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EARLY WARNING SYSTEM (EWS) FOR ALGAL BLOOMS USING SATELLITE IMAGERY IN JAKARTA BAY

SISTEM PERINGATAN DINI UNTUK MARAK ALGA MENGGUNAKAN CITRA SATELIT DI TELUK JAKARTA

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ABSTRACT
Jakarta Bay is experiencing eutrophication, primarily due to nutrient inflows from agriculture, industry, and urban sources. This abundance of nutrients has led to significant algae blooms. A study using Terra and Aqua MODIS satellite data from 2004 to 2007 monitored these blooms by measuring chlorophyll-a levels. During this period, large-scale fish kills were observed directly related to the algal blooms, as evidenced by high chlorophyll-a concentrations and blooms covering more than a quarter of the bay. Interestingly, not all intense blooms resulted in massive fish kills. The study suggests that this mortality is primarily due to oxygen depletion after peak bloom periods, compounded by poor water circulation in the bay. Using satellite imagery to monitor algal blooms is a practical tool for implementing an early warning system (EWS) in Jakarta Bay. Satellite imagery has proven effective in monitoring these blooms and could help develop an early warning system in Jakarta Bay despite limitations such as cloud cover.

Keywords: *algal blooms, satellite imagery, fish-killing, early warning system.*

ABSTRAK
Teluk Jakarta telah mengalami eutrofikasi, terutama disebabkan oleh masuknya nutrien dari sumber pertanian, industri, dan perkotaan. Kelimpahan nutrien ini telah menyebabkan terjadinya marak alga yang signifikan. Studi dengan menggunakan data satelit Terra dan Aqua MODIS dari tahun 2004 hingga 2007 telah memantau marak alga ini dengan mengukur tingkat klorofil-a. Selama periode ini, terjadi kematian massal ikan yang secara langsung terkait dengan peristiwa marak alga, seperti yang dibuktikan dengan tingginya konsentrasi klorofil-a dan marak alge yang menutupi lebih dari seperempat teluk. Menariknya, tidak semua marak alge yang intens mengakibatkan kematian ikan massal. Studi tersebut menunjukkan bahwa kematian ini terutama disebabkan oleh kekurangan oksigen setelah periode marak alge mencapai puncak, yang diperburuk oleh sirkulasi air yang lemah di teluk ini. Penggunaan citra satelit untuk memantau marak alga adalah alat yang praktis untuk menerapkan sistem peringatan dini (EWS) di Teluk Jakarta. Citra satelit telah terbukti efektif dalam memantau marak alga ini dan dapat membantu mengembangkan sistem peringatan dini di Teluk Jakarta meskipun terdapat keterbatasan seperti adanya penutupan awan.

Kata kunci: *marak alga, citra satelit, kematian ikan, sistem peringatan dini*

I. INTRODUCTION

Jakarta Bay, located in Indonesia, is an essential aquatic environment that faces numerous environmental challenges. One of the significant challenges in Jakarta Bay is the occurrence of harmful algal blooms (Sidabutar *et al*., 2016; Damar *et al*., 2020) Algal blooms in Jakarta Bay constitute a critical concern due to their negative impact on water quality and the ecosystem. Algae in the bay can produce toxins harmful to marine life and humans and cause taste and odor issues in the water. These algal blooms are often exacerbated by factors such as increased nutrient runoff from urban development and the effects of climate change (Perri *et al.,* 2015; Damar *et al*., 2019; Schleyer & Vardi, 2020).

Implementing an effective early warning system (EWS) is crucial to address these challenges and mitigate the impacts of harmful algal blooms (Anderson *et al.,* 2009; Klemas, 2022). An early warning system for algal blooms in Jakarta Bay is essential to detect and predict the occurrence of deleterious blooms, allowing authorities and stakeholders to take proactive measures to manage and mitigate their impacts. By integrating remote sensing data, in-situ monitoring, and predictive modeling techniques, the early warning system could detect and track the growth of harmful algal blooms in Jakarta Bay, providing timely and accurate information to inform decision-making processes. The early warning system will analyze data on chlorophyll-a concentration, water quality parameters, and environmental factors such as temperature, nutrient levels, and weather patterns to identify favorable conditions for algal bloom formation (Siswanto *et al*., 2013; Eberhart *et al*., 2012; Guan *et al*., 2022).

An early warning system (EWS) for algal blooms using satellite imagery in Jakarta Bay represents a strategic approach to mitigating the ecological impacts of such events. By monitoring chlorophyll-a concentrations from space, the system provides a wide-ranging, efficient, and cost-effective method for detecting early signs of algae blooms. Satellite uses sensors on satellites such as MODIS to take regular images of Jakarta Bay and measure chlorophyll-a levels, which indicate algal bloom activity—applying algorithms to interpret the satellite data to distinguish between normal and elevated chlorophyll-a levels that indicate possible blooms (Wouthuyzen, 2007). Combining satellite data with information on water temperature, nutrient levels, and tidal patterns improves the accuracy of bloom forecasts. Communication protocols will also inform relevant authorities, fisheries, and the public when a potential algal bloom is detected (Seltenrich, 2014).

An algal bloom is a rapid increase in the concentration of phytoplankton algae that occurs when conditions become favorable for algae growth (Schleyer & Vardi, 2020; GEOHAB, 2020). The algal bloom outbreaks are closely related to human coastal activities such as aquaculture, marine pollution, industry, and tourism. Of course, they are attributed to anthropogenic activity that leads to nutrient enrichment in the marine ecosystem and eutrophication, which is the leading cause of algal blooms (Damar *et al*., 2019; Ulloa *et al*., 2017; Al-Yamani *et al*., 2020; Xu *et al*., 2022). The increase in algal blooms has also been predicted to be due to global climate change. They are mainly attributed to natural processes such as circulation, buoyancy, river flow, and anthropogenic pressures that lead to eutrophication. Anthropogenic activity is generally believed to be the primary cause of all blooms. Algal blooms occur when algae respond to favorable environmental conditions and multiply, forming dense concentrations of cells or blooms (Zhang, *et al*., 2022; Schleyer & Vardi, 2020). Some algal blooms have harmful effects such as mass fish deaths, disruption of marine ecosystems, economic losses to fishermen, poisoning of consumers or human health, and tourism. This type of bloom is called a toxic or harmful algal bloom (Yan *et al*., 2022).

The occurrence of harmful algal blooms in Jakarta Bay has increased significantly in frequency and distribution in recent years (Sidabutar *et al*., 2021). They have led to massive fish kills, resulting in economic losses to local fisheries, water quality degradation, and even a threat to human health (Park *et al*., 2013). It causes discoloration of surface water, with its deleterious effects most commonly manifested in coastal biota. Therefore, their occurrence is crucial for managing marine resources in coastal zones (Kahru & Mitchell, 2008). Monitoring can be critical to detect the impact of damage or loss from algal blooms. Algal bloom monitoring using satellite imagery seemed very promising due to its comprehensive coverage and relatively low cost, although it has several drawbacks, particularly cloud cover (Kahru & Mitchell, 2008; Andreo *et al.*, 2016; Stumpf, 2001; Klemas, 2012).

