Efficient Detection of Floating Algal Blooms Using Sentinel-2 Imagery: The Introduction of the SFABI Index

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Abstract

Algal blooms are among the most serious challenges affecting inland waters, disrupting ecosystems, degrading water quality, and posing risks to human activities. Developing reliable monitoring and mapping methods is crucial for mitigating their harmful impact. This study introduces the Sentinel-2 Floating Algal Bloom Index (SFABI), designed for detecting and mapping algal blooms at varying densities. Lake Burdur was selected as the study area for this research. Sentinel-2 images from three different dates were used as the primary data source. As a pre-processing step, Sentinel-2 Level-1C images were converted to bottom-of-atmosphere reflectance values by applying the iCOR atmospheric correction technique. Subsequently, statistical analysis was conducted to compare the spectral separability of the bands based on the sample pixels. The pixels were categorized into three classes: low-and high-density algal blooms, and water. Based on the results, the proposed index was developed based on the vegetation red-edge (B06 and B07) and near-infrared (B08) with the highest average M-statistic values and the visible-region (B02 and B03) and short-wave infrared (B12) with one the lowest M-statistic values. Furthermore, three thresholding techniques were utilized and evaluated to automatically create thematic maps representing water and algae from the grey-level index maps. The accuracy of each SAFABI map, classified using a specific single threshold value, was evaluated based on the F-score metric. To ensure an objective evaluation, two additional spectral indices specifically designed for detecting algal blooms, namely, the Floating Algae Index (FAI) and the Adjusted Floating Algae Index (AFAI), were also applied, and their classified maps were thoroughly analysed and compared. The results showed that the SFABI achieved an F-Score of over 97% across all three datasets, significantly surpassing the performance of other indices, which remained under 70%. Additionally, the SFABI index achieved F-Score values of about 90% in detecting low-density algal blooms. This demonstrates the effectiveness of the proposed index in identifying low-density blooms, which are often overlooked in algal bloom analyses, even when using a single threshold value.

1. Introduction

Lakes serve as critical ecosystems, offering numerous ecological and socio-economic benefits, such as providing drinking water, supporting agricultural irrigation, preserving biodiversity, and mitigating urban heat island effects. However, these essential ecosystems have faced significant eutrophication challenges in recent years due to climate change and anthropogenic impacts (Smith, 2003; Le et al., 2010; Chen et al., 2020). Eutrophication is triggered by the excessive influx of nutrients like nitrogen and phosphorus into lake environments, leading to intense algal blooms. This phenomenon disrupts natural ecosystem functionality by causing oxygen depletion and altering water odour and colour (Vollenweider & Kerekes, 1982).

Severe algal blooms produce toxins and reduce oxygen levels, posing serious threats to lake ecosystems (Brooks et al., 2016). Global warming and increased nutrient loads have degraded water quality in lakes worldwide (Janssen et al., 2019; Woolway et al., 2020). The continued rise in anthropogenic nitrogen and phosphorus inputs, coupled with the adverse effects of climate change, is expected to further escalate the frequency and intensity of algal blooms in the future (Beusen et al., 2016; Visser et al., 2016).

Given that these phenomena pose a significant threat to freshwater biodiversity, regularly monitoring and detecting algal blooms are critical for mitigating their harmful impacts and developing sustainable water management strategies (Rolim et al., 2023; Colkesen et al., 2024). Moreover, temporal analyses of algal blooms can help assess the effects of climate change on lakes (Trainer et al., 2020). However, considering the spatial and temporal variability of algal formations, traditional monitoring and detection methods relying on in-situ measurements are often costly and time-consuming.

Advances in remote sensing technology, particularly in temporal, spatial, and spectral resolutions, have increasingly facilitated the analysis and monitoring of environmental changes. Remote sensing data enables high-accuracy and costeffective applications, such as evaluating water quality, detecting Chlorophyll-a concentrations, analyzing temporal changes in water surfaces, and identifying algal blooms and mucilage formations, outperforming conventional ground-based measurements (Ritchie et al., 2003; Le et al., 2013; Hill et al., 2020; Colkesen et al., 2021; Ugur et al., 2021).

