Evaluation and Local Calibration of Sentinel-2 Chlorophyll-a Algorithms in Kendal Coastal Waters, Indonesia

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Abstract
Monitoring chlorophyll-a (Chl-a) concentrations in coastal waters is crucial due to its role as a biogeochemical indicator sensitive to environmental changes. Remote sensing techniques have been widely utilized for Chl-a estimation; however, the precision and relevance of algorithms developed in other regions require comprehensive evaluation, validation, and calibration against in situ Chl-a data. This study evaluated a Sentinel-2A Chl-a algorithm using 10m blue, green, red, and near-infrared (NIR) resolution bands (hereafter, MR4B) and an algorithm based on the green-red (GR) ratio band from another region. The performance of both was compared against an algorithm generated through in situ Chl-a calibration. Calibration was performed on the green-blue, green-red ratio bands, and a single band, using in situ Chl-a data collected on April 24, 2025, coinciding with the S2A satellite's passing time. The results showed that the performance of MR4B and GR was outperformed by the algorithms generated through the calibration process, where the SB algorithm showed superior performance, followed by the green-blue ratio and the green-red ratio, with root mean square error (RMSE) of 0.74 µg/L, 0.89 µg/L, and 0.93 µg/L, respectively. This study showed that the single band algorithm, demonstrated in the use of the green band (SB) provides a more practical and robust approach for Chl-a monitoring in this coastal system, with its simpler structure compared to other algorithms. However, further research is needed to examine the algorithm in the different season.

Keywords: Algorithm, Band Ratio Green-Red, Calibration, Chlorophyll-A, Single Band

1. Introduction

The chlorophyll-a (Chl-a) concentration is a photosynthetic pigment commonly used as an indicator of phytoplankton abundance in the water column [1] and [2]. Due to its ability to respond to environmental conditions, Chl-a has been utilized to assess the level of eutrophication in water bodies [3]. Its presence in the water column can affect bio-optical properties [4] and [5], and therefore, it can be monitored using remote sensing methods. Remote sensing is considered more efficient in terms of time and cost [6]. However, this method still faces many challenges, particularly regarding the use of algorithms that are not always applicable to local Chl-a estimation, particularly in areas with different characteristics [7] and [8]. Kendal's coastal waters are influenced by several large rivers, such as the Kuto and Bodri rivers, which contribute to increased suspended sediment and have resulted in shallow bathymetry. Total suspended solid concentrations reach >50 mg/L [9]. In addition, the waters exhibit eutrophic conditions, as indicated by a Chl-a concentration of 10 µg/L [10]. These environmental conditions have implications for the water's properties, particularly its optical characteristics.

Monitoring Chl-a from satellite requires the selection of a suitable algorithm. Various algorithms for Chl-a estimation have been developed and successfully used [2][4] and [8]. Nevertheless, these algorithms are not always applicable in other regions because of potential differences in the optical properties of water [11] and [12] which poses a challenge for developing robust Chl-a algorithms for each area [13][14][15] and [16]. Coastal waters have highly complex optical properties, not only because of the green pigment from phytoplankton, but also because of other non-algal suspended particles and colored dissolved organic matter (CDOM) [17] and [18] their shallow bathymetry, which affect the absorption and backscattering detectable by satellite sensors. This influences the selection and use of bands in constructing Chl-a estimation algorithm models for water, which depend on regional characteristics and seasons.

The development of algorithms for estimating Chl-a in water has been carried out extensively, including band ratio inversion models such as the green-blue (applicable to clear waters, GB) and green-red (for medium to turbid waters, GR) as suggested by [3]. For turbid waters, red or Near Infra-Red (NIR) bands are frequently utilized [19]. Additionally, algorithm development has progressed through the integration of various band ratios, such as the Multi-band Ratio (MuBR) and the Normalized Difference Chlorophyll-a Index (NDCI) [20]. In the coastal waters of northern Central Java, Indonesia, an algorithm for estimating Chl-a has been proposed by [8], employing a multi-band (blue, green, red, and NIR) 10m resolution (hereafter as MR4B), alongside another based on the green-blue band ratio (GB) [21]. Nevertheless, the application of this approach to other coastal waters, characterized by complex optical properties (classified as case II waters), necessitates further investigation and evaluation, considering their unique and diverse characteristics. Based on their optical properties, water types are grouped into Case I and II. Case I waters, which are predominantly found in the open ocean, are mainly influenced by phytoplankton. In contrast, Case II waters, typical of inland and coastal regions, are characterized by the presence of Chl-a, total suspended solids (TSS), and colored dissolved organic matter (CDOM).

Algorithm models for estimating Chl-a in coastal waters can utilize single bands, band ratios, and machine learning integration with sensitive band selection [22]. Empirical methods are simple and often used in estimation, such as those found in MR4B. However, empirical methods must be evaluated before being implemented. Although Chl-a estimation from Sentinel-2 has been widely conducted, its application for coastal waters using a specific algorithm still requires evaluation. This is different from open ocean waters, where the optical properties are determined solely by phytoplankton (as case water I). Algorithms used in clear waters (such as open ocean) are often based on the use of the maximum ratio band in the green-blue domain of visible light [23] and have been used universally.

Based on these reasons, this study determined the accuracy of the MR4B algorithm (representing the algorithm for the waters of the northern coast of Java) and the GR algorithm (which is a ratio algorithm for waters in Vietnam), both of which are used to estimate Chl-a from Sentinel-2A (S2A) imagery. Furthermore, this research will compare these two algorithms with the algorithm resulting from in situ Chl-a calibration. The S2A has a reflectance value that has been corrected geometrically and atmospherically using the Sen2Cor platform [24]. The Sen2Cor-filtered reflectance data was utilized in the development of MR4B. Consequently, we employed the same dataset for the algorithm evaluation and local calibration in the coastal waters of Kendal. The findings of this study offer an alternative approach to sustainable monitoring practices by enhancing Chl-a estimates derived from previous ocean color observations in coastal regions. The study particularly emphasizes the application of Sentinel-2A/MSI technology in the coastal waters of Kendal. This region, recognized for its substantial fisheries potential, is currently experiencing considerable anthropogenic pressure. It is anticipated that this research will contribute to sustainable monitoring efforts.

2. Material and Methods

2.1 Study Area

The MR4B and GR chlorophyll-a (Chl-a) algorithms were evaluated in the coastal waters influenced by the Kuto River, specifically near Moro Beach. The Kuto River originates from Mount Prau in Bringinsari Village, Sukorejo District, Kendal Regency, and flows approximately 52 km before discharging into the Java Sea. The river drains a watershed area of 340.70 km² and has an estimated discharge of 880 m³/s. This substantial discharge delivers large quantities of suspended sediments to the coastal zone, promoting active sedimentation processes [25].