By implementing an efficient and accurate early warning system for algal blooms in Jakarta Bay, we can take proactive measures to prevent and mitigate the negative impacts of algae blooms. This can include implementing strategies to reduce nutrient runoff into the bay, improving wastewater treatment processes, and promoting sustainable practices in agriculture and aquaculture. Additionally, community education and awareness programs can be implemented to educate the public about the causes and effects of algal blooms, promote responsible behaviors to prevent nutrient pollution and promote the overall health of Jakarta Bay.

This preliminary study aimed to develop a prediction model of algal bloom using several vital parameters such as chlorophyll-a, nutrient concentration (phosphate, nitrate, and silicate), and spectral characteristics of the predominant phytoplankton to identify the causes of the phenomenon in Jakarta Bay. The predictive model of these critical parameters can produce a series of mappings that can be used to indicate algal bloom recurrence (Lee & Lee, 2018). The chlorophyll, a concentration map created from satellite images, is closely related to the presence of the phytoplankton population. It can be used to predict the relative abundance of phytoplankton that causes surface water discoloration. The result of this study can be used as an indicator of bloom phenomena and the possibility of fish mortality in Jakarta Bay using Terra and Aqua satellite images. Using satellite images and hydrological parameters, an early warning system (EWS) for algal blooms in Jakarta Bay can be developed (Buelo, 2022).

II. MATERIALS AND METHODS

2.1. Study Location

The study was conducted in Jakarta Bay (latitude: 55323.3 60746.9 and longitude: 1063710.9 1070140.8). Jakarta Bay is a shallow bay with an average depth of 15 meters and a coastline of about 149 km long, occupying an area of about 595 km^2. Map of Jakarta Bay and sampling stations as shown in Figure 1. There are problems in this bay due to the increasing input of organic matter from some rivers flowing into this bay, urban drainage, and land runoff during rainfall. It is also noted that water disasters, such as mass deaths of fish and other marine organisms, often occur due to bloom events.

2.2. Research Period

The study was conducted in the eastern or dry seasons of 2008, 2010, and 2015, considering that the algal bloom events in the waters usually occur in the eastern season. The season in this region is divided into the western/rainy season from October to March and the Easter season from April to September. Much organic material enters the waterways during the rainy season through sewage discharges, freshwater runoff, and rivers flowing into the bay. Therefore, in the rainy season, nutrients in the bay increase, especially phosphate and nitrate concentrations, which can trigger the growth of the phytoplankton population.

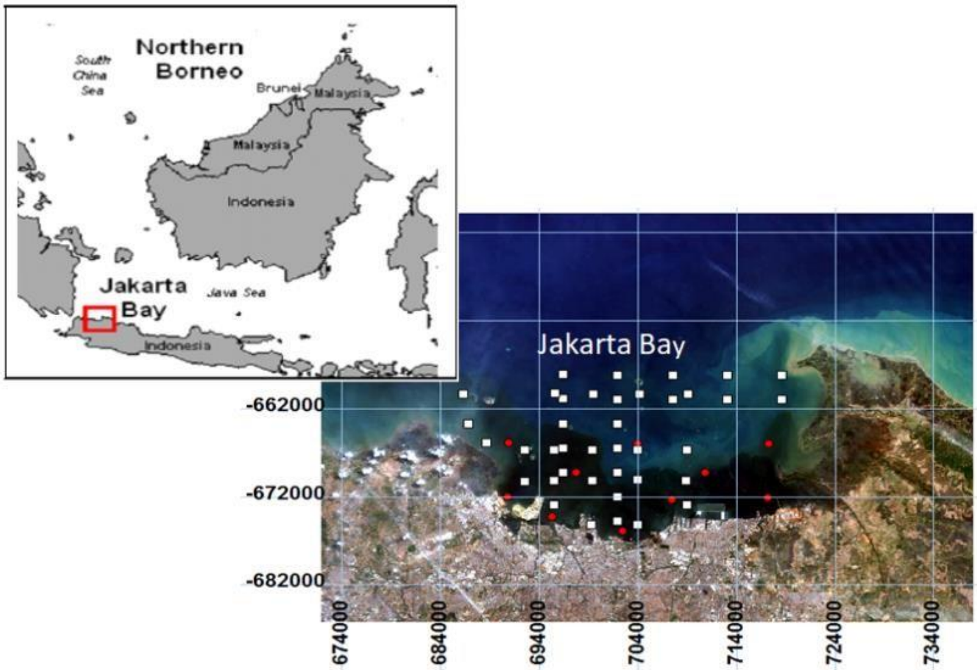


Figure 1. Sampling positions were randomly chosen for 2008 to 2010 and 2015 (gray circle) fixed at ten stations (red circle).

2.3. Phytoplankton Sampling

Phytoplankton samples were collected using a cone-shaped phytoplankton net with a squeeze device attached to the end to collect concentrated phytoplankton samples. The pore size or mesh size is 20 m, the net length is about 125 cm, and the mouth opening diameter is 25 cm. At the end of the net, it was equipped with ballast that could easily be pulled vertically downwards. The sampling technique involves dropping the phytoplankton net vertically to a depth of 7–10 m and then slowly and continuously pulling it to the surface from a certain depth. The samples were immediately preserved with an acidic Lugol solution. The preserved phytoplankton samples were brought to the laboratory for further quantitative and qualitative analysis under an Olympus inverted microscope (model IX50-S8F2). Calculation of cell abundance and identification of phytoplankton using the Sedgwick-Rafter Counting Cell (Sournia, 1978). References for phytoplankton identification using several identification books (Yamaji, 1966; Thomas, 1993; Newell & Newell, 1977). The phytoplankton cells are counted using the method described in Sournia (1978). The number of phytoplankton cells collected at each station was quantified per cubic volume.

2.4. Prediction Model

For monitoring, chlorophyll-a concentration maps derived from an empirical model developed with the Terra and Aqua satellites MODIS were used as follows:

Model prediction:

$Y = 250.09\ x^{3} - 106.92\ x^{2} + 11.781x + 0.0776.$

This model was developed using 48 Sea Truth chlorophyll A concentration datasets and a relatively free cloud of Terra and Aqua MODIS satellite images acquired almost simultaneously with the sampling times. These data comprised 18 datasets collected in 2004, 15 in 2005, and 15 in 2006, with 863 in situ or sea truth chlorophyll measurements. In this study, only three visible bands of MODIS were used in land/terrestrial applications, namely band 1 in the red region of the light spectrum (0.620–0.670 m), band 4 in the green region (0.545–0.600 m), and band 3 in the blue Region (0.4590.479 m). The idea of not using significant bands for ocean color (bands 816) is due, firstly, to the fact that the spatial resolution of these bands is coarser (1000 m) than the bands in the land application (500 m). Therefore, Jakarta Bay looks too small. Second, these ocean color bands and their algorithms are only valid for studying marine waters categorized as Case 1 or marine waters. At the same time, Jakarta Bay is classified as Case 2 waters or complex turbid coastal waters (Sathyendranath S.,1990; Lee *et al*., 2005). Based on the chlorophyll-a maps, we defined that algal blooms occur when the concentration exceeds 10 mg/m^3 and covers more than a quarter of the bay.