Using remotely sensed data, characterized as complex and large-scale, various methods such as band ratios, spectral indices, machine learning, and deep learning-based approaches have been proposed for detecting algal blooms. Among these, spectral indices have been widely used for algal bloom detection due to their simplicity, ease of implementation, and minimal data requirements. Unlike more complex methods such as machine learning or deep learning, which rely on extensive training samples, algorithm selection, and parameter tuning, spectral indices can quickly highlight the presence of algae by utilizing distinct spectral features. This makes them a practical and cost-effective solution for large-scale monitoring, especially in cases where ground-truth data is limited or unavailable.

Numerous spectral indices have been developed in the literature to detect algal blooms. For instance, the Floating Algae Index (FAI), introduced by Hu (2009), is one of the most commonly used spectral indices for identifying floating algae in open ocean environments. FAI offers a significant advantage over traditional vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) due to its lower sensitivity to atmospheric conditions.

The Adjusted Floating Algae Index (AFAI), on the other hand, developed based on the Floating Algae Index (FAI), is another spectral index used for detecting algal blooms. In a previous study focusing on faster and more accurate detection of algal formations in Hulun Lake, China, the AFAI spectral index was applied using Landsat and MODIS satellite imagery as primary datasets, relying on automatic threshold determination (Fang et al., 2018). Additionally, Cao et al. (2021) evaluated the Algal Bloom Detection Index (ABDI), another method for detecting algal blooms based on spectral indices, using Sentinel-2 satellite imagery in Hulun Lake. The ABDI demonstrated reduced sensitivity to atmospheric conditions compared to FAI, AFAI, NDVI, and EVI indices. Moreover, assessments conducted in various regions have proven ABDI's adaptability in detecting algal blooms under different environmental conditions.

The primary goal of this study is to introduce a spectral index that enables the rapid and accurate detection and monitoring of algal blooms at varying densities, utilizing publicly available Sentinel-2 satellite imagery. A range of statistical analyses were carried out to achieve this objective, resulting in the development of the Sentinel-2 Floating Algal Bloom Index (SFABI). The index leverages the visible (B02 and B03), Red Edge (B06 and B07), NIR (B08), and SWIR-2 (B12) spectral bands. Its performance in automating algal bloom detection was evaluated through various threshold algorithms, and its capability to detect algal blooms across different densities was compared with that of other commonly used spectral indices.

2. Methodology

The methodology developed for automatically detecting algal blooms, particularly focusing on low-density formations, is structured into three main stages. Data Acquisition and Preprocessing: This initial step involves obtaining Sentinel-2 satellite images, applying atmospheric corrections, and masking the lake area to exclude non-water pixels. tmospheric corrections improve the accuracy of subsequent analyses, while masking isolates relevant water pixels to enable objective threshold determination. Development of the SFABI Index: This stage encompasses the generation of spectral curves and histograms to analyze the spectral characteristics of the study area. Statistical tests were also conducted to identify the optimal spectral bands for detecting algal blooms. These analyses form the basis for refining the SFABI (Sentinel-2 Floating Algal Bloom Index), enhancing its precision and reliability in detecting algal bloom formations, particularly low-density blooms. Performance Evaluation and Validation: The final stage focuses on assessing the effectiveness of the proposed method. It involves accuracy assessments to measure detection performance, comparisons of the method across various thresholding algorithms, and validation against other widely used spectral indices in the literature. These evaluations highlight the reliability and applicability of the methodology in diverse scenarios.

