Estimation of chlorophyll-a concentration using smartphone camera: a case study in Banten Bay, Indonesia

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Abstract. The ocean is the most significant contributor to oxygen production on Earth due to the presence of chlorophyll-a contained in phytoplankton. One way to determine the concentration of chlorophyll-a is by using a smartphone camera through the HydroColor application. The data obtained through the HydroColor application does not directly provide chlorophyll-a data, instead, it provides red, green, and blue (RGB) wavelength data. This RGB wavelength data is then input into an equation to generate the chlorophyll-a concentration. This study aimed to evaluate the HydroColor application to estimate chlorophyll-a concentration. The research was conducted in Banten Bay, using field data collected with a smartphone and compared against laboratory test results and MODIS satellite imagery. Among several regression models tested, the logarithmic model showed the best correlation with laboratory results, with an R^2 value of 0.83 and a correlation coefficient of 0.876. The HydroColor application can be practical in coastal water bodies with a smartphone featuring a high-resolution camera. This study demonstrates that HydroColor has the potential to serve as an alternative method for estimating chlorophyll-a concentration in Banten Bay.
Keywords: chlorophyll-a, HydroColor, MODIS, RGB wavelength, empirical model.

Introduction. The ocean is the Earth's most significant source of oxygen, made possible by the presence of chlorophyll-a contained in phytoplankton (Falkowski, 2012). Phytoplankton are capable of performing photosynthetic activities similar to complex plants, also known as vascular plants (Yang et al., 2020). Due to their rapid growth rate, phytoplankton have great potential in absorbing carbon dioxide from the atmosphere (Zhang et al., 2023). In the oceanographic and limnological communities, it is known that instruments used to study water quality (chlorophyll-a) are often expensive. However, the widespread availability of smartphones with various sensors and high-speed wireless data connections has opened new opportunities for large-scale and cost-effective data collection. A simple mobile phone can measure chlorophyll a (Friedrichs et al., 2017). Crowdsourcing chlorophyll-a water quality data has produced results comparable to traditional assessment methods (Leeuw & Boss, 2018), offering a valuable complementary approach for evaluating water quality.

Chlorophyll-a is a green pigment found in phytoplankton and other plants in general. Phytoplankton can be found throughout the water column, from the ocean surface down to depths where light intensity still allows photosynthesis to occur (Walsby, 1997). The distribution and concentration of chlorophyll-a are closely related to the oceanographic conditions (Sumich, 1992; Siegel et al., 2013). Indonesian waters with high chlorophyll-a concentrations are often associated with river discharge, particularly along the north coast of Java and the coastal waters surrounding Sumatra and South Kalimantan (Xu et al., 2021), and with upwelling, such as in the Banda Sea, Arafura Sea, and the southern waters of Java, Bali, and Sumatra (Gordon, 2005; Susanto & Marra, 2005). As water depth increases, temperature decreases, water density increases, resulting in a slower phytoplankton sinking rate. The optimal temperature range for phytoplankton growth in aquatic environments is between 20°C and 30°C. Yamaguchi et al. (2015) stated that light is one of the factors determining chlorophyll-a content in the ocean. Limited light penetration affects the effectiveness of phytoplankton photosynthesis. Currents influence the distribution of marine organisms (Yoon et al., 2022). Ocean surface currents transport phytoplankton and other nutrients according to the speed and pattern of the current (McLaughlin et al., 2020; Lewitus et al., 1998). High chlorophyll-a concentrations in coastal and nearshore waters are caused by nutrient input through river runoff, whereas low chlorophyll-a concentrations in offshore waters are due to the absence of direct nutrient supply from land (Nybakken, 1992; Baek et al., 2019).

Banten Bay is an industrial and tourism area that attracts many visitors due to its natural beauty. However, the increasing industrial and tourism activities have led to higher marine traffic. As these activities grow, they will impact the environmental quality of the bay (Nedya et al., 2022). A decrease in phytoplankton abundance reduces the fertility of the waters, as the amount of chlorophyll-a available for photosynthesis also declines (Field et al., 1998). The reduction in phytoplankton also affects other organisms, such as fish, because phytoplankton form the base of the aquatic food chain (Ducklow et al., 2001). A decline in fish populations may also negatively affect the local economy (Lehtonen, 2025).

