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THE TENDENCY OF EUTROPHICATION LEVEL PREDICTION IN CHENGCHINGHU RESERVOIR, KAOHSIUNG CITY, TAIWAN

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Abstract

Introduction: *Reservoir management problems are increasing, and tools are needed to categorize and predict their eutrophication status in order to provide technical support for the government's decision to protect drinking water resource. Thus, this study aims to predict and classify the tendency of eutrophication level in Chengchinghu Reservoir, Kaohsiung City, Taiwan as one of major water sources for industrial and domestical needs by supplying 109,170,00 m3 for Southern Taiwan.* ***Method:*** *The CTSI (Carlson's Trophic States Index, which calculated from Chl-a, TP, and transparency) datasets in winter (December-February), spring (March-May), summer (June-August), and fall (September-November) from 2000 to 2017 was collected from Taiwan Environmental Protection Administration (EPA). This study used the Classification and Regresiion Tree (CART) model provides the explicit categorical rules for Chengchinghu Reservoir.* ***Results and Discussion:*** *The CART results for Chengchinghu Reservoir showed the good performance of prediction since the accuracy of the CART training process value reached 61.89%. According to the CART results, the eutrophic state condition is most probably occur in Chengchinghu Reservoir when the TP concentration is greater than 22.86 mg/L or Chl-a concentration is greater than 5.2 µg/L or SD is less than 1.1 m.* ***Conclusion:*** *The CART result may helps the local governments to understand the pollution conditions in Chengchinghu Reservoir and take responsibility for reservoir water management and conservation. Therefore, they could make policies to treat and manage water pollution sources in Chengchinghu Reservoir.*

INTRODUCTION

The challenge of water quality management associated with the sustainable development has been concerned to many researchers and managers in the current decade (1). It involved not only the reinforcement of established principles and technologies but also their enlargement to much wider, higher and freer scope for the realization of sustainability for water-quality management (2). However, the current situation of water quality management in the world is far from satisfactory, due to the burdens of increasing population and economic development (3). In developed countries around 2000's, the increase number of chemical toxic pollutions entering the environment through non-point sources has led to increasing eutrophication, ecotoxification or even health impact concerns; however, many harmful effects are unknown, due mainly to the lack of effective detection capabilities (4).

Water resource in reservoir is an essential resource for all living organisms (5). Reservoirs provides not only pure water for such diverse purposes as agriculture, industry, and everyday human consumption, but also habitats for a composite variety of aquatic life (6). Various water physical and chemical properties in reservoirs, especially its quality, must be assessed (7). The water quality assessment critically enables managers to develop ideal water resources management plans (8).

The UNEP (United Nation Environmental Protection) investigation result indicates that about 30%-40% of the lakes and reservoirs all over the world have been affected more or less by water eutrophication (9). The increasing severity of water eutrophication has been brought to the attention of both the governments and the public in recent years (10). The nutrient level of many lakes and rivers has increased dramatically over 50 years ago in response to increased discharge of domestic wastes and non-point pollution from agricultural practices and urban development (11). According to those complexity, it is not easy to predict the behavior of nutrient enriched water bodies because of the complex physical, chemical, and biological processes involved (12). During the last couple of decades, environmental engineers have used monitoring and simulation to predict and control eutrophication in reservoirs (13).

Specifically in Taiwan, eutrophication has been one of the most serious reservoir water quality problems (14-16). Moreover, the Taiwan reservoirs provide about 70% of drinking water for a population of nearly 23 millions and industrial water use. In Chengchinghu Reservoir, around 109.170.000 m^3 per month water supplies for industrial and domestical needs of Southern Taiwan (17).

Several empirical models based on linear relationships for hypothesised the environmental drivers have been derrived for fresh water ecosystem (18-20). Classification and regression trees (21) are a data mining method for empirical model building and hypothesis formulation. A classification and regression tree creates a set of decision rules for identifying response variable. group membership or value based on a dichotomous partitioning of predictor variables. A major advantage of partitioning trees is that assumptions which are required for the appropriate use of parametric statistics, such as Gaussian distribution of predictor variables, do not need to be satisfied. Traditional linear techniques such as multiple linear regression are also only able to identify a limited number of predictor variables, often due to multi-collinearity constraints, and predictor and response variables must show a linear relationship over their entire range. In contrast, tree-based models allow the complex interactions between the predictor variables to be represented, with no assumptions of linearity. Multiple linear regression identifies global relationships in the data set, whereas partitioning trees are able to identify local relationships. Although classification and regression trees can be used for empirical model building, large data sets are required for the development of statistically valid models.

