20].

Freshwater ecosystems, such as lakes, are prone to water pollution as a result of anthropogenic and industrial activities [23]. Any lentic water ecosystem which is surrounded by land and covers more than two hectares can be considered a lake [16]. Lakes have a double benefit for the environment as well as for their surrounding communities. They support biodiversity and are used as water sources and for aquaculture activities [18].

The focus of this study, RanuGrati, is located in Pasuruan Regency, East Java, Indonesia. 'Ranu' means lake in Javanese. This lake is widely utilized for floating-net aquaculture, fishing, agricultural irrigation, tourism, and domestic waste disposal [18]. Many of these uses of RanuGrati damage its water quality, creating pollution in the form of organic matter from fish waste, leftover feed, domestic waste, and agricultural runoff [9].

High concentrations of organic matter cause nutrient enrichment [4]. Uncontrolled growth of the nutrient content in water triggers phytoplankton blooms, also known as eutrophication [3]. This phenomenon is considered to be water pollution, because it threatens the aquatic environment by causing aquatic toxicity that kills other water biota [20, 22]. In order to prevent eutrophication, it is important to build a statistical model to predict phytoplankton biomass [8]. While linear regression has commonly been used as the standard model, it is not satisfactory for this purpose[6]. Therefore, this study aimed to propose an alternative model to predict phytoplankton abundance in relation to water quality variables using the Hybrid Neural Fuzzy Inference System (HyFIS).

II. MATERIALS AND METHODS

Research Location: The research was performed in Ranu Grati, Indonesia. The data collection period was from December 2018 to February 2019. A map ofthelocationmap is presented in Fig. 1.

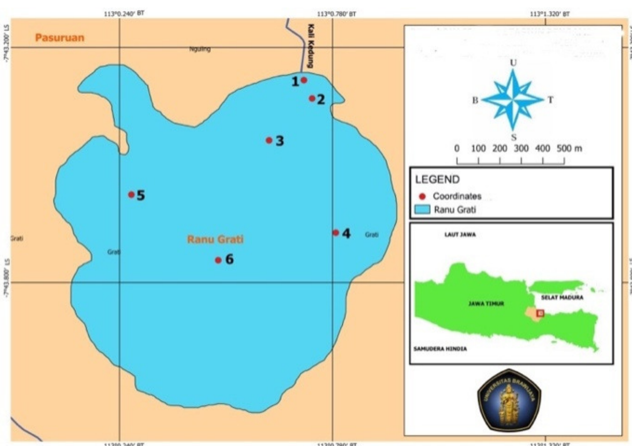


Fig. 1. Research location at RanuGrati, East Java, Indonesia

There were six sitesin the study: site 1: outlet; site 2: inlet; sites 3, 4, and 5: floating-net cages; and site 6: the centerofthelake.

Materials: This study employed several water quality parameters (temperature, pH, dissolved oxygen (DO), transparency, nitrate, and phosphate) and phytoplankton abundance as the main material. Temperature, pH, and DO were measured using AAQ Rinko, while secchi discs were used to measure transparency. These parameters were observed in-situ. Meanwhile, ex-situ observations were performed for nitrate and phosphate utilizing a spectrophotometer.

Phytoplankton species were identified using a microscope with 400x magnification, and the morphological characteristics were determined based on Prescott's book of algae identification [11]. Lackey's drop method was used to calculate the phytoplankton biomass.

Hybrid Neural Fuzzy Inference System (HyFIS). A fuzzy neural network is a combination of artificial neural networks with fuzzy logic [14]. HyFIS is a multilayered neural network with five layers, which is based on a fuzzy system. An explanation of each layer of the HyFIS network follows [2].

Layer 1: Layer 1 contains nodes that act as input linguistic variables. Each node in layer 1 corresponds to a node in layer 2 that represents its value.

