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Developing a Real-Time Trophic State Index of a Seawater Lagoon: A Case Study From Dapeng Bay, Southern Taiwan

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Algal blooms over the past years have caused considerable worldwide impacts on marine ecology, aquaculture, recreational activities, and human health. Therefore, there is an urgent need to develop indices for evaluating the nutritional status of seawater as a means of predicting algal blooms. A long-term water quality monitoring dataset from Dapeng Bay, Southern Taiwan, indicated that seawater dissolved oxygen (DO) concentrations and pH were significantly correlated with algal abundance. Using this dataset, we then developed a real-time trophic state index (RTSI) by (1) referring to the seawater nutrient grading system defined by Carlson's index and (2) incorporating an algorithm based on the relationship between DO, pH, and eutrophication status. The RTSI was superior to contemporary indices in its simplicity, as no complicated nutrient or chlorophyll *a* (Chl *a*) measurements were required, and real-time data were displayed on a personal computer. The index is sensitive to changes in seawater quality that will be of aid to managers.

Keywords: algal bloom, nutrients, trophic state index, water quality, Taiwan

INTRODUCTION

Lagoons are semi-enclosed seawater environments that are generally located between landmasses and sandy beaches (Boynton et al., 1996), thereby serving as a transition zone between land and sea (Tew et al., 2008). The calm and oftentimes nutrient-rich waters of a lagoon make for ideal nursery conditions for a wide variety of commercially important fish and invertebrates (Tew et al., 2008, 2010, 2014; Hsieh et al., 2010) and display a rich ecosystem (Araujo et al., 2015). Given the poor water exchange of lagoons, they are highly sensitive to exogenous inputs (Tew et al., 2010), especially nutrients (Pinckney et al., 2001; Hsieh et al., 2010; Tew et al., 2010, 2014). Nutrient influx results in eutrophication, which can stimulate primary production

(Nixon, 1995; Pinckney et al., 2001; Heisler et al., 2008), and consequently jeopardize the ecosystem and the economic activities associated with it such as fisheries and tourism (Andersen et al., 2006). Eutrophication is typically assessed by measuring chlorophyll *a* (Chl *a*) levels in the water, though phytoplankton density may also serve as a proxy (Carlson, 1977; Cloern, 2001; Gupta, 2014).

Eutrophication emerging from inland discharge (Paerl and Scott, 2010; Wang et al., 2015) can cause algal blooms (Smith, 2003; Heisler et al., 2008), which can fundamentally alter the ecosystem diversity, and function (Cloern, 2001; Islam and Tanaka, 2004). In the case of harmful algal blooms (HABs) and blue-green algal blooms in freshwater lakes [the latter of which releases toxic microcystins (Metcalf and Codd, 2009)], it can even impact tourism (Smith, 2003) and human health (Ulloa et al., 2017). Since detoxifying bodies of water is costly (Michalak, 2016), it is unfortunate that anthropogenic impacts are on the rise (Anderson et al., 2021). Global climate change and other human-associated factors have been associated with increases in the frequency, distribution, and economic impacts of HABs over the past two decades (Paerl and Paul, 2012; Rigosi et al., 2014; Anderson et al., 2021; Karlson et al., 2021), and management costs have risen commensurately (Ho and Michalak, 2015).

The occurrence of HABs is influenced by the phytoplankton assemblage, nutrient levels, temperature, and other abiotic parameters (Lv et al., 2014; Yang et al., 2016; Zhang et al., 2016). HABs are usually associated with abnormal seawater color, noxious odors, drops in dissolved oxygen (DO) content, death of aquatic organisms, and sometimes shellfish poisoning (Pitcher and Probyn, 2011; Reich et al., 2015; Mao et al., 2017). Specifically, poisons derived from some toxic dinoflagellates have caused epidemics in humans (Hoagland et al., 2014; Reich et al., 2015), fish, and birds (Fauquier et al., 2013; Brooks et al., 2016) and negatively impacted tourism (Brooks et al., 2016). The increasing risk from HABs has fueled research on developing a methodology for monitoring, and even attempting to control, HABs (Zhang et al., 2016; Ruiz-Ruiz et al., 2017; Page et al., 2018).