III. RESULTS AND DISCUSSIONS

3.1. Phytoplankton Blooms (discolorisation)

Table 1 shows the frequency of discoloration due to algal blooms in Jakarta Bay from 2004 to 2015. The frequency and distribution of algal bloom events have increased since 2004. The algal bloom that occurs usually reoccurs at a specific location in the bay (Figure 1). Algal blooms in Jakarta Bay have become a severe problem for the ecosystem and its impact on fisheries and local economic activities. Jakarta Bay has been classified as a high eutrophication water body. The occurrence of algal blooms is one of the symptoms of eutrophication, in which there is an increase in the concentration of nutrients, mainly phosphorus and nitrogen (Zhang *et al*., 2022). Increased nitrogen (N) and phosphorus (P) inputs often cause coastal eutrophication. Coastal eutrophication is not a new problem in Jakarta Bay and is often associated with algal blooms or red tide. The eutrophic state is the main factor responsible for the bloom of the phytoplankton population in Jakarta Bay (Damar *et al.*, 2019).

Algal blooms occurred in Jakarta Bay mainly from March to June and occasionally from September to November (transition from dry to wet season). During the rainy season from December to February, there is no noticeable discoloration in surface water due to algae blooms. The algal bloom phenomena in Jakarta Bay are associated with the dry season, in which the availability of nutrients, especially nitrogen and phosphorus, in the water is high enough after the rainy season (Figure 2). After the dry season, a transitional period, the phenomenon of algal blooms tends to disappear until the following season. At the end of the rainy season, the phenomenon tends to recur. Previous observations in Jakarta Bay also showed that algal blooms tended to occur in March and April at the end of the rainy season. Several algal bloom events occurred in Jakarta Bay between 2008 and 2015 during the study.

However, not all algal bloom events resulted in fish deaths. In 2008, two bloom phenomena caused two algal blooms to occur in April and November; in 2015, two algal blooms occurred in November and December. Physical factors can accompany bloom events that harm fish and other aquatic organisms. Eutrophication is the main factor that triggers phytoplankton growth, leading to bloom formation. Weak stratification and vigorous mixing of the water can influence the occurrence of algae blooms. Intense mixing and weak stratification can cause high nutrient flux in the lower layer to rise to the surface layer and be used by phytoplankton for growth, resulting in a bloom event. The tragedy of fish deaths during the bloom in Jakarta Bay was due to the decrease in oxygen concentration in the waters (Ladwig, N.,2016), where during the bloom, the dissolved oxygen concentration was less than 2.0 ppm and was almost zero at the bottom (Xu *et al*., 2010; Damar *et al.,* 2019).

Table 1. The frequency of discoloration due to algal blooms in Jakarta Bay (2004-2015).

Months	Year										Frequency
	2004	2005	2006	2007	2008	2009	2010	2011	2013	2015	
Jan	-	-	-	-	-	-	-	-	-	-	-
Feb	-	-	-	-	-	-	-	-	-	-	-
Mar	x	-	-	-	-	-	-	-	x	x	3
Apr	x	x	-	x	x	x	x	x	x	x	9
May	x	x	x	x	x	x	x	x	x	x	10
Jun	x	-	x	-	-	x	x	x	x	x	7
Jul	x	-	-	x	-	-	-	-	x	x	4
Aug	x	-	-	x	-	x	-	-	-	-	2
Sep	x	x	x	x	x	x	x	x	x	x	10
Okt	x	x	x	x	x	x	x	x	x	x	10
Nov	-	-	x	x	x	x	x	x	x	x	8
Dec	-	-	-	-	-	-	-	-	-	-	-

Note: Periods 2004-2007 compiled by Wouthuyzen *et al*. (2007). The data is organized by month and year, with an 'x' marking the occurrence of discoloration and a '-' indicating no occurrence.

3.2. Annual Rainfall and Bloom Incidents

The graph in Figure 2 shows the frequency of algal blooms and monthly precipitation data, presumably over a given year or averaged over several years. The bars representing the blooms indicate the frequency of algal blooms per month. If a higher frequency of blooms follows higher rainfall, it could suggest that nutrient runoff from rainfall could contribute to algal blooms. However, assume that the peak rainfall does not coincide with the peak frequency of blooms. This may indicate that other factors also play a role in forming algae blooms, such as temperature, water currents, or certain pollutants (Siswanto *et al*., 2013).

A seasonal pattern may be apparent, with heavy rainfall and frequent algal blooms occurring in certain months. This could indicate that algal blooms are more likely to occur after heavy rain, which could be due to runoff bringing additional nutrients into the bay. Suppose algal blooms are common in months with lower rainfall (Zhang *et al*., 2022). In this case, it suggests that factors other than direct runoff may contribute to nutrient levels in the bay, such as groundwater flow or upstream water movement. The graphic may also show delays between heavy rainfall and the subsequent algae bloom. This delay could be due to the time it takes for runoff nutrients to reach the bay and integrate into the ecosystem, resulting in blooms. Precipitation could contribute to nutrient input, but water temperature, light availability, and water circulation patterns could also be necessary (Wong *et al.,* 2007). The graphic could be invaluable to resource management and environmental protection agencies. This would help identify critical periods for monitoring and intervention to mitigate the effects of algal blooms. It could also lead research on the bay's ecology and help develop predictive models for algal blooms based on rainfall and other environmental data.

3.3. The Abundance of Phytoplankton

Phytoplankton abundance in Jakarta Bay was explicitly observed during the dry season (March to July) from 2008 to 2019 (Figure 3). Several peaks of phytoplankton bloom anomaly occurred during the study season. All bloom peaks reached multiple cells with more than a million per cubic meter. The color change can indicate bloom occurrence in Jakarta Bay in the surface water due to the increased phytoplankton

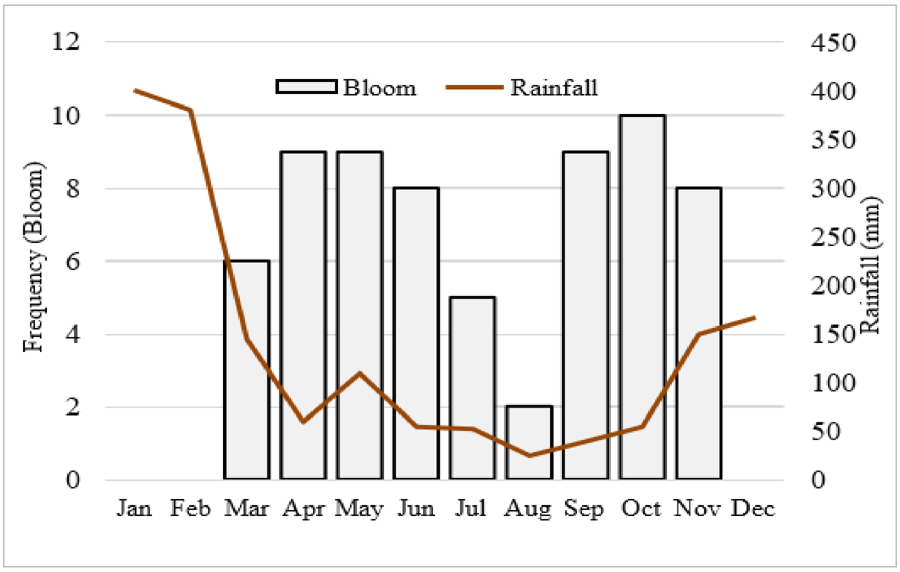


Figure 2. Graphic illustrating annual rainfall and bloom events in Jakarta Bay. The image is a combined bar and line graph showing the correlation between the frequency of algal blooms and rainfall over a year, from January to December. The bars represent the frequency of blooms, while the line graph represents rainfall in millimeters. A clear seasonal pattern is observed, with higher flower frequency associated with lower rainfall in certain months, while fewer flowers occur with higher rainfall in other months. This suggests a possible link between precipitation patterns and the occurrence of algal blooms, which could be crucial for understanding and managing algal bloom events.

population. The color change is usually visible when phytoplankton abundance reaches more than one million cells per cubic meter (Wouthuyzen *et al.*, 2007). During this study, the color change in surface water was often unevenly distributed, suggesting that the phytoplankton bloom phenomenon reoccurred in the bay.