Monitoring chlorophyll-a concentrations is highly relevant to aquaculture and fisheries, as phytoplankton (which contain chlorophyll-a) form the base of the aquatic food web. Optimal phytoplankton abundance ensures sufficient oxygen production and natural food availability, while an imbalance can cause algal blooms or depletion, which threaten water quality and fish health. In fisheries, chlorophyll-a is often used as a proxy for identifying productive fishing zones, especially in coastal waters like Banten Bay where small-scale fisheries rely on local productivity. By providing a cost-effective, accessible, and real-time method for monitoring chlorophyll-a, the HydroColor application supports early detection of ecosystem changes that may impact aquaculture operations or local fish stock. This study aims to evaluate the HydroColor application, which utilizes a smartphone camera to estimate chlorophyll-a concentration in Banten Bay.

Material and Method

Time and location of research. The study was conducted in Banten Bay, which is located on the northern coast of Java Island (Figure 1). Administratively, the coastal and marine areas of Banten Bay fall within the northern coastal region of Serang Regency. Geographically, the coast of Banten Bay is situated at 5°58'44"S, 106°10'15"E.

Figure 1. Map of the study area showing the research locations in Banten Bay, northern coast of Java Island.

The fieldwork in Banten Bay was carried out on October 27, 2019, with data collected from 8 sampling points. Water samples collected during the field survey were analyzed for chlorophyll-a concentration. In Banten Bay, some islands serve as tourist destinations, fish cages (aquaculture), and several industrial areas along its coast.

Data acquisition. The data used in this study are divided into two types: (1) data for developing the empirical chlorophyll-a model equation, obtained from field sampling followed by laboratory testing; and (2) field sampling data collected using the HydroColor application, along with imagery used for comparison of chlorophyll-a concentrations in Banten Bay. The field data in this study consist of water samples for laboratory analysis and red, green, and blue (RGB) light wavelength data collected using the HydroColor application (smartphone). The water samples for laboratory analysis were collected directly without prior filtration using filter paper. The samples were analysed at the Limnology Research Center Laboratory of LIPI (Indonesian Institute of Sciences).

Data processing. The empirical equation was developed using a Multivariate Regression statistical model, in which chlorophyll-a serves as the dependent variable (Y'), while the RGB wavelengths act as independent variables (X). In general, the regression equation can be written as follows (Rencher & Schaalje, 2008):

$$Y' = a + b_1X_2 + b_2X_2 + b_3X_3 + \dots + b_kX_k$$

Where:
Y' - regression response variable;
X - predictor variable;
a - intercept regression coefficient, or the value obtained when $X_{i=1, 2, \dots, k}=0$;
b_0, b_1, b_2, ..., b_k - regression coefficients.

The significance of the model was then tested using F-significance testing, Student's T-test, and p-value analysis with a significance level (α) of 5%, along with classical multiple linear regression assumption tests. Data processing began by downloading data from NASA's OceanColor Web, which was then processed using the SeaDAS application.

Results and Discussion

Empirical model estimation of chlorophyll-a from Hydrocolor. HydroColor data were collected using a Xiaomi Mi 8 SE smartphone with a 12 MP and 5 MP camera resolution, f/1.9 and f/2 aperture, and dual pixel PDAF. The laboratory chlorophyll-a data were obtained from laboratory tests conducted at the Limnology Research Center, Indonesian Institute of Sciences (LIPI). The red wavelength showed the highest correlation with the field chlorophyll-a values, with a correlation coefficient of 0.61 or 61%, indicating a strong relationship. This is because chlorophyll-a has a green-blue colour, meaning that among the three RGB wavelengths, only the red wavelength is absorbed, while the green and blue wavelengths are reflected by chlorophyll-a. The greater the amount of red wavelength absorbed, the higher the chlorophyll-a concentration. Figure 2 shows that the red wavelength has a similar pattern to the chlorophyll-a values when compared to the green and blue wavelengths. However, it is still possible that some green and blue wavelengths are also absorbed; therefore, a new variable was created using the ratio of the RGB wavelengths.