To evaluate the water quality of lakes and streams, the Carlson trophic state index (CTSI), which is calculated from the Secchi disc depth (SD) and concentrations of Chl *a* and total phosphorus (TP; Carlson, 1977), is routinely employed, though other indices have been proposed since this seminal work (Tew et al., 2014; Zhang et al., 2016; Page et al., 2018; Chen and Chen, 2021). A review of all published models and methods found that a reliable evaluation of water quality requires a professional sampling technician, 3–7 days of sample analysis, and at least one (but oftentimes more) analytical model (Ruiz-Ruiz et al., 2017). Given the speed at which data are generated and analyzed, the lack of real-time information has thwarted the efforts to reduce eutrophication impacts. Therefore, the aim of this study was to identify the key predictors of algal blooms by correlating data within a dataset obtained from Dapeng Bay, a highly impacted lagoon in Southern Taiwan with regular algal blooms. Specifically, Physicochemical parameters of seawater were analyzed using the National Institute of Environment Analysis (NIEA) methods, input into the CTSI model, and the results were compared with those of a novel, real-time monitoring system aimed at quickly and reliably assessing seawater quality parameters found to correlate strongly with algal blooms.

MATERIALS AND METHODS

Study Site

Dapeng Bay is a 3.5 km × 1.8 km lagoon (5.3 km^2) located off Pingtung county, Southern Taiwan, which has featured in several prior studies (Hsieh et al., 2010; Tew et al., 2010, 2014). The only connection with the open ocean (Taiwan Strait) is through a narrow channel (1 km long, 138 m wide, and ∼2 m deep), and water residence time in the lagoon is consequently over 30 days, but varies during different monsoon conditions (Lee et al., 2020). There are five small drainages discharging into the lagoon, all of which contain aquaculture and farming wastewater with high amounts of nitrogenous and phosphorous nutrients (Hsieh et al., 2010; Tew et al., 2010). Though the total amount of discharge into the lagoon is low relative to the exchange rate with the Taiwan Strait, the nutrient levels are nevertheless high in Dapeng Bay (Tew et al., 2010; Meng et al., 2017), resulting in repeated algal blooms in the lagoon (Tew et al., 2010, 2014). Such algal blooms are usually associated with low DO and consequently mass fish mortality (Hsieh et al., 2010, 2012; Tew et al., 2010). During the period 2015–2016, three locations in the lagoon were selected for long-term, real-time automated water quality monitoring (**Figure 1**), which include a site close to the lagoon outlet (R1), a site in the middle of the lagoon (R2), and the most remote location from the lagoon outlet (R3). Based on our previous studies, these three continuous monitoring stations have been chosen according to the following reasons: (1) R1 station is the closest to the opening channel of the lagoon, where the circulation and flushing rate is the best among all; (2) R2 station is in the middle of the lagoon, where the circulation and flushing rate is moderate; and (3) R3 is the inner station, where the circulation and flushing rate is the poorest (Tew et al., 2014). Another ten stations (DP1–DP10) around the lagoon were also established for seasonal water quality monitoring.

Sampling Methods and Water Quality Analysis

Long-term, real-time monitoring of water quality at the three primary sites (R1–R3) was achieved *via* a multi-parameter sonde (YSI-6600-V2, YSI EXO 2), a wireless transmission system, and a data receiving and analysis base (**Figure 2**). The sonde simultaneously measured DO saturation (%) and content (mg/L), conductivity, specific conductance, temperature, salinity, pH, and turbidity. The water quality data were sent back to the monitoring base every 30 min, and the sonde was calibrated every 2 weeks according to the manufacturer's recommendations. Furthermore, data were periodically compared with those analyzed in the laboratory using the NIEA 102.51C guidelines.[1] At the other 10 stations, water was collected every 3 months for 2 years. Temperature, salinity, DO, pH, and transparency were measured *in situ* with an Ocean Seven 304 CTD (temperature and salinity),

