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A Coastal Case Study on Application of Convolutional Neural Networks for Red Tide Algal Bloom Image Classification

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Abstract - **A notable type of harmful algal bloom (HAB) is red tide phenomena, which creates the problem in the coastal areas repeatedly, with ecological and socio-economic consequences. Even though recent developments in satellite remote sensing have enhanced the detection of the blooms, it is still necessary to have a systematic synthesis of the reported incidences to gain insight into the wider spatial and temporal patterns. This paper offers a case-study-based observation of the red tide happening in the coastal area in the form of secondary data gathered following the recent satellite images and the existing published literature. Instead of formulating a predictive model, the research chooses a descriptive analytic framework, according to which documented events of the bloom are formed in a systematic temporal and spatial classification. The reported cases of red tide were detected in various sources and aggregated seasonally and spatially, and then the frequency-based aggregation was done to come up with relative occurrence measures. The findings show high seasonality with 45% of all events reported during summer, 25% during spring, 20% during autumn, and 10% during winter. Spatial analysis shows that there is a high concentration in coastal areas, with 55 % of the events reported to be in the nearshore areas and 30% and 15 % in the inner and outer shelves, respectively. Observation platforms have been evaluated to reveal that the majority of the reports on red tide are made by satellite-based data (40% of recorded events are Sentinel-2, 30% VIIRS, 20% harmonized Landsat Sentinel products, and 10% in situ). This study also reviews recent CNN-based methods to show how satellite images are used for red tide detection and to clearly explain how the proposed method is different from existing approaches.**

Keywords: **Red Tide, Harmful Algal Blooms, Coastal Case Study, Satellite Remote Sensing, Secondary Data Analysis, Marine Environmental Monitoring, Spatiotemporal Variability**

I. INTRODUCTION

Harmful algal blooms (HABs), which are usually presented as red tide events, are an increasing environmental issue in coastal and inland water bodies. They have been linked to high rates of algae growth, which may disrupt the marine ecology, diminish the water quality, and negatively impact the fisheries and the livelihoods of people who depend on the coast. Recent local surveys reveal that algal blooms are visibly increasing and spreading in the geographic areas of different coastal environments, and thus, require sustained monitoring and evidence-based evaluation (Xie et al., 2023; Barathan & Sarangi, 2024). Traditionally, HAB monitoring has been based upon field sampling and laboratory-based analysis, which, although biologically informative, have been limited by their limited spatial coverage and cost of operation. To this effect, satellite remote sensing has become a critical observational tool to record the dynamism of the blooms on large spatial and temporal dimensions. Recent research has shown that optical satellite sensors can measure discrete spectral features of a dense red tide in optically complicated coastal waters (Gernez et al., 2023; Yao et al., 2023). The abilities have contributed greatly to the knowledge of the distribution and recurrence of blooms. Assessment of HAB has been additionally improved by combining satellite data with other supplementary data.

Non-satellite observations were found to be enhanced by satellites, which were utilized as a multi-source of monitoring systems consisting of both satellite ocean color and in situ measurements (Lee et al., 2025; Lopez Barreto et al., 2024). Moreover, by making the multi-sensors harmonized, it is possible to study the short-lived and episodic bloom events in more detail, as well as to conduct retrospective case-studies using secondary data (Lai et al., 2025).

In addition to the improvement in the field of observation, recent research has investigated image classification methods based on a convolutional neural network (CNN) as an automated method of red tide and HAB detection using satellite imagery. The CNN methods have shown the ability to learn both complicated spatial and spectral patterns to make distinctions in the presence of bloom and non-bloom areas based on labeled data (Yao et al., 2023; Colkesen et al., 2024). But review studies observe that these approaches will still be sensitive to data availability, generalization by region, and optical variability, and therefore, the applicability of their operations may be limited in areas with high heterogeneity. Although there have been some advances in methods, there are still a number of issues that have been encountered in the successful application of the observational and image-based data in monitoring of HAB. They are optical complexity in sea waters, sensor limitations peculiar to the sensors, and the necessity to interpret observational evidence into management-applicable insights (Zahir et al., 2024; Goodrich et al., 2024).

