Application of Wang-Mendel fuzzy algorithm to predict freshwater phytoplankton biomass in East Java, Indonesia

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Abstract. Phytoplankton are important aquatic biota which act as the primary producer in waters. Nutrient enrichment can lead to excessive abundance of phytoplankton or eutrophication that harms other aquatic organisms. Especially freshwater areas are susceptible to anthropogenic activities that produce organic waste discharges. These activities can worsen the nutrient enrichment in the aquatic ecosystem. This study aimed to predict the freshwater phytoplankton biomass by using the Wang-Mendel fuzzy algorithm as the function of nutrient concentration (nitrate, phosphate) and other water quality parameters (temperature, transparency, pH, dissolved oxygen). The data were collected from various sources that cover 10 rivers/lakes/reservoirs located in East Java province, Indonesia. The results showed that the proposed model performed well in predicting actual phytoplankton biomass. A better model was produced by utilizing all water quality parameters as the predictors instead of the eutrophication model that only accommodated nutrient predictors. Moreover, this model also outperformed the prediction resulting from multiple linear regression.

Key Words: eutrophication, fuzzy logic, phytoplankton, prediction model, Wang-Mendel algorithm.

Introduction. Plankton are small organisms found in water. They can be divided in two categories, namely zooplankton and phytoplankton (Al-Hashmi et al 2013). Phytoplankton serves as the base of the food chain in aquatic ecosystems. It depends on sunlight for photosynthesis (Inyang & Wang 2020). Therefore, phytoplankton plays a role as natural feed for other aquatic organisms and determines the productivity or trophic status of the waters (Lusiana et al 2019a). It is also a major biological indicator of water quality, as it rapidly reacts to the environmental dynamics (Hallegraeff 2010).

The biomass of phytoplankton needs to be maintained at certain levels (Glibert et al 2010). Low phytoplankton biomass is not proper for aquatic biota growth (Kozak et al 2015), while excessive abundance of phytoplankton (algae bloom, eutrophication) will pollute the water (Sugiura et al 2004). It is harmful to the aquatic ecosystem because it has toxic effects and covers the water area, reducing water transparency (Arend et al 2011). Furthermore, it causes oxygen depletion as the result of the bloom sinking and being decomposed by bacteria (Gobler 2020).

Eutrophication or algae bloom is mainly caused by nutrient enrichment (Lv et al 2011). Nutrients such as nitrates and phosphates are essential for phytoplankton growth (Davidson et al 2014). However, their high concentration in the waters will result in algal bloom that threatens the water system (Wisha et al 2018). Nutrient enrichment is highly associated with organic matter (Barraza-Guardado et al 2013). Escalation of organic matter in waters is usually a consequence of anthropogenic activities which produce waste discharged into waters (Herbeck et al 2013). Specifically, freshwater streams are susceptive to domestic pollution because they are based inland and are directly engaged by human activities (Amoatey & Baawain 2019). Therefore, good water quality management is needed.

The control of phytoplankton biomass as part of water management can be monitored through environmental indicators, especially nutrient concentration (Xu et al 2015). Regression analysis is widely used to predict the abundance of phytoplankton as the function of nutrients (Bode et al 2015; Niu et al 2015; Yuan & Pollard 2018). Nevertheless, it has a low accuracy (Lusiana et al 2019a). The fuzzy method, such as a Wang-Mendel algorithm, can be considered as an alternative to the regression analysis (Alvarez-Estevez & Moret-Bonillo 2018). This algorithm had been implemented to produce better predictions for many problems in finances (Wang 2017) and bioinformatics (Gasparovica et al 2010). The aim of this study was to apply the Wang-Mendel algorithm in predicting freshwater phytoplankton abundance in East Java, Indonesia. This area has many rivers, lakes and reservoirs that suffered pollution because of industrial and domestic activities (Roosmini et al 2018; Musa et al 2019).