Recently, partitioning trees have been used to identify potential causal relationships in a variety of environmental data sets (22-24). The approach has also been used to investigate controls on soil NO_3 -N in a large watershed with heterogeneous land use (25), but has not previously been used to analyse the dynamics of nitrogen pollution in a large number of forested ecosystems. Thus, we inisiated to connect this phenomenon with eutrophication since nitrogen is one of the pollutant driving factor causing eutrophication.

In order to mitigate the uncontrolled nutrient increasement of Chengchinghu Reservoir ecosystem, this paper aims to use classification and regression tree analysis to determine the prediction classification of eutrophication conditions in Chengchinghu Reservoir. A future aim is to describe if the outcomes from this classification and regression tree can help the policymakers to create regulations and implement the monitoring program for adaptive management strategies in the future.

METHOD

Study Area

Chengchinghu Reservoir (22°39'39.0″E, 120°21'08.1″N) located in Kaohsiung City was selected since its major purpose to supply water for industrial and domestic need in Tainan City, Kaohsiung City, and others region in Southern Taiwan. Chengchinghu Reservoir is currently managed by Taiwan Water Cooperation. The type of Chegchinghu Reservoir is Embankment dam which Caogong River as a watershed and pumped from Mengli Pumping Station, Jiuqutang Pumping Station, and Gaoping River Wier. Chengchinghu Reservoir has 19 m height, 600 m length and 28 km^2 catchment area. Full water level area and full water level of Chengchinghu Reservoir are 1,1 km^2 and 17,8 m, respectively. The effective storage capacity of Chengchinghu Reservoir is 109,17 x 106 m^3 (26).

Figure 1 shows the water quality monitoring stations obtained from Taiwan EPA. There are four water monitoring station, described as Station 1 (22° 39' 16.0992'' E, 120° 21' 16.4016'' N), Station 2 (22° 39' 37.2996'' E, 120° 21' 8.8992'' N), Station 3 (22° 39' 42.5016'' E, 120° 20' 52.1016'' N), Station 4 (22° 39' 50.2992'' E, 120° 21' 1.8'' N).

Water Quality Dataset

The water quality dataset was obtained from Taiwan EPA for CTSI factors (Chl-a, TP, SD) since 2000 to 2017. Water quality monitoring data were collected