[1] https://www.epa.gov.tw/niea/32A85B63C9EC18C0

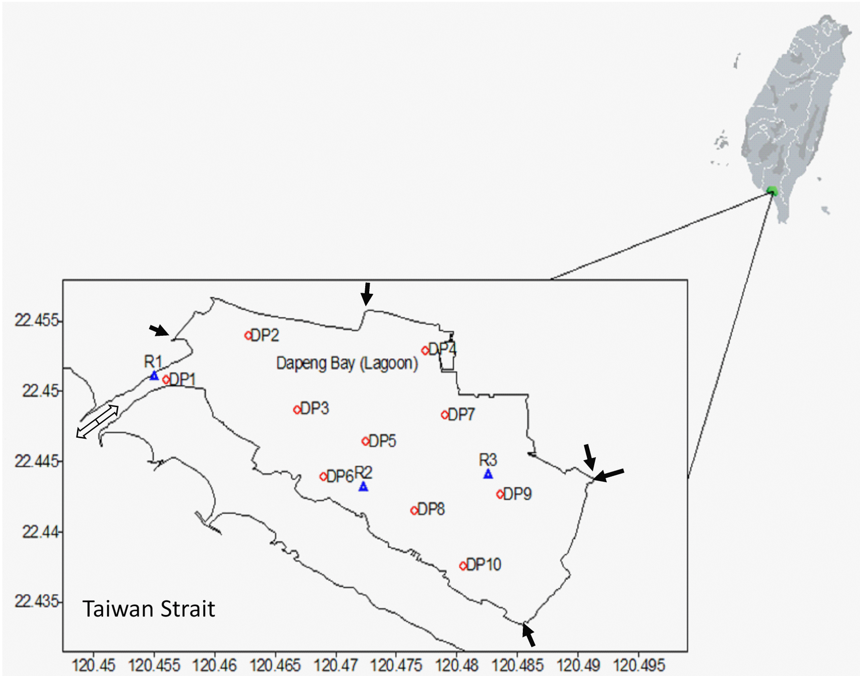

FIGURE 1 | Long-term real-time monitoring sites (R1–R3) and seasonal survey stations (DP1–DP10) of water trophic levels in Dapeng Bay, Southern Taiwan. The five arrows represent the small drainage channels. The hollow arrow represents the inlet-outlet to the sea.

a pH meter (Hach, Sension 1), and a YSI Pro ODO DO meter. Oxygen saturation percentages were converted to oxygen concentrations as suggested by Chen (1981).

Surface water samples (30 cm below the surface) were collected with Niskin samplers, stored at 4°C during transport to the laboratory, and later analyzed for Chl *a* and phytoplankton composition and abundance. To determine the Chl *a*, water samples were first filtered through GF/F filter paper (Whatman, United Kingdom) and desiccated in the dark at −20°C before extraction in 10 ml of 90% acetone in complete darkness for 20 h (Lobban et al., 1988). After centrifugation at 1000 × *g* for 15 min, Chl *a* in the supernatant was measured with a Turner (model 450) fluorometer. For the analysis of phytoplankton, 1 L samples were fixed immediately with Lugol's solution and neutralized with formalin to a final concentration of 4%, concentrated by settling to 30 ml in the laboratory (Tew et al., 2010), and the phytoplanktons were then counted and identified to the lowest possible taxon in Utermöhl sedimentation chambers under an inverted microscope at ×400 magnification. All analytical procedures followed the quality assurance (QA) and quality control (QC) guidelines set forth by the Environmental Protection Administration of Taiwan, and the data obtained from the real-time monitoring system were compared to those obtained from these standardized methods.

Statistical Analyses

Each dataset was examined for normality with Minitab14, and data were *ln*-transformed when they were not normally distributed. Simple correlation (Pearson's correlation coefficient) was used to determine the relationship between Chl *a* content, phytoplankton abundance, oxygen saturation, and pH.

