Exploring the interplay of chlorophyll-a, sea surface temperature, and sea surface salinity in aceh waters during january and july 2022

Muh. Nur Hidayat[1], *Reza* Wafdan[2], *Marwan* Ramli[3], *Zainal A.* Muchlisin[1,4,6], *Ichsan* Rusydi[4], *Muhammad* Muhammad[5], and *Syamsul* Rizal[1,2,6,*]

[1]Graduate School of Mathematics and Applied Sciences, Universitas Syiah Kuala, Banda Aceh 23111, Indonesia
[2]Department of Marine Sciences, Faculty of Marine and Fisheries, Universitas Syiah Kuala, Banda Aceh, 23111, Indonesia
[3]Department of Mathematics, Universitas Syiah Kuala, Banda Aceh 23111, Indonesia
[4]Department of Aquaculture, Faculty of Marine and Fisheries, Universitas Syiah Kuala, Banda Aceh 23111, Indonesia
[5]Department of Fisheries Resource Utilization, Faculty of Marine and Fisheries, Universitas Syiah Kuala, Banda Aceh, 23111, Indonesia
[6]Research Center for Marine Sciences and Fisheries, Universitas Syiah Kuala, Banda Aceh 23111, Indonesia

Abstract. This study investigates the relationship among chlorophyll-a (Chl-a), sea surface temperature (SST), and sea surface salinity (SSS) in Aceh Waters, Indonesia using data from January and July 2022. Chl-a, SST, and SSS data were retrieved from the Copernicus Marine Environment Monitoring Service (CMEMS) database. Pearson correlation analysis was employed to assess the connections among Chl-a, SST, and SSS within the Aceh Waters region. The findings reveal that all three parameters - Chl-a, SST, and SSS - conform to the seasonal monsoon patterns observed in January and July 2022. The correlation analysis conducted for January revealed the following relationships: a negative correlation between Chl-a and SST (-0.649), an inverse correlation between Chl-a and SSS (-0.215), and a positive correlation between SST and SSS (0.493). Conversely, correlations for July reveal a negative correlation between Chl-a and SST (-0.503), a positive correlation between Chl-a and SSS (0.039), and a negative correlation between SST and SSS (-0.478). Overall, this study elucidates the complex relationship among Chl-a, SST, and SSS in Aceh Waters, which is influenced by seasonal monsoon variations. Understanding this relationship is essential for assessing marine environmental dynamics and their potential impacts on ecosystems and human activities in the region.

[*] Corresponding author : srizal@usk.ac.id

1 Introduction

Aceh Waters, situated at the northwestern tip of Sumatra Island, Indonesia, possesses unique aquatic characteristics strongly influenced by seasonal shifts in wind patterns. The active southwest monsoon from June to September and the northeast monsoon from December to February play a crucial role in determining the locations of fishing grounds. These monsoon systems not only impact the region's fishing resources but also affect the abilities of the fishermen in Aceh Waters [1].

Furthermore, Aceh Waters, one of the largest sea regions in Indonesia, is considered to hold immense potential for marine and fisheries resources owing to its distinct aquatic characteristics. Due to its vital role in the regional marine ecosystem, over the years, many research efforts have been directed towards this area [1-7]. Research conducted by Ilhamsyah et al. [8] identified four different types of water masses within this area, including a salt-lens formation measuring 60 miles in diameter and 25 meters in thickness. This salt-lens possesses a core salinity exceeding 35 psu and is located at a depth of 75-100 meters below the thermocline layer in the Northern Weh Island region. This salinity front may serve as an early indicator of upwelling, a phenomenon closely linked to the presence of pelagic fish. This discovery implies that Aceh Waters holds promising potential for the future development of marine resources.

In the pursuit of understanding the marine dynamics of Aceh Waters, it is crucial to investigate the connection between oceanographic factors, such as chlorophyll-a (Chl-a) and sea surface temperature (SST). Chl-a acts as a proxy or indicator of phytoplankton biomass, which forms the foundation of the marine food chain. Additionally, SST and sea surface salinity (SSS) are critical environmental variables that significantly impact capture fisheries. The research conducted by [9] has revealed noteworthy findings concerning Chl-a and SST. It reveals a distinct inverse relationship between Sea Surface Temperature (SST) and the yellowfin tuna (*Thunnus albacares*) catch. This discovery suggests that as sea surface temperatures increase, the yellowfin tuna catch tends to decrease.

