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Seasionality of *Kappaphycus alvarezii* production trends in South Sulawesi using UAV monitoring

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ABSTRACT

Climate change poses significant challenges to seaweed farming, particularly in South Sulawesi, where seasonal variations influence the production dynamics. This study examined the impact of climate variability on *Kappaphycus alvarezii* seaweed farming by analyzing production trends across four key seasons: the west monsoon, east monsoon, transition from east to west monsoon, and transition from west to east monsoon. Using satellite and UAV imagery, we assessed environmental parameters, such as temperature, salinity, and eutrophication levels, to understand their effects on seaweed growth. Our findings indicated that seasonal fluctuations significantly affected seaweed productivity, with environmental stressors leading to variable growth rates and production yields. A predictive model integrating geospatial data and climate variability from 2019 to 2024 illustrates production trends and their spatial patterns. These insights contribute to climate adaptation strategies, allowing policymakers and farmers to optimize farming schedules based on changing environmental conditions. In addition to economic benefits, aligning seaweed farming with ecosystem dynamics supports sustainable coastal management by improving nutrient regulation and aiding marine ecosystem recovery. This study underscores the importance of integrating geospatial technology into aquaculture practices, offering a scalable approach to enhance the resilience of coastal communities to climate change.

1. Introduction

The global importance of seaweed continues to grow, providing essential raw materials for established food industries and emerging applications, such as biofuels and pharmaceuticals. In Indonesia, marine seaweed farming is a cornerstone of the aquaculture sector, with South Sulawesi being the country's largest seaweed-producing province (FAO, 2022). The region's dominance in seaweed production underscores its critical role in meeting domestic and international demands. However, this position faces challenges, particularly in adapting to the impacts of climate change, which disrupts critical environmental factors such as temperature, salinity, and nutrient availability, affecting seaweed growth and productivity (Duarte et al., 2021). These issues highlight the urgent need for targeted research to sustain production levels and enhance the resilience of seaweed farming practices in the face of environmental

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changes. The aquatic environment, influenced by parameters such as sea surface water temperature, salinity, nutrient levels, and light intensity, significantly affects the productivity of seaweed farming (Msuya and Porter, 2014a; Langford et al., 2023a, 2023b). With the increasing pressures of climate change that may affect seasonal distributions and climate variability, understanding the seasonal effects on seaweed production is essential (Bennett et al., 2022). As demonstrated by (Chen et al., 2023), integrating these technologies utilizing UAVs to complement PlanetScope and Sentinel-2 satellite data enhances the accuracy of benthic seaweed biomass inversion in the intertidal zones. This approach combines non-multicollinear vegetation indices derived from satellite imagery with UAV-based biomass data as a reference, enabling a more precise analysis of the spatial distribution patterns of seaweeds (Nurdin et al., 2023). This study integrated UAV data to estimate production trends based on seasonal variations and satellite data to analyze the environmental factors affecting seaweed production over the past five years.

A closer look at seaweed production and seasonal variations can provide invaluable insights into enhancing aquaculture sustainability and supporting climate adaptation initiatives. By examining seasonal fluctuations, such as the West Monsoon, East Monsoon, and the transitional periods between them, this research offers predictive tools to support farmers and other stakeholders in adapting their practices to environmental conditions. This can support supply chain management, help farmers manage the risks of crop failure, and support long-term ecological balance by managing the production levels.

Despite the rapid growth of the Indonesian seaweed industry, models for understanding the effects of environmental factors, such as water temperature, salinity, and nutrient levels, on seaweed growth are not well developed (Barillé et al., 2024; van Oort et al., 2022). Such knowledge is essential for stakeholders to identify optimal planting and harvesting times and to facilitate higher yields and more stable market supplies. Moreover, this research can assist in mitigating risks associated with climate change by enabling the adaptation of farming practices in response to shifting environmental conditions, such as increased water temperatures and more erratic weather patterns (Dewayany et al., 2024). In light of these challenges, studying seasonal environmental variations, such as the West Monsoon, East Monsoon, and their transitional phases is crucial for developing adaptive strategies for seaweed cultivation. Seasonal climatic fluctuations affect parameters such as sea surface temperature, salinity, and nutrient dynamics, which are critical to seaweed farming success (Christopher et al., 2023). Advanced geospatial technologies, including satellite remote sensing and UAV-based data collection, have emerged as powerful tools for monitoring environmental factors at high spatial and temporal

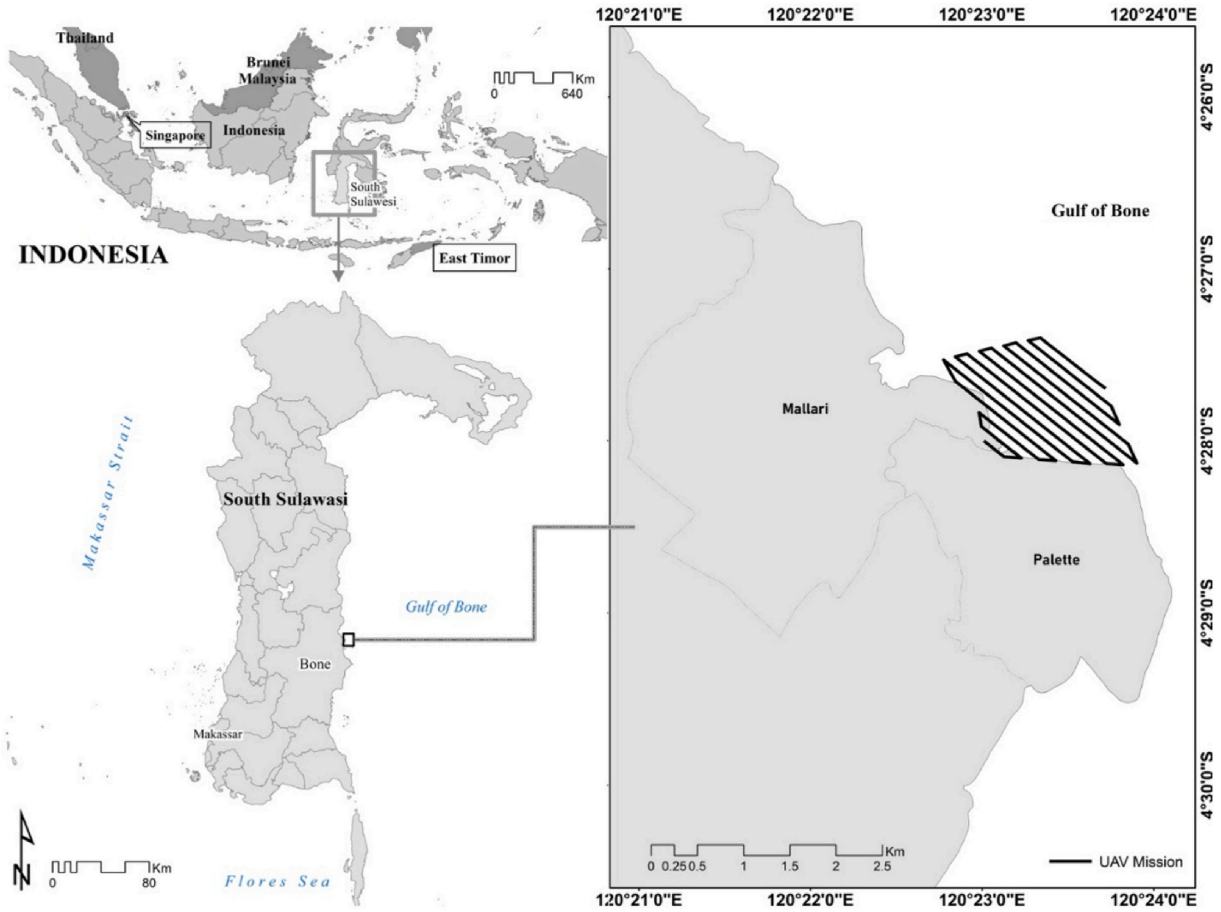


Fig. 1. The field study is the Gulf of Bone, which is marked by a black line box, and two villages located along its shores, Pallete Village and Mallari Village, where most of the population is seaweed farmers.

resolutions. These technologies provide actionable insights for managing aquaculture systems in response to dynamic environmental changes (Langford et al., 2021).