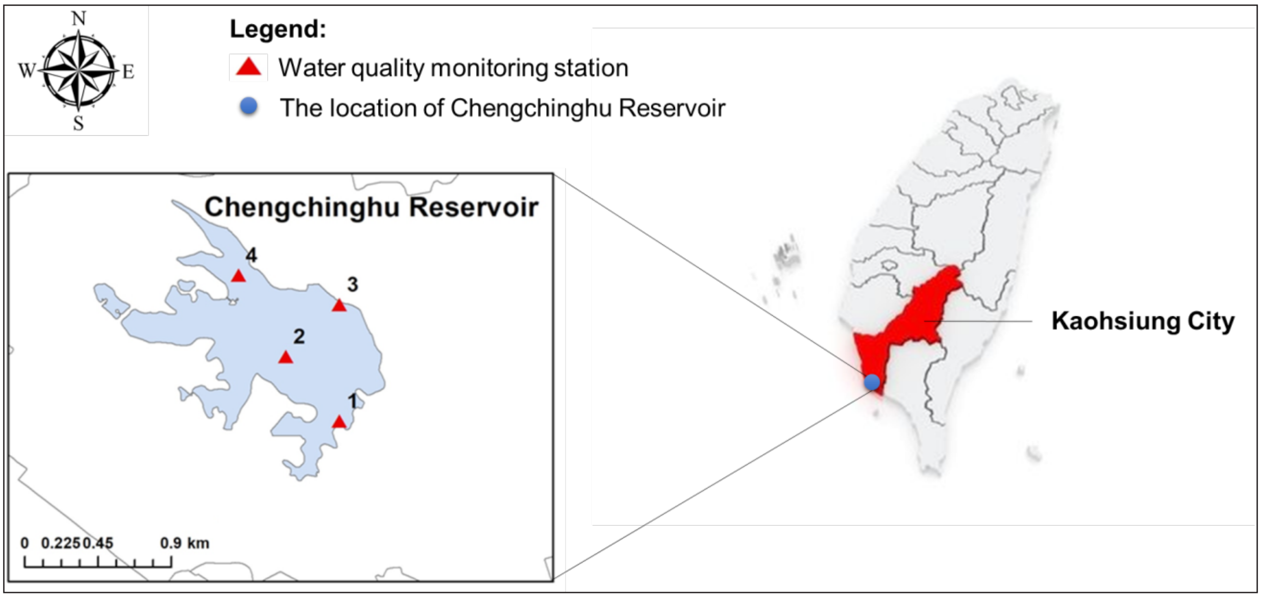

Figure 1. Study Area

once in a season: spring (from March to May), summer (from June to August), autumn (from September to November), and winter (from December to February). Every month has two times data sampling in each station. The water quality parameters which selected for water quality evaluation were measured using the following: TP using Spectrophotometer method / Vitamin C method, SD (transparency) using Sechi disk.

Carlson's Trophic State Index

The TSI defined as the total weight of living biological material (biomass) in a waterbody at a specific location and time. Time and location-specific measurements can be aggregated to produce waterbody-level estimations of trophic state. Trophic state is understood to be the biological response to forcing factors such as nutrient additions, but the effect of nutrients can be modified by factors such as season, grazing, mixing depth, etc (27).

In accordance with the definition of trophic state given above, the CTSI uses algal biomass as the basis for trophic state classification (28). Three variables including Chl-a concentration, SD, and TP, independently estimate algal biomass. The trophic continuum is divided into units based on a base-2 logarithmic transformation of SD, each 10-unit division of the index representing a halving or doubling of SD. Because TP often correlates with SD, a doubling of the TP often corresponds to a halving of SD (29).

The index range is from approximately zero to 100. The index has the advantage over the use of the raw variables in that it is easier to memorize units of 10 rather than the decimal fractions of raw phosphorus or Chl-a values. An early version of the index was based on a scale of one to ten, but it became tempting to add 1, 2, or more numbers after the decimal. For this reason, the scale was multiplied by ten to discourage any illusory precision obtained by using more than whole numbers.

The logarithmic transformation of the data normalizes the skewed data distribution, allowing the use of parametric statistics (mean, standard deviation, parametric comparison tests). This facilitates not only comparison and data reduction, but communication as well, because the user does not need to resort to graphs with logarithmic axes. The three index variables are interrelated by linear regression models, and should produce the same index value for a given combination of variable values. Any of the three variables can therefore theoretically be used to classify a waterbody. This is particularly useful in citizen lake monitoring programs. TP may be better than Chl-a at predicting summer trophic state from winter samples, and transparency should only be used if there are no better methods available (30). The index is relatively simple to calculate and to use. The CTSI can determined from average of TSI can be computed from three interrelated factors as follows:

$$TSI\ (SD) = 60 - 14.41 \ln(SD)$$

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$$TSI\ (Chl-a) = 9.81 \ln(Chl-a) + 30.6$$

$$TSI\ (TP) = 14.42 \ln(TP) + 4.15$$

$$CTSI = \frac{[TSI(SD) + TSI(Chl-a) + TSI(TP)]}{3}$$

Where:

CTSI : Carlson Trophic State Index

TSI : Carlson trophic state index calculated from each variable, such as:

SD (m); Chl-a (µg/L); and TP (µg/L).

The trophic states are defined as oligotrophic, mesotrophic, and eutrophic states, when the value is determined in Table 1.

Table 1. Range of Variable Values Associates with CTSI

CTSI	Trophic State Status	Attributes
CTSI < 40	Oligotrophic	High water clarity Low algae value Low phosphorus
40 ≤ CTSI ≤ 50	Mesotrophic	Moderate water clarity Moderate algae value Moderate phosphorus
CTSI > 50	Eutrophic	Low water clarity High Chl-a value High phosphorus

Source: Taiwan EPA Standard

Classification and Regression Tree

A decision tree analysis is widely used for classification and prediction. A decision tree classifies data in the form of a tree structure which is generated from the use of training data in a top-down fashion or general-to-specific direction. The root node, initial state of a decision tree, is assigned all data. If data at the node of tree structure belong to the same class, so that no more decisions are needed, the node will be a leaf node which indicates the value of the target attribute (or class). If data at the node belong to two or more classes, such that the node has to be split, the node will be a decision node (31).