The graph shows a significant increase in phytoplankton blooms during the 2010 dry season. Usually, there is a relationship between the increasing amount of phytoplankton and the nutrient availability in the waters (Lee *et al.*, 2005). A high phytoplankton population may indicate that the waters are being eutrophicated or enriched by anthropogenic nutrients discharged into the bay (Zhang *et al.*, 2022). The increasing anthropogenic activities in the surrounding areas have led to an increase in environmental nutrients. The city's recent exponential population and urban development growth may contribute to the increasing intensity of algal blooms in Jakarta Bay. Likewise, ample evidence exists that the increasing frequency and magnitude of algal bloom events worldwide is linked to cultural eutrophication (Li *et al.*, 2010). This study was conducted during the dry season from 2008 to 2019. During the rainy season, nutrient concentrations tend to increase due to high rainfall, causing a lot of

3.4. The Relation of Phyto-Abundance, Chlorophyll-A, Fish Kills, and Tidal

Table 2 shows that phytoplankton blooms occurred frequently during the dry season, with five events (50%), while the highest frequency occurred in July (40%). During the dry season, the rainfall that can provide nutrients to Jakarta Bay is low (118.1

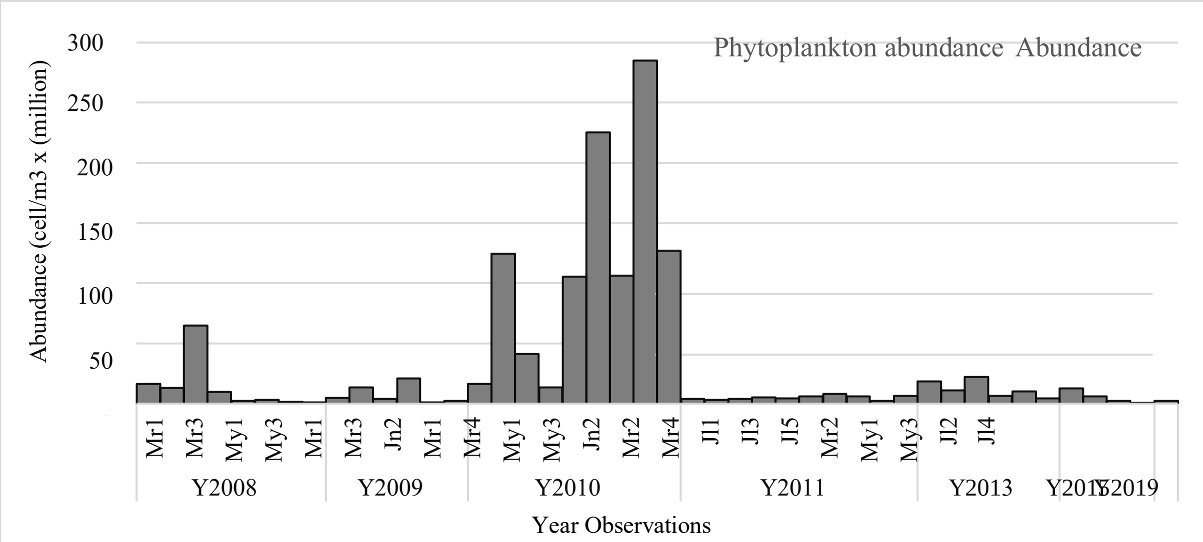


Figure 3. The image is a bar graph depicting fluctuations in phytoplankton abundance from 2008 to 2019. Each bar represents an observation point, with the Y-axis showing phytoplankton abundance measured in cells per cubic meter (multiplied by a million) and the X-axis showing observations. In 2011, there was a significant peak in phytoplankton abundance, with the number of cells reaching the highest value compared to other years. The graph shows the variability of phytoplankton populations over the observed years and the dynamic nature of the aquatic ecosystem in the study area.

mm per month) compared to other seasons under the two normal conditions of 2008, 2009, 2011, and 2013, especially during the El Niño Events 2015 (40.4 mm per month), except during the 2010 anomaly. Wind patterns in Jakarta Bay likely influence the frequency of phytoplankton blooms during the dry season. The wind speed in Jakarta Bay was between 1.0 and 3.5 m/s and around 2.5 m/s in the dry season. The wind blows steadily from east to west with a direction of 90, with a period of about 2-3 months in the dry season. The same steady wind blows from northeast to southwest and southeast to northwest during the 2015–2018 dry season with a direction in the range of 45135 and an average wind speed of 2.5 m.sec-1. The pattern of wind direction blowing continuously westward during the dry season caused a mixing process that resulted in nutrient-rich water masses from the bottom of the bay to the surface, which could trigger phytoplankton blooms during dry seasons and often until the rainy season (December-January-February) stops. There are two seasons when massive fish kills can occur in Jakarta Bay: first, in the dry season (March-April-May), after the bay is enriched with nutrients during the rainy season, and second, in the rainy season (September- May). October November) after nutrient enrichment during long-lasting westerly winds in the dry season.

Table 2 shows data from a study of phytoplankton abundance and chlorophyll-a concentration, as well as associated notes on fish mortality events and tidal information. Such data could be used to look for links between high phytoplankton abundance and chlorophyll-a levels and the occurrence of fish kills. Tidal information could be used to infer whether certain tidal conditions are associated with higher frequencies of fish kills or algae blooms. Using this data, it is also possible to estimate the impact of algal blooms on marine life and understand how physical conditions such as tides can influence the severity of these events. This table shows how often high phytoplankton abundance and high chlorophyll-a levels are associated with fish mortality. This could help understand the environmental impacts of algal blooms in the region and develop management practices to mitigate these impacts.

The data provides a timeline that identifies seasonal patterns in phytoplankton abundance and chlorophyll content that could correlate with environmental factors such as temperature and sunlight. A high correlation would be expected in the relationship between phytoplankton abundance and chlorophyll-a concentration, as more phytoplankton usually means more chlorophyll-a. Still, anomalies could provide insights into the bay's ecology. When determining when fish kills occur, you can use the high levels of phytoplankton and chlorophyll-a to conclude the ecological impact of the bloom. Assume that fish deaths only occur when phytoplankton or chlorophyll-a levels are exceptionally high. This could indicate a threshold effect, where only very dense blooms consume enough oxygen or produce enough toxins to affect fish populations.

Information about the highest and lowest tides can provide insight into water movement and its possible role in the concentration or spread of algal blooms. Slow water movement at low tide could lead to more significant oxygen deprivation and higher fish mortality. In conclusion, this data type could be crucial for predicting and preventing fish kills by identifying the conditions that lead to harmful algal blooms. Understanding these relationships helps develop effective management strategies to protect aquatic life and maintain the bay's ecological balance (Imai *et al*., 2021).

Table 2. Phytoplankton abundance, chlorophyll-a concentration, and remarks on fish kills and tidal information.