Based on the relationship between the RGB wavelengths and chlorophyll-a (Chl-a), it is evident that the RGB wavelengths have a significant correlation with chlorophyll-a. Thus, an empirical model can be developed using regression analysis, with the laboratory-tested chlorophyll-a values as the dependent variable and the simplified RGB wavelength ratio (Cchl) as the independent variable. Out of the 8 data points, 6 were used to develop the empirical model, while the remaining 2 were used to verify the model. After performing the regression analysis, the resulting model is presented in Table 1.

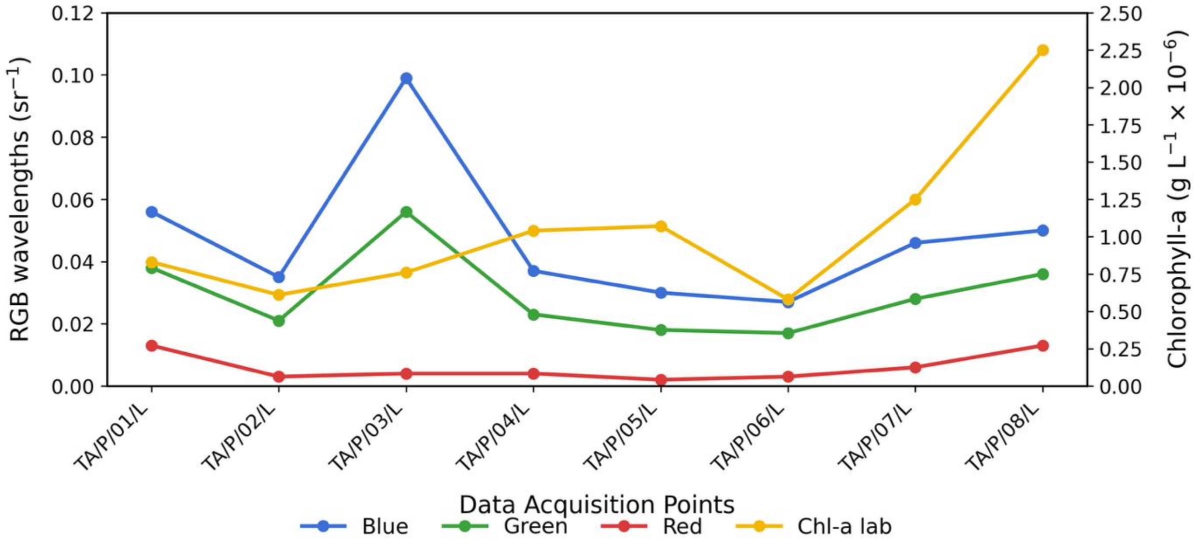

Figure 2. Comparison between RGB wavelength values obtained from the HydroColor application and chlorophyll-a concentrations from laboratory analysis.

Table 1

Empirical chlorophyll-a estimation models developed using RGB wavelength ratios (Cchl)

Model	*Equations*
Linear	Chl-a = 2.534 – 2.454(Cchl)
2^{nd} order polynomial	Chl-a = 3.494 – 7.41(Cchl) + 4.99($Cchl^2$)
3^{rd} order polynomial	Chl-a = 5.496 – 23.21(Cchl) + 38.973($Cchl^2$) – 21.866($Cchl^3$)
Exponential	Chl-a = 2.912 x $e^{(-1.89 \times Cchl)}$
Logarithmic	Chl-a = -1.099 x ln(Cchl) + 0.397

To assess how the independent variables affect the dependent variable, or to test whether the regression model is significant (good) or not significant (poor), an F-test was conducted as shown in Table 2.