2.1 Study Area and Data Set

The study area for this research was selected as Lake Burdur, known for its frequent occurrences of high-density algal blooms (Figure 1). Located in southwestern Türkiye, Lake Burdur is the country’s deepest and largest saline lake, covering an area of approximately 117 km². It has an average depth of 31 meters, with a maximum depth of 61 meters. Over the past 40 years, its surface area has decreased by 42% due to various environmental factors (Kaya et al., 2023). The lake's primary contributors to algal bloom formation are nutrient-loading elements like nitrogen and phosphorus, predominantly sourced from domestic wastewater and agricultural activities.

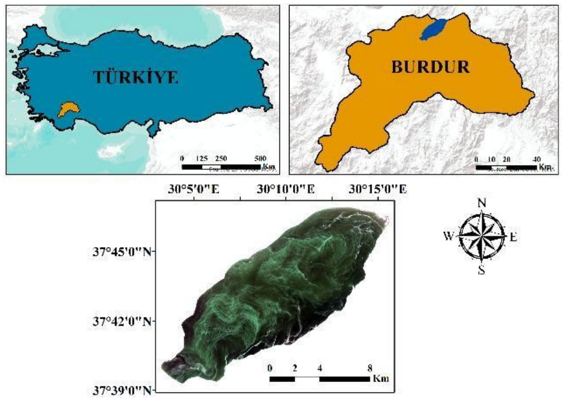

Figure 1. Study Area: Lake Burdur.

The proposed method was developed using Sentinel-2 satellite images with medium spatial resolution (10m). Specifically, Level-1C images were obtained from the Copernicus program's official platform (https://dataspace.copernicus.eu), managed by the European Space Agency (ESA). Cloud-free images from periods of intense algal blooms were selected to ensure higher accuracy and minimize the impact of atmospheric conditions. Additionally, images acquired on August 27 2021, July 30 2022, and June 4 2024 were used as the primary data sources to assess the method’s effectiveness under varying environmental conditions.

As highlighted in previous studies, applying suitable atmospheric correction techniques improves the spectral distinction between water and non-water pixels (Pahlevan et al., 2021; Colkesen et al., 2024). In this study, the iCOR atmospheric correction technique, developed by De Keukelaere et al. (2018), was used to correct the Level-1C images. This technique estimates aerosol optical thickness using only terrestrial pixels, ensuring effective atmospheric correction for water-dominated regions. Following the correction, the images were resampled to a uniform spatial resolution of 10 m using the Nearest Neighbor interpolation technique.

As the final preprocessing step, the lake area was masked to exclude terrestrial pixels, enabling the more objective determination of threshold values for algal bloom detection— one of the primary objectives of this study. The Modified Normalized Difference Water Index (MNDWI) was applied for this masking process, effectively isolating water pixels from surrounding land features.

2.2 Development of Proposed Method

Various statistical analyses were conducted to identify the most suitable spectral bands for developing the proposed spectral index. Mean spectral signatures of water and algal blooms (both low- and high-density) were estimated using sample pixels to examine the spectral characteristics of the study areas. Additionally, histograms were created to analyze the distribution of different classes across spectral bands, and a spectral separability analysis was performed to evaluate the discriminability of algal blooms and water surfaces. To enable these analyses, atmospherically corrected Sentinel-2 images were utilized, and 1.000 sample pixels were collected for the three images, representing algal blooms and clean water surfaces within the study area. Samples were also collected for both low- and high-density algal bloom occurrences to examine the detection accuracy of low-density algal blooms, which have spectral characteristics similar to water but are classified as algal blooms.

Several analyses were performed to identify the most effective spectral bands for the proposed method. Using the collected sample pixels, mean spectral signatures were calculated to explore the spectral characteristics of the study area. Figure 2 illustrates the spectral curve for the image acquired on August 27 2021. The mean signatures of water, low- and high-density algal blooms exhibited similar behaviour in the visible region (0.490–0.665 µm). However, significant differences were observed in the NIR band (B08), with distinct separations among the formations. Similarly, bands such as B06 (Red Edge2), B07 (Red Edge-3), and B8A (Narrow NIR) showed clear distinctions among the three classes, making them strong candidates for the formulation of the proposed method. However, like the visible region, SWIR bands (B11 and B12) provided limited spectral information in distinguishing pixels representing algal blooms from those respresenting water.