No.	Date	Mean Phyto. abund.(cell.m^{-3}), and (% cover)	Mean Chl-a, (mg.m^{-3}) and (% cover)	Remarks
1	Apr. 2004	10^{10} (73.0%)	18.66 (72.9%)	Massive fish kills; The difference: the highest - the lowest tides 0.51 m
2	Nov. 2007	10^{11} (63.2%)	27.30 (67.2%)	Massive fish kills, The difference: the highest - the lowest tides 0.55 m
3	Nov. 2015	10^{10} (57.7%)	8.89 (24.0%)	Massive fish kills; The difference: the highest - the lowest tides 0.50 m
4	Jun. 2007	10^{8}.0 (25%)	10.4 (33.3%)	Fish kills not occurred; The highest - the lowest tides 0.94 m
5	Sep. 2007	10^{8} (32.5%)	11.22 (43.4%)	Fish kills not occurred; The highest - the lowest tides 0.85 m
6	Mar 2010	10^{9} (32.4%)	12.12 (44.8%)	Fish kills not occurred; The highest - the lowest tides 0.75 m
7	Jul. 2010	10^{9} *)	-	Fish kills not occurred; The highest - the lowest tides 0.97 m
8	Jul. 2012	10^{8} (32.1%)	9.8 (41.2%)	Fish kills not occurred; The highest - the lowest tides 0.90 m
9	Jul. 2014	10^{8} (35.3%)	12.28 (55.9%)	Fish kills not occurred; The highest - the lowest tides 0.65 m
10	Jul. 2016	10^{8} (43.1%)	8.89 (31.3%)	Fish kills not occurred; The highest - the lowest tides 0.63 m

*) Field sampling data (not estimated using empirical model C owing to MODIS image covered by cloud)

Notes: Based on the data, it is shown that higher mean chlorophyll-a (Chl-a) concentrations and higher percentages of phytoplankton abundance are associated with massive fish kills, such as those observed in April 2004 and November 2007, which were significantly higher than in other recorded events. and the percentage coverage of both phytoplankton and Chl-a was also higher. Notably, during these periods, the difference between the highest and lowest tide levels was relatively small (0.51 m and 0.55 m, respectively), contributing to lower water circulation and potentially exacerbating the conditions that led to hypoxia. Conversely, in the cases where there were no fish kills (June 2007, September 2007, March 2010, July 2010, July 2012, July 2014, and July 2016), phytoplankton abundance was lower, Chl-a concentrations were moderate, and tides were lower fluctuations were more significant (ranging from 0.63 m to 0.97 m), which may have allowed for better water mixing and oxygenation, thereby preventing fish deaths. A combination of lower phytoplankton abundance, moderate Chl-a levels, and greater tidal differences create conditions in which fish are less likely to die.

3.5. Algal Bloom and Mass Fish Mortalities in Jakarta Bay.

During the monitoring, 372 chlorophyll-a maps were created using the empirical model for monitoring algal blooms in Jakarta Bay. The most common algal bloom events were recorded from April to May (the transition from the wet to the dry season) and from September to October (the transition from the dry to the wet season). High chlorophyll-a concentrations in April to May were due to increased nutrient input from human activities (domestic/urban, agricultural, industrial) in the landscape around Jakarta and hinterland cities, flowing into the bay via 13 rivers during the rainy season. Between September and October, there was a lower nutrient input from river runoff due to low rainfall in the dry season (June to August). Nevertheless, persistent easterly winds from June to August caused turbulence that enriched the bay with higher nutrients from the deeper layer (Wouthuyzen *et al.,* 2007; Tarigan *et al*., 2013; Damar *et al*., 2020; Sidabutar *et al*., 2021). Seven algal bloom and water discoloration tragedies (red tide phenomenon) resulted in massive fish kills during the study periods. Two tragedies occurred in 2004 (May and December), three cases in 2005 (April, June 2015, and October 2015), no cases in 2006, and two cases in 2007 (April and November). The pattern of massive fish kills could be recognized by recording the date of algal blooms on the chlorophyll maps before and after the bloom events. In most cases, massive fish kills occurred several days after signs of an algae bloom (Wouthuyzen *et al.,* 2007).

Although the pattern of fish kills following algal blooms was known, many solid and intense algal bloom events, such as those always observed in October, particularly in October 2006, did not result in fish kills. Examination of the tidal pattern a few days after bloom events revealed that the probability of a fish kill would be low if the differences between the highest and lowest tides were > 0.5, indicating strong water mass movement, or vice versa (see insert table in Figure 5, Figure 6). This likely explains why the significant algal bloom events did not occur in 2006 and during the algal bloom tragedy of May 24-June 3, 2010. No fish deaths happened during the bloom. Therefore, monitoring the movement of dissolved oxygen and water masses is crucial for establishing an early warning system for algal blooms in Jakarta Bay.

3.5.1 Algal Blooms Lead to Fish Deaths

Figure 4 included satellite images or maps showing chlorophyll-a concentrations in Jakarta Bay during algal bloom events. These maps are color-coded to indicate chlorophyll-a levels, with different colors representing different concentrations, often used as indicators of the presence and density of algal blooms. The cards are divided into three sets, each representing another year that experienced significant algae blooms and fish kills: 2004, 2005, and 2007. Each set contains three images marked before, during, and after, and the time before and after the algal bloom events.

The before images would show normal chlorophyll-a levels, the during images would show elevated levels, indicating the presence of a bloom, and the after images would show the consequences once the bloom has subsided - the connection between the Chlorophyll-a concentration during bloom and fish mortality. If high concentrations are linked to the timing of fish deaths, it would further support the idea that dense algal blooms can harm marine life due to factors such as lack of oxygen or toxin production. Evaluate spatial distribution to determine where blooms are most concentrated in the bay, which could impact water circulation patterns, nutrient distribution, and potential sources of the nutrients that fuel blooms. Some anomalies or unexpected patterns, such as areas with high chlorophyll levels or concentrations without corresponding fish kills, could indicate other factors protecting or harming