Table 2

F-test results of regression models, performed using SPSS

Model	F_{table}	$F_{calculated}$	*α*	*Significance*
Linear		12.661		0.024
2^{nd} order polynomial		8.133		0.061
3^{rd} order polynomial	6.61	4.523	0.05	0.189
Exponential		9.061		0.040
Logarithmic		19.700		0.011

Table 2 presents the F-test results for each model formulation. Three of the five empirical models developed (linear, exponential, and logarithmic) have F-calculated values greater than the F-table value and significance levels lower than 0.05. These results indicate that the independent variables in the linear, exponential, and logarithmic models have a significant relationship with the dependent variable. In other words, the linear, exponential, and logarithmic models are statistically significant and can be used for prediction purposes.

To evaluate the adequacy of fit for the linear, exponential, and logarithmic models, a model fit test was performed using the coefficient of determination, commonly referred to as R^2. This will measure how well the model explains the variability of the dependent variable or provides all the information needed to predict the dependent variable. The R^2 value is also one of the goodness-of-fit criteria for selecting the best model.

Table 3

R^2 values for regression models, performed using SPSS

Model	*R-Square (R^2)*
Linear	0.76
Exponential	0.69
Logarithmic	0.83

Table 3 shows the R^2 values for the linear, exponential, and logarithmic models. Among these, the logarithmic model has the highest R^2 value of 0.83, meaning that 83% of the variability in the laboratory-tested chlorophyll-a concentrations can be explained by the logarithmic model using Cchl (the RGB wavelength ratio) as the independent variable. With the highest R^2 value, the logarithmic model is considered the best model.

Comparison of chlorophyll-a results from laboratory tests, Hydrocolor, and MODIS. To evaluate the quality of the HydroColor application, a comparison was conducted between chlorophyll-a values obtained from HydroColor, the MODIS satellite image, and laboratory test results. The comparison results are presented in Table 4 and Figure 3.

Table 4

Comparison of chlorophyll-a concentrations from laboratory tests, HydroColor (Leeuw and logarithmic models), and MODIS satellite data

Data acquisition points	*Laboratory tested*	*MODIS*	*HydroColor (Leeuw)*	*HydroColor (Logarithmic)*
TA/P/01/L	0.83	2.17	2.29	1.16
TA/P/02/L	0.61	1.99	1.99	0.74
TA/P/03/L	0.76	2.03	1.90	0.63
TA/P/04/L	1.04	NaN	1.99	0.74
TA/P/05/L	1.07	NaN	2.01	0.77
TA/P/06/L	0.59	NaN	2.00	0.75
TA/P/07/L	1.25	NaN	2.07	0.84
TA/P/08/L	2.24	NaN	2.74	2.17
Correlation		0.875	0.85	0.876

The HydroColor (Logarithmic) results show a stronger correlation with laboratory test data than the correlation between MODIS and HydroColor (Leeuw) to laboratory data. The correlation value for HydroColor (Logarithmic) is 0.876 or 87.6%, while the MODIS correlation is 0.875 or 87.5%, and the HydroColor (Leeuw) correlation is 0.85 or 85% (Table 4).

From sampling points 4 to 8, MODIS does not provide chlorophyll-a values due to proximity to land, which introduces significant errors. However, using the HydroColor application, data near the coast can still be obtained since it collects data directly on-site, reducing light wave detection errors by the sensor. The graph of HydroColor (Logarithmic) shows values and patterns that closely match those of the laboratory chlorophyll-a results. In contrast, the MODIS graph shows values and patterns that differ from the laboratory data. The HydroColor (Leeuw) values exhibit a similar pattern to the laboratory data graph but are closer to the chlorophyll-a values from MODIS. Figure 3 shows that the chlorophyll-a values from the laboratory tests are not significantly different from the HydroColor (Logarithmic) results compared to the MODIS and HydroColor (Leeuw) values. This further supports the conclusion that laboratory chlorophyll-a values are nearly equivalent to those of HydroColor (Logarithmic), resulting in a similar spatial distribution pattern. The logarithmic equation is more suitable for this study than the Leeuw equation, and the HydroColor application can be considered a viable new method for determining chlorophyll-a concentrations in the waters of Banten Bay.