Classification and regression tree (CART) is probably the most well-known decision tree learning algorithm in the literature (32). Given a set of samples, CART identifies one input variable and one break-point, before partitioning the samples into two child nodes. Starting from the entire set of available training samples (root node), recursive binary partition is performed for each node until no further split is possible or a certain terminating criterion is satisfied. At each node, best split is identified by exhaustive search, i.e. all potential splits on each input variable and each break-point are tested, and the one corresponding to the minimum deviations by respectively predicting two child nodes of samples with their mean output variables is selected. After the tree growing procedure, typically an overly large tree is constructed, resulting in lack of model generalization to unseen samples. A procedure of pruning is employed to remove sequentially the splits contributing insufficiently to training accuracy. The tree is pruned from the maximal-sized tree all the way back to the root node, resulting in a sequence of candidate trees. Each candidate tree is tested on an independent validation sample set and the one corresponding to the lowest prediction error is selected as the final tree (33, 34). Alternatively, the optimal tree structure can be identified via cross validation. After building a tree, an enquiry sample is firstly assigned into one of the terminal leaves (non-splitting leaf nodes) and then predicted with the mean output value of the samples belonging to the leaf node. Despite its simplicity, good interpretation and wide applications for environmental assessment (35), the simple rule of predicting with mean values at the terminal leaves often means prediction performance is compromised (36).

The decision tree model used in this study was produces a classification tree that partitions data into parent and child nodes (37-39). The parameters within circles of the non-terminal nodes are the ones selected as attributes, and the data that reach these nodes are divided into some child nodes based on these attributes. The decision tree finally does not increase with further nodes and become terminal nodes after series of successive subdivisions (39). The values inside the terminal nodes at the lowest part of the tree indicate the classification results estimated by CART (40). CTSI factors (SD, TP, and Chl-a) were selected as independent variables and the trophic states (eutrophic, mesotrophic, and oligotrophic) were selected as dependent variables in the CART methodology. The accuracy of the CART training process would be defined as high accuracy when the performance achieve more than 50% (41).

The criterion used for selecting the splits on the nodes was set to 'Max Split Statistic'. This split selection method examines all possible splits for each predictor variable at each node. Missing values were assigned to 'Closest' and the minimum split size for nodes was set to three. With no independent test sample, a k-fold cross validation procedure was used. This procedure randomly partitions the data set into *k* equal sized groups. Each group is then sequentially used as a test set for the model derived` from the combined set of remaining groups. This ensures that roughly unbiased estimates for predictions are obtained. In this application five was selected for the *k*-fold cross validationda value commonly used for this type of validation (42). Model goodness-of-fit was assessed using the G^2 statistic. The G^2 statistic is a likelihood-ratio chi-square, analogous to a sum of squares for continuous data. The significance of each additional split in the tree was assessed using the Akaike Information Criterion (AIC). Statistical significance was assessed at $p \leq 0{,}05$. Splitting was stopped immediately prior to the first split that would have resulted in a leaf node with an AIC probability $p > 0{,}05$.

Data display and analysis tools

This work aims to assess both predictive accuracy and applicability of statistical evaluations for the particular demand. Therefore, the software packages that provide the user-friendly interface and powerful predictive applications are necessary. Microsoft Excel 2016 for data sorting and organizing, ESRI ArcGIS 10.2 for geographic information system data, and JMP 5.1 (SAS Institute) for CART analysis.

RESULT

Seasonal evaluation of water quality parameters

Table 2 shows the seasonal summary trend of water quality and CTSI data in Chengchinghu Reservoir currently (from 2000-2017). According to the result, the level of CTSI mostly in eutrophic status in average which highest in winter. The nutrients presence (in this study described as total phosphate) level were getting worse in winter (dry season).

Table 2. Descriptive Statistic of CTSI Parameters in Chengchinghu Reservoir

Water Qality Parameters	Fall	Spring	Summer	Winter
CTSI observation data				
Min	44,79	46,13	46,03	48,43
Mean	54,13	55,08	54,01	57,74
Max	68,20	68,63	65,13	70,58
Standard Deviation	6,27	7,13	5,97	7,16
Total phosphate (mg/L)				
Min	0,01	0,01	0,01	0,02
Mean	0,05	0,05	0,04	0,07
Max	0,22	0,14	0,09	0,25
Standard Deviation	0,05	0,04	0,03	0,07
Chlorophyll-a (μg/L)				
Min	2,34	1,22	3,19	0,25
Mean	7,78	12,51	9,10	13,28
Max	25,36	44,63	33,60	46,33
Standard Deviation	6,88	13,41	9,26	13,07
SD (meter)				
Min	0,65	0,59	0,35	0,38
Mean	0,98	1,07	1,03	0,83
Max	1,68	1,65	1,78	1,43
Standard Deviation	0,27	0,35	0,35	0,31

Result from study in Basin River has supported this study result according to their analysis of managing water quality in Kaoping River which is Chengchinghu Reservoir's upstream (43). Water quality in Chengchinghu Reservoir may become even worse in the dry season according to the point and nonpoint source pollution investigation.