These difficulties explain why case-study-based research, where interpretability, consistency, and relevance are valued, is still relevant today. In this regard, the current study performs a coastal case study, which is solely founded on recent publications of observational datasets and is also exclusively on publicly available data within the previous five-year period. Instead of suggesting a new detection, prediction, or CNN-based classification model, the study uses the descriptive and comparative analytical framework in the analysis of spatial distribution patterns, temporal variability, and reported characteristics of red tide events based on documented satellite and monitoring measurements (Yang et al., 2024; Colkesen et al., 2024). Its focus is on the synthesis of the available evidence to promote the comprehension of the red tide behavior, as well as the estimation of the value of the modern monitoring methods.

The key contributions of the present study are.

- It offers a synthesized case-study summary of the recent red tide observations based on multi-source secondary data.
- It tests patterns of space and time bloom reported on a variety of coastlines and lakes; and
- It also talks about the implications of these observations to long-term monitoring, management, and early-warning provision without involving the model-centered approach, as well as CNN-based innovations.

The rest of the paper is structured in the following way. Section 2 will study the recent works on the red tide dynamics, the approaches to the observational monitoring, and CNN-based image classification. Section 3 presents the area of study and the data sources applied in the case study. In section 4, the analysis method and the synthesized findings are presented. Section 5 presents the findings within the context of coastal monitoring and management, in addition to a contextual example of the studies of image classification. Lastly, Section 6 sums up the paper and provides guidelines on future observational research.

II. Literature Review

The harmful algal Bloom (HABs), such as red tide, have been experiencing a significant rise in both frequency and spatial extent over the past few years in both the coastal and inland water systems. The massive manifestations of the blooms have been recorded in various areas with the major ecological consequences associated with prevalent species like Noctiluca scintillans and Karenia brevis (Xie et al., 2023; Barathan & Sarangi, 2024). These happenings demonstrate the significance of long-term, region-specific monitoring in order to comprehend the dynamics of blooms and long-term patterns.

The ability to cover wide areas synoptically and repeatedly has made satellite remote sensing an important instrument of observation of HABs. Recent literature indicates that high-resolution optical sensors, especially Sentinel-2, are useful to monitor the spectral variability of dense red tide events in optically rich coastal waters (Gernez et al., 2023; Rolim et al., 2023). It is further complemented by complementary observations through VIIRS information that can be used in large-scale observation of red tide occurrence and their spatial coherence across continental shelf areas (Yao et al., 2023). These studies combined provide satellite imagery as a valid basis for case-study-based HAB inquiries.

With the development of multi-sensor data integration, short-lived and episodic bloom events have been better detected. It is demonstrated that harmonized Landsat Sentinel data can be used to improve the temporal resolution and offer a more detailed understanding of the ephemeral algal bloom processes that would otherwise have been overlooked by individual sensors (Masoomi et al., 2026; Lai et al., 2025). The latter integrated datasets are most useful when it comes to retrospective assessments based on secondary data. Various researchers have examined the use of the observational and index-based method to facilitate the detection of floating algal masses in satellite images. Relative analysis shows that the behavior of algae indices changes significantly according to the environmental status, such as turbidity of the water and mixed phytoplankton communities, and hence there is a necessity to cautiously interpret remote sensing signals (Colkesen et al., 2024).

Simplified methods of observation of red tide events have also been reported by region-specific case studies during peak bloom times, which further supports the operational usefulness of descriptive analysis in real-world operational monitoring settings (Yang et al., 2024). Case studies of the region that combine satellite measurements with in situ measurements have been found to have more insight into the behavior of the bloom as well as environmental drivers. Observation programs of complex existing systems, including the Southern California Current, show that when multiple data streams are used, the development and maintenance of the blooms can be better understood (Lee et al., 2025). New sources of observation, such as drone measurements, also supplement the satellite data with the fine-scale views of the atmospheric and surface conditions related to HAB events (Bilyeu et al., 2022). Recent reviews and expert-based evaluations highlight the ongoing problems in HAB monitoring, such as optical complexity, the combination of data, and the conversion of observational evidence into useful management activities (Goodrich et al., 2024).