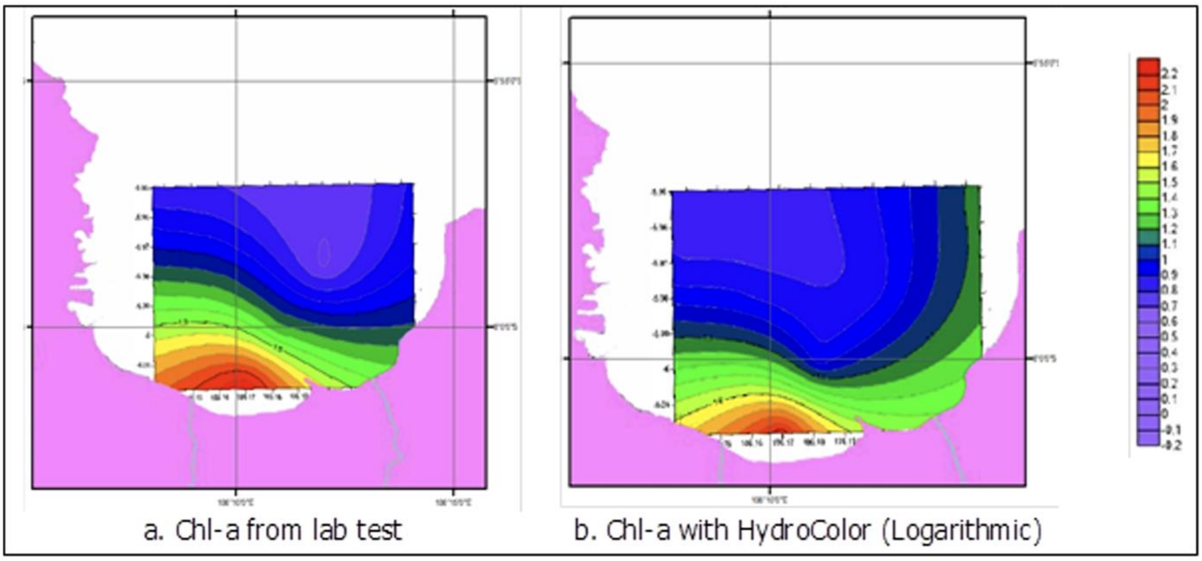

Figure 3. Comparison of chlorophyll-a concentrations from laboratory tests, HydroColor estimations (Leeuw and logarithmic models), and MODIS satellite imagery.

Figure 4a shows that the chlorophyll-a concentration from the laboratory test has a more similar pattern to the chlorophyll-a from HydroColor (Logarithmic) (Figure 4b). Compared to MODIS, which has only 2 points in this area, therefore, from MODIS, the distribution pattern cannot be made, because there are many error chlorophyll-a data (NaN) in the MODIS data. The similarity of the pattern is also related to the strong correlation between laboratory test chlorophyll-a data and HydroColor (Logarithmic) chlorophyll-a data.