From an optical standpoint, the study area is characterized by turbid coastal waters with elevated total suspended solids (TSS) and strong terrestrial inputs. Previous observations in Kendal waters have reported TSS concentrations exceeding 50 mg/L, indicating high turbidity conditions. In addition to particulate matter, riverine runoff introduces nutrients and colored dissolved organic matter (CDOM), which strongly absorbs light in the blue wavelengths and alters the spectral response of the water column. Based on its optical characteristics, the study area can be classified as Case-2 waters. In this classification, water optical properties are influenced not only by phytoplankton (chlorophyll-a) but also by non-algal suspended particles and CDOM. This differs from Case-1 waters (typically open ocean), where optical variability is predominantly controlled by phytoplankton alone. In Case-2 environments such as Kendal coastal waters, the combined effects of TSS, CDOM, and Chl-a create optically complex conditions that complicate satellite-based chlorophyll retrieval.

Beyond transporting total suspended solids (TSS), the river also conveys nutrients derived from terrestrial runoff, which stimulate phytoplankton growth and influence Chl-a variability. These hydrological and optical characteristics make the area particularly suitable for evaluating and calibrating Chl-a algorithms under turbid, optically complex coastal conditions. The study area is geographically located between 110°01′06″ E and 110°03′12″ E longitude and 6°53′27″ S and 6°54′30″ S latitude, as illustrated in Figure 1.

2.2 In situ Chlorophyll-a

Following the procedures described in [3] and [24], water samples were collected within ±1 hour of the Sentinel-2A overpass to ensure temporal consistency, with the satellite passing the study area at approximately 09:30 Western Indonesian Time (WIB). On April 30, 2025, in situ chlorophyll-a (Chl-a) measurements were obtained from 70 sampling stations for algorithm tuning and validation. The geographic positions of all stations were recorded using a Global Positioning System (GPS), and their locations are shown in Figure 1. Surface water samples were collected using a 1-liter bucket. The samples were subsequently filtered, and the pigments were extracted using 90% acetone. Chl-a concentrations in the extracts were determined spectrophotometrically, and the final concentrations were calculated using Equations (1) and (2).

$$Chl-a = \frac{c_e V_1}{V_0}$$

Equation 1

Where: *Chl-a* = chlorophyll-a concentration (µg/L), V_1 = extract volume (acetone, ml), V_0 = volume of filtered sample (liter, L), c_e = concentration of the Chl-a pigment in the extract, calculated according to Equation 2:

$$c_e = 11.85 D_{664} - 1.54 D_{647} - 0.08 D_{630}$$

Equation 2

Where D_{664}, D_{647}, and D_{630} = the optical densities at *664* nm, *647* nm, and *630* nm, respectively.

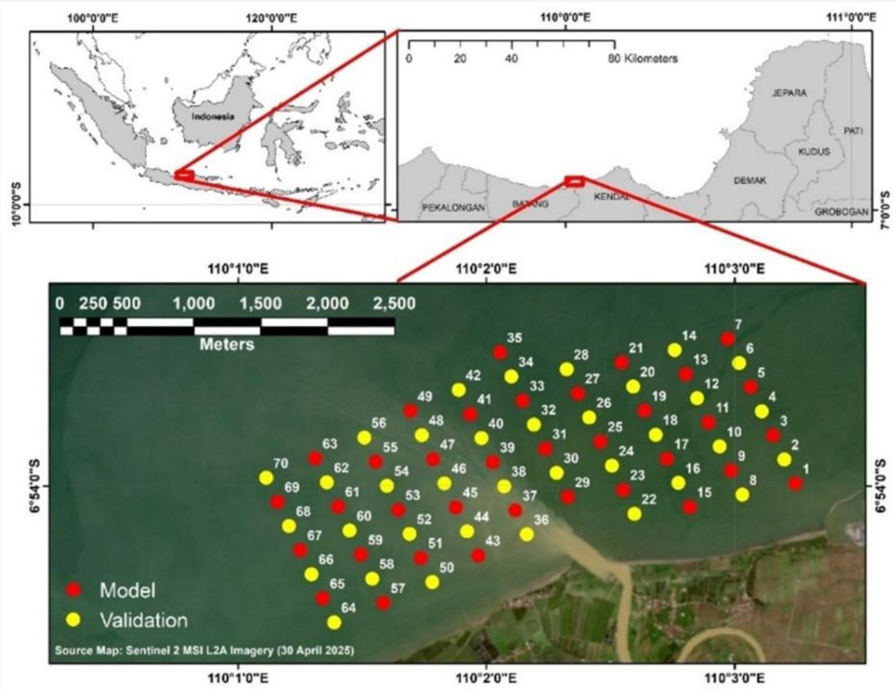

Figure 1: Study area in Kendal coastal waters, Indonesia

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2.3 Satellite Data and Image Pre-Processing
For the satellite analysis, this study utilized Sentinel-2 Level-2A imagery (MSIL2A product) covering the Kendal coastal waters. The Level-2A data have undergone geometric and radiometric corrections and provide Bottom-of-Atmosphere (BOA) surface reflectance values [24]. The Sentinel-2A (S2A) satellite acquired the image over the study area at approximately 09:30 AM Western Indonesian Time (WIB), corresponding to the field sampling period. The imagery was obtained from the Copernicus Data Space Ecosystem (browser.dataspace.copernicus.eu). Sentinel-2 carries a multispectral instrument (MSI) comprising 12 spectral bands spanning wavelengths from 443 nm to 2,202 nm, covering the visible, near-infrared (NIR), and shortwave infrared (SWIR) regions of the electromagnetic spectrum. These data have already undergone radiometric and geometric correction, as well as atmospheric correction using Sen2Cor. The reflectance was converted into physical reflectance by dividing the pixel values by 10,000, following Sentinel-2 product specifications.

To ensure consistency with ocean color methodology, the BOA reflectance was further converted to remote sensing reflectance (Rrs) by dividing the reflectance by π. The resulting Rrs values (sr^{-1}) were used in the correlation and regression analyses. This step ensures that the satellite-derived variable represents a standardized radiometric quantity appropriate for bio-optical modeling. For algorithm tuning, the visible bands were checked against *in situ* Chl-a to produce a band ratio-based algorithm for the area outside the Moro River. The bands used in this study are those with a resolution of 10m from the Sentinel-2 Scientific Data Hub, which were collocated with the field data. The 10m re-sampling was performed using the Sentinel Application Platform (SNAP). The correlation analysis was conducted using Pearson's correlation coefficient between in situ Chl-a concentrations (μg/L) and the satellite-derived Rrs values from individual bands, as well as selected band ratios (green-blue and green-red).

In this study, outliers were identified using a two-step procedure combining analytical and statistical criteria. First, we screened the *in situ* chlorophyll-a (Chl-a) measurements for laboratory anomalies. Two samples (Stations 42 and 48) showed no detectable Chl-a concentration due to spectrophotometric readings below the detection limit. Because regression calibration requires physically meaningful positive values, these samples were excluded from further analysis. Second, a statistical screening was performed on the match-up dataset (in situ Chl-a and satellite-derived reflectance). We examined scatterplots and calculated standardized residuals from an initial regression model.