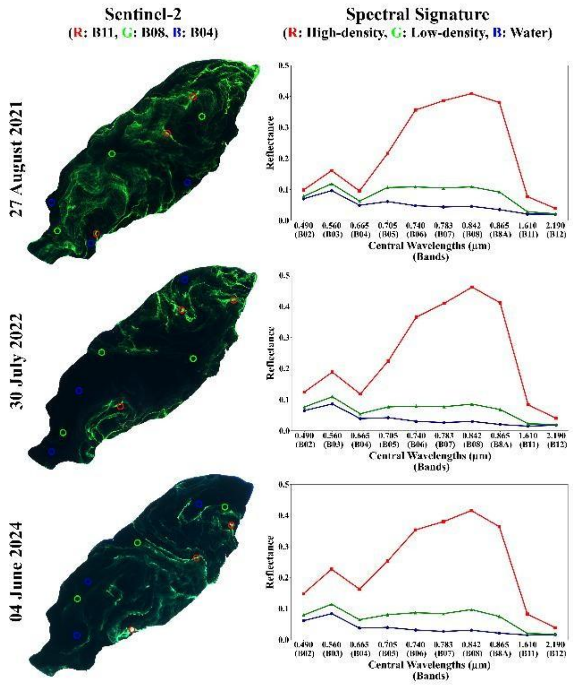

Figure 2. Spectral signatures of Sentinel-2 images.

To analyze the spectral separation between the classes in more detail, histograms of the sample pixels representing each class were created based on the ten spectral bands (Figure 3). These histograms revealed clear separations between high-density algal bloom pixels and water pixels across all bands. However, when low-density algal blooms were considered, consistent with the spectral curve analysis, strong separability was observed in the Red Edge, NIR, and Narrow NIR bands, while significant overlap occurred in the SWIR bands. This overlap emphasizes the role of SWIR bands in influencing spectral band selection for the proposed method.

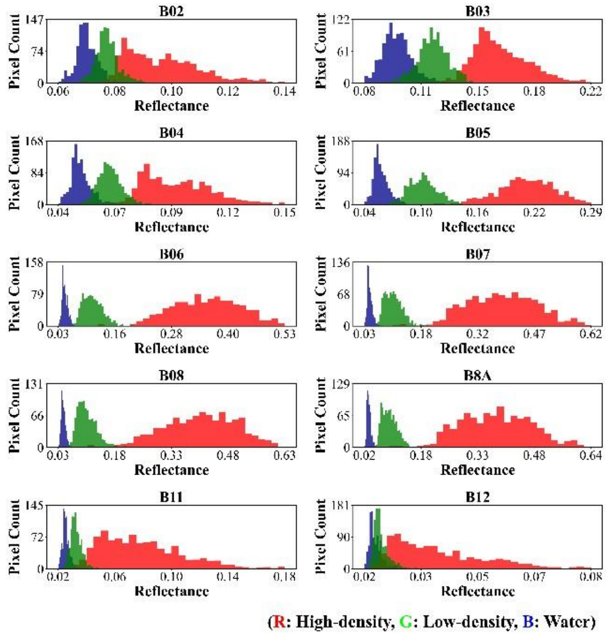

Figure 3. Histogram graphs of 27.08.2021 Sentinel-2 image.

In addition to qualitative analyses, the M-statistic (M-S) test was employed to assess spectral separability quantitatively. Developed by Kaufman and Remer (1994), the M-S measures the ratio of the mean differences between classes to the sum of their standard deviations. Theoretically, a higher M-statistic value indicates greater separability between the classes. Using sample pixels from the Sentinel-2 image dated August 27 2021, the separability of low-density algal bloom and water pixels was tested for each spectral band. Consistent with visual analyses, quantitative results indicated high separability within the 0.740–0.865 µm wavelength range.