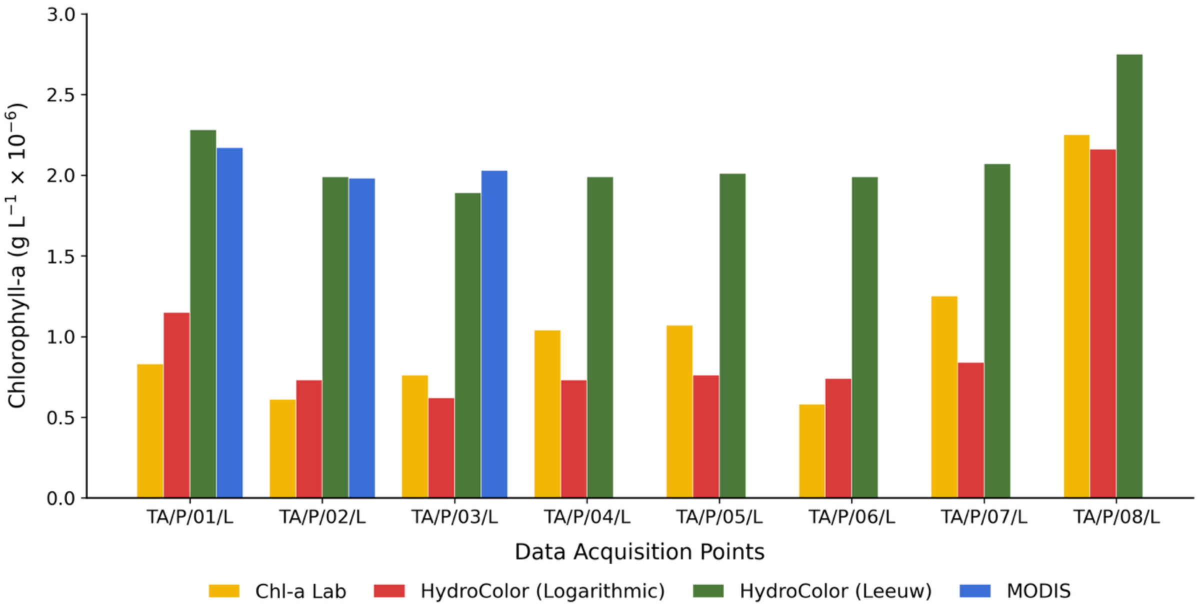

Figure 4. Spatial distribution of chlorophyll-a concentrations in Banten Bay on 27 October 2019: (a) based on laboratory test results; (b) estimated using the HydroColor application with the logarithmic model.

Comparison with previous smartphone- and satellite-based chlorophyll-a studies. The logarithmic model's R^2 of 0.83 and correlation coefficient of 0.876 obtained in this study place the Banten Bay HydroColor algorithm within, and arguably at the upper end of, the range of accuracy reported for comparable smartphone-based reflectance monitoring elsewhere, Leeuw and Boss (2018), who originally developed the

HydroColor application, cautioned that a single, globally applicable chlorophyll-a algorithm based on the green/blue reflectance ratio was unlikely to be reliable because of the confounding influence of coloured dissolved organic matter (CDOM), and recommended that locally or regionally calibrated relationships would be more appropriate. The present findings support that recommendation: rather than adopting a generic RGB ratio, the empirical logarithmic equation was tuned specifically to Banten Bay conditions, which likely explains why its performance compares favourably with the R^2 of 0.65–0.85 reported for HydroColor-based chlorophyll and CDOM estimates validated against fluorometric measurements in the tidal tributaries of Chesapeake Bay (Neale et al., 2024), and with the R^2 of 0.68 obtained for smartphone-based chlorophyll-a estimation in three Taiwanese reservoirs (Santosa et al., 2025). It is also broadly consistent with the findings of Gallagher and Chuan (2018), who evaluated HydroColor chlorophyll-a and turbidity retrievals across two contrasting coastal bays in Sabah, Malaysia, and reported that accuracy was strongly site-dependent, improving markedly where a location-specific calibration was applied instead of a generic equation. Taken together, these comparisons suggest that the performance of the Banten Bay algorithm is not an isolated result but part of an emerging and fairly consistent pattern, in which locally tuned, RGB-ratio-based empirical models can approach or exceed $R^2=0.8$ in coastal and estuarine waters, even though a single universal chlorophyll-a algorithm for HydroColor remains elusive.

The improvement from a single-band correlation (red channel alone, r=0.61) to the multivariate RGB-ratio model (r=0.876) is also consistent with the optical rationale underlying most ocean-colour chlorophyll algorithms. Because chlorophyll-a preferentially absorbs light in the red portion of the visible spectrum while the green and blue wavelengths are comparatively reflected, the red channel alone captures only part of the pigment signal, whereas a ratio that combines all three channels helps compensate for variations in overall illumination, sun glint, and CDOM absorption that could otherwise be misread as a chlorophyll-a signal. This is the same logic that underlies two- and three-band reflectance-ratio approaches used in satellite ocean-colour retrieval more broadly, and it helps explain why the Cchl ratio-based models tested here outperformed the raw red-band correlation obtained from the same dataset.