2.4 Algorithm for Estimating Chl-a
In this study, two previously developed chlorophyll-a (Chl-a) estimation algorithms were evaluated for accuracy. The MR4B algorithm was developed for coastal waters and incorporates four Sentinel-2 bands, blue (B2), green (B3), red (B4), and near-infrared (NIR, B8), within a linear regression framework. This multi-band formulation results in a relatively complex empirical model designed to account for the optical variability of coastal environments. The MR4B algorithm is presented in Equation 3 [8]:

$$\begin{aligned}\log(Chl-a) = 2.723 - 0.725\log(c \cdot B2) \\ - 0.625\log(c \cdot B3) + 1.623\log(c \cdot B4) \\ + 0.809\log(c \cdot B8)\end{aligned}$$

Equation 3

Where: *B2, B3, B4,* and *B8* are the reflectance of blue band, green band, red band, and NIR band, respectively, and $c = 0.036/B8$.

In contrast, the GR algorithm is structurally simpler, relying solely on a band ratio approach. It uses the green-to-red band ratio and was originally developed for freshwater systems [3]. Despite its simpler formulation, it has been applied in optically complex waters. The GR algorithm is defined in Equation 4 [3]:

$$Chl-a = 0.80 Exp^{0.35B3/B4}$$

Equation 4

Both algorithms are based on Sentinel-2 multispectral reflectance data.

2.5 Tuning Algorithm Band-Ratio
In addition to evaluating previously published algorithms, this study recalibrated band-based models using locally collected *in situ* chlorophyll-a (Chl-a) data and satellite-derived remote sensing reflectance (Rrs). The calibration process employed both linear and exponential regression approaches. The reflectance variables used were Rrs values from the blue (B2), green (B3), and red (B4) bands of Sentinel-2. Specifically, the green-to-blue (GB) band ratio was calibrated against in situ Chl-a using an exponential regression model, following the approach adopted by [3] and [21]. In parallel, a linear regression model was also tested as a simpler and more parsimonious alternative, consistent with the methodology applied by [24].

This comparative approach allowed us to evaluate model performance and select the most appropriate functional form for the optical characteristics of the study area.

Before calibration, a correlation analysis was conducted between in situ Chl-a and several Sentinel-2 reflectance bands with a 10m spatial resolution, specifically bands 2, 3, 4, and 8. Of the 70 data samples collected, 35 were utilized for calibration, while the remaining 33 were used for validation, with two (2) data identified as outliers (the concentrations of Chl-a in the sample no detection in stations 42 dan 48). Calibration data were collected at odd-numbered stations (red circle, ●), whereas even-numbered stations were employed for validation (yellow circle, ●) (Figure 1).

2.6 Validation

The validation procedure employed three statistical metrics: root mean square error (RMSE), mean absolute error (MAE), and bias, following [26] and [27]. The mathematical formulations used to evaluate algorithm performance are presented in Equations (5), (6), and (7). The optimal algorithm was identified based on the lowest RMSE and MAE values, indicating minimal prediction error, as well as the smallest bias, reflecting reduced systematic overestimation or underestimation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(E_i - O_i\right)^2}{N}}$$

Equation 5

$$MAE = \frac{1}{N}\sum_{i}^{N}\left(E_i - O_i\right)$$

Equation 6

$$Bias = \frac{1}{N}\sum_{i=1}^{N}\left(E_i - O_i\right)$$

Equation 7

Where:

E_i = estimated Chl-a
O_i = in-situ Chl-a
N = the total number of the samples

Figure 2 illustrates the overall methodological framework applied for the evaluation and calibration (generation) of chlorophyll-a (Chl-a) estimation algorithms. The workflow begins with the acquisition of Sentinel-2 Level-2A imagery and in situ Chl-a measurements collected during the satellite overpass period. The satellite data undergo reflectance extraction and preprocessing, including band selection and spatial collocation with field sampling stations. Subsequently, two parallel analyses are conducted: (1) evaluation of existing algorithms (MR4B and GR) using the match-up dataset, and (2) development of locally calibrated models through regression analysis using selected spectral bands and band ratios. The dataset is divided into calibration and validation subsets to ensure independent model assessment. The final stage involves statistical validation using RMSE, MAE, and bias to determine the optimal algorithm. This structured workflow ensures a systematic comparison between previously published models and newly generated local algorithms, leading to the selection of the most accurate Chl-a estimation approach for the study area.

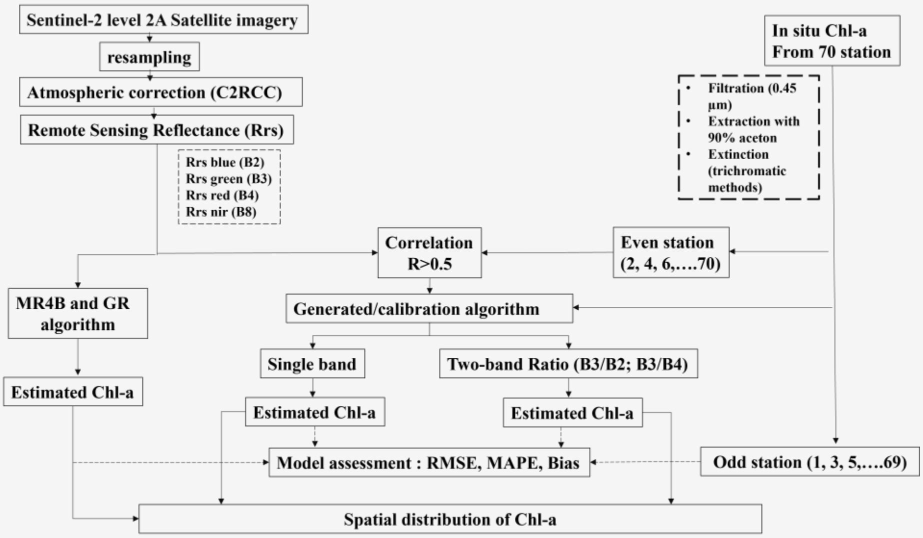

Figure 2: Chl-a estimation algorithms

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3. Results and Discussion

3.1 Evaluation of the MR4B and Green Red (GR) Ratio

The concentrations of Chl-a measured at 68 locations in this study ranged from 0.11 µg/L to 4.04 µg/L, with an average concentration of 1.64 µg/L. Concurrently, the algorithmic values derived from MR4B and GR are presented within the ranges specified in Table 1, and their validation is illustrated in Figure 3. Table 1 indicates that the application of algorithms from other regions, such as MR4B and GR proposed by [8] and [3], results in significant errors, rendering them unsuitable for use in Kendal coastal waters, particularly near the Moro River. Specifically, the MR4B algorithm tends to overestimate, while the GR algorithm tends to underestimate. This overestimate (underestimate) of Chl-a is related to changes in conditions, both temporally and spatially, in response to environmental changes. Changing conditions will affect the spectral response associated with Chl-a. Thus, algorithm constants need to be recalibrated or optimized to reflect new patterns in the data [28]. In the MR4B tuning, the average Chl-a concentration was >9.49 µg/L [8], while the GR generated with in situ Chl-a was <3.77 µg/L [3]. This in situ Chl-a influenced the overestimation (underestimation) of Chl-a in Kendal waters, with the average Chl-a value being <1.77 µg/L.