Material and Method

Description of the study sites and materials. East Java is the eastern province in Java Island, Indonesia (Figure 1). The water quality data were obtained from 8 freshwater sources in this province. They are Brantas River (Roosmini et al 2018), Bengawan Solo River (Setyaningrum & Agustina 2020), Lake Grati (Mahmudi et al 2019), Lake Pakis (Lusiana et al 2020), Sengguruh Reservoir (Mulyanto 2019), Wlingi Raya Reservoir (Mardiastuti 2019), Sutami Reservoir (Lusiana et al 2019a), Selorejo Reservoir (Manalu 2019), Tanjungan Reservoir (Sari 2020), and Lahor Reservoir (Putra 2017). The datasets were comprised of 7 water quality parameters (temperature, transparency, pH, dissolved oxygen, nitrate, orthophosphate, and phytoplankton biomass) collected from 2016 to 2019. In total, there were 101 samples used in this research. Temperature, transparency, pH and dissolved oxygen were measured *in situ* by a thermometer, Secchi disc, pH meter, and DO meter, respectively, while nitrate and orthophosphate were evaluated *ex situ* in the laboratory of Brawijaya University by using a spectrophotometer (Spectroquant Pharo 300 and GENESYS 10S UV-Vis). The procedures were conducted in accordance to standard methods of APHA (APHA 1989). Water samples were obtained to quantify the phytoplankton at euphotic depth by using plankton nets (pore size 30 μm). Formalin was used for preservation. Phytoplankton biomass was calculated based on the Lackey drop method (Kadim & Arsad 2016), as follows:

$$D = \frac{C.A_t}{A_s.S.V}$$

Where: D - phytoplankton density (cell mL^{-1}); C - number of organisms counted; At - area of cover slip (mmÇ); A_s - area of one strip (mmÇ); S - number of strips counted; V - volume of sample under the cover slip (mL).

Wang-Mendel fuzzy algorithm. Fuzzy ruled based systems (FRBS) are based on fuzzy logic in soft computing utilized solve real-world problems (Riza et al 2015). It is usually used to tackle problems relating to identification, classification, and regression which contain uncertainty and nonlinearity (Gokulachandran & Mohandas 2012). The basic rule of FRBS is "IF A THEN B", where A and B are fuzzy sets (Tundo & Sela 2018). One of the algorithms that accommodates FRBS is the Wang-Mendel Fuzzy Algorithm. It requires learning and prediction phases in modelling (Figure 2). The learning process in Wang-Mendel Fuzzy Algorithm consists of five steps (Riza et al 2015): 1 - divide input and output spaces into fuzzy sets; 2 - generate the rules of fuzzy from the given datasets; 3 - assign a degree for each generated rule; 4 - produce fuzzy rules combinations; 5 - determine the mapping based on the combination of fuzzy rules. The model resulted from this algorithm is called the Mamdani model (Riza et al 2015) and it can be used to make predictions of desired responses for known predictors.

Figure 1. Research location, East Java, Indonesia.