RESULTS AND DISCUSSION

To develop a trophic state index that could be evaluated in real time, we examined the relative precision deviation (RPD; %) between the data from the real-time system and the standard methods (**Table 1**). Except for Chl *a* content (>90% RPD values), the RPDs of the temperature, salinity, pH, and oxygen saturation measurements were low (<2% in some cases), implying that the real-time monitoring system could provide highly reliable data on those four parameters. Therefore, we chose pH and DO saturation, instead of directly using real-time Chl *a*, to develop a quick and reliable prediction method. Given that Chl *a* is a major indicator for the trophic state of water, developing a correlation model using reliable data to evaluate Chl *a* is needed when applying a real-time monitoring system.

The correlation between seasonal Chl *a* concentration and phytoplankton abundance from the 10 stations was examined in 2015 and 2016 (**Figure 3**), and these two parameters were positively and significantly correlated ($R^2 = 0.45$, $p < 0.001$, $n = 80$). Algal photosynthesis in the water system could change water pH in different ways. During the light cycle, algal consumption of CO_2 generally results in elevated pH. However, during algal blooms, high levels of algal respiration lead to CO_2 release and a consequent decrease in pH (Mao et al., 2017). From our data, both pH and oxygen saturation displayed significant

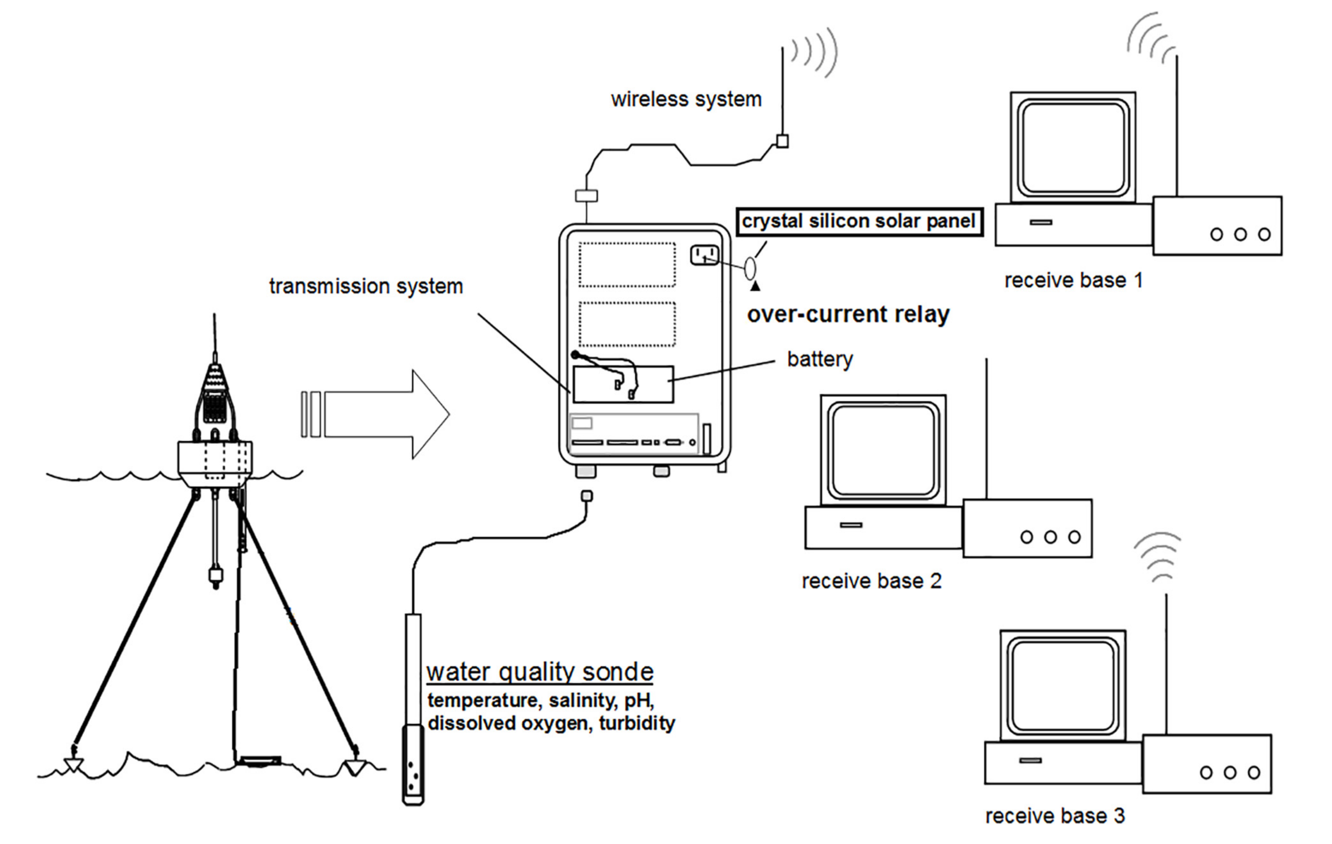

FIGURE 2 | Schematic diagram of the novel real-time water quality monitoring system.