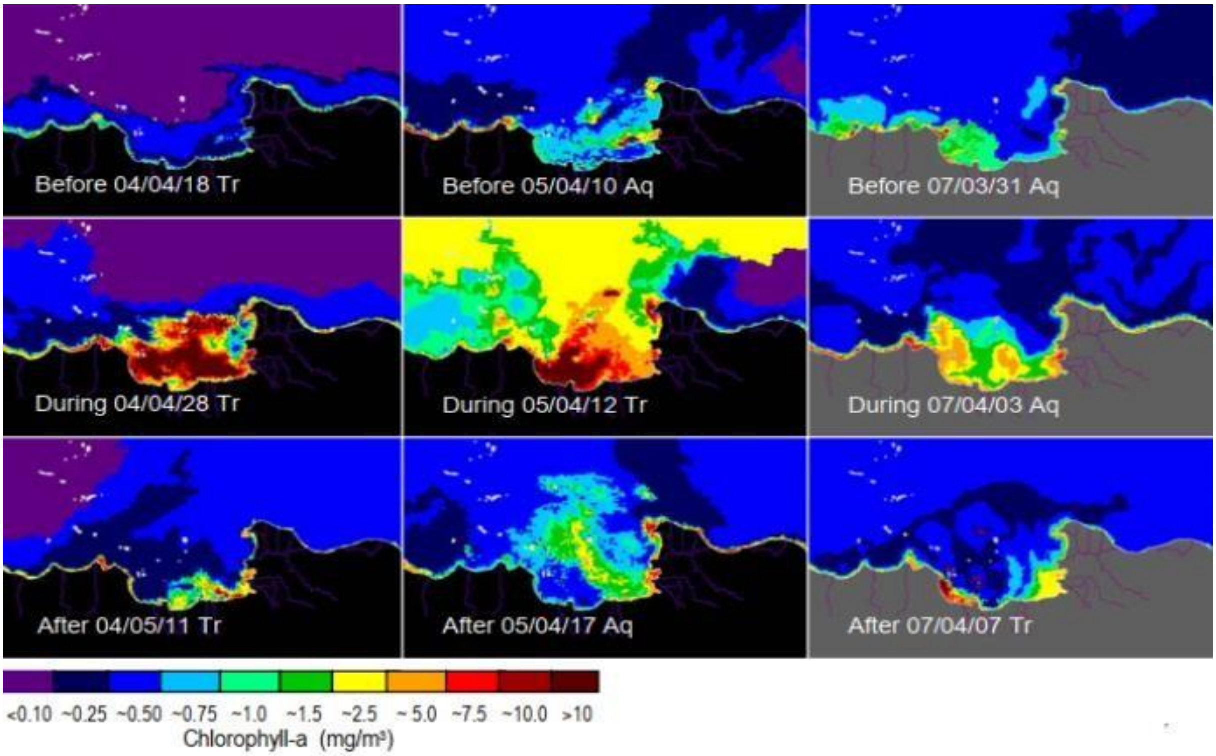


Figure 4. The image shows satellite images documenting algae blooms and fish kills in Jakarta Bay in 2004, 2005, and 2007. Three phases represent the bloom event: before, during, and after, with specific dates. The images use color coding to indicate the concentration of chlorophyll-a, which is associated with the presence of algae. High concentrations in red and yellow indicate a significant algal bloom that can lead to oxygen depletion and fish kills. The visual history illustrates the environmental changes in the bay throughout these events.

the local fish population. These visual data representations can be powerful tools for understanding ecological phenomena and informing environmental policy and response strategies. However, it is essential to note that chlorophyll-a concentration is only an indicator of algal blooms and should be considered along with other ecological data for a comprehensive analysis. By examining the after images, one can assess the potential recovery of the bay or the persistence of algal bloom effects over time. Recovery rates can provide insight into the resilience of the marine ecosystem and the effectiveness of any mitigation measures. If the dates of the images correspond to different seasons, it may be possible to determine how seasonal factors influence the growth and decline of algal blooms. Blooming can become more intense due to higher temperatures and better sunlight (Yue *et al*., 2021; Kim, 2018).

Comparing images across years can help identify long-term bloom frequency and intensity changes. This could be crucial for understanding the impacts of climate change and the effectiveness of measures to reduce nutrient runoff. The images can serve as evidence of the efficacy of environmental management strategies. If the intensity of blooms decreases over the years or their spatial extent becomes more limited, this could indicate that measures to control nutrient inflow are working. Such visual data can be very effective in raising public awareness about the ecological health of Jakarta Bay. They can illustrate the direct consequences of human actions and the importance of sustainable practices. These images could be crucial for guiding research and management efforts. They provide a clear visual representation of the environmental status of Jakarta Bay and highlight the urgency of combating eutrophication and algal blooms. Combined with field data, these images provide a powerful representation of the changing conditions in the Bay and the urgent need for continued monitoring and intervention (Siswanto *et al.,* 2013; Seltenrich, 2014).

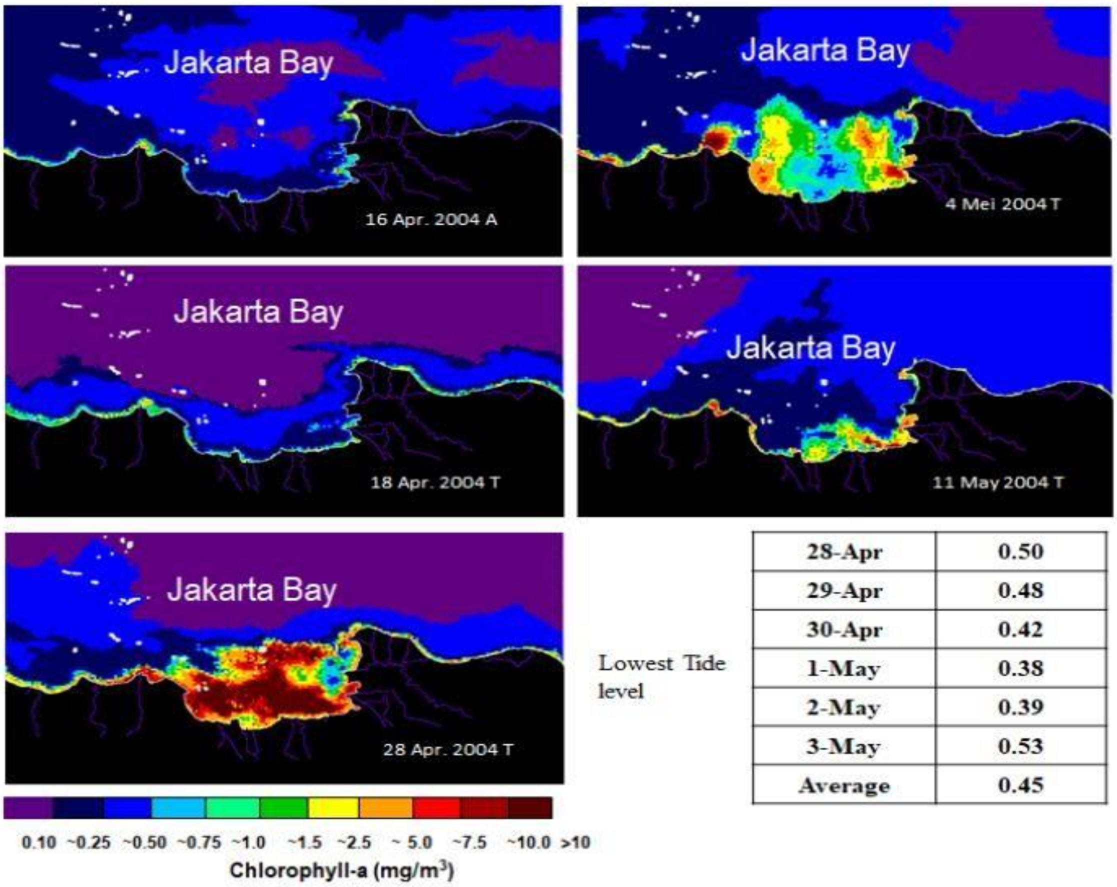
3.5.2. Fish Deaths Due to Oxygen Depletion After Noctulica Bloom

Figure 5 shows satellite images showing chlorophyll-a concentrations in Jakarta Bay during an algal bloom. The event in question occurred on November 15-28 and December 9, 2004, with a tragic fish kill occurring on December 2, 2004. The fish kill was attributed to a lack of oxygen following a heavy bloom of green *Noctiluca* algae in November. The images likely illustrate the progression of algal blooms, with different colors representing different levels of chlorophyll-a concentration, an indicator of algal biomass. The intensity of the colors, particularly reds and yellows, would indicate higher concentrations, thus signaling the presence and severity of the bloom.