Layer 2: Nodes in layer 2 are membership functions of the linguistic variables in layer 1. Input from the nodes in layer 1 are used to calculate the membership level by using the Gaussian membership function:

$$y_i^{II} = \text{Gaussian}(x;c,\sigma) = e^{-\frac{(x-c)^2}{\sigma^2}}$$

Where: c=mean; σ^2=variance

Layer 3: Each node in layer 3 stands for a probable IF-part in fuzzy rule. These nodes conduct the AND operation. Hence, all of the nodes in layer 3 form a fuzzy rule base.

$$y_j^{III} = \min_{i \in I_j}\left(y_i^{II}\right)$$

Where: I_j is the set of nodes in layer 2 that connects to the j^th node in layer 3; y_i^{II} is the output node from layer 2

Layer 4: Similarly to layer 3, the nodes in layer 4 represent THEN-parts, but they perform the OR operation. The level of activation of these nodes represents the degree to which this membership function is supported by all of the fuzzy rules together. It is for integrating field rules that will lead to the match output linguistic variables. The weight connection between layers 3 and 4 was randomly designated as an interval from -1 to 1.

$$y_k^{IV} = \max_{j \in I_k}\left(y_j^{III} w_{kj}^2\right)$$

Where I_k is a set of indices of nodes in layer 3 that connect to the k^th node in layer 4

Layer 5

Layer 5 represents the output variables of the system. These nodes and the links attached to them act as defuzzifiers. Each node calculates a crisp output signal using the Gravity method.

The architecture of HyFIS is depicted in Fig. 2.

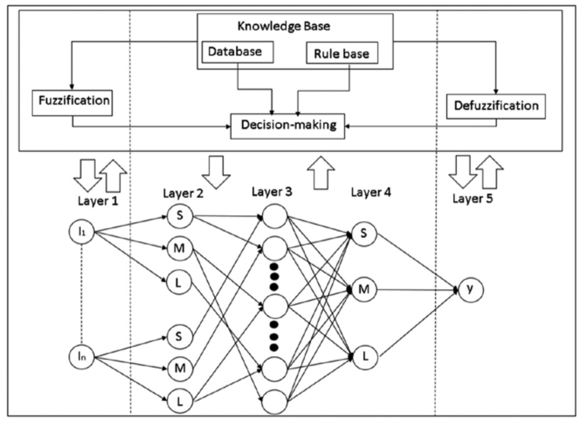


Fig. 2. Architecture of HyFIS[5].

Data preparation and input selection: The data used in this study consisted of training (80%) and testing (20%). Two models were built into this research. The first model (HyFIS1) was a eutrophication model that used nutrients (nitrate and phosphate) as predictors, while the second model (HyFIS2) used all water quality parameters as predictors. The data was transformed into a logarithm due to differences in unit and magnitude. The accuracy of the proposed model was indicated by low MAE and RMSE measures and a high correlation coefficient (R).

III. RESULTS AND DISCUSSION

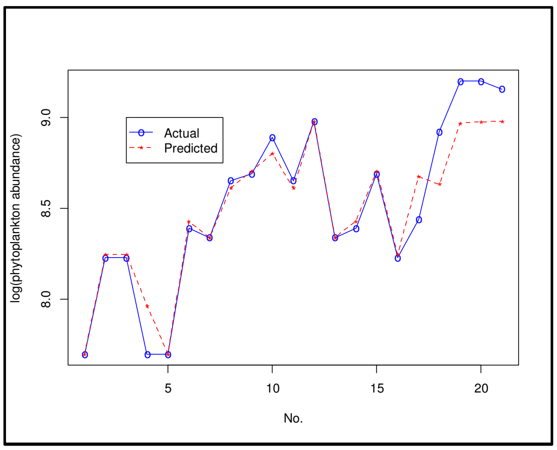
Summary of water quality parameter: According to Table 1, the minimum temperature was 29.33℃, which can be classified as an ideal temperature for algae [13]. The average water transparency was recorded at 0.82 m. This parameter plays a role in the success of photosynthesis, as it allows sunlight to penetrate into the water [23]. The pH values in this study ranged from 6.52 to 7.59. This is a permissible range for pH, as lower pH levels damage chloroplast [24].

Table 1: Basic statistics of water quality parameters in RanuGrati.