Bands	M-S
B02	1.1411
B03	1.2854
B04	1.5860
B05	1.9625
B06	2.2309
B07	2.2161
B08	2.0447
B8A	2.3000
B11	1.1956
B12	0.4030

Table 1. Results of M-S for spectral bands.

In addition to evaluations of individual spectral bands for class separability, the ability of different spectral band combinations to distinguish low-density algal blooms from water pixels was also assessed (Table 2). Considering the M-S statistic, this analysis used band combinations of the most and least separable bands. Incorporating the least separable bands into specific combinations was intended to minimize the impact of water pixels and improve overall separability. The results showed that including B8A slightly improved separability compared to B08, reinforcing that B8A provides more detailed spectral information, especially for subtle variations like low-density algal blooms. On the other hand, the combination with the lowest M-S value (i.e., B02, B03, and B12) indicated that these bands were less effective at distinguishing between water and algal blooms, thereby reducing overall separability for class discrimination.

Number	Band Combinations	M-S
1	B06+B07+B08	2.22
2	B06+B07+B8A	2.25
3	B02+B03+B12	1.25
4	((B06+B07+B8A) - (B02+B03+B12))/(B06+B07+B8A)	2.93
5	((B06+B07+B08) - (B02+B03+B12))/(B06+B07+B08)	2.97

Table 2. Results of M-s for the combination of spectral bands.

Based on these analyses, the final formula for the proposed method was structured into three components: Optimal Algal Blooms, Water Suppressive, and Water Highlight. The Optimal Algal Blooms component includes spectral bands with the highest separability for detecting algal blooms (i.e., B06, B07 and B08). The Water Suppressive component comprises bands with the lowest separability (i.e., B02, B03 and B12), which minimize water pixel influence. Finally, the Water Highlight component serves as a baseline to emphasize water pixels, enhancing the index's robustness. Normalizing the formula with the sum of algae-reflective bands maintains stability under varying lighting conditions and atmospheric effects, improving its reliability for aquatic monitoring applications. Eventually, the proposed method is given in Equation 1 below.

$$SFABI = \frac{(B06 + B07 + B08) - (B02 + B03 + B12)}{(B08 + B07 + B06)} \tag{1}$$

2.3 Accuracy Assessment

In remote sensing applications, the accuracy assessment of thematic maps is a crucial step to validate the reliability of the study and enhance confidence in the proposed methodology. This study uses a thresholding process to evaluate the thematic map, which classifies algal bloom and water classes derived from the grey-level SFABI map. The primary objectives are identifying the most suitable thresholding algorithm, comparing it with commonly used spectral indices for algal bloom detection, and assessing its applicability to images from different dates within the same study area.

To achieve this, 1.000-pixel samples were systematically extracted from the study area's images, representing three distinct classes: high-density algal blooms, low-density algal blooms, and clean water surfaces. Subsequently, widely recognized accuracy metrics, including precision, recall, Fscore, and overall accuracy, were calculated to assess the performance of the proposed method quantitatively. The findings are critically analyzed by comparing the results with established studies in the literature and exploring their potential for application across diverse scenarios.

3. Result and Discussion

3.1 Threshold Selection

The developed method generates grey-level images where each pixel represents a brightness value, similar to traditional index maps. These images need to be categorised to isolate target objects, such as algal blooms, from the rest of the scene.
Thresholding is a widely employed technique, particularly in water surface studies (Seketekin, 2019; Colkesen et al., 2023).