Annual evaluation of CTSI

Figure 2 shows the average of CTSI values in Chengchinghu Reservoir were tended to be decreased from 2000 to 2017. In 2000, the average of CTSI in Chengchinghu Reservoir was the highest (64.12). In summary, the average of TSI (TP) and TSI (SD) showed the high contribution for CTSI than TSI (Chl-a). According to the figure above, we can conclude that the CTSI in Chengchinghu Reservoir were mostly eutrophic. nutrients have given the high contributed from farming activity running off to the Kaoping River as an inflow to the Chengchinghu Reservoir (42).

Prediction of CTSI classification using CART

The CART algorithm identifies three independent variables (SD, TP and Chl-a) affecting CTSI and provides explicit categorical rules for Chengchinghu Reservoir. The CART results for all reservoirs showed the good performance since the accuracy of the CART training process were 61,89%, The CART result provides the terminal and non-terminal nodes in each reservoir. The total of terminal nodes is 6 and non-terminal nodes is 3. In Figure 3., the CART result for Chengchinghu Reservoir was successfully conducted. The 396 samples of TP with the concentration less than 22,86 μg/L indicating the mesotrophic state and TP greater than 22,86 μg/L indicating the eutrophic state. Samples in the "Node 1" was divided into two discriminators. The first condition was if TP concentration less than 22,86 μg/L and SD less than 1,1 meters then, it indicates eutrophic states. The second condition was if TP concentration greater than 22,86 μg/L and SD greater than 1,1 meters then, it indicates mesotrophic states.