Beyond economic benefits, integrating these findings into coastal management strategies promotes the sustainability of seaweed farming and preservation of coastal ecosystems. Adapting farming schedules according to changing environmental conditions could also enhance nutrient management in coastal areas and support the recovery of marine ecosystems, particularly during less productive seasons. This aligns with global efforts to utilize sustainable aquaculture practices as part of broader climate change mitigation strategies.

This study aimed to explore the impacts of the environment on seaweed farming in South Sulawesi by analyzing production trends based on four main seasons: the west monsoon, east monsoon, transition from east to west monsoon, and transition from west to east monsoon. By utilizing satellite and UAV imagery to map key environmental parameters, such as temperature, salinity, and eutrophication levels, this study will identify the effects of these factors on seaweed growth. Orthomosaic imagery from UAVs was used to map the seaweed cultivation areas. GIS analysis identified and digitized farming units based on line length and spatial proximity to support production estimation. One of the key outputs of this study was an estimate of seaweed farming production trends integrated with a model depicting fluctuations in production results based on seasons and environmental variability from 2019 to 2024. This enabled a detailed spatial depiction of the impact of environmental parameters on seaweed production.

The primary benefit of this research is that it provides deeper insights into the relationship between seasonal variations and seaweed productivity and the impact of climate change on the seaweed farming sector in South Sulawesi. This will assist policymakers, seaweed farmers, and industry stakeholders in developing better adaptation strategies to cope with climate change. Furthermore, seasonal trend estimations provide more sustainable coastal resource management opportunities, particularly in integrating aquaculture practices with local ecosystem conditions. For example, seasonal fluctuations in production levels can be integrated into environmental management provisions to support coastal ecosystem restoration and water nutrient management. As such, these estimates have the potential to support local economic development and contribute to environmental preservation. Ultimately, this study provides essential information to inform the sustainable management of seaweed farming in South Sulawesi by understanding how seasonal and climatic factors influence production. This study's integration of cutting-edge geospatial tools and environmental data serves as a model for addressing similar challenges in other coastal regions, supporting economic resilience and ecological preservation.



Fig. 2. The seaweed species cultivated in the research area is Kappaphycus alvarezii, which consists of 2 different colors: green and brown.

2. Materials and methods

2.1. Study area

The research was conducted in two villages within Bone Regency, Palette Village and Mallari Village, located in South Sulawesi Province, Indonesia (Fig. 1). Bone Regency is a seaweed-producing region of national importance, producing around 2 % of Indonesia's seaweed. According to data from BPS 2024, the area of Mallari Village is 7.57 km^2, whereas Palette Village covers 6.7 km^2. These villages have populations of 3050 and 1875 individuals, respectively.

2.2. Data collection

2.2.1. Seaweed distribution

This study conducted a field survey to collect data on seaweed distribution. The Avenza Map application was used to record the coordinates of the points of interest. In addition, seaweed species were identified to understand their species composition and contribution to the local ecosystem (Fig. 2). The results of the field survey served as validation data for the digitization results obtained from the aerial photo analysis. By comparing field data with digitization results, we assessed the accuracy and consistency of the information obtained from both methods. To ensure the precision of digitization, high-resolution UAV imagery was validated against 27 representative field control points, which strengthened the reliability of the visual interpretation and on-screen digitization. This approach not only improves data accuracy but also provides deeper insights into the dynamics of the seaweed ecosystem in the study area.

2.2.2. UAV data acquisition

The image acquisition in this study utilized aerial photography technology with the assistance of an Unmanned Aerial Vehicle (UAV) or drone. The imaging process was carried out using two UAV models with different sensors: DJI Phantom 4, which was equipped with an RGB sensor, and DJI Phantom Multispectral with a multispectral sensor. Both UAVs were operated using the DJI GS Pro mobile application, which facilitates flight path planning and the configuration of the mapping parameters required for aerial image acquisition.

The flight altitude was 300 m, with a Ground Sampling Distance (GSD) of 15.9 cm for the multispectral sensor and 13 cm for the RGB sensor. Each image capture was performed with 70 % lateral (side lap) and frontal (front lap) overlap to ensure optimal area coverage and consistency in data mapping. One of the significant challenges in identifying seaweed farms using remote sensing imagery is the presence of clouds, which can reduce the light intensity and potentially affect the quality of the resulting images. Before undertaking UAV image acquisition, the dronecast application provided weather forecasts for the flight area and indicated no-fly zones. The ground conditions during the flight included a wind speed of 1 m/s, a gust speed of 3 m/s, 0 % precipitation, 16 km visibility, and 99 % cloud cover. Flight operations were conducted between 07:00 and 09:00 a.m. and between 16:00 and 17:00 a.m. to minimize the influence of sunglint on the resulting orthomosaic.

Aerial mapping was conducted in a 226-ha area covering the border between the Palette and Mallari villages (Fig. 1). The study area selection was based on an initial survey that showed that variability tends to occur in the area and the results of visual interpretation of satellite imagery, which is known to have the highest distribution and level of seaweed production in Bone Regency in 2024. This location was chosen because it exhibited significant changes in the distribution of seaweed cultivation each month. The collected data included aerial photographs, as summarized in Table 1.

This study employed 17 control points, consisting of 10 Ground Control Points (GCPs) and 7 Independent Check Points (ICPs) (see Table 2). The selection of these points was focused on coastal land areas that are easily identifiable and less susceptible to change over time. Specifically, the corners of buildings and roads were chosen as control point locations. Based on the geometric correction of UAV imagery acquired in February, a Root Mean Square Error (RMSE) of 0.611 m and a horizontal accuracy of 0.928 m were obtained. Although Digital Surface Models (DSMs) and Digital Terrain Models (DTMs) were not directly used for seaweed and water quality mapping, the orthomosaic generation process using Agisoft Metashape required a Digital Elevation Model (DEM) as a mandatory preprocessing step. The DEM corrects terrain-related distortions, ensuring topographic accuracy in orthomosaic imagery. The resulting

Table 1
Aerial photo of seaweed cultivation area Specification using UAV.

Acquisition	Number of photos	Sensor	Overlap
January 28, 2024	3672	Multispectral,	Front: 70 %
March 10, 2024	4728	Side: 70 %,	
April 8, 2024	4068		
May 19, 2024	4014		
June 20, 2024	534	RGB	
July 14, 2024	598		
August 10, 2024	538		
September 14, 2024	550		
November 4, 2024December 3, 2024	420 430		

Table 2
Number of ground control points (GCP) and independent Check point (ICP), Root mean Square error (RMSE), and horizontal accuracy in February to December 2024.