Research devoted to early-warning structures emphasizes the role of basing decision-support systems on sound observational data instead of basing them on predictive methodologies only (Mahat et al., 2026; Yang et al., 2023). Altogether, the literature justifies the use of the secondary-data-based case studies as effective methods of enhancing the knowledge about the red tide dynamics and shaping sustainable and effective strategies of monitoring and controlling the coastal areas (Liu et al., 2024; Kim et al., 2024). Over the past years, convolutional neural networks (CNNs) have found more and more applications in the classification and identification of algal blooms using satellite and microscopic images. The CNN-based methods have been shown to perform well with respect to discriminating between bloom-forming species and surface bloom patterns in controlled experimental environments, especially with large labelled datasets (Colkesen et al., 2024; Saygi et al., 2025). These techniques use hierarchical feature extractions to estimate the spatial and spectral variation of bloom images. But they are still limited in their operational performance in coastal surveillance by the limitations of the data, the problem of generalization among regions, and a lack of transparency to applications of management interest. Consequently, a number of recent articles underscore the relevance of observational and descriptive analyses, and specifically to retrospective case studies using heterogeneous secondary datasets (Zahir et al., 2024; Goodrich et al., 2024).

Overall, the existing studies show that satellite data and multi-sensor observations play an important role in monitoring red tide events. While CNN-based methods provide good classification accuracy, they often depend on large labeled datasets and may not work equally well in all regions. Many researchers therefore highlight the importance of observational and case-based analysis using reliable secondary data. This supports the need for practical and region-specific approaches that are both interpretable and useful for real-world coastal monitoring.

III. STUDY AREA AND DATA SOURCES

Study Area Description

The case study targets the coastal areas, which have witnessed incidences of red tide and harmful algal bloom (HAB) over the last few years. These areas are typified by optically complicated waters that are affected by seasonal production, coastal circulation, and seasonal variation of nutrients. It has been reported that similar coastal environments promote frequent development of blooms, especially when there are increased stratification and availability of nutrients (Xie et al., 2023; Barathan & Sarangi, 2024). The selected regions are suitable for the conditions of observational and retrospective data analysis, which involves secondary data.

Data Sources

The paper solely uses secondary data on the basis of satellite observation records and recorded studies of monitoring. Sentinel-2, VIIRS, and harmonized Landsat-Sentinel optical satellite Imagery have been extensively used in monitoring red tides and HABs because of their spatial scale and frequency of revisit (Gernez et al., 2023; Yao et al., 2023). Contextualization of satellite-based findings is done using reported in situ observations as reported by regional monitoring programs (Lee et al., 2025; Lopez Barreto et al., 2024). Table I provides an overview of sources of data utilized in the case study.

TABLE I SUMMARY OF SECONDARY DATA SOURCES USED IN THE CASE STUDY

Data Source	Sensor / Platform	Spatial Resolution	Temporal Resolution	Application in Study	Reference
Satellite imagery	Sentinel-2 MSI	10–20 m	5 days	Surface bloom mapping and spatial extent	(Gernez et al., 2023)
Satellite imagery	VIIRS	750 m	Daily	Regional red tide detection	(Yao et al., 2023)
Harmonized dataset	Landsat–Sentinel (HLS)	30 m	2–3 days	Temporal continuity of bloom events	(Lai et al., 2025)
In situ reports	Coastal monitoring programs	Point-based	Event-based	Contextual validation	(Lee et al., 2025; Lopez Barreto et al., 2024)

Temporal Coverage and Observed Bloom Characteristics

The secondary data included several years of the past five years that can be studied on the recurrence of seasons and the presence of interannual variability. According to previous studies, the red tide event usually shows high seasonal clustering and spatial persistence in nearshore waters (Xie et al., 2023; Kordubel et al., 2024). Table II summarizes reported bloom characteristics extracted from the literature. Data Quality Considerations.