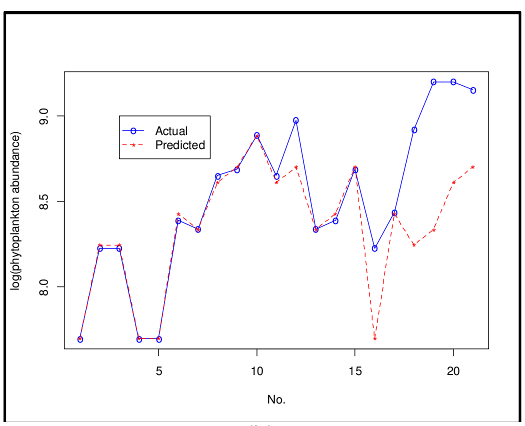
Variable	Unit	Minimum	Maximum	Mean	SD
Temperature	℃	29.33	31.67	30.25	0.64
Transparency	m	0.82	1.66	1.27	0.22
pH	–	6.52	7.59	7.15	0.32
DO	$mg.L^{-1}$	10.27	13.30	11.45	0.84
Nitrate	$mg.L^{-1}$	1.15	2.81	1.81	0.40
Orthophosphate	$mg.L^{-1}$	0.10	0.19	0.15	0.03
Phytoplankton abundance	$cell.mL^{-1}$	2200	9900	5468.57	2412.27

The relatively high DO concentrations (greater than 10 mg.L^{-1}) promoted phytoplankton growth and diversity [21]. The nutrient parameters (nitrate and orthophosphate) showed values under the standards set by the Indonesian Ministry of Environment (the nitrate standard is set at <20 mg.L^{-1} and the orthophosphate standard is set at <0.20 mg.L^{-1}). On the other hand, the mean phytoplankt on abundance recorded was 5468.57 cell.mL^{-1}. Despite the nutrient concentration being beneath the regulation standard, the orthophosphate value was quite high, indicating nutrient enrichment. This can lead to eutrophication [7], which has many negative impacts[10]. Primarily, eutrophication can shift the structure of thephytoplankton community and increase the presence of toxic algaespecies[17].

Prediction of phytoplankton abundance in RanuGrati: Fig. 3 depicts the predicted and actual values of phytoplankton abundance in RanuGrati using HyFIS1 and HyFIS2, while Table 2 shows the accuracy of each model's prediction.



(a)



(b)

Fig. 3. Comparison of predicted and actual values of log(phytoplankton abundance) (a) HyFIS1 (b) HyFIS2.

Table 2: Accuracy of HyFIS model in predicting phytoplankton abundance.

Model	Dataset	MAE	RMSE	R
HyFIS1	Training	0.033	0.072	0.987
	Testing	0.425	0.350	0.342
	Full	0.124	0.235	0.864
HyFIS2	Training	0.034	0.074	0.985
	Testing	0.520	0.582	0.743
	Full	0.173	0.317	0.796

Note that the horizontal axis in Figure 3 does not show the data organized chronologically. Figure 3 shows that the prediction results from HyFIS1 showed greater resemblance to the actual phytoplankton biomass than the prediction results from HyFIS2. This is because some of the predicted values from HyFIS2 deviated significantly from the actual values that were observed. This conclusion is also supported by the accuracy indices of the HyFIS1 model, which are preferable to those associated with HyFIS2. An exception is the testing dataset of HyFIS1, which hasa lower correlation coefficient than that of HyFIS2.

The HyFIS1 model implemented for training and the full dataset it produced was able to adequately predict the actual phytoplankton biomass (R>0.85). However, while the MAE and RMSE measures for this model were satisfactory, low R indices show that it was not consistent in predicting the testing data. Unlike the HyFIS1 model, the HyFIS2 model demonstrated stable accuracy measures, although the values were generally inferior to the HyFIS1 model in terms of predicting actual phytoplankton biomass.

Generally, the HyFIS model performed quite well in predicting phytoplankton abundance in RanuGrati. However, the HyFIS1 model outperformed the HyFIS2 model. Given that phytoplankton abundance is heavily determined by the nutrient concentration in the water, a eutrophication model is preferable to a model with many predictors (HyFIS2). Moreover, using the HyFIS1 model is also more effective and efficient than the HyFIS2 model.

IV. CONCLUSION

Eutrophication is a main concern in freshwater ecosystems, especially lakes. Surrounded by land, lakes such as RanuGratiare prone to pollution resulting from anthropogenic activities that release organic waste into the water. This leads to nutrient enrichment and may trigger eutrophication, threatening aquatic ecosystems. Phytoplankton abundance needs to be controlled to prevent this issue. The hybrid neural fuzzy inference system (HyFIS) estimated phytoplankton biomass with relatively high accuracy. However, the HyFIS model that used nutrients as the primary predictors was preferable to the HyFIS model with many independent variables.

V. FUTURE SCOPE

Further observations are needed to increase the sample size to provide better model fitting.

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Conflict of Interest. The authors declare that they have no conflict of interest.

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