Month	GCP	ICP	RMSE	Horizontal Accuracy (m)
February	10	7	0.611	0.928
March	14	15	0.365	0.554
April	14	15	0.398	0.604
May	13	14	0.543	0.824
June	14	15	0.466	0.707
July	14	16	0.471	0.715
August	14	15	0.456	0.691
September	14	15	0.535	0.812
November	14	17	0.522	0.793
December	14	17	0.49	0.74

UAV image is georeferenced, as all acquired aerial photos are equipped with geographic information in the form of coordinate points, which is input during the orthomosaic process. The resulting UAV image was used in the image classification process to classify the distribution of seaweed.

2.2.3. Social-economic characteristics

Socioeconomic data were obtained using questionnaires and interviews to collect quantitative and qualitative data. The questionnaire covered respondent identification, general aspects of seaweed farming, pest and disease issues, and farmers' perceptions of the impacts of climate change. The sample included marine seaweed farmers whose primary livelihood was seaweed farming. As this population included fewer than 1000 individuals, a census sampling method was implemented, in which the entire population of seaweed farmers was approached for inclusion. This resulted in 228 seaweed farmers. This research utilized a digital platform and Avenza mapping software for data collection and analysis.

2.3. Seaweed mapping

Geometric correction was performed to enhance the spatial accuracy of aerial photographs. An image-to-image registration method was applied using the UAV orthomosaic from February as a reference to maintain geometric consistency between UAV datasets. Subsequently, the geometric correction process for the orthomosaics from April to December was performed using control points that were easily identifiable on the geometrically corrected February orthomosaic. The number of control points varied, ranging from 14 to 17. Ground Control Points (GCPs) were derived from Global Navigation Satellite System (GNSS) measurements and previously corrected UAV orthomosaics, which were the reference for registering subsequent monthly UAV orthomosaics.

Independent Check Points (ICPs) were used to assess the accuracy of the georeferenced datasets obtained through GNSS surveys conducted only in coastal land areas. For aquatic areas, corrected UAV orthomosaics were used as a reference. The GCPs and ICPs in aquatic areas are placed at several corners of traditional fishing gear structures installed in water. This process was repeated to correct the UAV datasets from March to December 2024.

Monthly accuracy variability showed that the highest accuracy was achieved in March, with the lowest Root Mean Square Error (RMSE) of 0.365 m and the lowest Circular Error 90 % (CE90) of 0.554 m CE90 is a measure of the horizontal geometric accuracy, defined as the radius of a circle within which 90 % of the errors or differences between the horizontal position of an object on the map and its assumed actual position do not exceed that radius. In contrast, the lowest accuracy occurred in February, with the highest error values (RMSE: 0.611 m; CE90:0.928 m). Overall, the results indicated that the data were suitable for large-scale mapping.

Orthomosaic results that were geometrically corrected were used for classification based on visual interpretation of the distribution of seaweed farming units, followed by on-screen digitization.

Table 3
Environmental parameters, data sources, spatial and temporal resolutions for seaweed.

No	Data Collecting	Source	Spatial Resolution (Km^2)	Temporal (Month, Hour)
1	Sea Surface Temperature (2019–2024)	Aqua Modis & GLOBAL_ANALYSISFORECAST_PHY_001_024 (Marine Copernicus)	4 Km^2	Month
2	Rainfall (2019–2024)	CHIRPS (Climate Hazards Group Infrared Precipitation with Stations)	5,57 Km^2	Month
3	Salinity (2019–2024)	GLOBAL_ANALYSISFORECAST_PHY_001_024 (Marine Copernicus)	9,24 Km^2	Hourly
4	Current (2019.- 2024)	GLOBAL_ANALYSISFORECAST_PHY_001_024 (Marine Copernicus)	9,24 Km^2	Hourly
5	Wave (2019–2024)	ERA5 (Climate Copernicus)	55,66 Km^2	Hourly
6	Wind (2019–2024)	ERA5 (Climate Copernicus)	55,66 Km^2	Hourly
7	Tide (2024)	Geospatial Information Agency, Indonesia (BIG)	–	Hourly

2.4. Environmental analysis

In this study, GIS tools were used to analyze environmental parameters influencing seaweed growth, with data sourced from Aqua Modis (sea surface temperature), CHIRPS (rainfall), Marine Copernicus (salinity and currents), and ERA5 (wave and wind data) (Oliveira et al., 2022) (Table 3). The data were processed in QGIS, generating thematic maps and organizing the data from 2019 to 2024. Statistical methods, such as correlation and regression analyses, were used to identify patterns of environmental change and their impact on seaweed distribution. This allowed the identification of patterns of environmental changes and their impact on seaweed growth (Meyer et al., 2023). The 2024 data will focus on evaluating the relationship between environmental parameters and seaweed growth, helping to identify the key contributing factors (Bennett et al., 2022; Duarte et al., 2017). In the 2024 dataset, the relationship between environmental parameters and seaweed distribution was evaluated using multiple regression analysis (see Table 4).

2.5. Statistical analysis

Statistical analysis was conducted to evaluate the relationship between environmental parameters and seaweed production. The methods employed included normality tests, correlation analyses, and regression analyses. A normality test was employed to determine whether the data obtained followed a normal distribution. The Shapiro-Wilk method is one of the most commonly used techniques owing to its sensitivity to deviations from normality, particularly with small sample sizes (Ghasemi and Zahediasl, 2012). The statistical analyses we performed, in sequence, are as follows: 1) A normality test was conducted to determine whether the data (environmental variables and seaweed production) followed a normal distribution. A normal distribution is an important assumption before conducting further parametric analyses; 2) correlation analysis was conducted to determine the strength and direction of the relationship between each environmental variable (temperature, salinity, current, rainfall, wind, and waves) and the dependent variable (seaweed production); 3) correlation analysis was conducted as an initial step to determine which variables had the potential to have a significant relationship before entering the regression model; and 4) simple regression analysis was conducted to measure the influence of one variable or environmental factor on seaweed production. This analysis provided an initial picture of the influence of individual environmental factors on seaweed production. 5) Multiple regression analysis was conducted to simultaneously measure the influence of multiple environmental variables on seaweed production.

After confirming that the data met the normality assumption, a correlation analysis was conducted to evaluate the relationship between various aquatic environmental parameters and seaweed production. Pearson's correlation test was employed if the data followed a normal distribution, whereas Spearman's correlation test was used for non-normally distributed data. The statistical analyses performed included (1) Normality Test, (2) Correlation Analysis, (3) Simple Regression Analysis, (4) Multiple Regression Analysis, and (5) Multicollinearity Handling.