The comparatively poor performance of MODIS in the near-shore stations of Banten Bay is also consistent with the wider literature on satellite ocean-colour retrieval in optically complex coastal waters. Jiang et al. (2017) reported that MODIS chlorophyll-a estimates in the shallow, turbid, near-shore waters of Hawke Bay, New Zealand, carried average errors of 40–60%, well above the approximately 35% accuracy benchmark expected for the open ocean, and attributed the discrepancy largely to adjacency effects, bottom reflectance, and atmospheric-correction failure close to the coastline. Comparable degradation of MODIS chlorophyll-a retrievals in turbid, semi-enclosed bays has been reported elsewhere. The complete absence of usable MODIS values at stations 4 to 8 in the present study, all located close to shore, mirrors this well-documented limitation and reinforces the practical case for handheld, in-situ RGB sensing as a complement to, rather than a replacement for, satellite ocean-colour products in the shallow, nearshore waters used for fisheries and aquaculture in Banten Bay. These results also lend support to the broader case, made by Leeuw and Boss (2018) and more recently demonstrated by the Chesapeake Water Watch participatory-science programme (Neale et al., 2024), that smartphone-based reflectance measurements collected by trained non-specialists can meaningfully densify chlorophyll-a monitoring networks in areas that are chronically undersampled by laboratory campaigns and satellite overpasses alike. In a setting such as Banten Bay, where fish-cage aquaculture and small-scale fisheries operate in close proximity to industrial and tourism activity, the ability to generate spatially dense, near-real-time chlorophyll-a data at negligible cost strengthens the argument for HydroColor-type tools as an early-warning complement to conventional water-quality monitoring. At the same time, several features of the present dataset call for caution before the Banten Bay logarithmic equation is generalised. The empirical model was calibrated and validated using only eight paired observations (six for calibration and two for validation) collected on a single day in October 2019. A sample of this size increases the risk that the reported R^2 and correlation coefficients are partly a function of the specific range of chlorophyll-a concentrations sampled on that occasion, and it offers limited statistical power to detect non-linearity or seasonal variability. Leeuw and Boss (2018) further showed that HydroColor reflectance retrievals can differ measurably between smartphone models and operating systems (iOS versus Android), and the present results likewise point to a sensitivity of chlorophyll-a estimates to camera resolution; together, these observations suggest that, before the Banten Bay algorithm is adopted for routine or crowdsourced monitoring, it should be re-evaluated using a larger, multi-season dataset and, ideally, cross-checked across several smartphone devices to establish how transferable the empirical coefficients really are. Overall, these comparisons indicate that a locally calibrated, RGB-ratio-based HydroColor algorithm can provide chlorophyll-a estimates for Banten Bay that are both statistically robust and spatially more complete than concurrent MODIS retrievals, particularly in the near-shore zone that matters most for coastal aquaculture and small-scale fisheries. This finding is consistent with, rather than exceptional relative to, a growing body of evidence from other coastal, estuarine, and inland waters, and it positions HydroColor as a genuinely complementary, low-cost tool for chlorophyll-a monitoring rather than a wholesale substitute for either laboratory analysis or satellite remote sensing.

Conclusions*.* The logarithmic model is the most accurate empirical model in this study. The values and distribution patterns of chlorophyll-a obtained from laboratory tests are more closely aligned with the results from HydroColor than those from MODIS. Camera resolution and the amount of data influence the results obtained from HydroColor, the better the camera resolution and the more data available, the better the outcomes. Camera resolution has a greater impact than the amount of data of the chlorophyll-a model derived from HydroColor. The HydroColor application, which uses a smartphone camera, can serve as an alternative method for estimating chlorophyll-a levels in the waters of Banten Bay. The applicability of the HydroColor holds potential for coastal fisheries and aquaculture management. Regular assessment of chlorophyll-a concentrations using this tool can help monitor water conditions that affect fish and shellfish health. Additionally, small-scale fishers can utilize this method to identify productive zones and anticipate changes in primary productivity that may influence spawning grounds. Thus, this approach promotes more responsive, localized, and sustainable management practices in the aquaculture and fisheries sectors.

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Conflict of Interest. The authors declare that there is no conflict of interest.

Data Availability. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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