In addition to constants, the suboptimal performance may be attributed to the inclusion of the red band and near-infrared (NIR) in both algorithms. The incorporation of these two bands in Chl-a estimation is associated with the significant absorption occurring in the green pigment (Chl-a), which results in a reduction of reflectance values when Chl-a levels are elevated [29]. This phenomenon is not observed in Kendal waters, where the average Chl-a concentration is considerably lower, with concentrations below 1 µg/L accounting for 25%. The application of MR4B estimation of Chl-a concentrations exceeding 9 µg/L, whereas in situ measurements never surpassed 4 µg/L. When elucidated that when predicting Chl-a values using Sentinel, it is imperative to calibrate the algorithm against local Chl-a values [19]. A divergent pattern emerged with the application of the GR algorithm, which yielded Chl-a values with a reduced root mean square error (RMSE) and a tendency towards underestimation. Additionally, the average Chl-a values were higher than the in situ estimated (GR = 1.63 µg/L and in situ = 1.64 µg/L). These findings underscore that algorithms developed for specific water bodies cannot be universally applied without calibration using *in situ* data [19] and [29].

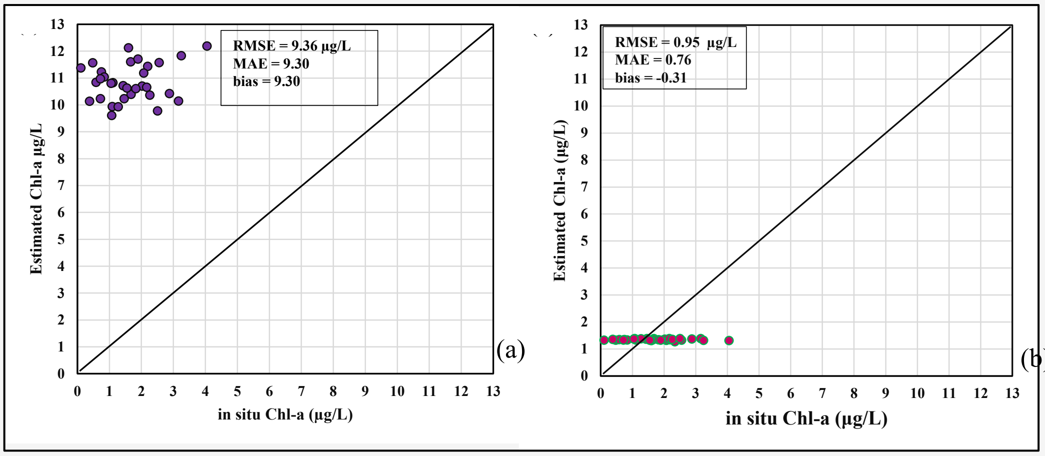

Figure 3: Validation of estimated Chl-a: (a) MR4B and (b) GR

Table 1: Generated algorithm model for SB, GBR, and GRR

Band ratio	Model	R-squared
SB	$Chl-a = 67.008 Rrs_{green}$	0.49
GBR	$Chl-a = 0.0652 Exp^{2.6495 Rrs_{green}/Rrs_{blue}}$	0.14
GRR	$Chl-a = 28.697 Exp^{-2.003 Rrs_{green}/Rrs_{blue}}$	0.21

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Therefore, it is essential to adapt the algorithm to *in situ* data to derive constants in the algorithm model that accurately reflect actual conditions, as noted by [30] and [31]. Calibration is pivotal in refining Chl-a estimation algorithms to enhance accuracy, reduce errors, and facilitate their broad application in diverse ecological and environmental studies [32].

In this study, Sentinel-2 Level-2A data atmospherically corrected using Sen2Cor were employed to obtain Bottom-of-Atmosphere (BOA) reflectance. While Sen2Cor is widely used for land and coastal applications, its reliability over highly turbid Case-2 waters remains subject to uncertainty. In optically complex environments, near-infrared (NIR) reflectance from suspended sediments is often non-negligible, which can violate the dark-object assumptions used in standard atmospheric correction approaches. This may introduce errors in aerosol retrieval and propagate biases into visible-band reflectance, ultimately affecting chlorophyll-a estimation. Similar limitations of atmospheric correction in coastal and inland waters have been discussed by [11][14], and [29], who emphasized that atmospheric correction is a critical source of uncertainty in water quality retrieval.

3.2 *Generating Chl-a Algorithm*

Following this evaluation, future research will aim to compare the algorithms produced through the GR calibration process and to generate new algorithms. The model derived from the in situ Chl-a calibration is termed a local model. According to [33], local models have the potential to enhance estimation accuracy. In our study, we formulated a new algorithm that employs a single band (SB), specifically the green band, which demonstrated the highest R^2 value (R^2=0.49). In contrast, the band ratios for green-blue (GBR) and green-red (GRR) were lower, with R^2 of 0.14 and 0.21, respectively (Table 1). Despite the lower performance of the band ratio, the three models generally show similar spatial distribution patterns. Differences are noted in the range of Chl-a values, with the SB model exhibiting the broadest range, although the most extensive range is in situ Chl-a.

Using other *in situ* data (validation data), the RMSE (MAE) value for the single band of green (SB) using equation 8, GBR (equation 9), and GRR (equation 10) are similar, at 0.79 µg/L (0.65 µg/L), 0.89 µg/L (0.67 µg/L) and 0.93 µg/L (0.73 µg/L), respectively (Figure 4). The validation test results showed that the use of a single band and the band ratio had similar performance, with a smaller RMSE value for the single band. A scatter plot of in situ Chl-a and the estimation is shown in Figure 4. When using a single band, the linear regression model showed the best performance with a smaller standard error of estimate (RMSE). In contrast, in the band ratio, it was found in the blue-green ratio algorithm.

Several studies related to determining the best regression models (linear, power, and exponential) have not yet been conducted. When estimating Chl-a concentrations using Sentinel satellite data, the choice between linear and exponential regression models depends on various factors, including the nature of the dataset and the specific conditions of the study area. The results of the statistical test on paired data (Friedman test) indicate that *in situ* Chl-a, linear, and exponential estimation show differences ($p=0.00$, $p<0.05$). However, the test for differences in the mean values (Kruskal-Wallis test) shows no significant difference ($p=0.307$, $p>0.05$). The linear model is considered due to its simplicity and practicality for an initial assessment of Chl-a concentration. The selection of an appropriate model, linear, exponential, or power, is crucial for testing and validating various water quality datasets to determine the most effective analytical approach. According to research by [24] on the TSS algorithm of Sentinel-2, the exponential model demonstrated superior performance, whereas [34] findings indicated a preference for the linear model. Additionally, [3] reported that exponential regression outperformed both linear and logarithmic regression. Descriptive statistics (minimum, maximum, mean) for Chl-a values derived from equations 8, 9, and 10 are presented in Table 2.