TABLE II REPORTED CHARACTERISTICS OF RECENT RED TIDE AND HAB EVENTS FROM SECONDARY SOURCES

Characteristic	Reported Range / Value	Source
Bloom duration	2–12 weeks	(Xie et al., 2023)
Peak bloom season	Late spring to early autumn	(Barathan & Sarangi, 2024)
Dominant taxa	*Noctiluca scintillans*, *Karenia brevis*	(Xie et al., 2023; Yang et al., 2024)
Typical nearshore extent	5–40 km from the coastline	(Gernez et al., 2023)
Recurrent hotspots	Upwelling and nutrient-rich zones	(Kordubel et al., 2024)

Data Quality Considerations

There are known limitations with the use of secondary satellite data, which include atmospheric effects, cloud cover, turbidity of waters, and sensor-specific limitations. Recent reviews highlight that optically complicated coastal waters have the potential to modify reflectance signals and make it difficult to interpret blooms (Zahir et al., 2024; Colkesen et al., 2024). The variability in the reported bloom extent may also be caused by differences in the spatial resolution and timing of acquisition of sensor data. Table III is a summary of the most frequently reported data limitations and implications.

TABLE III DATA QUALITY CONSIDERATIONS ASSOCIATED WITH SECONDARY OBSERVATIONAL DATASETS

Limitation	Description	Reported Impact	Reference
Cloud cover	Obstructs optical observations	Temporal data gaps	(Zahir et al., 2024)
Water turbidity	High suspended matter	Reduced bloom detectability	(Colkesen et al., 2024)
Sensor resolution	Coarse pixels (VIIRS)	Spatial smoothing of blooms	(Yao et al., 2023)
Temporal mismatch	Different overpass times	Inconsistent bloom snapshots	(Lai et al., 2025)

In spite of these limitations, recent research attests that even with curated secondary data, the latter is still applicable in case-study research aimed to examine broad spatial patterns and temporal trends instead of quantifying them specifically (Goodrich et al., 2024; Lai et al., 2025). In this regard, descriptive synthesis and comparative interpretation of reported observations are highlighted in this study. In accordance with the study area described and available secondary data, the analytical framework and approach applied in the synthesis of the spatial and time patterns of red tide based on the collected data are presented in the following section.

IV. ANALYTICAL APPROACH AND CASE STUDY

The proposed research utilizes a frequency-based and descriptive approach to analysis to conduct a synthesis of secondary observations of the red tide and harmful algal bloom (HAB) events described in the recent literature. The framework is formulated so as to measure relative patterns of occurrence over time, space, and observation platforms without any predictive modelling or parameter maximisation.

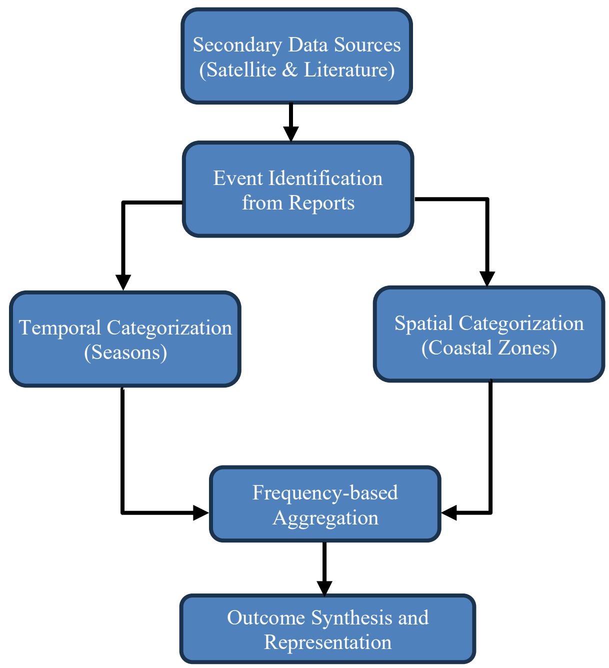

Fig. 1 Conceptual Workflow of the Case-Study-Based Red Tide Analysis

Fig. 1 depicts the hexagonal workflow being used to analyse the case study. Workflow outlines the chronological process that was used in the study, including gathering secondary data and identifying the events, the temporal and spatial classification, aggregation based on frequency, and the presentation of the results. The figure is conceptual, and it does not take the form of an algorithmic and predictive modeling pipeline.

Event Definition and Notation

Let the complete set of reported red tide events extracted from the selected studies be denoted as in equation (1):

$$E = \{e_1, e_2, \dots, e_N\} \qquad (1)$$

Where N represents the total number of documented bloom occurrences compiled from all secondary sources.