Moreover, the study underscores the influence of chlorophyll-a on fish quantity caught, establishing a robust positive correlation between chlorophyll-a levels and the yellowfin tuna catch. This implies that regions with higher chlorophyll-a levels in the ocean are more likely to yield greater yellowfin tuna catches. The influence of chlorophyll-a (Chl-a), sea surface temperature (SST), and sea surface salinity (SSS) on fish aggregation in the Red Sea is significant [10]. Chl-a is an indicator of phytoplankton biomass, which is the base of the marine food chain. Fish are attracted to areas with high Chl-a concentrations because there is more food available. SST and SSS affect the distribution and abundance of marine life, including fish. Some fish species are more tolerant of high salinity than others.

In the Red Sea, fish aggregation is highest during the winter months when Chl-a concentrations are high and SST and SSS are lower [10]. This is likely due to a combination of factors, including strong vertical mixing and upwelling, which bring nutrients to the surface and promote phytoplankton growth. Fish are also attracted to the open waters of the Red Sea, where Chl-a concentrations are higher than in the coastal waters.

Several studies have examined the relationships between Chl-a, SST, and SSS. In the Bay of Bengal (BoB) and the Northern Bay of Bengal (NBoB), researchers Hidayat et al. [11-12] conducted analyses to determine the correlations among Chl-a and SST, Chl-a and SSS, as well as SST and SSS. Research by Torregroza-Espinosa et al. [13] identified spatial-temporal variations and trends and calculated correlations of Chl-a, SST, and SSS at the Magdalena River mouth in the Caribbean Sea. Research by Zhang et al. [14] calculated the correlation between Chl-a and SST in the East China Sea. These studies have revealed connections between Chl-a, SST, and SSS in various research areas. However, this relationship is context-dependent and can be influenced by regional factors, requiring specific regional studies.

Based on the description above, the research questions can be formulated as follows. Firstly, what is the seasonal variability of chlorophyll-a (Chl-a), sea surface temperature (SST), and sea surface salinity (SSS) in Aceh Waters? Secondly, what relationships exist between Chl-a, SST, and SSS within Aceh Waters? This study aims to explore the interplay between three vital oceanographic variables—Chl-a, SST, and SSS—within Aceh Waters. Chl-a serves as a metric for phytoplankton biomass, a cornerstone of the marine food chain. Additionally, SST and SSS are crucial environmental parameters that exert significant influence on fisheries. By comprehending the seasonal fluctuations of these variables and their intricate interactions, we can enhance our comprehension of Aceh Waters' marine dynamics. This knowledge can subsequently contribute to the effective management of marine resources in the region, including fisheries and coastal ecosystems.

The study's specific objectives encompass quantifying the seasonal variations of Chl-a, SST, and SSS within Aceh Waters, identifying the correlations between Chl-a, SST, and SSS within Aceh Waters. Additionally, this study seeks to assess the repercussions of these relationships on marine ecosystems within Aceh Waters. The data used in this analysis were sourced from the Copernicus Marine Environment Monitoring Service (CMEMS) database, a comprehensive global repository of marine environmental data. This database encompasses satellite-derived information on Chl-a, SST, and SSS.

To analyze the data, we employed both descriptive statistics and correlation methods. Descriptive statistics aided in summarizing key aspects of the data, including mean values, medians, and standard deviations. Meanwhile, correlation methods were employed to scrutinize the connections between these oceanographic variables.

2 Materials and Methods

The research was conducted in the waters of Aceh, with coordinates ranging from 3°N to 6.75°N and 93°E to 97.5°E, as depicted in Figure 1. The research employed monthly mean datasets for Chl-a, SST, and SSS for both January and July 2022. These datasets were sourced from the Copernicus Marine Environment Monitoring Service (CMEMS) database [15, 16].