Figure 4 illustrates that the range of Chl-a values is broader (0.86 - 2.82 µg/L) for SB (Single Band) compared to the band ratio-based algorithms GBR (Figure 4(b)) and GRR (Figure 4(c)). The GBR and GR algorithms exhibit patterns similar to the GR proposed by [3]. Nonetheless, statistical analyses revealed that the application of the GR, GBR, and GRR algorithms resulted in a significant difference when compared to in situ Chl-a ($p<0.05$), whereas no significant difference was observed for SB ($p=0.224$, $p>0.05$).

Table 2: Estimated of in situ Chl-a (µg/L), MR4B, and ratio GR algorithms

	In-situ	**Estimated MR4B**	**Estimated GR**	**Estimated SB**	**Estimated GBR**	**Estimated GRR**
Min	0.11	9.61	1.27	0.86	1.10	1.28
Max	4.05	14.10	1.40	2.82	1.96	2.39
Average	1.64	10.92	1.35	1.72	1.53	1.67

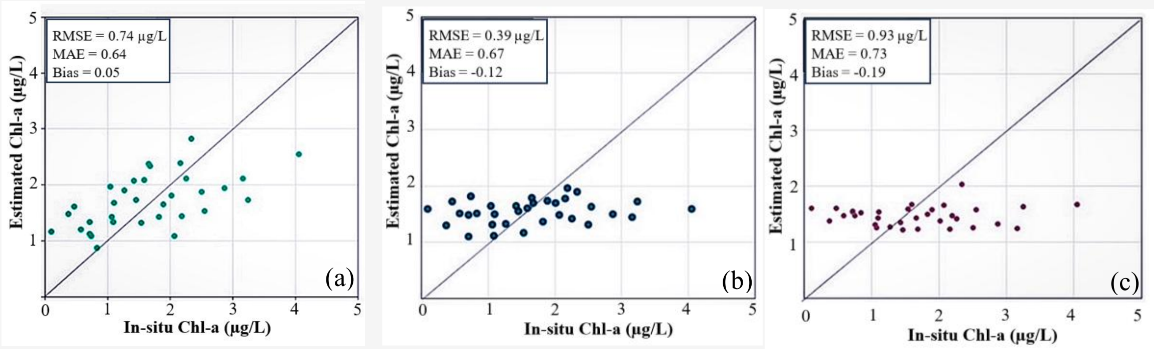

Figure 4. Scatterplot of in situ Chl-a versus estimated Chl-a from:
(a) single band green with linear regression, (b) Green-Blue d ratio (GBR) with exponential regression
(c) Green-Red ratio (GRR) with exponential regression

The enhanced performance of the green band (SB) algorithm in this study is attributed to the concentration levels of Chl-a within the aquatic environment. The Chl-a, a primary pigment present in phytoplankton, exhibits differential light absorption across the spectrum, and its concentration can be effectively detected by analyzing reflectance in the green wavelength region (approximately 530–550 nm). The findings of the study [35] have demonstrated the algorithm's efficacy in utilizing the green band for estimating Chl-a from Sentinel-2 data, thereby underscoring its robustness in capturing variations in chlorophyll-a levels and enhancing the accuracy of predictive models. Nevertheless, the band algorithm used for Chl-a estimation requires further examination, as it is contingent upon the optical properties of marine, coastal, or inland waters, including the application of specific band ratios for each water type [16] and [36].

The involvement of the red band resulted in a narrower range of estimated Chl-a concentrations, with values < 1 μg/L remaining undetectable. The enhanced performance of the green band algorithm in this study is attributed to the concentration levels of Chl-a within the aquatic environment. Chl-a, a primary pigment present in phytoplankton, exhibits differential light absorption across the spectrum, and its concentration can be effectively detected by analyzing reflectance in the green wavelength region (approximately 530–550 nm). The findings of the study [35] have demonstrated the algorithm's efficacy in utilizing the green band for estimating Chl-a from Sentinel-2 data, thereby underscoring its robustness in capturing variations in Chl-a levels and enhancing the accuracy of predictive models.

The use of other single bands in Sentinel-2 has been done in estimating other water quality parameters such as total suspended solids (TSS), namely the red band [24] and [34]. TSS consists of algae particles (which have Chl-a pigments) and non-algae particles. The contribution of the two dominant factors will determine the specific properties of the type of water [37]. Previous research by [10] in the coastal water of Kendal found a significant correlation between TSS and Chl-a, as evidence that the dominance of TSS is green-pigmented phytoplankton (Chl-a). The estimated spatial distribution patterns of Chl-a (MR4B, GR, SB, GBR, and GRR) are comprehensively illustrated in Figure 5.

Figure 5 illustrates that the Chl-a estimation maps derived from the five algorithmic models exhibited similar spatial patterns, characterized by elevated Chl-a concentrations in coastal regions, which diminish as one moves toward the open sea. A more distinct pattern was discernible off the river areas, specifically at the Kuto and Bodri rivers, where plumes indicated higher Chl-a concentrations than the surrounding regions. The elevated Chl-a concentrations off the river align with previous research [16], which attributed this phenomenon to nutrient supplies from upstream areas. Despite the similarity in spatial patterns, the five algorithms displayed variations in the estimated Chl-a values. The MR4B algorithm yielded the highest values (Chl-a >14 μg/L), whereas the GR algorithm produced the lowest values (<1.4 μg/L), with the three generated algorithms (SB, GBR, and GRR) exhibiting minor variations. Notably, the use of a single band (SB) in the green band resulted in the most effective distribution model, as corroborated by the validation test (Figure 4). The range of values closely aligns with in situ Chl-a, which exhibits greater variability. The efficacy of the green band in estimating Chl-a is attributed to the inherent properties of chlorophyll, which predominantly absorbs light at blue (430-450 nm) and red (640-680 nm) wavelengths while reflecting green light (500-550 nm).