The insert table in the image Figure 5 shows tide data for the same period, suggesting that the lowest tide levels occurred in late April and early May. This information could be used to understand the environmental conditions that may have contributed to the intensity of algal blooms and subsequent fish kills. The connection between algae blooms, tidal levels, and fish mortality can shed light on the complex dynamics of marine ecosystems. Low water levels can result in reduced water circulation and worsen the effects of algal blooms by causing algae buildup and a lack of oxygen (Yan *et al.,* 2022).

The images would show the evolution of the algal bloom over time, with colors transitioning from normal (presumably blue tones indicating low chlorophyll-a levels) to more intense colors (reds and yellows for high chlorophyll-a levels). These visual changes can often be associated with the bloom's growth phase, biomass's peak, and the decline as the algae die and decompose, leading to oxygen deprivation. The timing of fish kills in December after blooming in November is crucial. This suggests a delayed impact of bloom on the bay's ecology, which is not uncommon. The bloom itself may not immediately reduce oxygen levels. Still, it could trigger a chain of biological processes that eventually lead to hypoxic conditions, especially when the bloom begins to decay.

The tide levels (insert table in Figure 5) may provide additional context. Low tides can reduce water exchange with the open sea and potentially trap algae and decomposing organic matter in the bay, worsening oxygen deficiency. The reported average tide level (0.45) can be compared to individual tide levels on specific dates to understand the conditions under which the bloom worsen-deteriorated. Understanding the timing and duration of algal blooms and tidal patterns can help predict potential hypoxic events and take countermeasures, aerating the water or controlling nutrient inputs that promote algae growth. Finally, this incident highlights the need for integrated coastal management practices that consider the various physical and biological interactions in the marine environment. It highlights the potential of satellite imagery to monitor environmental change and the importance of timely, comprehensive data for policy decisions and conservation efforts.



Lowest Tide level

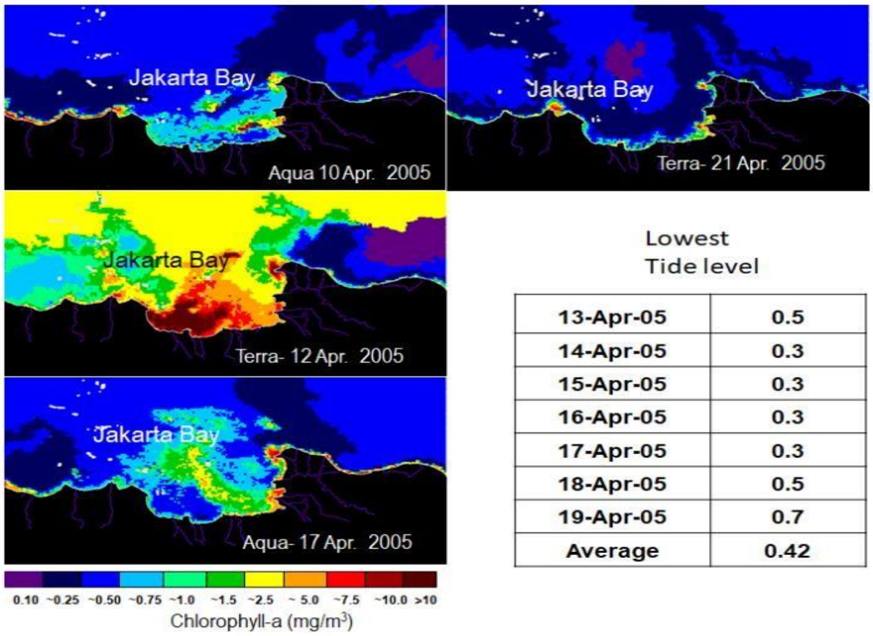
28-Apr	0.50
29-Apr	0.48
30-Apr	0.42
1-May	0.38
2-May	0.39
3-May	0.53
Average	0.45

Figure 5. An algal bloom tragedy in Jakarta Bay from November 15 to 28 and December 9, 2004. The fish kill occurred on December 2, 2004, following the heavy bloom of green Noctiluca in November 2004. The mass mortality in Jakarta Bay was due to low dissolved oxygen levels (hypoxia). This was related to a weak current, as shown by the difference between the highest and lowest tide levels of <0.5 m, as shown in the supplementary table.

3.5.3. Fish Deaths Due to Oxygen Depletion After the Bloom Decreased

Based on the description, Figure 6 contains satellite images showing chlorophyll-a concentrations in Jakarta Bay during an algal bloom between November 10 and 21, 2005. These images would show the spatial distribution and intensity of the bloom, with the gradient representing different concentrations of chlorophyll-a. A fish kill recorded on April 13, 2005, was attributed to a lack of oxygen after the bloom had subsided. The relationship between the timing of algal blooms and fish mortality is crucial because it has a direct ecological impact due to the eutrophic conditions in the bay. The table in the image shows tidal level data surrounding the algal bloom, which can help understand how tidal dynamics may have influenced the development of the bloom and the resulting oxygen deprivation. Tidal mixing can play a role in spreading algae blooms and re-oxygenating the water, so shallow tides could exacerbate conditions that lead to fish kills.

These data are essential for ecological monitoring and management. It highlights the need for timely measures to mitigate the effects of algal blooms, such as reducing the flow of nutrients into the bay or improving water circulation at critical times. The satellite images and tidal data provide a



Lowest Tide level

13-Apr-05	0.5
14-Apr-05	0.3
15-Apr-05	0.3
16-Apr-05	0.3
17-Apr-05	0.3
18-Apr-05	0.5
19-Apr-05	0.7
Average	0.42

Figure 6. An algal bloom occurred in Jakarta Bay on 10-21 April 2005. After the high bloom event, fish killed occurred on April 13th, 2005. The fish-killing occurred due to oxygen depletion after the bloom decreased. Mass mortality in Jakarta Bay was due to low dissolved oxygen (DO, hypoxia) levels after HAB. This was related to a weak current, as indicated by the difference between the highest and lowest tide levels of <0.5 m, as shown in the insert table.

comprehensive overview that can guide interventions to prevent future fish kills and maintain the health of marine ecosystems in Jakarta Bay.

Figure 6 shows the image progression of the intensity and spread of the algae bloom in Jakarta Bay. The chlorophyll-a concentrations indicated by the color coding would visually represent the density of the flower. The most intense areas of the bloom are likely to be presented in shades of red and yellow, indicating higher levels of chlorophyll-a. At the same time, lower concentrations are likely to be found in more beautiful colors, such as blue. The fish kill on April 13, 2005, suggests a significant delay between the peak of the bloom in November 2005 and the observed ecological impacts. This delay could indicate a complex cascade of environmental stressors contributing to fish mortality. After the peak of the bloom, the decay process of the algae may have consumed significant amounts of oxygen over time, leading to hypoxia (low oxygen levels) and eventual fish kills.

The tidal level data contained in the table would be essential to understanding the environmental context of algal blooms and fish kills. Lower tide levels can result in poor water circulation, leading to a lack of oxygen as the water becomes more stagnant. The average tide level, reported at 0.42, could be a critical factor if it is significantly lower than the usual tide level in the region, potentially exacerbating the oxygen deprivation process. This information highlights the importance of monitoring biotic factors, such as algal blooms, and abiotic factors, such as tidal changes in coastal management. Predictive modeling incorporating these variables could be developed to predict future blooms and potential hypoxic events, enabling preventive measures to mitigate damage to the marine ecosystem (Wong *et al*., 2007; Pal *et al.,* 2020). Understanding the time lag between bloom events and fish kills is critical for appropriate monitoring and response strategies.