positive correlations with Chl *a* concentration (**Figure 4**; $R^2 = 0.15$, $p < 0.001$ and $R^2 = 0.07$, $p < 0.05$, respectively) across 2015 and 2016.

When we compared the CTSI calculated from the 2-year dataset with Chl *a* and phytoplankton abundance, we also found significant correlations (**Figure 5**; $R^2 = 0.44$, $p < 0.01$ for Chl *a*; $R^2 = 0.51$, $p < 0.01$ for phytoplankton). The CTSI defines four nutrient levels: oligotrophic (CTSI = 30–40), mesotrophic (CTSI = 40–50), eutrophic (CTSI = 50–70), and hyper-eutrophic (CTSI > 70). Therefore, we used CTSIs of 40, 50, and 70 as references to calculate the corresponding Chl *a* concentration using the regression equations obtained in **Figure 5**. Then, the calculated Chl *a* value was then converted to its corresponding pH and oxygen saturation with the correlation obtained in **Figure 4**. The corresponding Chl *a* concentration, oxygen saturation, and pH against the CTSI are shown in **Table 2**. Given that the Chl *a* concentration calculated from the CTSI was consistent with *in situ* algal blooming in Dapeng Bay, we

TABLE 1 | The relative precision deviation (RPD) of data from the real-time monitoring system and standard methods developed by the Environmental Protection Administration, Taiwan.

	Relative precision deviation (%)				
Year	**Temp. (°C)**	**Salinity (psu)**	**pH**	**Oxygen saturation (%)**	**Chl *a* (μg/L)**
2015	1.6	1.9	1.0	14.9	89.9
2016	1.9	0.9	0.9	9.8	116.6

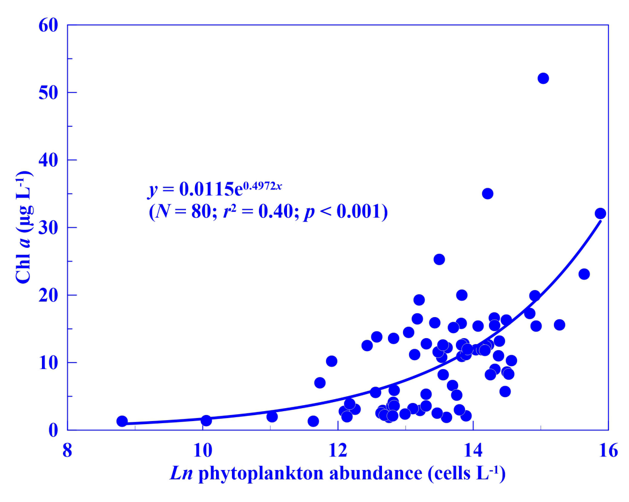

FIGURE 3 | Correlation analysis between seasonal chlorophyll a (Chl *a*) concentration and phytoplankton abundance in Dapeng Bay (2015–2016).