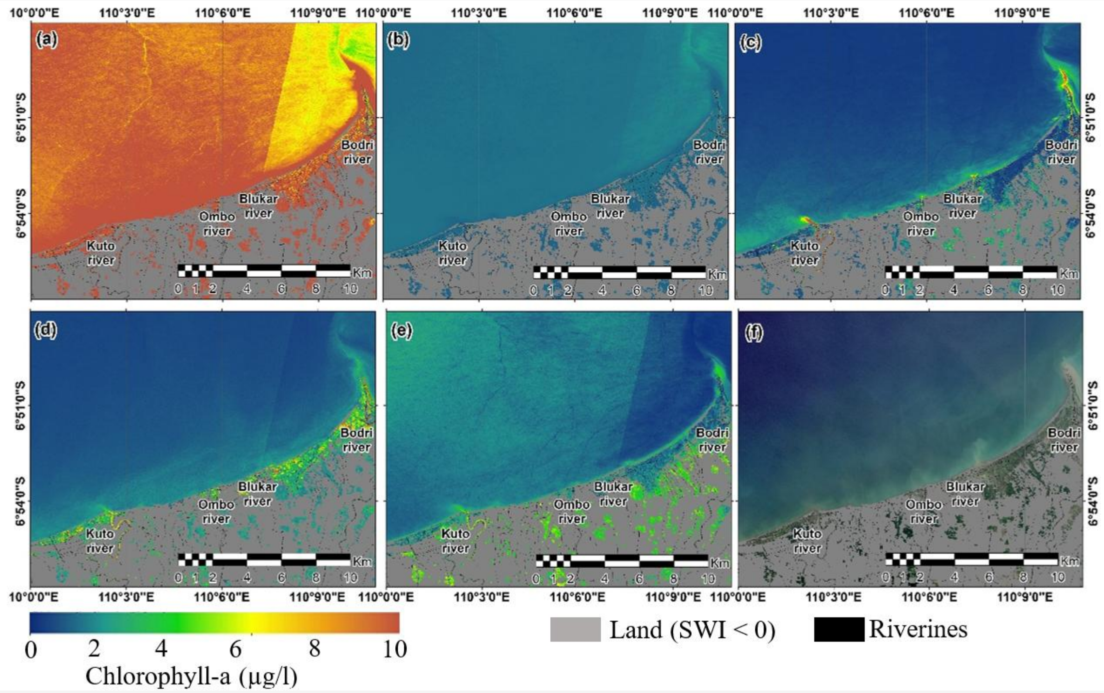

Figure 5: Spatial distribution of Chl-a data from April 30, 2025, from different algorithms: (a) MR4B; (b) GR; (c) single band of green linier (SB), (d) ratio band of green/blue exponent (GBR), (e) ratio band of green/red exponent (GRR), (f) the initial satellite view

Although the SB model yielded the highest coefficient of determination ($R^2 = 0.49$), this value indicates only moderate explanatory power and does not represent a strong predictive relationship. In optically complex coastal (Case-2) waters, moderate R^2 values are frequently reported due to the combined influence of chlorophyll-a, non-algal suspended particles, and colored dissolved organic matter (CDOM), which collectively affect spectral reflectance [38]. Unlike Case-1 waters, where phytoplankton primarily controls optical variability, Case-2 environments typically produce weaker empirical relationships because reflectance is not governed solely by chlorophyll-a [39]. Therefore, moderate R^2 values in such environments should be interpreted cautiously and supported by additional statistical metrics. In this study, the SB model demonstrated lower RMSE and bias compared to the other tested models, indicating relatively better performance; however, its predictive capability remains limited. Consequently, the SB algorithm should be considered as a locally optimized empirical approximation rather than a fully validated operational model. Further multi-seasonal sampling, radiometric validation, and potentially semi-analytical or machine learning approaches are required to improve robustness.

4. Conclusions

This study represents an initial effort to evaluate and locally calibrate Sentinel-2 chlorophyll-a (Chl-a) estimation algorithms in the coastal waters off the Kuto River, Kendal, using 68 match-up observations consisting of in situ Chl-a measurements and collocated satellite reflectance data. The previously published multi-band (MR4B) and green-to-red ratio (GR) algorithms were first assessed, and the results indicated systematic overestimation by MR4B and underestimation by GR under the optical conditions of the study area. Subsequently, locally calibrated empirical models were developed using a single green band (SB) and two band ratios (GBR and GRR). The resulting coefficients of determination were modest ($R^2 = 0.49$ for SB, 0.21 for GRR, and 0.14 for GBR), indicating limited explanatory power. Although the SB model produced comparatively lower RMSE and bias values than the other tested models, its predictive capability remains moderate and should be interpreted with caution. Given the relatively small dataset, single-date acquisition, and the optically complex Case-2 nature of the study area, none of the proposed models can yet be considered fully robust for operational Chl-a retrieval. Instead, the SB model should be regarded as a preliminary local approximation that demonstrates relative improvement over the other tested algorithms under the specific conditions examined. These findings highlight the importance of local calibration in turbid coastal environments, while also emphasizing the need for multi-seasonal datasets, expanded sampling, and further methodological refinement to improve reliability for long-term monitoring applications.

While these findings offer more precise estimates, their temporal accuracy remains untested. This study has several limitations, most notably the in-situ Chl-a measurement data used to develop the algorithm, which represents only one season. Thus, it is crucial to conduct examination covering all seasons with more *in situ* data to improve the reliability of the generated algorithm. Furthermore, the reflectance data depends solely on Sentinel 2A data with atmospheric correction via Sen2Cor, lacking *in situ* validation. Because in situ radiometric measurements were not available in this study to independently validate BOA reflectance, part of the discrepancy between satellite-derived and measured Chl-a may be attributed to atmospheric correction uncertainty. Further research is needed, particularly in algorithm development, such as the use of S2A data processed by other atmospheric correction methods (such as ACOLITE/ Atmospheric correction for OLI 'lite', OC-SMART/, NASA-AC/ Ocean Color Simultaneous Marine and Aerosol Retrieval Tool or C2RCC/Case 2 Regional Coast Colour) and the application of deep learning or machine learning methods, to facilitate comparisons with this study. The potential use of the near-infrared band or the red edge also warrants investigation, as coastal waters typically fall within the case-2 category. The results of this study have implications for discovering a Chl-a determination algorithm and its effectiveness. This can be developed based on band ratios or a single algorithm for estimating Chl-a using Sentinel 2 data, thereby supporting more cost-effective and efficient Chl-a monitoring, a crucial biogeochemical parameter. The spatial distribution map generated in this study can provide an overview of critical areas for monitoring priority.

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References

[1] Zheng, H., Yang, F., Ma, Y., Yang, J., Su, D., Huang, J. and Wang, X. H., (2022). Deriving Vertical Profiles of Chlorophyll-a Concentration in the Upper Layer of Seawaters Using Icesat-2 Photon-Counting Lidar. *Optics Express,* Vol. 30(18). https://doi.org/10.1364/oe.463622.

[2] Shi, W. and Wang, M., (2022). Phytoplankton Biomass Dynamics in the Arabian Sea from VIIRS Observations. *Journal of Marine Systems,* Vol. 227. https://doi.org/10.1016/j.jmarsys.2021.103670.

[3] Ha, N. T. T., Thao, N. T. P., Koike, K. and Nhuan, M.T., (2017). Selecting the Best Band Ratio to Estimate Chlorophyll-a Concentration in a Tropical Freshwater Lake, Using Sentinel 2A Images from a Case Study of Lake Ba Be (Northern Vietnam). *ISPRS International Journal of Geo-Information.* Vol. 6(9). https://doi.org/10.3390/ijgi6090290.