To ensure data quality and reliability, rigorous data quality control procedures were implemented. Any erroneous or inconsistent data points were identified and corrected, preserving the dataset's integrity. Additionally, data preprocessing techniques were applied to standardize and prepare the data for subsequent analysis.

The geographical distribution of sampling points within Aceh Waters was thoughtfully selected to encompass a representative and diverse range of environmental conditions. This strategic selection aimed to capture variations in Chl-a, SST, and SSS across different areas of Aceh Waters, accounting for potential local influences and gradients.

To assess the seasonal variability of Chl-a, SST, and SSS, a variety of statistical analyses were employed. These included boxplot analysis, QQ plot analysis, and correlation matrix analysis. Boxplot analysis was utilized to visualize the statistical distribution of key data parameters such as the lowest value, the value at the 25th percentile, median, the value at the 75th percentile, and the highest value. It also served as a means to identify outliers and compare data groups [17].

Quantile-quantile (QQ) plot analysis, a simple yet powerful method, was used to visualize data distribution [18] and examine theoretical distributions, such as the normal distribution, within the Chl-a, SST, and SSS datasets. If data points on the QQ plot align with a straight line, it indicates that the data approximates a normal distribution. In general, statistical methods like correlation analysis, regression, t-tests, and analysis of variance assume that data follows a normal distribution. However, if the sample size exceeds 100 observations, deviations from normality are not a major concern [19, 20].

The correlation matrix was employed to determine the relationships between Chl-a and SST, Chl-a and SSS, as well as SST and SSS in Aceh Waters. This matrix depicted Pearson correlation coefficients between all pairs of variables. The Pearson correlation coefficient is expressed in Eq. 1 [11]:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (1)$$

where x_i and y_i represent pairs between Chl-a and SST, Chl-a and SSS, as well as SST and SSS, and $\bar{x}$ and $\bar{y}$ denote the averages of the data. Additionally, each subplot off the diagonal contained a scatterplot of a variable pair with a least-squares regression line, the slope of which matched the displayed correlation coefficient. Each diagonal subplot presented the distribution of a variable as a histogram.

The p-value served the purpose of hypothesis testing, indicating whether there was a relationship between the observed phenomena (null hypothesis). If the elements off the diagonal had a p-value smaller than the significance level of 0.05 (α=5%), the corresponding correlation in R was deemed significant. Correlation coefficient values were interpreted as follows: if 0≤R≤1, the correlation was considered insignificant or negligible; if 0.1≤R≤0.39, it was deemed weak; if 0.4≤R≤0.69, it was moderate; if 0.7≤R≤0.89, it was strong; and if 0.9≤R≤1, it was very strong [21].

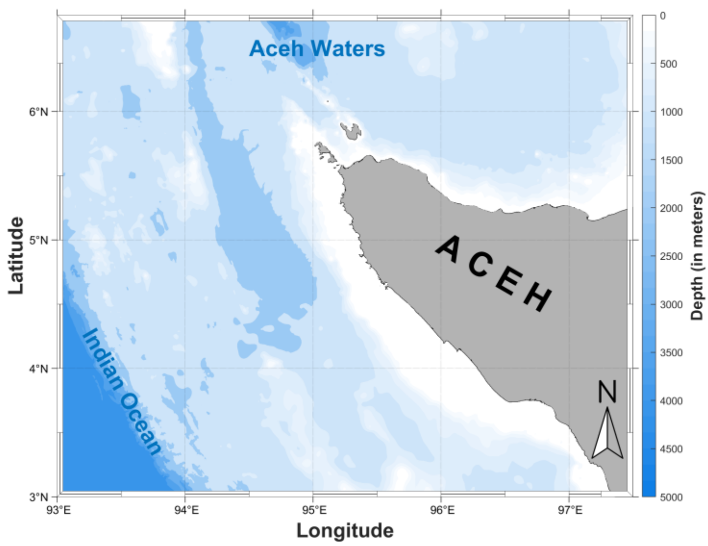

Fig. 1. Bathymetry for Aceh Waters. Colors indicate varying depths from 0 to 5000 meters. Data derived from SRTM15+ [22].