3.5.4. No Fish Deaths During the Bloom Periods

Based on the description, Figure 7 seems to depict satellite imagery data that illustrates the progression of an algal bloom in Jakarta Bay from May 24 to June 3, 2010. The images would likely show changes in chlorophyll-a concentration, with the color gradient ranging from blue (low concentration) to red (high concentration), providing a visual representation of the bloom's intensity and spread over time. The caption suggests no fish kill was reported despite the significant algal bloom. This is attributed to the strong water mass movement, as indicated by a tidal pattern showing a difference of more than 0.5 between the highest and lowest tides. The strong tidal currents would have helped to disperse the algal bloom and maintain oxygen levels, preventing the hypoxic conditions that can lead to fish kills.

This scenario contrasts with previous events where fish kills occurred due to stagnant water and oxygen depletion following algal blooms. It highlights the critical role that water movement plays in the health of marine environments. Adequate tidal circulation can mitigate the negative impacts of algal blooms by dispersing nutrients and algae and promoting water reoxygenation. The absence of fish kills in the presence of a significant algal bloom also underscores the complexity of predicting ecological impacts. It suggests that not all blooms lead to catastrophic outcomes and that other environmental factors, such as tides and currents, influence the ecological balance (Gheilani *et al.*, 2011).

For environmental monitoring and management, this data emphasizes the importance of considering biological indicators (like chlorophyll-a levels) and physical factors (such as tidal patterns) to understand and manage the health of coastal ecosystems. It also demonstrates the utility of satellite imagery in tracking and responding to dynamic marine events. The sequence of images would be a powerful tool for visualizing the temporal and spatial dynamics of the algal bloom. The solid tidal movements indicated in the data suggest that the waters of Jakarta Bay were sufficiently oxygenated during this period, thus preventing the occurrence of a fish kill despite the high levels of chlorophyll-a (Lee *et al.*, 2005).

This situation represents a counter-example to the typical association between algae blooms and fish kills and suggests that under certain conditions, such as adequate water circulation, the ecosystem can withstand the harmful effects usually associated with high concentrations of algae. This reinforces the need for a differentiated approach to ecological management that considers the interplay between biological phenomena and physical oceanographic processes. The detailed color-coded chlorophyll-a concentrations would allow researchers and environmental managers to identify the areas with the highest concentrations of algal blooms and see how these areas shift and change over time. This can be crucial for local authorities and stakeholders when developing targeted measures against algal blooms, including where and when to introduce artificial ventilation or algaecides. Furthermore, these observations can serve as a basis for future algal bloom prediction models (Yan *et al.,* 2022). Understanding the conditions under which an intense bloom does not result in fish kills could help predict the ecological consequences of similar events and make informed decisions to protect marine life and the interests of communities that depend on the bay for their livelihoods (Al-Yamani *et al.*, 2022; Imai *et al.*, 2021; Gheilani *et al.*, 2011).

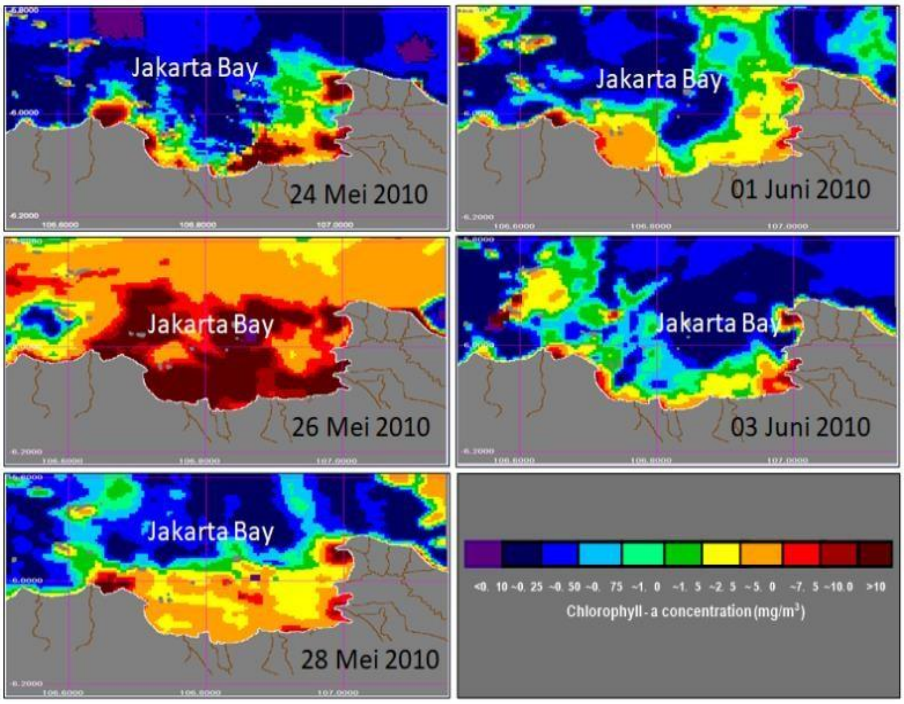


Figure 7. An algal bloom tragedy in Jakarta Bay from May 24 to June 3, 2010. No fish deaths occurred during the bloom. A few days after the bloom events, the tidal pattern showed differences between the highest and lowest tides of >0.5, indicating strong water mass movement. The possibility of fish dying would be insufficient.

Finally, the data presented in Figure 7 could be crucial for education and awareness campaigns, illustrating to the public and policymakers the importance of maintaining healthy tidal flows and water quality. It could also serve as a basis for advocating for the conservation and sustainable management of coastal areas, often subject to multiple stressors, including pollution and climate change impacts.

IV. CONCLUSION

Using satellite imagery as part of an early warning system (EWS) for algal blooms in Jakarta Bay represents a highly effective tool for monitoring and managing the region's ecological health. Analysis of satellite-derived chlorophyll-a concentrations over time provides crucial insights into the development and spread of algal blooms, critical to preventive environmental management strategies. Satellite imagery offers comprehensive bay coverage, providing a comprehensive and timely view of chlorophyll levels indicative of algal blooms. This makes it easier to detect potential bloom events before they can escalate into ecological disasters, such as fish kills due to lack of oxygen. Additionally, integrating tidal data with satellite imagery in the EWS allows for a more in-depth understanding of the factors that influence the severity and impact of algal blooms.

The EWS can benefit from the following strengths of satellite imagery: It can monitor large areas of water, which is crucial for the extensive Jakarta Bay. Satellite data can be accessed relatively quickly and frequently, allowing for near real-time monitoring. The availability of historical satellite data enables the analysis of trends and patterns over time, which is critical for predictive modeling. Satellite imagery can be more cost-effective than in situ monitoring, especially for routine monitoring of large ocean areas.

However, the EWS must also consider the limitations of satellite imagery, which include issues such as cloud cover, which can obscure bay visibility, and the inability to directly measure certain bloom-related toxins or oxygen levels in the water column. Satellite imagery-based EWS represents a significant advance in addressing the environmental and economic risks of algal blooms in Jakarta Bay. By facilitating early detection and providing detailed spatial information on bloom events, the system is essential for the sustainable management of Marine Resources. For maximum effectiveness, this tool should be integrated with other data sources and management strategies to address the diverse challenges of algal blooms.

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