[4] Ogashawara, I., Hölker, F., Grossart, H. P., Nejstgaard, J. C., Kiel, C., Kohnert, K., Jechow, A., Ruhtz, T., Wollrab, S. and Berger, S. A., (2021). The Use of Sentinel-2 for Chlorophyll-a Spatial Dynamics Assessment: A Comparative Study on Different Lakes in Northern Germany. *Remote Sensing,* Vol. 13(8). https://doi.org/10.3390/rs13081542.

[5] Woźniak, S. B., Meler, J. and Stoń-Egiert, J., (2022). Inherent Optical Properties of Suspended Particulate Matter in the Southern Baltic Sea in Relation to the Concentration, Composition and Characteristics of the Particle Size Distribution; New Forms of Multi Component Parameterizations of Optical Properties. *Journal of Marine Systems*, Vol. 229. https://doi.org/10.1016/j.jmarsys.2022.103720.

[6] Kirtiloğlu, E. and Karabörk, H., (2022). Evaluating the Performance of Algorithms in Estimating the *Chl-a* Concentration of Lake Bafa. *Turkish Journal of Geosciences*, Vol. 3(1); 30–38.

[7] Ouma, Y. O., Noor, K. and Herbert, K., (2020). Modelling Reservoir Chl-a, TSS, and Turbidity Using Sentinel-2A MSI and Landsat-8 OLI Satellite Sensors with Empirical Multivariate Regression. *Journal Sensor*. Vol. 2020; 1–21. https://doi.org/10.1155/2020/8858 408.

[8] Maslukah, L. Wirasatriya, A., Wijaya, Y. J., Ismunarti, D., Widiaratih, R. and Krisna, H. N., (2024). The Assessment of Chlorophyll-a Retrieval Algorithm and Its Spatial-Temporal Distribution Using Sentinel-2 MSI off the Banjir Kanal Timur River, Semarang, Indonesia. *Regional Studies in Marine Science*, Vol. 75. https://doi.org/10.1016/j.rsma.2024.103556.

[9] Maslukah, L., Basayep, I., Wirasatriya, A., Indrayanti, E., Prasetyawan, I. B. and Wijaya, Y. J., (2024). Application of Sentinel-2 Imagery

for Total Suspended Solids Mapping off the Bodri River, Kendal Regency, Indonesia, *Remote Sensing Applications: Society and Environment*, Vol. 36. https://doi.org/10.1016/j.rsase.2024.101379.

[10] Amna, A. M., Maslukah, L. and Wulandari, S. Y., (2022). Distribusi Horizontal Klorofil-A dan Material Padatan Tersuspensi di Muara Bodri, Jawa Tengah [Horizontal Distribution of Chlorophyll-a and Suspended Solids in Muara Bodri, Central Java]. *Jurnal Kelautan Tropis*, Vol. 25(2); 232-240. https://doi.org/10.14710/jkt.v25i2.13949.

[11] Arabi, B., Salama, M. S., Pitarch, J. and Verhoef, W., (2020). Integration of In-situ and Multi-sensor Satellite Observations for Long-Term Water Quality Monitoring in Coastal Areas. *Remote Sensing of Environment*, Vol. 239. https://doi.org/10.1016/j.rse.2020.111632.

[12] Tong, Y., Feng, L., Zhao, D., Xu, W. and Zheng, C., (2022). Remote Sensing of Chlorophyll-a Concentrations in Coastal Oceans of the Greater Bay Area in China: Algorithm Development and Long-Term Changes. *International Journal of Applied Earth Observation and Geoinformation*, Vol. 112. https://doi.org/10.1016/j.jag.2022.102922.

[13] Moutzouris-Sidiris, I. and Topouzelis, K., (2018). Assessment of Chlorophyll-a Retrievals Algorithms from Sentinel-2 Satellite Data. *Proc. SPIE 10773, Sixth International Conference on Remote Sensing and Geoinformation of the Environment*, Vol. 1077303. https://doi.org/10.1117/12.2326675.

[14] Pereira-Sandoval, M., Soria, J., Tenjo, C., Urrego, P., Moreno, J., Ruiz-Verdu, A., Vicente, E., Delegido, J., Pena, R., and Soria, J. (2018). Calibration and Validation of Algorithms for the Estimation of Chlorophyll-a in Inland Waters with Sentinel-2. *IEEE International Geoscience and Remote Sensing Symposium,* Vol. (2018); 9276–9279. https://doi.org/10.1109/igarss.2018.8517371.

[15] Xiong, Y. J. and Liu, J. F., (2018). Can Saltwater Intrusion Affect a Phytoplankton Community and Its Net Primary Production? A Study Based on Satellite and Field Observations. *Estuaries and Coasts*, Vol. 41(8); 2317-2330.

[16] Yoon, J. E., Oh, H. J., Youn, S. H., Lim, J. H., Kim, I. N., Son, S., Kwon, J. I., Hwang, J. D. and Kim, S. S., (2019). Assessment of Satellite-Based Chlorophyll-a Algorithms in Eutrophic Korean Coastal Waters: Jinhae Bay Case Study. *Frontiers in Marine Science*, Vol. 6. https://doi.org/10.3389/fmars.2019.00359.

[17] Amran, M. A. and Daming, W. S., (2023). Estimation of Coastal Waters Turbidity Using Sentinel-2 Imagery. *Geodesy and Cartography,* Vol. 49(4); 180–185. https://doi.org/10.3846/gac.2023.18132.

[18] Kolluru, S., Gedam, S. S., Chander, S. and Sahay, A., (2023). Development of Chlorophyll-a Concentration Estimation Algorithm for Turbid Productive Inland Waters in India. *Geocarto International*, Vol. 38(1). https://doi.org/10.1080/10106049.2023.2171143.

[19] Bramich, J., Bolch, C. J. S. and Fischer, A., 2020. Improved Red-edge Chl-a Detection for Sentinel-2. *Ecological Indicators*, Vol. 120. https://doi.org/10.1016/j.ecolind.2020.106876.

[20] Tran, M. D., Oliveira, E. N., Vantrepotte, V., Mériaux, X., Jorge, D., Tran, K. T., Paranhos, R. and Loisel, H., (2023). Band Ratios Combination for Estimating Chlorophyll-a from Sentinel-2 and Sentinel-3 in Coastal Waters. *Remote Sensing,* Vol. 15(6). https://doi.org/10.3390/rs15061653.

[21] Nuzapril, N., Susilo, S. B. and Panjaitan, J. B., (2017). Hubungan antara Konsentrasi Klorofil-a dengan Tingkat Produktivitas Primer Menggunakan Citra Satelit Landsat-8 [Relationship between Chlorophyll-a Concentration and Primary Productivity Rate Using Landsat-8 Imagery]. *Jurnal Teknologi Perikanan dan Kelautan,* Vol. 8(1); 105-114.