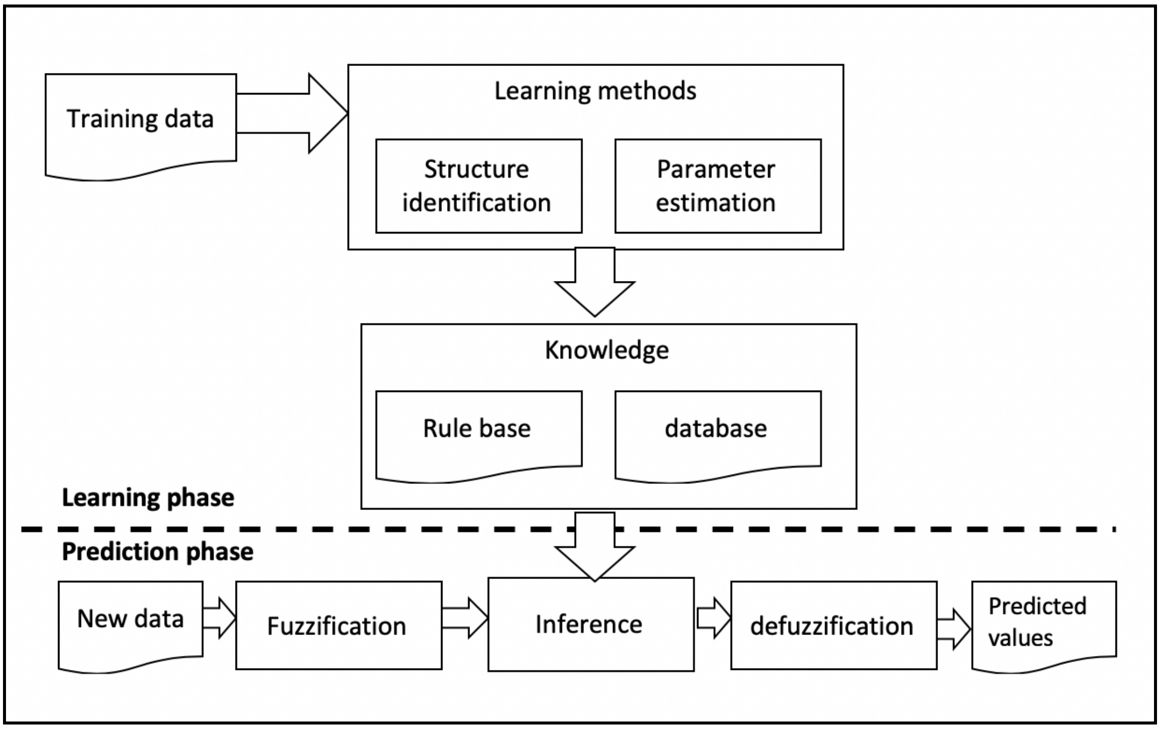

Figure 2. Phase of learning and prediction of a fuzzy ruled based system (Riza et al 2015).

Data preparation, input selection, and performance evaluation. 3 types of models using the Wang-Mendel algorithm were employed in estimating phytoplankton biomass: 1 - WM1 or the eutrophication model which used nutrient concentration (nitrate and orthophosphate) as the predictors; 2 - WM2 model that used all water quality parameters; 3 - WM3 model which included water quality parameters that had significant relationships with phytoplankton biomass. The raw dataset in this study was transformed by natural logarithm transformation to reduce bias due to differences in the magnitude and units (Hazra & Gogtay, 2016) of variables. The data were then analyzed using the Pearson correlation (Schober & Schwarte, 2018) as in the following equation to determine the association of each water quality parameter to phytoplankton biomass.

$$r_{xy} = \frac{n\sum_{i=1}^{n} X_i Y_i - \sum_{i=1}^{n} X_i \sum_{i=1}^{n} Y_i}{\sqrt{\left[n\sum_{i=1}^{n} X_i^2 - \left(\sum_{i=1}^{n} X_i \right)^2 \right]\left[n\sum_{i=1}^{n} Y_i^2 - \left(\sum_{i=1}^{n} Y_i \right)^2 \right]}}$$

Where: X=first variable; Y=second variable; n=sample size

Every significant parameter ($p<0.05$) was included as a predictor to estimate phytoplankton biomass in the WM3 model. The dataset partitioned into data training (80%) and data testing (20%) (Prashanth et al 2020). In addition, to measure the performance of the Wang-Mendel fuzzy algorithm, a multiple linear regression (MLR) of each model was also run, for comparison. The accuracy of each method was indicated by the high coefficient of correlation (R), lower Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) (Ahmed & Shah 2017).

Results and discussion

Water quality parameters. Table 1 presents basic statistics of data used in this research.

Table 1

Basic statistics of physico-chemical water quality parameters and Pearson correlation results

Variable	*Unit*	*Minimum*	*Maximum*	*Mean*	*SD*	*CorrPhyto*	*p*
Temperature	^{0}C	25	32	28.82	1.87	-0.118	0.245
Transparency	m	0.06	2.36	0.83	0.58	-0.268	0.007*
pH	-	6.52	8.3	7.51	0.46	-0.341	0.0005*
DO	mg.L^{-1}	5.39	13.3	8.87	1.71	0.023	0.823
Nitrate	mg.L^{-1}	0.05	2.81	0.88	0.74	-0.155	0.876
Orthophosphate	mg.L^{-1}	0.01	0.87	0.24	0.26	0.027	0.793
Phytoplankton biomass	cell mL^{-1}	280	25850	4573.75	4875.5	-	-

Note: SD - standard deviation; CorrPhyto - correlation with phytoplankton biomass; DO - dissolved oxygen; * - significant correlation.