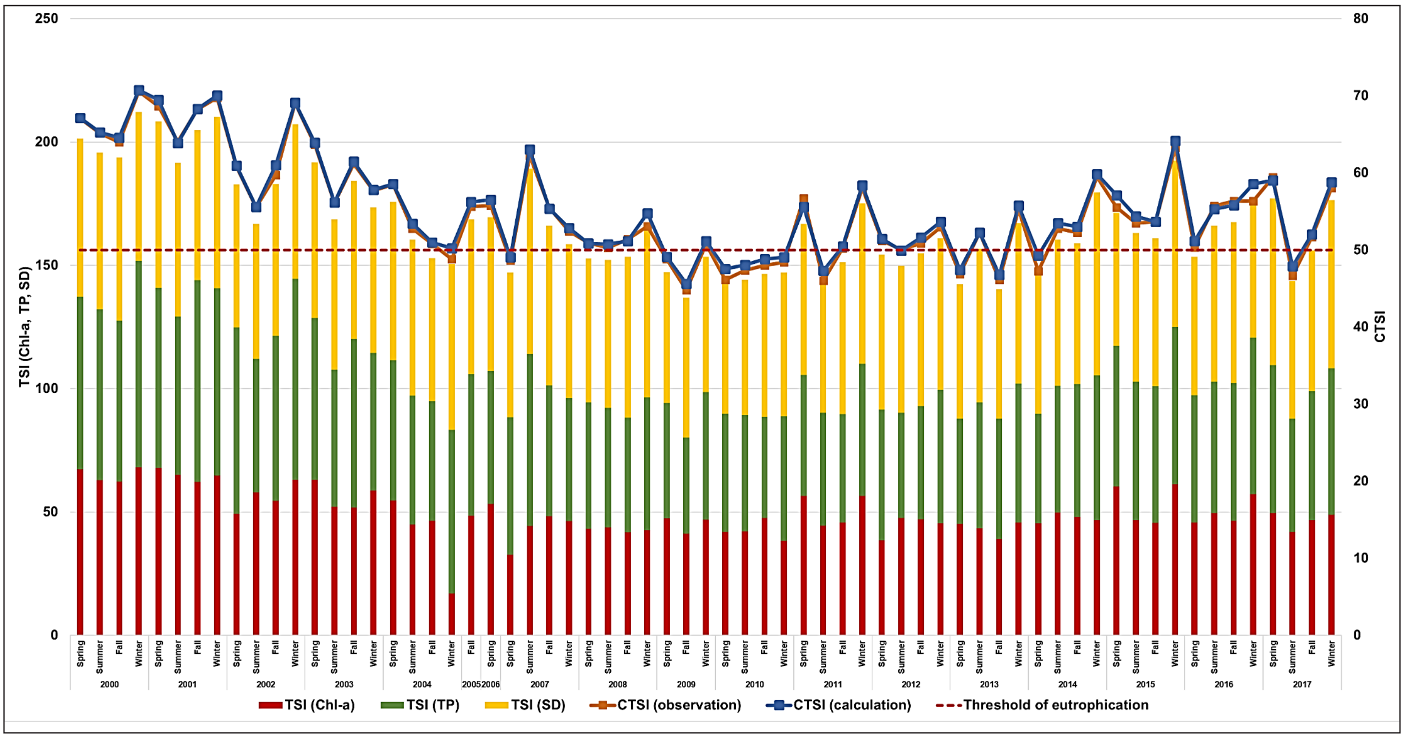

Figure 2. Annual Evaluation Trend of CTSI in Chengchinghu Reservoir

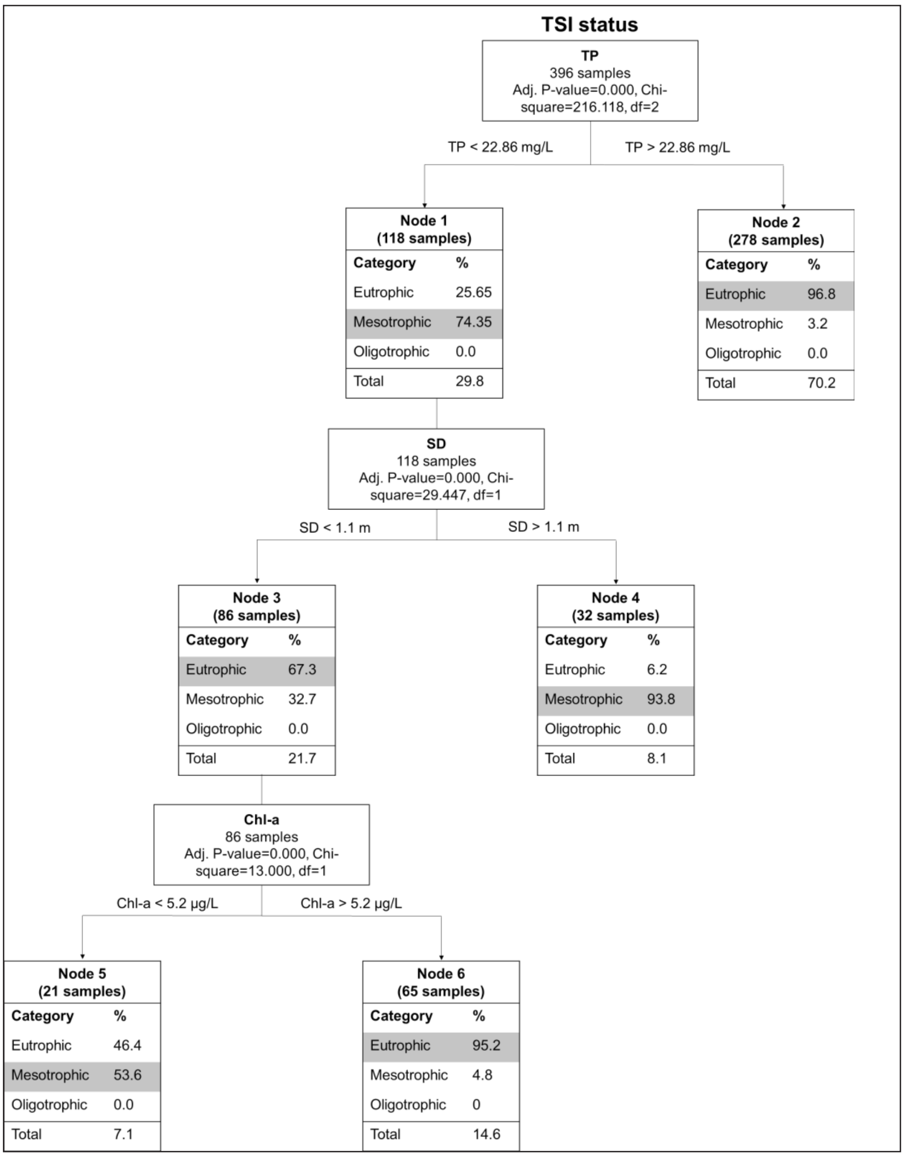

Figure 3. CART Prediction of CTSI Classification

In “Node 4” there were two discriminators. First condition, if TP concentration greater than 22,86 μg/L, SD greater than 1.1 meters, and Chl-a concentration less than or equal to 5,2 μg/L, then it would be mesotrophic condition. Second condition, if TP concentration greater than 22,86 μg/L, SD greater than 1,1 meters, and Chl-a concentration greater than or equal to 5,2 μg/L then it would be eutrophic condition.