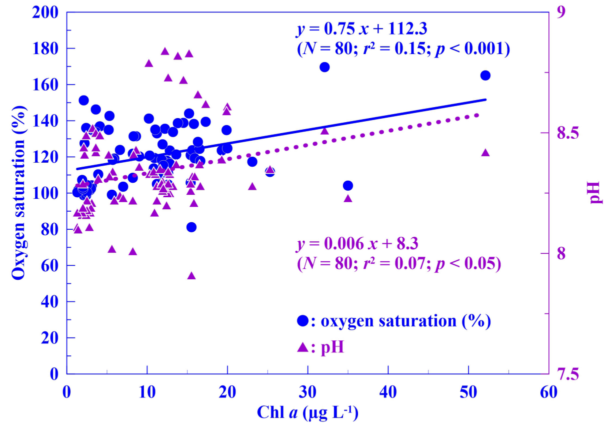

FIGURE 4 | Correlation analysis of chlorophyll a (Chl *a*) concentration vs. oxygen saturation (circle) and pH (triangle) in Dapeng Bay (2015–2016).

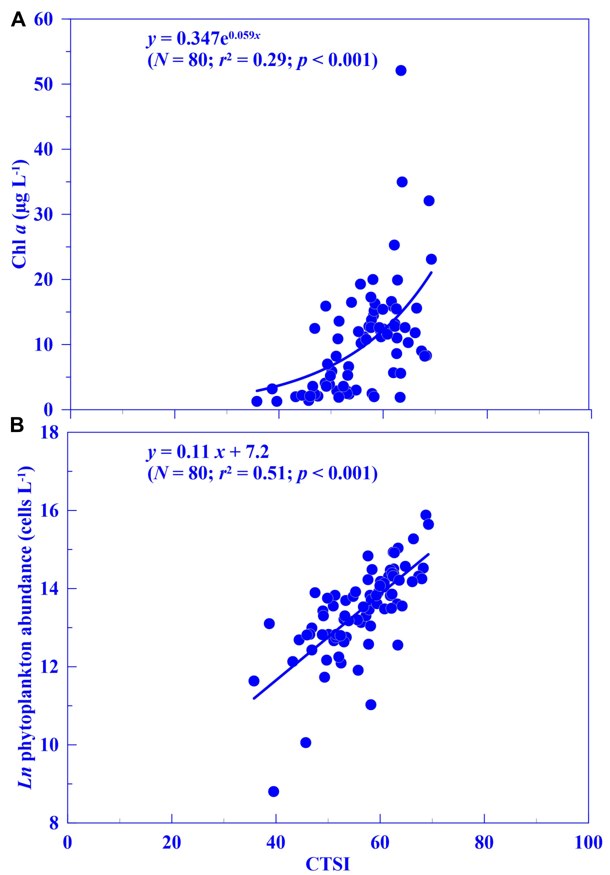

FIGURE 5 | Correlation analysis of **(A)** chlorophyll a (Chl *a*) concentration and **(B)** phytoplankton abundance against the Carlson Trophic State Index (CTSI, Carlson, 1977) in Dapeng Bay (2015–2016).

defined an index called the real-time trophic state index (RTSI) by combining the parameters of oxygen saturation and pH obtained from a real-time monitoring system to classify trophic status

TABLE 2 | The corresponding values of chlorophyll a (Chl *a*), oxygen saturation (%), and pH to the Carlson trophic state index (CTSI) based on the water quality data obtained from Dapeng Bay (2015–2016).