Table 1 shows that the average temperature in the studied sites was 28.82^{o}C. It is optimum for algae growth (Renaud et al 2002). On the other hand, water transparency was 0.83 m, with big deviations. The major threat of water eutrophication is that it can damage the balance of water ecosystems. It can reduce sunlight penetration and decrease the photosynthesis rate of plants in the water (Yang et al 2008). The pH values were 7.51 on average, with small deviations. This is ideal for freshwater algae, because lower pH can cause the deterioration of chloroplasts (Kim et al 1999).

The concentration of dissolved oxygen (DO) was between 5.39 and 13.3 mg L^{-1}. DO is heavily influenced by temperature. An increase in temperature will decrease DO and reduce phytoplankton abundance and biodiversity (Takarina & Patria 2017). Nitrate and orthophosphate are two parameters which directly determine the phytoplankton standing stock. The lack of nutrients is a limiting factor in the growth of phytoplankton (Vrede et al 2009). Nutrient enrichment can result in alga blooming and eutrophication

(Lusiana et al 2019b). The phytoplankton biomass in this research revealed high variations from the lowest of 280 cells mL^{-1} to 25850 cell mL^{-1}. Therefore, it can be classified into oligotrophic to eutrophic categories (Baban 1996). Eutrophication has many bad effects for the ecosystem (Pasztaleniec 2016). Commonly, it contributes to the alteration of phytoplankton community as well as uncontrolled production of toxic species such as *Cyanobacteria* and filamentous green algae (Søndergaard et al 2011).

Based on the correlation analysis, only pH and DO that have significant correlation with phytoplankton biomass ($p<0.05$). Hence, these parameters were included in the WM3 model in this present study. Finally, the three models used in this study were WM1 (nitrate and orthophosphate predictors), WM2 (all water quality parameters predictors), and WM3 (pH and DO predictors).

Model prediction results and performance evaluation. The model of Wang-Mendel (WM) fuzzy algorithm used training, testing, and complete datasets (training+testing) for various predictor combinations. The 3 performance indicators were calculated to evaluate the accuracy of the phytoplankton biomass prediction model. Table 3 shows the MAE, RMSE, and correlation coefficient (R) between observed and predicted values of each proposed model. Generally, the WM model performances were adequate for each model in predicting phytoplankton biomass. The WM1 model or eutrophication model worked well with high correlation coefficient, greater than 0.9 except for the testing dataset (R=0.21), while the RMSE and MAE were 0.322 and 0.445 for training, respectively, and 0.467 and 0.554 for testing, respectively. On the other hand, all correlation coefficients for WM2 model were greater than 0.9, supporting low RMSE and MAE. Meanwhile, the performance of WM3 was poorer than that of other models for all indicators. Therefore, out of the 3 proposed Wang-Mendel fuzzy algorithm models, the model with all water quality parameters as predictors (WM2 model) was the best model because it had the best performance.

Table 2

Peformance evaluation of Wang-Mendel (WM) fuzzy algorithm for training, testing, and whole dataset

Model	*Dataset*	*MAE*	*RMSE*	*R*
	Training	0.322	0.445	0.927
WM1	Testing	0.467	0.554	0.21
	Complete	0.35	0.468	0.916
	Training	0.099	0.135	0.993
WM2	Testing	0.676	0.867	0.993
	Complete	0.21	0.399	0.938
	Training	0.44	0.603	0.855
WM3	Testing	1.29	1.591	-0.494
	Complete	0.603	0.883	0.672

Note: WM1 - Wang-Mendel fuzzy algorithm model with nitrate and orthophosphate predictors; WM2 - Wang-Mendel fuzzy algorithm model with all water quality parameters predictors; WM 3 - Wang-Mendel fuzzy algorithm model with pH and dissolved oxygen predictors; MAE - Mean Absolute Error; RMSE - Root Mean Square Error; R - correlation coefficient.