DISCUSSION

Over 67% of nutrient specifically total nitrogen and total phosphate loads come from point source pollution. Wastewater from livestock farming is still the main source of point source pollution during low flow periods. In the downstream region, a number of small and medium scale industries also generate activities detrimental to water quality (43). The nitrification of nitrite and ammonium nitrogen would become nitrate which can be consumed by algae (44). Ammonium nitrogen can be produced during decomposition of algae and then returned nitrogen to the aquatic system. When COD increases in lakes or reservoirs, ammonia concentration will be increased by denitrification (45). In eutrophic reservoir, most of the nitrate is reduced from biological use by algae (46-47). Nitrogen concentration is thus regarded as key influence factor for increase the Chl-a and altering trophic states in Chengchinghu Reservoir (48-49). In addition, there was a good relationship between SS and SD regarding to the high rainfall intensity and high nutrient intake withdraws to the Chengchinghu Reservoir.

The high trophic states level of Chengchenghu Reservoir was high due to population growth, industrial wastewater and agriculture activities in Kaohsiung since this city is the second big city in Taiwan after Taipei (45). The other study about eutrophication factor identification in Taiwan by 2018 clearly explained that there are three possible factors which dominantly contributed for trophic states level in Chengchinghu Reservoir (50). The first factor might come from rainfall factor, the second factor might come from nutrient factor, and the third factor might come from temperature factor. The high contribution of total precipitation in the first component might have the high negative correlation with SD. The Chengchinghu Reservoir is the downstream reservoir of Kaoping River as its intake water. Another study conducted Taiwanese by 2018 reported that the SS, dissolved inorganic nitrogen, dissolved oxygen, biological oxygen demand and COD in river discharge, and ammonia in submarine groundwater discharge significantly influenced Chl-a dynamics (51). In the Kaoping River Basin, most of the upper catchment is used for agricultural activities, and some protected areas of water resource have been developed illegally into farmland (48). Study conduct in the Kao-Ping River Basin reported that population growth, industrial development and hog farming generate excess nutrients and high wastewater loads, thereby causing a serious water quality problem in Chengchinghu Lake (43). In the Kao-Ping River Basin, most of the flat area in the upper part is used for agricultural activities including cropland and livestock farming. Nutrients, pesticides, and sediments are the main hazardous nonpoint source pollution constituents. As for the point source pollution, hog farming is a particularly harmful activity. There were over 1 million pigs raised in the upstream of the Kao-Ping River Basin in 1992. The estimated hog population in the basin reached 1,7 million in 1996. Most of the untreated hog farm wastewater was indiscriminately discharged into the Kao-Ping River, causing the deterioration of river water quality. However, due to the occurrence of the overwhelming foot-and-mouth disease in 1997, the hog population dropped to approximately 0.8 million that year. The decrease in hog population also coincided with the improvement of river water quality. Nevertheless, after two years of breeding, the total hog population was estimated to be 1 million in the whole Kao-Ping River Basin. In addition, for the second factor, the air temperature associates with weather or seasonal factor plays the important contribution for trophic states level in Chengchinghu Reservoir. A marked seasonal variation is commonly observed in many eutrophication effects and driving forces such as water and air temperature, freshwater runoff, and salinity. Similarly, COD, dissolved inorganic nitrogen (DIN), and DO concentrations in the bottom water change seasonally.

Study conducted in Kaohsiung Harbor by 2016 has analyzed the role of eutrophication in the seasonal succession of these major measurement elements and compared the comprehensive indices of eutrophication between the dry and wet seasons (52). Another study in two Irish Estraries by 2016 indicated that nutrient loading can change seasonally in estuaries and coastal systems (53). Phosphorous defiency frequently occurs in the spring, whereas nitrogen is often limited during the summer months. During summer, algae mass increases significantly, accelerating the phosphorous cycle in water and releasing nutrients from sediments.