In this study, the effectiveness of various thresholding algorithms was evaluated to enhance the efficiency and accuracy of algal bloom detection using the proposed method. Specifically, three thresholding algorithms, namely, Jenks Natural Breaks (JNB), Otsu, and Triangle, were applied to the grey-level index maps generated by the SFABI index. These algorithms, designed for single-threshold determination, were assessed for their ability to delineate algal bloom formations, particularly in distinguishing bloom-affected regions from clean water surfaces. By comparing the performance of these algorithms, the study aimed to identify the most suitable approach for accurately detecting and categorizing algal blooms, ensuring the robustness and adaptability of the proposed method across varying scenarios.

JNB, also called the Jenks Optimization Method, is a thresholding technique to optimise the classification process by minimizing within-class variance while maximizing betweenclass variance (Jenks, 1967). This method is particularly effective when dealing with datasets exhibiting natural groupings, as it ensures that the divisions between classes are as distinct as possible. On the other hand, the Otsu Method is a global, non-parametric thresholding technique widely used for image segmentation (Otsu, 1979). Its primary goal is to determine an optimal threshold that minimizes the intra-class variance while maximizing the separation between two distinct classes. This method is particularly advantageous in scenarios where the histogram of pixel intensities has a bimodal distribution, allowing for effective differentiation between classes such as algal bloom regions and clean water. Finally, the Triangle thresholding algorithm proposed by Zack et al. (1977) is used. The Triangle thresholding method was developed for cases where the histogram over-converges to two extremes.

Using Sentinel-2 imagery acquired on three different dates, the SFABI index was calculated to produce grey-level index maps. To identify algal bloom formations from these continuous data, threshold values were determined using the thresholding algorithms. The lake areas were masked prior to threshold computation for more precise analysis and to achieve a more effective histogram segmentation. Accuracy assessment metrics were calculated to evaluate the sensitivity and precision of the method in detecting algal blooms (Table 3). Additionally, spatial differences in the detected areas were quantified (Table 4).

	27.08.2021	30.07.2022	4.06.2024
JNB	99.85%	99.15%	99.84%
Otsu	99.78%	99.07%	99.80%
Triangle	96.62%	99.81%	99.80%

Table 3. Accuracy assessment results of different thresholding algorithms for SFABI.

The results demonstrated that all thresholding algorithms applied to the SFABI index achieved over 97% accuracy (FScore) in detecting algal bloom formations. Moreover, the classification of water pixels was also highly successful, with an accuracy exceeding 95%. The JNB method was identified as the most effective for detecting algal blooms using the SFABI index among the three evaluated thresholding algorithms. In analyses conducted across three different dates, the JNB algorithm achieved a detection accuracy of over 99% for algal blooms.

These findings underscore the robustness of the SFABI index, which consistently demonstrated high accuracy regardless of the thresholding algorithm used. This highlights its reliability and effectiveness for algal bloom detection across varying conditions and datasets.

3.2 Comparative Analysis with Existing Methods

To highlight the effectiveness of the proposed method, widely used spectral indices specifically developed for detecting algal blooms in the literature, such as the Floating Algae Index (FAI) and Adjusted Floating Algae Index (AFAI), were calculated for Sentinel-2 satellite imagery acquired on three different dates. Three distinct approaches were employed to emphasize the superiority of the proposed method.

Firstly, histograms of the indices were generated using sample pixel points previously identified and utilized in other analyses, and the segmentation performance of different thresholding algorithms on these histograms was examined. Secondly, the m-statistic test, which was used to formulate the proposed method, was applied to assess the separability of the indices. Lastly, accuracy assessments were conducted to compare the proposed method with existing approaches.

In this context, histograms of the FAI and AFAI spectral indices, along with the proposed method, were first generated for the imagery dated August 27, 2021. Subsequently, threshold values were derived for each spectral index using thresholding algorithms, and the corresponding points on the histograms were analyzed (Figure 4).