3 Results and Discussion

3.1 Boxplot and QQ plot

This study employed a total of 248 data points for each of Chl-a, SST, and SSS in Aceh Waters. Figure 2 presents Boxplots and QQ Plots for these datasets in both January and July. Figure 2(a) displays the Boxplot for Chl-a in January. Chl-a values in January exhibited a minimum of 0.15 mg/m^3 and a maximum of 1.59 mg/m^3. The median Chl-a value reached 0.4 mg/m^3. The long upper whisker indicates high variability in Chl-a within the range of 0.8

mg/m^3 to 1.59 mg/m^3. In contrast, Chl-a showed uniformity within the range of 0.15 mg/m^3 to 0.8 mg/m^3.

Figure 2(b) illustrates SST in January. SST ranged from a minimum of 28.5°C to a maximum of 30.6°C, with a median SST of 29.4°C. The median line evenly divides the box, indicating symmetrical data. Overall, SST values concentrated within the range of 29.0°C to 29.8°C. Figure 2(c) presents SSS in January. SSS had a minimum of 32.2 PSU, a maximum of 34.5 PSU, and a median of 33.6 PSU. The median SSS closely aligned with the upper quartile, indicating data skewness or uniformity at values >33.6 PSU.

Figure 2(d) displays the Boxplot for Chl-a in July. The minimum Chl-a value in July was 1.13 mg/m3, while the maximum was 0.36 mg/m3, with a median Chl-a value of 0.2 mg/m3. It is also evident that Chl-a in July exhibited outliers above 0.36 mg/m3. Figure 2(e) shows the Boxplot for SST in July. SST ranged from a minimum of 28.9°C to a maximum of 30.3°C, with a median of 29.3°C. SST values in July were concentrated within the range of 29.1°C to 29.6°C. Some outliers were also detected above 30.3°C. Figure 2(f) illustrates the Boxplot for SSS in July. Minimum, maximum, and median SSS values were 32.5 PSU, 33.8 PSU, and 33.2 PSU, respectively. The median, located at the center of the box, along with equal lengths of upper and lower whiskers, indicated a symmetrical Boxplot, suggesting no skewness in the data.

Comparison of the Boxplots for Chl-a, SST, and SSS in January (Figure 2(a-b)) and July (Figure 2(d-e)) reveals that these variables had higher values in January compared to July. This is evident from the range of minimum and maximum values for each variable Chl-a, SST, and SSS.

Figure 2(c) presents the QQ Plot for Chl-a (green dots), SST (dark blue dots), and SSS (light blue dots) in January. The Chl-a data follows a straight line pattern and tends to align with the red line at theoretical quantiles -1 and 2.3. Deviation from the line occurs for values less than -1 (above the line) and greater than 2.3 (below the line). This indicates that data within the central range, between -1 and 2.3, approximates a normal distribution. Values less than -1 indicate longer tails to the left or left skewness (negative). Values greater than 2.3 indicate longer tails to the right or right skewness (positive). SST and SSS data exhibit similar patterns. Theoretical quantile values for SST and SSS from -1 to 1 approximate a normal distribution, but there is deviation in the tails of the distribution, suggesting some skewness in the data.

Figure 2(d) presents the QQ Plot for Chl-a, SST, and SSS in July. It is evident that all Chl-a data points follow a straight line pattern and closely align with the red line, indicating that the dataset conforms to a normal distribution. Conversely, SST and SSS data show slight deviation in the tails of the distribution. For SST, data deviates from the line at values <-1.4 and >1.3, while for SSS, data deviates from the line at values <-2 and >2.2.