CTSI	30	40	50	70
Chl *a*	1.0	2.1	4.7	22.5
Oxygen saturation	113	114	116	129
pH	8.28	8.29	8.30	8.41

(**Table 3**). The same idea has been applied in developing the river pollution index (Liou et al., 2004). For the RTSI calculation, we administered 1 point when oxygen saturation ≤ 114% and 1 point when pH ≤ 8.29, resulting in an RTSI ≤ 2, which we classified as oligotrophic. At oxygen saturation levels between 114 and 116% and pH between 8.29 and 8.30, 3 points were given to each parameter, resulting in 2 < RTSI ≤ 4, which we classified as mesotrophic. At oxygen saturation levels between 116 and 129% and pH between 8.30 and 8.41, 5 points were given to each parameter, respectively, resulting in 4 < RTSI ≤ 6, which we classified as eutrophic. At oxygen saturation levels >129% and pH > 8.41, 7 points were given to each parameter, respectively, resulting in RTSI > 6, which we classified as hypereutrophic (**Table 3**).

To verify the applicability of the RTSI, we compared the eutrophication categories defined by CTSI and RTSI. For the site R1 dataset, the RTSI and CTSI gave similar classifications in 21,609 out of 34,108 water samples (63%). Agreement percentages were similar at sites R2 (20,450 out of 34,244 datasets = 60%) and R3 (20,403 out of 33,241 = 61%). Seasonal survey data from sites DP1, DP6, and DP9, which were close to sites R1, R2, and R3, respectively, were also used to compare the CTSI and RTSI classifications. Among 24 datasets, 91.7% of the RTSI were in agreement with CTSI, suggesting that the RTSI is as good as CTSI in predicting the trophic status of a water body.

The trophic state of the aquatic environment is crucial for the formation of algal blooms (Heisler et al., 2008; Rigosi et al., 2014). Understanding the trophic status of a water body can provide

TABLE 3 | The index scores of oxygen saturation (%) and pH, and the conversion table between the real-time trophic state index (RTSI) and the Carlson trophic state index (CTSI), corresponding to the trophic status of the lagoon.

	Water quality criteria for index score			
Oxygen saturation	≤114	>114 – ≤116	>116 – ≤129	>129
pH	≤8.29	>8.29 – ≤8.30	>8.30 – ≤8.41	>8.41
Index scores (S_i)	1	3	5	7
	Trophic status			
	Oligotrophic	**Mesotrophic**	**Eutrophic**	**Hypereutrophic**
RTSI	≤2	>2 – ≤4	>4 – ≤6	>6
CTSI	>30 – ≤40	>40 – ≤50	>50 – ≤70	>70

S_1: pH index score.
S_2: Dissolved oxygen saturation index score.
$RTSI = (S_1 + S_2)/2$.

an early warning of the pressures and problems confronted by the aquatic ecosystem (Saluja and Garg, 2017; Sruthy et al., 2021). Although algal blooming has occurred worldwide, no consensus has been achieved about the main causes of this phenomenon, suggesting the need for more survey locations and intensive sampling (O'Neill et al., 2015). However, previous methods developed to monitor the eutrophication of lake or coastal water usually lack real-time information (Tew et al., 2014; Page et al., 2018; Chen and Chen, 2021). In addition, the published models and methods also suggest that a reliable evaluation of the trophic state of an aquatic environment requires a professional sampling technician, 3–7 days of sample analysis, and sometimes more than one model (Ruiz-Ruiz et al., 2017). Thus, there exists the need for rapid real-time monitoring of aquatic ecosystems. However, since the algal communities vary among different environments, the equations established in this study and the coefficients in the RTSI will vary. Thus, data must be accumulated and the coefficients must be calculated in order to establish an RTSI suitable for each local environment.

CONCLUSION

Whether the RTSI is a better predictor of algal blooms than the CTSI remains to be tested. Since high deviations usually occur using a Chl *a* sensor, and pH or DO data alone is insufficient in predicting the trophic state of an aquatic environment, the RTSI that uses both pH and oxygen saturation data seems promising. If such results are ultimately shown, then we may soon possess the capacity to monitor the likelihood of algal bloom formation in real time, thereby ensuring that managers are promptly informed as to where mitigative actions could be taken.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

KT and P-JM conceived the presented idea. P-JM developed the theory and performed the computations. C-CC and J-TW verified the analytical methods and wrote the manuscript. C-YH assembled and analyzed the preliminary data. KT, P-JM, and H-YH supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.