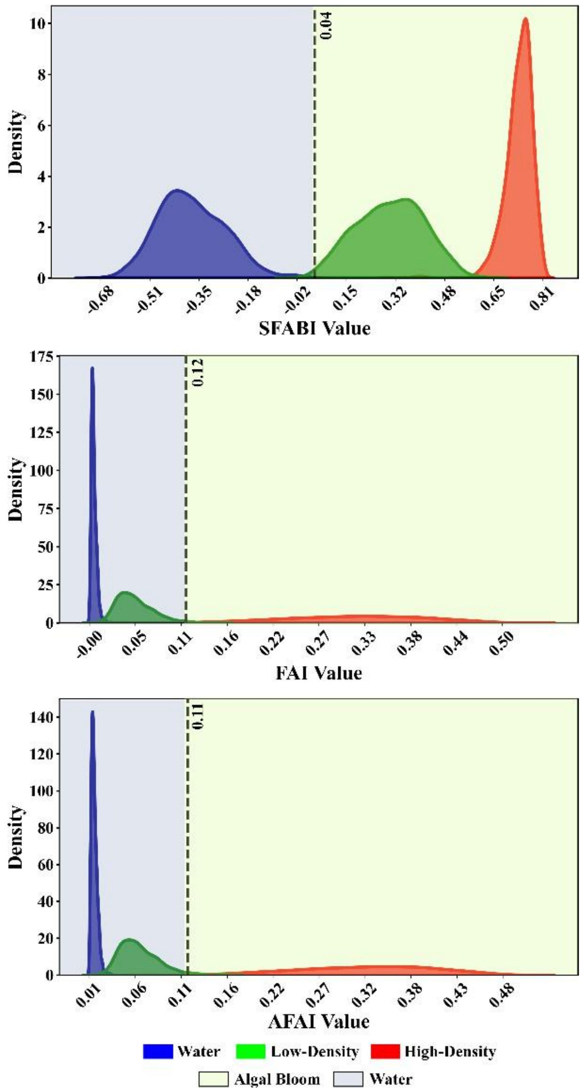

Figure 4. Histogram thresholds for spectral indices.

In analyses based on visual interpretation, the histogram of the SFABI index revealed distinct peaks corresponding to three different classes, with clear separability between them. In contrast, the histograms of the FAI and AFAI indices showed a broad distribution of pixels associated with high-density algal bloom formations, while the separation of low-density algal blooms and water classes was notably challenging.

Furthermore, all threshold values calculated for SFABI were observed to lie within the region separating low-density algal blooms and water pixels. This demonstrated that the proposed method successfully includes low-density algal bloom formations in the detection process. However, when considering the positions of the threshold values derived for FAI and AFAI in their respective histograms, it was evident that the JNB and Otsu thresholds fall between high-density and low-density algal blooms, whereas the Triangle threshold was centered within the low-density algal blooms. This indicated the inadequacy of both indices in detecting low-density algal bloom formations.

In addition to histogram analyses, the spectral separability of the indices was evaluated using the M-S for three different dates covered in the study (Table 4). This assessment aimed to quantify the ability of the grayscale, unclassified spectral indices to distinguish between low-density algal blooms and water pixels.

	27.08.2021	30.07.2022	4.06.2024
SFABI	2.9393	2.8705	3.1206
AFAI	1.9701	1.6504	1.8280
FAI	1.9542	1.5736	1.6747

Table 4. Results of M-S for 3 different date of spectral indices.

The results showed that the SFABI index consistently achieved statistic values above 2 for all analyzed dates, confirming its effectiveness and highlighting potential. In contrast, the other two spectral indices failed to surpass a value of 2 on any date. Among these, the AFAI index, which recorded values closest to SFABI, was on average 0.5 units lower than SFABI. These findings further substantiated the superior performance of SFABI in detecting low-density algal bloom formations, consistent with the patterns observed in the histogram analyses.

In addition to the two distinct analyses conducted, the effectiveness of the SFABI spectral index in classifying algal bloom formations was further demonstrated by applying the JNB thresholding algorithm. Grayscale index maps were classified into algal blooms and water surfaces (Figure 5). Subsequently, accuracy assessments were performed using previously identified sample pixels for three dates.