Comparison of the WM2 and MLR depicted in scatter plots (Figure 3) revealed that the WM2 model performed better than the latter model. This is indicated by the coefficient of correlation of WM2, which was double the value of the correlation coefficient of the MLR model. The WM2 model produced predicted values that had a strong correlation with the observed data. Hence, the results of this study recognized that the suggested WM models are effective in estimating predictions of the freshwater phytoplankton biomass by utilizing all possible other water quality parameters.

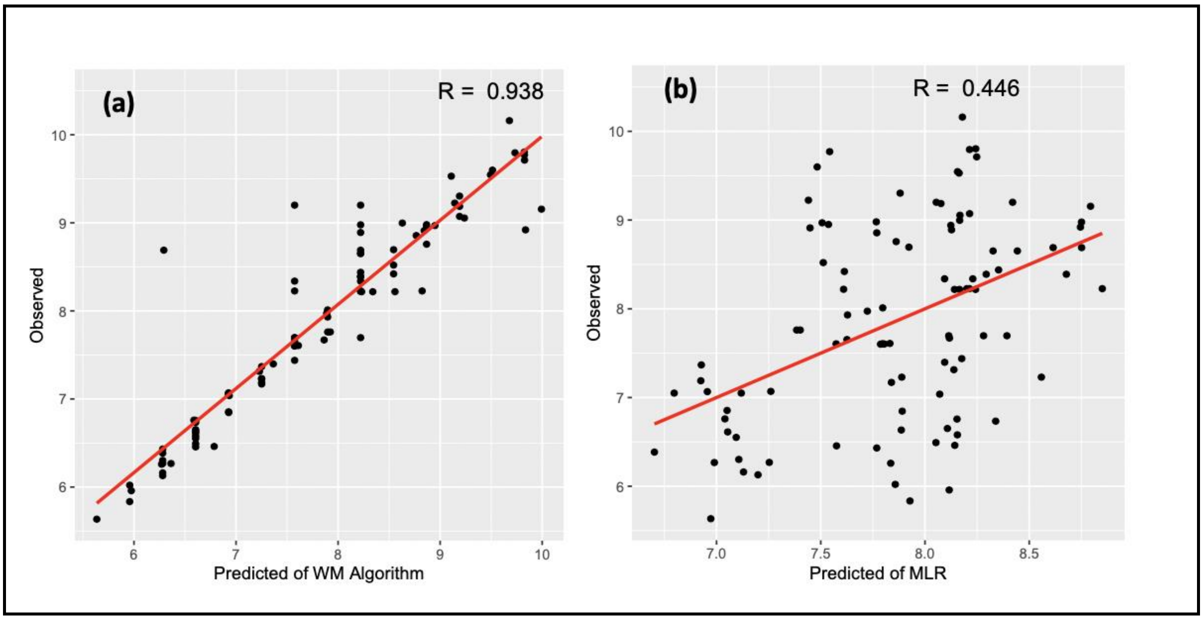

Figure 3. Scatter plot of observed and predicted biomass of freshwater phytoplankton; a - Wang-Mendel fuzzy algorithm model with all water quality parameters predictors model (WM2); b - multi linear regression (MLR) model.

Conclusions. The estimation of freshwater phytoplankton biomass is essential to prevent water eutrophication that may harm the aquatic ecosystem. Eutrophication is mainly caused by nutrient (nitrate and phosphate) enrichment. The results of this study indicated that WM models worked effectively in predicting freshwater phytoplankton biomass in East Java, Indonesia. It also showed that, rather than the eutrophication model (WM1), WM3 that included other water quality parameters was preferable. Moreover, this model also outperformed the MLR model that has been widely used as standard model for phytoplankton biomass.

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