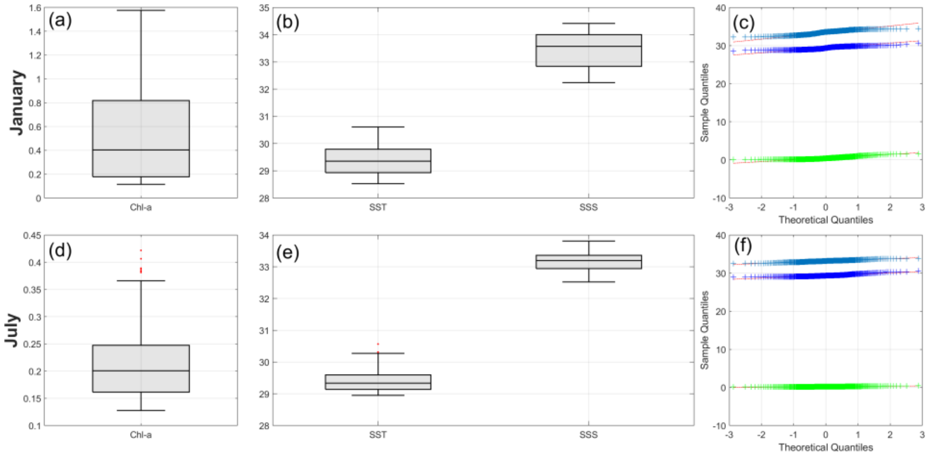

Fig. 2. Boxplots for (a) Chl-a, (b) SST, and SSS for January, and (d) Chl-a, (e) SST, and SSS for July, while (c) QQ plot for January and (f) QQ plot for July. Box plots depict the median and interquartile range (IQR) of data for the 3 variables. Whiskers extend up to 1.5 times the IQR. Red dots represent outliers. Colors. Green in the QQ plot indicates Chl-a, dark blue indicates SST, and light blue indicates SSS.

3.2 Correlation Matrix

Figures 3(a) and 3(b) depict the correlation matrices of Chl-a, SST, and SSS data for the months of January and July, respectively. Figure 3(a) illustrates the correlations between Chl-a and SST, Chl-a and SSS, as well as SST and SSS, along with the distribution of each variable in histograms for January. Each variable pair in January is marked significant, as indicated by the red-colored correlation values. In January, the correlation between Chl-a and SST is moderate and negative, the correlation between Chl-a and SSS is weak and negative, and the correlation between SST and SSS is moderate and positive. Negative correlation indicates an inverse relationship, in this case, when Chl-a is high, SST tends to be low, or when Chl-a is high, SSS tends to be low. Positive correlation indicates a direct relationship, in this case, when SST is high, SSS is also high.

Figure 3(b) illustrates the correlations in July. The Chl-a and SSS pair in July is not significant, as indicated by the black-colored correlation value. Meanwhile, the Chl-a and SST, as well as SST and SSS pairs in July, exhibit moderate and negative correlations, respectively. The non-significant correlation indicates either no or very little linear relationship between Chl-a and SSS in July. On the other hand, the negative correlation suggests an inverse relationship between Chl-a and SST, as well as SST and SSS in July.

Table 1 presents the corresponding correlation coefficient values and p-values for the Chl-a and SST, Chl-a and SSS, as well as SST and SSS pairs. All p-values in January are smaller than the significance level of 0.05, indicating that all variable pairs in January have significant correlations. In contrast, not all p-values in July are smaller than 0.05. Only the Chl-a and SST, as well as SST and SSS pairs, exhibit significant correlations. This indicates that only these pairs have significant correlations in July.

The Pearson correlation coefficient (r) serves as a metric to gauge both the magnitude and direction of a linear relationship between two variables. It falls within the range of -1 to 1, where -1 signifies a perfect negative correlation, 1 indicates a perfect positive correlation, and 0 denotes an absence of any discernible relationship between the movements of the variables [23]. As observed in January, all combinations of variables—Chl-a and SST, Chl-a and SSS, as well as SST and SSS—display significant correlations, supported by p-values below the threshold of 0.05 (refer to Table 1).

Conversely, upon analysis in July, the scenario shifts, revealing that solely the Chl-a and SST, as well as the SST and SSS pairs, exhibit noteworthy correlations. Notably, the Chl-a and SSS pair fails to meet the criteria for significance due to its inability to satisfy the requirement of p-values falling below 0.05, as indicated in Table 1.