Pearson's correlation calculates the correlation coefficient (r), which indicates the strength and direction of the linear relationship between two variables. The r Value ranges from -1 to 1, where 1 represents a perfect positive relationship, -1 represents a perfect negative relationship, and 0 indicates no relationship. A significance test was also performed to determine whether the relationship was statistically significant ($p < 0.05$) (Dunn et al., 2019). The formula for calculating the. The value of Pearson's method is as follows:

$$r = \frac{n\sum_{i=1}^{n} X_i Y_i - \sum_{i=1}^{n} X_i \sum_{i=1}^{n} Y_i}{\sqrt{n\sum_{i=1}^{n} X_i^2 - \left(\sum_{i=1}^{n} X_i\right)^2}\sqrt{n\sum_{i=1}^{n} Y_i^2 - \left(\sum_{i=1}^{n} Y_i\right)^2}} \quad (1)$$

Here, n refers to the number of observations, x is the independent variable, and y is the dependent variable. The Pearson correlation coefficient r measures the strength and direction of the linear relationship between x and y, ranging from -1 to 1, with values closer to 1 or -1 indicating a stronger relationship.

Spearman Rank Correlation is a method used to determine the relationship between two variables. This correlation is included in the non-parametric method, meaning that it does not require certain assumptions about the data distribution. Therefore, it can be used when the data distribution does not meet the assumption of normality, or when there are outliers. The main concept in Spearman rank correlation is to use the value ranking of each of the two variables, not using the original values in the data (Schober et al., 2018). The Spearman rank correlation was calculated based on the ranking of each value in the variable. The correlation coefficient or level of

Table 4
Differences in *P-Value* between seasons based on post-hoc test results.

Time Period Comparison	*P-Value*	Decision
Transition 1 - East	0.7275047	Not Significant
Transition 2 - East	0.1641167	Not Significant
West - East	0.0819346	Not Significant
Transition 2 - Transition 1	0.0376608	Significant
West - Transition 1	0.0190194	Significant
West - Transition 2	0.9575704	Not Significant

relationship between variables in the Spearman rank order ranges from −1 to 1. Spearman's Rank Correlation Formula:

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

The Spearman rank correlation coefficient, d_i is the difference in rank between two variables, and n is the amount of data. The Spearman rank correlation is performed with the hypothesis H_0. There is no correlation between two variables and H_1 There is a correlation between the two variables. Then, with the test criteria reject H_0 jika $r_s \geq r_{table}$. r_{table} is obtained in the Spearman rank table is obtained for $n \leq 30$.

Regression analysis was used to identify the pattern of relationships between environmental parameters and seaweed production. This relationship was described using a regression equation derived from the analysis. The coefficient of determination (R^2) is used to measure the extent to which environmental parameters explain the variability in seaweed production. The value of R^2 ranges from 0 to 1, with values closer to 1 indicating a stronger ability of environmental parameters to explain seaweed production. One-Way ANOVA (Analysis of Variance One-Way) is a statistical method used to compare the means of more than two groups based on a single independent factor. The primary objective of the One-Way ANOVA was to determine whether there were significant differences among the group means.

3. Results

3.1. Spatial distribution patterns and production of seaweed cultivation

3.1.1. Spatial distribution patterns

The spatial analysis presented in Fig. 3 reveals distinct seasonal patterns in the distribution of the seaweed cultivation areas. During the **rainy season** (December–February), seaweed distribution (indicated by green) is predominantly concentrated in shallow waters (0–5 m, shown in white) near the coastline. This pattern is attributed to calmer water and nutrient enrichment from rainfall runoff. As the season transitions from **rainy to dry** (March–May), seaweed distribution begins to expand further offshore into deeper waters (>5 m, shown in light blue). This shift was influenced by changing weather conditions and increasing temperatures associated with the onset of the dry season. In the **dry season** (June–August), the distribution of seaweed became more uniform across both shallow and deep waters. This spread is likely driven by stable weather conditions and increased sunlight intensity, which promote optimal growth. During the **transition from dry to rainy** (September–November), seaweed cultivation areas shifted back to shallow waters, reflecting adaptation to changing environmental conditions ahead of the rainy season. The geographic characteristics of the Bone Gulf, including the presence of forests, aquaculture ponds, and rivers, significantly influence the seaweed distribution. As highlighted in previous studies, river nutrient inputs during the rainy season further support seaweed growth.

Fig. 3 presents the results of UAV-based data analysis, illustrating the spatial patterns of seaweed cultivation by local farmers during four seasonal periods: **(a)** west/rainy season (December–February), **(b)** transition from west/rainy to East/dry season (March–May), **(c)** East/dry season (June–August), and **(d)** transition from dry to rainy season (September–November). Notably, in panels **(a)** and **(b)**, the central area is unoccupied because of the shallow waters with coral reefs, which are unsuitable for seaweed farming.

Using high-resolution imagery, the map identifies distinct cultivation areas, revealing detailed distribution patterns of seaweed-farming activities. These spatial patterns reflect the preferences and practices of seaweed farmers, influenced by environmental conditions such as water depth, nutrient availability, and seasonal weather variations.

3.1.2. Seaweed production Calculation

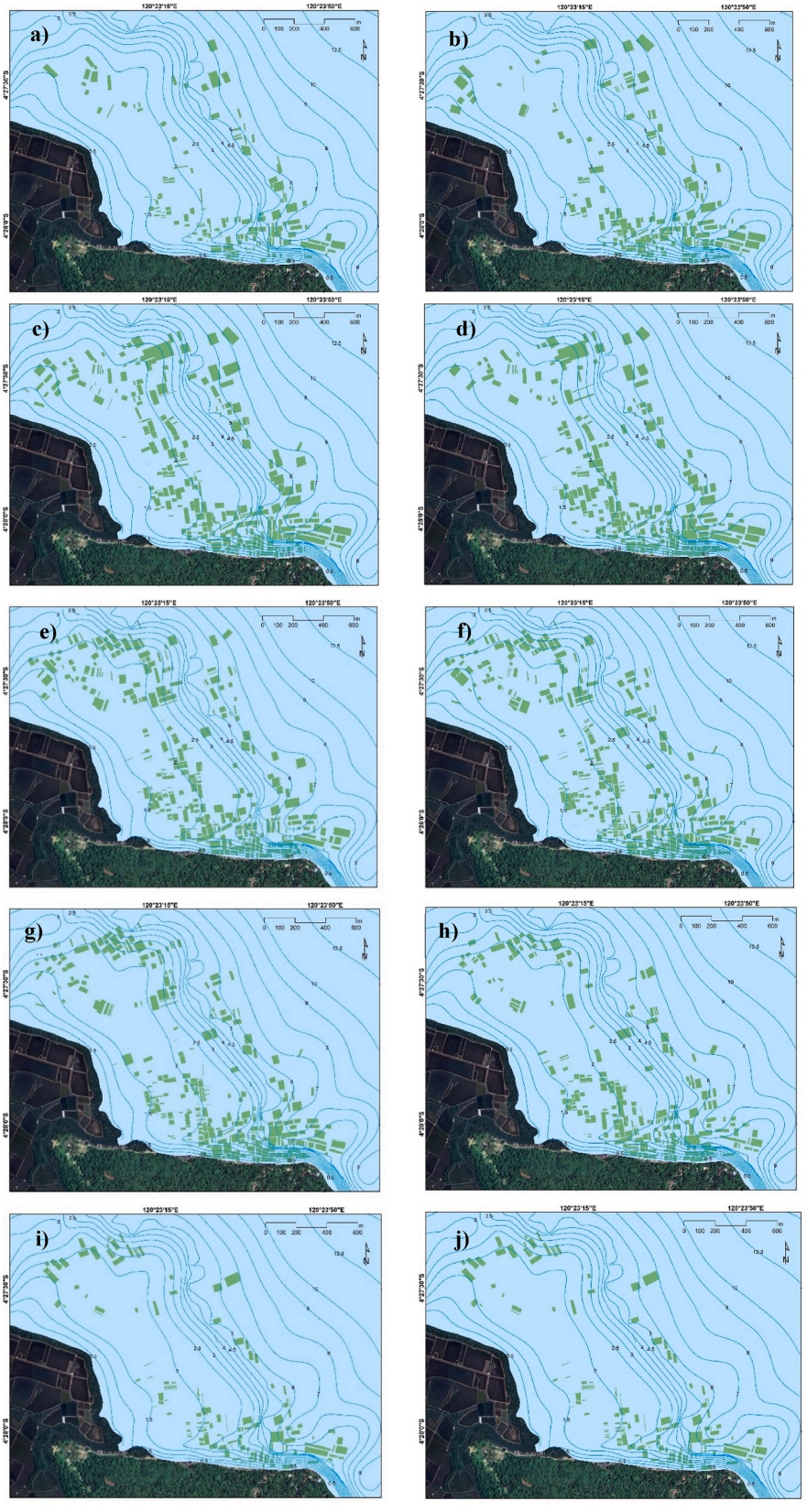
Seaweed production estimation is conducted by calculating the harvested biomass's wet and dry weight based on the length of the cultivation lines, along with additional parameters such as the spacing between seedlings, wet weight per bundle, and the dry-to-wet weight ratio (see Fig. 4). This method is essential for determining seaweed farming productivity and optimizing land use efficiency. In longline cultivation, seedlings are attached to the ropes at uniform intervals. Therefore, the total production estimate can be derived by considering the length of the cultivation line, the spacing between seedling bundles, and the average wet weight of seaweed per bundle at harvest. Mathematically, suppose the cultivation line length is denoted as x meters. In that case, the spacing between bundles as d, meters, and the dampt weight per bundle as d kilograms, the estimated total wet weight at harvest (y can be calculated using the following equation:

$$y = \left(\frac{x}{d}\right) \times w \tag{2}$$

Where.

- x is the total length of the cultivation line (m),
- d is the spacing between seedling bundles (m),
- w is the wet weight per bundle (kg),
- y and is the total wet weight of harvested seaweed (ton).

ANOVA analysis results indicate a significant difference in seaweed production across seasons ($\mathbf{p = 0.0127}$). The most notable



(caption on next page)

Fig. 3. Changing seaweed cultivation locations during 2024: a) January, b) March, c) April, d) May, e) June, f) July, g) August, h) September, i) November, and j) December.

differences were observed between the **Transition 1** and **West Monsoon** sea andl as between **Transition 1 ion 2**, based on the post-hoc Tukey test presented in Table 3. This finding aligns with the production estimates, which exhibit seasonal fluctuations, where **Transition 1** recorded the highest production, whereas the **West Monsoon** had the lowest.

Fig. 5 shows the variation in seaweed production across different seasons. The Transition 1 season has the highest median production at 809.02 tons, reflecting consistently high production levels compared to other seasons. However, the wide interquartile range (IQR) in this season indicates considerable variation in production across locations or times within the season. In contrast, the West season shows the lowest median production at 350.72 tons, with a narrow IQR, indicating relatively homogeneous production distribution and low variation (see Fig. 6).

The East season has a median production of 655.59 tons, with a narrower spread than Transition 1, suggesting its production variation is also relatively low. The Transition 2 season shows a median production of 432.14 tons, lower than East, but with a wider IQR, indicating higher production variability. Based on tVhe box plot visualization, no significant outliers were detected in the four seasons. These findings emphasize that season significantly affects seaweed production levels, with Transition 1 consistently showing higher production results than other seasons.

3.2. Correlation between seaweed cultivation production and marine environmental

3.2.1. Trends in marine parameters influencing seaweed cultivation from 2019 to 2024: A six-year analysis

Over six years, this study examines the environmental dynamics shaping seaweed production in Bone District, South Sulawesi (Appendix A1-A7). Situated in a tropical monsoonal climate, Bone experiences distinct wet and dry seasons that influence key oceanographic parameters. Sea surface temperatures, ranging from 28.60 °C to 30.67 °C, remain optimal for seaweed growth. However, seasonal fluctuations, particularly during the West monsoon, may alter metabolic processes and biomass accumulation rates.

Salinity levels, recorded between 32.81 and 34.44, exhibit substantial seasonal variability, closely linked to precipitation patterns. Heavy rainfall during the West monsoon (December–February) reduces surface water salinity, potentially stressing seaweed crops, whereas lower precipitation in the East monsoon results in increased salinity, fostering more stable growing conditions. These fluctuations necessitate adaptive management strategies, including optimized cultivation schedules to mitigate salinity-induced stress.

Ocean currents in the study area are generally moderate, with marginal intensification during the East monsoon. While excessive current velocity can cause structural damage to seaweed farms, prevailing conditions in Bone remain within tolerable thresholds. Seasonal wave height variations, particularly during the East monsoon, pose additional risks to farming infrastructure, necessitating the implementation of resilient farm designs and strategic site selection.

Satellite-derived rainfall data from Copernicus corroborate observed precipitation trends, offering critical insights for forecasting environmental conditions. However, interannual variability introduces challenges in predicting optimal cultivation windows. Understanding these seasonal oceanographic dynamics is crucial for improving seaweed farm resilience, optimizing production strategies, and ensuring the long-term sustainability of seaweed aquaculture in the Bone District.

3.2.2. Influence of environmental variables on seaweed production

Before conducting a correlation analysis, a normality test was performed to ensure data distribution. The results in Table 5 indicate that most variables follow a normal distribution, except for temperature ($p = 0.038$).

Correlation analysis was conducted to identify the relationship between environmental variables and seaweed production. Pearson correlation test was used for variables with normal distribution, while Spearman Rank test was used for temperature variables that did not meet the normality assumption. The results showed that the salinity variable had a strong negative correlation with seaweed production ($r = -0.73$; $p = 0.0071$). The rainfall and wave variables showed positive correlations of ($r = 0.39$; $p = 0.2067$) and ($r = 0.44$; $p = 0.1551$), respectively, but were not statistically significant. Wind also showed a positive correlation ($r = 0.32$; $p = 0.3114$), while current had a weak negative correlation ($r = -0.18$; $p = 0.5840$), for the temperature variable, which was analyzed using the Spearman Rank method, a very weak negative correlation was obtained with seaweed production ($r_s = -0.17$; $p = 0.5883$). In addition, powerful relationships were found between several environmental variables. An almost perfect negative correlation was found between temperature and wind ($r_s = -0.99$; $p < 0.0001$), as well as strong correlations between temperature and waves ($r_s = -0.87$; $p = 0.0003$), temperature and currents ($r_s = -0.82$; $p = 0.0020$), and currents and winds ($r = 0.76$; $p = 0.0043$), indicating multicollinearity among the environmental variables.

However, the correlation analysis (Fig. 7) also reveals high multicollinearity among several independent variables. To overcome the problem of multicollinearity, the Ridge and Lasso regression methods are used. Both of these approaches reduce the impact of multicollinearity through regularization techniques. Ridge regression works by shrinking the coefficient values of all variables towards zero without eliminating them, thus maintaining all variables in the model. Meanwhile, Lasso regression not only performs regularization but also variable selection by eliminating variables that have a small or insignificant contribution to the model, which can affect the stability of the regression model. Temperature and wind exhibit an almost perfect negative correlation ($r = -0.99$), indicating that they carry nearly identical information. Furthermore, temperature shows a strong negative correlation with waves ($r = -0.87$) and currents ($r = -0.82$), while currents and wind also have an almost perfect correlation ($r = 0.98$).