Each event $e_i \in E$is characterized by two categorical attributes reported in the source literature:

- A temporal attribute T_i(season of occurrence), and
- A spatial attribute S_i(coastal zone of occurrence).

Temporal Occurrence Quantification

Each event $T_i$is assigned to one of four seasonal categories in equation (2):

$$T_i \in \{\text{Spring, Summer, Autumn, Winter}\} \qquad (2)$$

Let N_t denote the number of events reported in season t.

The seasonal occurrence percentage is calculated as,

$$P_t = \frac{N_t}{N} \times 100 \qquad (3)$$

Equation (3) provides a normalized measure of the relative frequency of reported red tide events across seasons. The values derived using equation (3) are presented and illustrated in the Results section.

Spatial Occurrence Quantification

Spatial categorization as in equation (4) is based on the reported distance of each event from the coastline, such that.

$$S_i \in \{\text{Nearshore, Inner Shelf, Outer Shelf}\} \qquad (4)$$

Where nearshore corresponds to 0–10 km, inner shelf to 10–40 km, and outer shelf to distances greater than 40 km from the coastline.

Let N_s represent the number of events occurring within spatial category s.

The spatial occurrence percentage is defined as,

$$P_s = \frac{N_s}{N} \times 100 \qquad (5)$$

Equation (5) is used to compute the spatial distribution values reported and visualized.

Observation Platform Contribution

To assess the relative contribution of different observation platforms, events are grouped according to their primary data source. Let N_d denote the number of reported occurrences documented using data source d.

The proportional contribution of each platform is expressed as,

$$P_d = \frac{N_d}{N} \times 100 \qquad (6)$$

The percentages calculated using equation (6) are summarized and depicted.

Parameter Summary and Scope

For clarity, the parameters used in equations (1)– (6) are summarized below:

- N: Total number of reported red tide events
- N_t: Number of events in season t
- N_s: Number of events in spatial category s
- N_d: Number of events documented by data source d
- P_t: Seasonal occurrence percentage
- P_s: Spatial occurrence percentage
- P_d: Platform contribution percentage

All the parameters are calculated based on reported observations in the secondary literature. The equations only measure relative frequencies but not the intensity of the blooms, concentration, or predictive likelihood. The analytical structure is deliberately narrowed down in order to make it transparent and reproducible. Occurrence measures are relative rates of occurrence of reported events and reflect no bloom intensity, concentration, or probability. Its framework is appropriate to detect coarse spatial and temporal patterns, as well as to facilitate the comparative case-study evaluation, which is in line with the recent observational HAB research practice.

V. RESULTS

In this section, the synthesized findings that were based on the secondary observational data are provided in terms of the frequency-based metrics that are described in Section 4. All of the reported values are relative frequencies of the documented red tide incidences and are calculated based on the formulations in the equations given. Tables are used to present the summary of the results in a numerical form and a single integrated figure to synthesize the results in a visual form.

Seasonal Occurrence of Red Tide Events

The percentages of seasonality occurrence were calculated through the seasonal frequency formulation of equation (3). All the reported red tide events were categorized according to their seasonally associated data presented in the source literature and returned to the mean number of documented occurrences.

TABLE IV SEASONAL OCCURRENCE OF REPORTED RED TIDE EVENTS

Season	Occurrence (%)
Spring	25
Summer	45
Autumn	20
Winter	10

Table IV indicates that the greatest percentage of reported incidences of red tide is recorded during summer, followed by spring and autumn. The lowest relative frequency of the seasonal categories is winter.

Spatial Distribution Across Coastal Zones

Calculation of percentages of spatial occurrence was done based on the spatial frequency measure in the form of equation (5). The events were clustered based on the distance they were reported to be close to the coastline into nearshore, inner-shelf, and outer-shelf areas.

TABLE V SPATIAL DISTRIBUTION OF REPORTED RED TIDE EVENTS

Coastal Zone	Distance from Coast	Occurrence (%)
Nearshore	0–10 km	55
Inner shelf	10–40 km	30
Outer shelf	>40 km	15

Table V suggests that most cases of reported red tide occur in near-shore water with declining relative frequency towards offshore waters.