Both Chl-a and SST exhibit a negative correlation, evident in both January and July. This indicates that as Chl-a values increase, SST values tend to decrease, and vice versa. Conversely, SST and SSS demonstrate a positive correlation in January but switch to a negative correlation in July. This shift indicates a dynamic relationship between sea surface temperature and sea surface salinity across these two months.

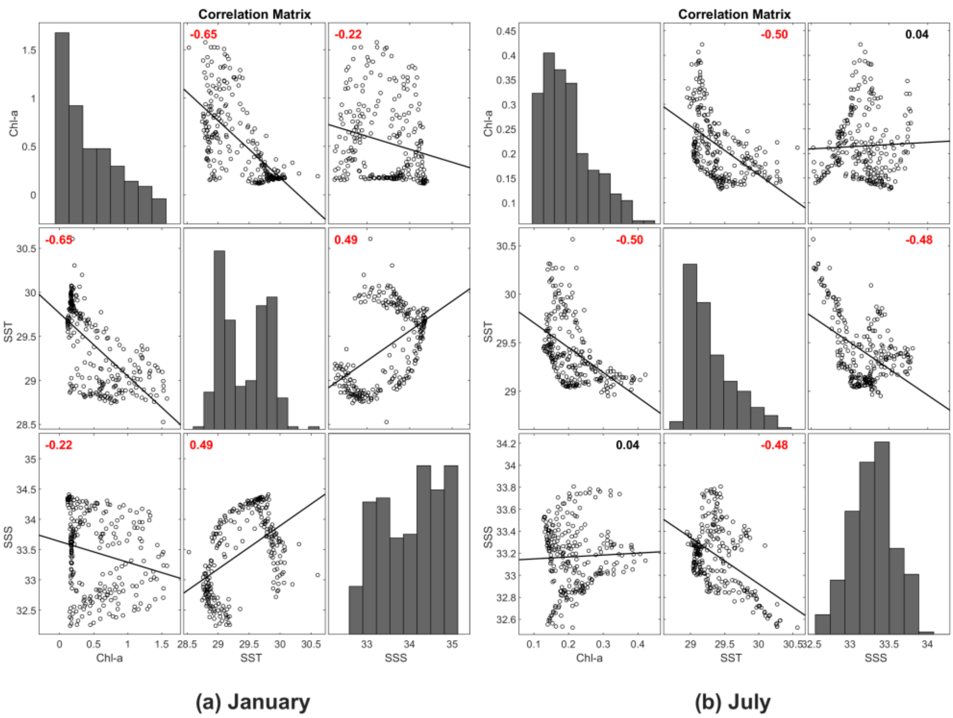

Fig. 3. Correlation matrix for Chl-a and SST, Chl-a and SSS, as well as SST and SSS pairs in (a) January and (b) July.

Table 1. Correlation coefficients (r) and p-values

No	**Pairs**	**January**		**July**	
		r	**p-value**	**r**	**p-value**
1	Chl-a and SST	-6.5×10^{-1}	5.2×10^{-31}	-5.0×10^{-1}	2.4×10^{-17}
2	Chl-a and SSS	-2.2×10^{-1}	6.5×10^{-4}	Not significant	5.4×10^{-1}
3	SST and SSS	4.9×10^{-1}	1.4×10^{-16}	-4.8×10^{-1}	1.4×10^{-15}

4 Conclusions

The analysis of Chl-a, SST, and SSS data in Aceh Waters revealed significant seasonal variability, notably higher values in January compared to July across all variables. Boxplots and QQ Plots provided insights into the distribution and normality of these variables, showing variations in values and patterns between the two months. Correlation analysis highlighted significant relationships among the variables in January, with Chl-a negatively correlated with SST and exhibiting weaker correlations with SSS, while SST and SSS displayed a moderate positive correlation. However, in July, while Chl-a and SST, as well as SST and SSS, remained significantly correlated, the Chl-a and SSS pair did not, indicating differing ecological contexts between the two months. These findings emphasize the dynamic nature of the marine environment in Aceh Waters and the need for comprehensive understanding to support effective marine resource management and ecosystem conservation efforts in the region. Further research is warranted to uncover the underlying mechanisms driving these seasonal shifts in correlations.

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