A simple regression analysis was conducted to evaluate further the relationship between environmental factors and seaweed

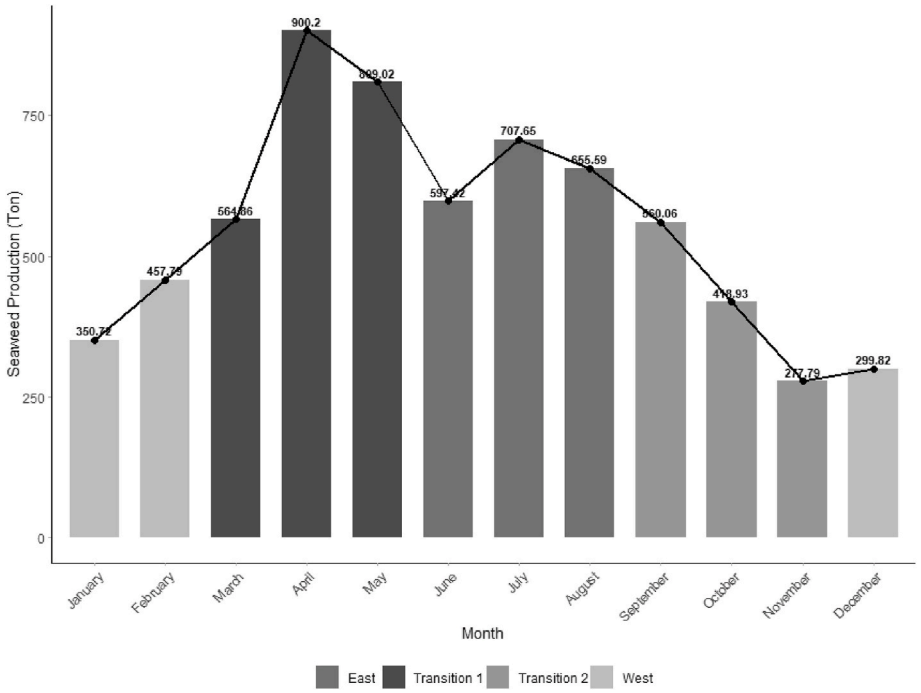


Fig. 4. Estimated monthly seaweed production (tons) based on cultivation line length.

production (Appendix B1). The results indicate that most variables exhibit weak correlations with seaweed production, except for salinity. Salinity showed a relatively strong influence, with $\mathbf{R2 = 0.532}$ and a statistically significant negative correlation $(R^2 = 0.532, p = 0.007)$, suggesting that increasing salinity may reduce output.

In contrast, **temperature ($R2 = 0.077$, $p = 0.382$), rainfall ($R2 = 0.154$, $p = 0.207$), ocean currents ($R2 = 0.031$, $p = 0.584$), wave height ($R2 = 0.191$, $p = 0.155$), and wind speed ($R2 = 0.102$, $p = 0.311$)** did not exhibit significant relationships with seaweed production (Fig. 8).

4. Discussion

The seasonal variation in seaweed production observed in the present study highlights the strong influence of environmental factors on aquaculture productivity. The significant differences in production across seasons, particularly the pronounced contrast between Transition 1 and the West monsoon, suggest that environmental fluctuations are critical for determining seaweed growth rates. Transition 1 exhibited the highest productivity, whereas the West Monsoon had the lowest yield. This pattern is likely associated

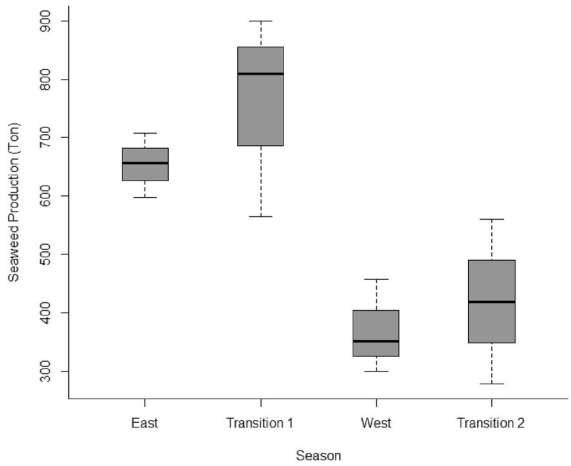


Fig. 5. Distribution of seaweed production by season.

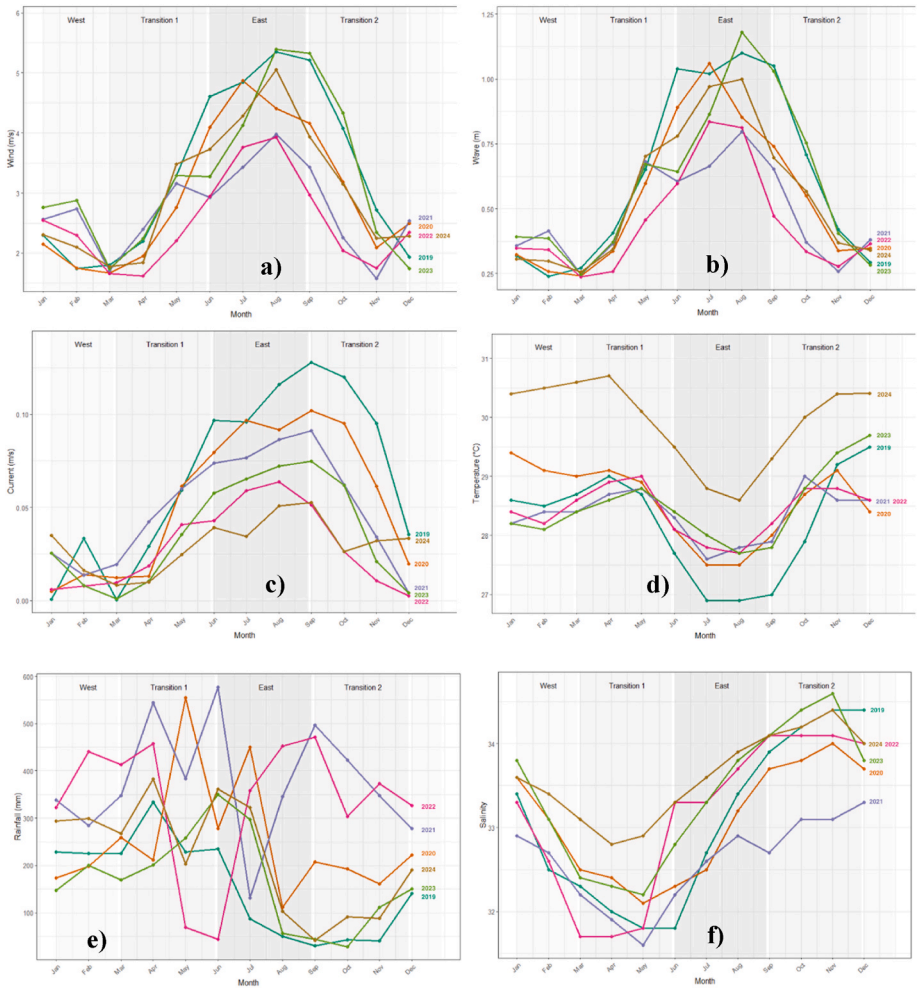


Fig. 6. Average monthly seasonal variation of water parameters at the study site during 2019–2024. (a) wind speed (m/s), (b) wave height (m), (c) ocean current speed (m/s), (d) sea surface temperature (°C), (e) rainfall (mm), and (f) salinity. Each line represents the monthly value for each observation year. The areas in the graph are divided based on the division of seasons in Indonesia: West, Transition I, East, and Transition II.

with changes in temperature, salinity, and hydrodynamic conditions, which is consistent with findings from previous studies, indicating that seasonal shifts significantly affect macroalgal growth (Msuya and Porter, 2014b; Largo et al., 2020).