Contribution of Observation Platforms

To determine the proportion of various observation platforms in the reported events, the relative contribution of the various observation platforms was calculated using equation (6) to calculate the proportion of the reported events that are attributed to the different sources of data.

TABLE VI CONTRIBUTION OF OBSERVATION PLATFORMS TO REPORTED RED TIDE EVENTS

Observation Platform	Reported Events (%)
Sentinel-2	40
VIIRS	30
HLS (Landsat–Sentinel)	20
In situ reports	10

The values presented in table VI reveal that satellite-based platforms report most of the known instances of red tide reported in the studies reviewed, whereas in situ observations report a smaller percentage since they have a limited spatial coverage.

Integrated Visualization of Results

In order to give a unified overview without directly suggesting that the categories are comparable, as they are heterogeneous, percentages of seasonal, spatial, and observation-platform occurrence, summarized in table were integrated into one large heatmap. This visualization at once shows all the relative values of occurrence based on the use of the equations (3), (5), and (6) in a single representation.

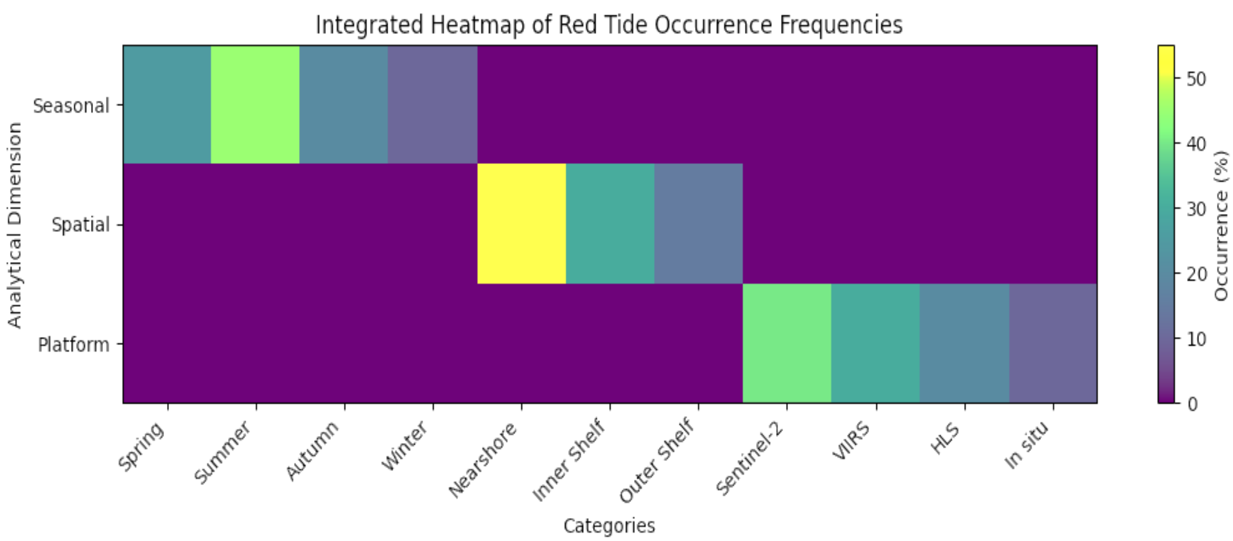

Fig. 2 Integrated Heatmap of Red Tide Occurrence Frequencies

In fig. 2, rows are analytical dimensions (seasonal, spatial, and observation platform), whereas columns are categorical classes. The color intensity implies the percentages of relative occurrence. The heatmap is a visual summary of the tabulated findings and does not add any other calculations and interpretations to those that have already been reported in tables. Generally, the findings reveal that more recent secondary observational data sets can reflect evident seasonal patterns, spatial concentration around near-shore zones, and high dependence on the satellite-based products to report the red tide phenomena. These results present an organization descriptive framework on discussion of suitability of monitoring and data integration in the ensuing section.