We have briefly explained the fundamentals of classification and regression trees, and have shown how they can model complex ecological data. Trees were used to determine the environmental characteristics and classification of scenario prediction of eutrophication phenomenon in Chengchinghu Reservoir. From this research, we could describe that CART are powerful tools for analyze some features include: (1) the ability to use different types of response variables; (2) the capacity for interactive exploration, description, and prediction; (3) invariance to transformations of explanatory variables; (4) easy graphical interpretation of complex results involving interactions; (5) model selection by cross-validation; and (6) procedures for handling missing values. In summary, classification and regression trees are a valuable addition to the statistical toolbox of every ecologist and environmental scientist.

The comprehensive use of CART in long-term trend analysis for water quality evaluation and prediction could offer effective support for government implementing reservoir water resources management and regulation. The results obtained from CART provide insights into the prediction in water quality and eutrophication phenomenon, making it possible to carry out a sampling arrangement in a more rational way (42, 44). The prediction of water quality may also help local governments to understand the pollution conditions in the area under administration and to take responsibility for conservation of the respective aquatic ecosystems. The CART can be used to predict the water quality and eutrophication not only in one area, but also could be useful too in different areas. Thus, it helps the government to determine their priorities by emphasizing the regional distinction. Based on the information extracted from this study, different policies can be established to treat the pollution sources in different areas. Study in in the Kao-Ping River Basin find that eutrophication will become a problem again after 2017 without new wastewater treatment plants in the Kao-Ping River and Chengchinghu Reservoir (43). Then, the new approach technology of water treatment to remove the nutrient (TP or TN) before discharge to the water surface body is indispensable. Some studies using ultrafiltration membrane microreactor (MMR) (54), adsorbents (55), chalcogenide (56), and many more appropriated processes or technologies for water treatment as long as they have the features of high efficiency and stability, lower energy consumption and operational cost, easy operation and maintenance, and lower specific footprint to reduce the occupied land area and the investment. Furthermore, the natural purification methods to treat domestic wastewater or stormwater has become a popular study in recent years. If the pollutant concentrations are not too high, natural purification methods, like structural free water surface (FWS) wetland, are a cheaper approach that also considers wild life rehabilitation and ecosystem. The reported average pollutant removal rates of BOD5, ammonia nitrogen and inorganic phosphorus are 58,3%, 58,1% and 37,5%, respectively (57).

In general, another study conducted in Bhindara Lake of India by 2017 has reviewed the general important features of a long-term monitoring and assessment program to control the trophic state level include: Sampling to detect the trophic states index trends; routine monitoring, spatially and temporally extensive monitoring of key environmental variables, using continuous and time-integrative sampling of water quality, productivity, and turbidity, possibly making use of satellite- and aircraft-remote sensing, and large-scale, long term, real time monitoring using existing infrastructure such as bridges, platforms, commercial and government vessels, and ferries; assess the sediments which contain a wealth of paleo-climate and paleo-sea level information for the past 10.000 years of coastal history (58). Recent paleo-sediment studies using indicators aimed at elucidating the history of cultural eutrophication of another previous studies, such as the Chesapeake Bay (59) and the Baltic Sea (60) are examples of the applicability of this approach; aggregation of meteorological data on storm paths, winds, rainfall, and flooding to provide a quantitative context for large-scale storm events and consequent environmental perturbations; and assessment of effects of hydrologic, chemical, and sediment loading on biotic communities impacting production, nutrient cycling, finfish and shellfish habitats, including water column (planktonic), salt marsh, sea grass, and sediment habitats.

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CONCLUSION

According to the observed data the trophic state status from 2000 to 2017, we can conclude that CTSI trend in Chengchinghu Reservoir were mostly eutrophic. The eutrophic state probably would occur in Chengchinghu Reservoir when the TP concentration is greater than 22,86 mg/L or Chl-a concentration is greater than 5,2 µg/L or SD is less than 1.1 m. Thus, according to this study we suggest the government create the strict regulations and standard for phosphorous usage or the other nutrients and do the countinous monitoring and assessment. We also suggest the next future study considering the temperature level as a CART factor prediction.

Water quality and eutrophication evaluation and prediction agendas require the complex multidimensional data that need statistical model treatment for analysis and interpretation to obtain better information about the quality of reservoir ecosystem. Such information can help environmental managers or desicion maker create better decisions regarding action plans. The management of nutrient influent to should strive for low accumulation in reservoir for minimize environmental degradation. This objective can be achieved by installing proper treatment methods for municipal and industrial wastewater before being released to the environment.

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