The integration of geospatial technologies, particularly Unmanned Aerial Vehicles (UAVs) and satellite imagery, has significantly enhanced the accuracy and efficiency of seaweed production assessments. UAV imagery is instrumental in classifying seaweed distribution through image processing techniques, enabling precise spatial mapping of cultivation areas. This high-resolution approach allows for the detailed monitoring of seaweed growth, harvesting cycles, and potential environmental stressors affecting production. In contrast, satellite-derived data provide broader environmental insights, including sea surface temperature, salinity, and wave dynamics, which influence seaweed productivity at a regional scale.

Among the environmental variables examined, salinity was the most influential factor, exhibiting a strong negative correlation with seaweed production. This finding is consistent with previous research demonstrating that elevated salinity levels can inhibit seaweed growth by inducing osmotic stress, which affects cellular function and photosynthetic efficiency (Hurtado et al., 2015). The inverse relationship between salinity and production underscores the necessity of site selection in aquaculture because areas with excessive salinity fluctuations may pose risks to sustainable farming. Additionally, our results indicated that wave height and rainfall positively influenced seaweed yield. Moderate wave heights facilitate optimal water circulation, whereas excessively high waves can lead to seaweed damage. Rainfall showed a positive relationship with seaweed production ($r = 0.39$); however, this result was not statistically significant ($p = 0.2067$) and was only able to explain about 15,4 % of the variation in production based on simple regression analysis ($R^2 = 0.154$). This shows that the direction of the relationship is indeed positive, but the strength of the relationship is insufficient to provide a significant predictive influence. This suggests that increased water movement and freshwater input contributed to nutrient mixing and mitigated excessive salinity stress. Similar observations have been reported in Kappaphycus and Eucheuma farming studies, where moderate hydrodynamic activity enhanced nutrient availability and prevented epiphyte overgrowth.

Although temperature and current velocity exhibited weak correlations with seaweed production, their roles in influencing growth dynamics could not be entirely dismissed. The limited impact of temperature in this study contrasts with research conducted in other tropical regions, where temperature fluctuations have been linked to stress responses in seaweeds. This discrepancy may be attributed to site-specific factors, such as the local adaptation of seaweed strains or the buffering effects of hydrodynamic conditions that moderate temperature extremes. Furthermore, the weak correlation between current velocity and production suggests that, while water movement is essential for nutrient exchange, excessive turbulence may lead to mechanical damage or detachment of thalli, ultimately reducing yields.

Multicollinearity among environmental variables, particularly between temperature, wind speed, and wave height, indicates the interconnected nature of these factors in shaping coastal ecosystem dynamics. Variance Inflation Factor (VIF) analysis confirmed that wind speed, wave height, and temperature exhibited high collinearity, necessitating advanced modeling approaches, such as Lasso and Ridge regression, to isolate key production drivers. The Variance Inflation Factor (VIF) shows the presence of multicollinearity among several variables. High VIF values indicate strong correlations between independent variables, which can affect the stability of regression estimates. In this analysis, the wind (VIF = 116.12), wave (VIF = 57.69), and temperature (VIF = 21.02) variables had VIF values that significantly exceeded the common threshold of VIF $\leq$10, indicating strong multicollinearity.

The findings of this study highlight the critical role that environmental factors play in seaweed production. The Lasso regression model identified salinity and wave height as the primary predictors of seaweed yield, reinforcing the hypothesis that salinity stress and hydrodynamic conditions are crucial determinants of productivity. The Ridge regression model retained all environmental variables and provided slightly higher explanatory power ($R^2 = 0.82$) than the Lasso model ($R^2 = 0.79$). This suggests that although multiple factors influence production, their relative contributions may vary depending on local conditions and interactions.

By employing the Lasso and Ridge regression models, we can discern key predictors and mitigate multicollinearity issues, thereby improving the robustness of our predictive models. The Lasso regression model identified salinity and wave height as the two most influential factors, explaining 79 % of the variance in seaweed production. The negative correlation between salinity and production suggests that elevated salt levels may hinder seaweed growth, likely due to osmotic stress, which affects cellular function and metabolism. Conversely, the positive association between wave height and production indicated that moderate hydrodynamic conditions may enhance nutrient exchange, reduce biofouling, and improve seaweed growth.

In contrast, the ridge regression retained all six environmental variables (temperature, rainfall, salinity, current, wave height, and wind speed), explaining 82 % of the variance in seaweed production. This model suggests a more complex interplay of environmental factors, in which the combined effects of multiple variables better capture the seasonal fluctuations observed in seaweed yields. The advantage of ridge regression lies in its ability to mitigate overfitting while incorporating all relevant predictors, offering a more comprehensive understanding of environmental influences on seaweed production. However, it is important to note that retaining all variables may reduce interpretability, making it more challenging to identify the dominant drivers of production.

The implications of these findings extend beyond site-specific aquaculture management to broader applications of climate adaptation strategies for coastal communities. Given the projected increase in extreme weather events and changes in oceanographic patterns due to climate change (Barange et al., 2018), understanding how environmental variables influence seaweed production is essential for developing resilient aquaculture systems. Future studies should explore long-term monitoring and integrate UAV and remote sensing technologies to assess the spatial and temporal variability in key environmental parameters. Additionally, experimental approaches that manipulate salinity and hydrodynamic conditions could provide deeper insights into the physiological responses of seaweed to ecological stressors, ultimately informing best practices for site selection and cultivation techniques.

Statistical methods, such as Bayesian change of support (Bradley and Holan, 2014) and Spatio-Temporal Change-of-Support (STCOS) (Raim and Bradley, 2019), can be used to handle scale differences between predictor and response variables through a statistical downscaling approach. The latent Gaussian approach (Chacón-Montalván et al., 2024) can also be used to overcome the limitations of simple interpolation by considering the uncertainties owing to scale differences. For long-term purposes, particularly if there are many predictors, it is recommended to use dimensionality reduction techniques such as Principal Component Analysis (PCA).

Several studies, such as (Pacifici et al., 2019) and (Paciorek, 2010), emphasize the importance of considering differences in scale (resolution) in spatial analysis to avoid estimation bias. However, in this study, which focused on seaweed production and environmental factors in a fixed location with continuous observation, the impact of spatial mismatch tended to be minimal if the environmental variables were relatively homogeneous (Parada and Liang, 2008). Therefore, differences in the resolution of environmental variables (X) are not a major problem in the regression analysis in this case, as long as the X value comes from the same location or is close enough to point Y (the location of the UAV flight for production estimation) and the time of data collection X and Y are aligned.