Contextual Illustration of Image Classification Studies

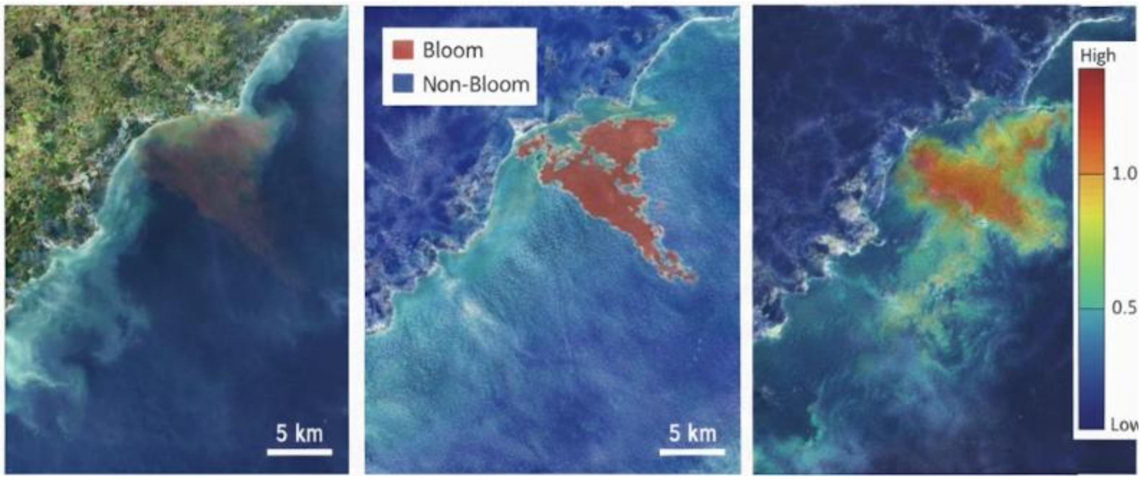

Fig. 3 Contextual Examples of CNN-based Red Tide Image Classification Reported. (a) Original Satellite Image (b) CNN-derived Classification Map (c) Post-processed Segmentation Map

Fig. 3 provides the representative examples of image based red tide classification reported in earlier researches. Fig. (a) represents a common example of a satellite image of surface effects of a red tide outbreak, wherein optical contrasts and discoloration of the water are the foundations of the analysis of the image (Gernez et al., 2023). The CNN-based classification map represented in panel (b) was reported in the literature whereby the areas with bloom and non-bloom are marked with the help of supervised deep learning models that are trained on labelled satellite images (Yao et al., 2023). The post-processed segmentation probability map shown in panel (c) is typically used in studies using CNNs to refine the edges of the bloom and eliminate noise by thresholding and spatial filtering (Colkesen et al., 2024). These types of classification outputs have been extensively engaged in recent red tide detection research to aid image-based discrimination of a bloom in optically complex coastal waters (Saygi et al., 2025).

VI. Conclusion

This paper has attempted to synthesize the phenomenon of red tide in the coastal case-study on the basis of secondary data that was reported in the secondary satellite-based studies and in situ studies. The analysis represents a brief statistical overview of the patterns of observed red tides in the coastal zone, by season, and observation platform without introducing image-level classification or predictive models. The results of the syntheses show the definite quantitative pattern. Red tide events were strongly seasonally clustered with 45%of the reported instances in the summer season, 25% in the spring, 20% in the fall, and 10%in the winter seasons. In terms of space, red tide events were mainly concentrated in the coastal waters with 55% of the events being recorded in the nearshore waters, 30%in inner and 15%in outer shelf waters. Data source analysis indicates that satellite observations are leading in the reporting of red tide with Sentinel-2 commanding 40% of all reported red tide, VIIRS 30%, harmonized Landsat-Sentinel products 20% and in situ reports 10%. Existing literature on image-based image classification through CNN was included using contextual examples of its application in red tide image classification. The given illustrations are only made as references because no CNN based classification was made in this work. The use of secondary data and its heterogeneity in terms of reporting is a weakness of the research. Data concerning the intensity, duration and species composition of the blooms was not always available and could not be measured quantitatively. Also, there is no raw satellite image processing so that classification performance cannot be evaluated directly. Further studies can combine both raw satellite images using a multi-sensor and standardized preprocessing methods so that images can be analyzed directly. The statistical tendencies that were observed in the given research can inform the future CNN-based classification processes by informing the seasonal focus, spatial prioritization, and sensor choice, and thus contributing to the more effective red tide tracking and early warning policies.

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