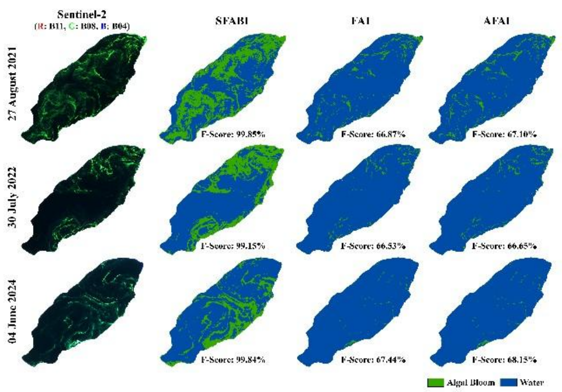

Figure 5. Accuracy assessment results of JNB algorithms for spectral indices.

Qualitative and quantitative evaluations based on the generated classified thematic maps revealed that the SFABI index achieved over 99% (average F-Score) success in detecting algal bloom formations across all three analyzed dates. In contrast, the other indices, AFAI and FAI, failed to surpass an average (algal blooms and water) F-Score of 70% for any of the dates.

Finally, the effectiveness of the indices in detecting only lowdensity algal bloom formations was compared using classified maps generated based on threshold values calculated via the JNB algorithm (Table 5). The results showed that SFABI consistently achieved an F-Score above 90% for all dates, demonstrating strong performance. In contrast, the other two indices failed to exceed an F-Score of 10%. These findings confirmed that the proposed method, SFABI, performed better in detecting low-density algal bloom formations with a single threshold determination, fulfilling its primary objective compared to the other indices.

	27.08.2021	30.07.2022	4.06.2024
SFABI	99.80%	98.80%	99.79%
AFAI	4.50%	4.00%	8.21%
FAI	3.15%	3.38%	4.09%

Table 5. Accuracy assessment results of low-density algal blooms.

4. Conclusions

This study proposes the SFABI, a simple and practical spectral index for automatically detecting algal blooms using openaccess Sentinel-2 satellite imagery spectral bands. Visual analyses were carried out using spectral signatures and histogram plots to develop this index. Additionally, spectral separability tests using the M-S were performed on individual spectral bands and their combinations. These tests identified the most effective bands and band combinations for detecting algal blooms, and the method was refined accordingly.

The effectiveness of the proposed method was also evaluated using thresholding algorithms such as JNB, Otsu, and Triangle. Results revealed that SFABI achieved high detection accuracy with an F-score exceeding 97% for all thresholds obtained from these algorithms. Furthermore, SFABI was evaluated alongside two widely used spectral indices, FAI and AFAI, focusing on four main aspects. Firstly, histogram plots of SFABI and the other indices were created, and the results of single-threshold classification were analyzed. The visual interpretations revealed that low-density algal blooms were effectively separated from water pixels in the grey-level SFABI index histogram using a single threshold, unlike the other two indices. This underscores SFABI's effectiveness in detecting low-density algal bloom formations. Second, the spectral separability of the indices, based on M-S, was evaluated for three different dates. Quantitative results demonstrated that SFABI outperformed the other two indices, exhibiting superior spectral distinguishability. Third, accuracy was assessed using sample pixels representing both algal blooms (high- and low-density) and clear water surfaces across multiple dates. Qualitative and quantitative findings confirmed SFABI's superior performance, achieving Fscores exceeding 99% for all dates, while FAI and AFAI did not surpass 70%. Finally, additional tests focused on low-density algal blooms and water surfaces showed that SFABI consistently achieved an F-score above 98%, whereas the other indices failed to exceed 9%.

While the analyses conducted in this study demonstrated SFABI's superiority, future research should explore its performance across different study areas, employing diverse spectral indices, atmospheric correction techniques, and varying meteorological conditions.

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