The limitation of this study lies in the relatively small amount of data, which covers only 12 months of observation at one location.

Table 5
Normality test results for seaweed production and environmental factors.

Variable	*P-Value*	Decision
Seaweed production	0.46559044	Fail to reject H_0
Temperature	0.03780773	Reject H_0
Rainfall	0.33450236	Fail to reject H_0
Salinity	0.81175161	Fail to reject H_0
Current	0.81509876	Fail to reject H_0
Wave	0.06322062	Fail to reject H_0
Wind	0.22696072	Fail to reject H_0

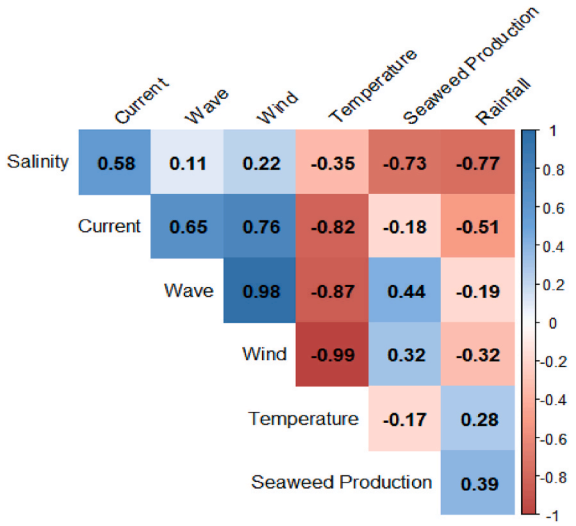


Fig. 7. Heatmap of correlation between environmental variables and seaweed production.

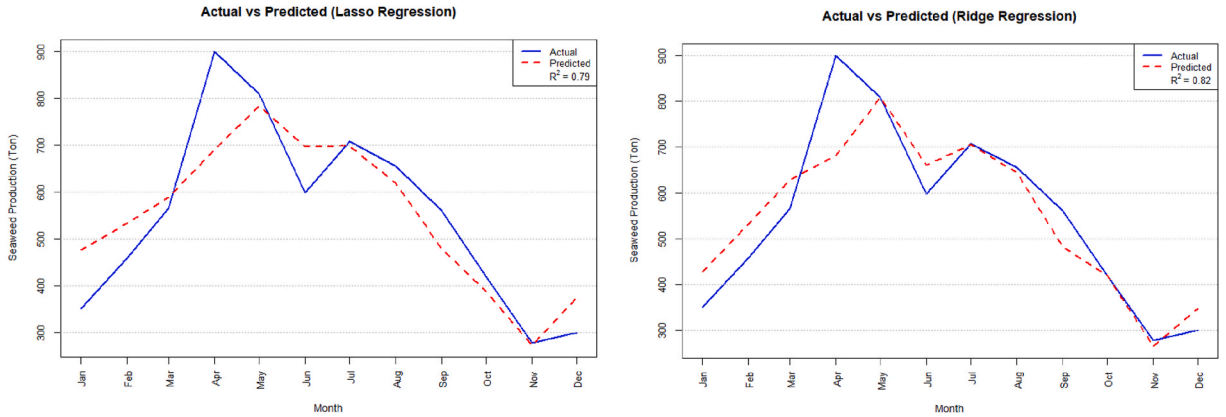


Fig. 8. (a) Comparison of actual seaweed production and predicted results using Lasso regression, (b) Comparison of actual seaweed production and predicted results using ridge regression.

This limits the ability of the model to comprehensively capture the long-term temporal patterns and seasonal dynamics. Therefore, if this study is sustained, it is recommended that the data be collected over a longer period to form an adequate time-series data structure. Thus, time-series statistical methods such as ARIMA or SARIMA can be applied to identify trends and seasonal patterns. If external environmental variables are included as predictors, methods such as ARIMAX or state-space models can be used. This approach provides a more accurate model of seaweed production fluctuations over time, and supports long-term predictions.

From an ecological perspective, these results reinforce the importance of understanding the seasonal environmental variability in seaweed aquaculture. Similarly, wave action corroborates the findings suggesting that dynamic water movement can enhance nutrient uptake and mitigate competition from epiphytes and sedimentation. The weak correlations observed for temperature, rainfall, current velocity, and wind speed suggest that, while these factors may influence seaweed growth, their effects are either independent or dependent on interactions with other environmental variables.

These findings have significant implications for seaweed farming management. Farmers should consider site selection strategies that minimize exposure to extreme salinity variations, particularly in regions prone to seasonal hypersalinity events. Additionally, optimizing farm designs to leverage moderate wave action can enhance productivity. Understanding these environmental interactions also provides valuable insights into climate adaptation strategies, as changes in precipitation patterns, ocean currents, and storm intensities may alter the suitability of traditional farming areas.

Despite the strengths of our study, some limitations should be acknowledged. Multicollinearity among environmental variables, as indicated by high Variance Inflation Factor (VIF) values, suggests potential redundancies in the dataset. While Ridge regression addresses this issue by distributing the effect across correlated variables, further research using advanced techniques, such as Principal Component Analysis (PCA) or machine learning approaches, may provide deeper insights into the underlying relationships. This study focused primarily on environmental predictors, whereas biological factors such as genotype variation and disease prevalence were not

considered. Future studies incorporating genetic and physiological data could refine our understanding of the seaweed production dynamics.

Furthermore, while this study focused on South Sulawesi, its findings should be validated in regions with different climatic and oceanographic conditions. Expanding this research to other coastal areas would provide a broader understanding of how geospatial technologies can support sustainable seaweed farming in diverse environmental settings. Integrating real-time AI-based analytics could further enhance predictive capabilities, enabling dynamic decision making to optimize farm management and climate adaptation strategies. Overall, this research underscores the potential of UAV and satellite integration for advancing seaweed aquaculture. By linking seasonal patterns, environmental conditions, and production trends, this study provides a data-driven foundation for improving site selection, enhancing productivity, and mitigating climate risk in seaweed farming.

5. Conclusions

This study demonstrates the critical role of UAV and satellite imagery in improving seaweed production. UAV-based classification provides high-resolution spatial data on seaweed distribution, enabling precise yield estimations, while satellite-derived environmental parameters offer a broader perspective on the ecological factors influencing production. Lasso and Ridge regression models further elucidated the relationships between environmental variables and seaweed productivity, with salinity and wave height emerging as key drivers.

Integrating UAV-derived production data with satellite-based environmental monitoring represents a promising approach to sustainable seaweed aquaculture management. However, challenges such as data calibration, water turbidity effects, and optimal frequency of UAV surveys must be addressed. Future research should focus on refining predictive models by incorporating real-time environmental data and exploring advanced remote sensing techniques to enhance forecasting of seaweed production and ecosystem management strategies.

CRediT authorship contribution statement

Nurjannah Nurdin: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Agus Aris:** Funding acquisition, Formal analysis, Data curation. **M. Akbar AS:** Visualization, Validation, Project administration, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Nurjannah Nurdin reports financial support was provided by Department of Foreign Affairs and Trade Australia through KONEKSI. Agus Aris reports financial support was provided by Department of Foreign Affairs and Trade Australia through KONEKSI. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2025.101659.

Data availability

No data was used for the research described in the article.

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