[22] Chen, J., Fu, R., Li, D., Zheng, Q., Wang, L., Peng, Y., Wang, C., Chen, S. and Jiang, H., (2021). Remote Sensing Estimation of Chlorophyll-a in Case-II Waters of Coastal Areas: Three-band Model versus Genetic Algorithm–Artificial Neural Networks Model. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 14; 3640–3658. https://doi.org/10.1109/jstars.2021.3066697.

[23] O'Reilly, J. E. and Werdell, P. J., (2019). Chlorophyll Algorithms for Ocean Color Sensors - OC4, OC5 & OC6. *Remote Sensing of Environment*, Vol. 229; 32–47. https://doi.org/10.1016/j.rse.2019.04.021.

[24] Wirasatriya, A., Maslukah, L., Indrayanti, E., Yusuf, M., Milenia, A. P., Adam, A. A. and Helmi, M., (2023). Seasonal Variability of Total Suspended Sediment off the Banjir Kanal Barat River, Semarang, Indonesia Estimated from Sentinel-2 Images. *Regional Studies in Marine Science*, Vol. 57. https://doi.org/10.1016/j.rsma.2022.102735.

[25] Afrianto, D., Hariadi, H. and Indrayanti, E., (2016). Laju Sedimentasi pada Plur Pelayaran di Muara Sungai Kali Kuto, Kabupaten Kendal [Sedimentation Rate in the Shipping Channel at the Kali Kuto River Estuary, Kendal Regency]. *Journal of Oceanography*, Vol. 5(1); 126-136.

[26] Watanabe, F. S. Y., Alcântara, E. and Stech, J. L., (2018). High Performance of Chl-a Prediction Algorithms Based on Simulated OLCI Sentinel-3A Bands in Cyanobacteria-Dominated Inland Waters. *Advances in Space Research*, Vol. 62(2); 265–273. https://doi.org/10.1016/j.asr.2018.04.024.

[27] Lyu, H., Li, X., Wang, Y., Jin, Q., Cao, K. Wang, Q. and Li, Y., (2015). Evaluation of Chlorophyll-a Retrieval Algorithms Based on MERIS Bands for Optically Varying Eutrophic Inland Lakes, *Science of the Total Environment*, Vol. 530–531; 373-382. https://doi.org/10.1016/j.scitotenv.2015.05.115.

[28] Huang, H., Liu, Q., Lv, J., Xie, S., Feng, J., Liu, X., Wang, F. and Wang, W., (2022). Relationship between Chlorophyll-a and Environmental Factors in Lakes Based on the Random Forest Algorithm. *Water*, Vol. 14(19). https://doi.org/10.3390/w14193128.

[29] Tavora, J., Hesketh, G., Souza, L. F., Jiang, B., Kiffney, T., Bourdin, G., Boss, E., Gray, P. C., Carvalho, L. S., Brady, D. C. and Schild, K. M., (2023). Recipes for the Derivation of Water Quality Parameters Using the High-Spatial-Resolution Data from Sensors on Board Sentinel-2A, Sentinel-2B, Landsat-5, Landsat-7, Landsat-8, and Landsat-9 Satellites. *Journal of Remote Sensing*, Vol. 3. https://doi.org/10.34133/remotesensing.0049.

[30] Kutser, T., Paavel, B., Verpoorter, C., Ligi, M., Soomets, T., Toming, K. and Casal, G., (2016). Remote Sensing of Black Lakes and Using 810 nm Reflectance Peak for Retrieving Water Quality Parameters of Optically Complex Waters. *Remote sensing*, Vol. 8(6). https://doi.org/10.3390/rs8060497.

[31] Maslukah, L., Wirasatriya, A., Indrayanti, E. and Krisna, H., (2023). Estimation of Chlorophyll–a and Total Suspended Solid (TSS) Based on Observation and Sentinel 2 Imagery in Coastal Water Teluk Awur, Jepara-Indonesia. *International Journal of Geoinformatics*, Vol. 19(8); 18–27. https://doi.org/10.52939/ijg.v19i8.2777.

[32] Brown, L. A., Williams, O. and Dash, J., (2022). Calibration and Characterisation of Four Chlorophyll Meters and Transmittance Spectroscopy for Non-destructive Estimation of Forest Leaf Chlorophyll Concentration. *Agricultural and Forest Meteorology*, Vol. 323. https://doi.org/10.1016/j.agrformet.2022.109059.

[33] Chu, H. J., Chang, C. H., Chusnah, W. N., Jaelani, L. M. and He, Y. C., (2021). Multi-Reservoir Water Quality Mapping from Remote Sensing Using Spatial Regression. *Sustainability*, Vol. 13(11). https://doi.org/10.3390/su13116416.

[34] Sabila, A. Y., Maslukah, L., Wirasatriya, A., Indrayanti, E., Prasetyawan, I. B. and Widada, S., (2024). A Robust Algorithm for Estimating Total Suspended Solids (TSS) Using Sentinel-2: Case Study in Coastal Waters of Teluk Awur, Jepara, Indonesia. *ILMU KELAUTAN: Indonesian Journal of Marine Sciences*, Vol. 29(4); 495-502. https://doi.org/10.14710/ik.ijms.29.4.495-502.

[35] Rakasachat, C., Chaichana, C., Phonmat, P., Klongvessa, P., Moukomla, S., Chanthorn, W., and Bruun, T. (2026). Evaluating Tropical Chlorophyll-a Algorithms from Sentinel-2 Satellite Imagery: A Comparative Study with In Situ Observation Data in Freshwater Bodies of Thailand. *International Journal of Geoinformatics*, Vol. 22(3), 138–153. https://doi.org/10.52939/ijg.v22i3.4873.

[36] Toming, K., Kutser, T., Laas, A., Sepp, M., Paavel, B. and Nõges, T., (2016). First Experiences in Mapping Lake Water Quality Parameters with Sentinel-2 MSI Imagery. *Remote Sensing,* Vol. 8(8). https://doi.org/10.3390/rs8080640.

[37] Abbas, M., Melesse, A., Rehage, J. and Scinto, L., (2019). Satellite Estimation of Chlorophyll-a Using Moderate Resolution Imaging Spectroradiometer (MODIS) Sensor in Shallow Coastal Water Bodies: Validation and Improvement. *Water*, Vol. 11(8). https://doi.org/10.3390/w11081621.

[38] Martin, S., Bryère, P., Gernez, P., Renosh, P. R. and Doxaran, D., (2025). Towards Reliable High-Resolution Satellite Products for the Monitoring of Chlorophyll-a and Suspended Particulate Matter in Optically Shallow Coastal Lagoons. *Remote Sensing*, Vol. 17(20). https://doi.org/10.3390/rs17203430.

[39] Tessin, E., Hamre, B. and Kristoffersen, A. S., (2024). Testing the Limits of Atmospheric Correction Over Turbid Norwegian fjords. *Remote Sensing*, Vol. 16(21). https://doi.org/10.3390/rs16214082.