Spectral Characterization in Seaweed, *Kappaphycus alvarezii,* using AS7285x Spectroscopy Sensor Device

Hollanda Arief Kusuma[1*], Tonny Suhendra[1], Aidil Fadli Ilhamdy[2], Carel Candigia Sahid Ilhami[1], Dwi Eny Djoko Setyono[3], Muhammad Zainuddin Lubis[4,5]

[1]Department of Electrical Engineering, Faculty of Engineering and Maritime Technology,
Universitas Maritim Raja Ali Haji
[2]Department of Fisheries Products Technology, Faculty of Marine Science and Fisheries,
Universitas Maritim Raja Ali Haji
Jl. Politeknik Senggarang, Tanjungpinang, Kepulauan Riau, 29115, Indonesia
[3]Research Center for Food Technology and Processing, National Research and Innovation Agency
Jl. Jogja, Wonosari KM. 31,5. Gading IV. Gading. Kec. Playen, Gunung Kidul, Indonesia
[4]College of Oceanography and Ecological Science, Shanghai Ocean University
Shanghai 201306, China
[5]Geomatics Technology Program, Politeknik Negeri Batam
Batam 29461, Indonesia
Email: hollandakusuma@umrah.ac.id

Abstract

This study explores the spectral characterization of seaweed, Kappaphycus alvarezii, using the SparkFun Triad Spectroscopy Sensor AS7265x to assess the relationship between water content and light intensity. This research aims to provide a foundation for non-destructive monitoring of post-harvest seaweed quality using spectral techniques. The SeaSpec device was constructed using an ESP32 microcontroller, a TFT display, and the AS7265x sensor. Seaweed samples were collected from the coastal area of Karimun Islands and subjected to a controlled drying process at 40 °C to determine the water content in the seaweed. The spectral data were recorded across 18 channels in the visible and infrared spectra, highlighting distinct patterns that correlate with varying moisture levels. A multiple linear regression analysis was employed to determine the contributions of individual spectral channels to water content prediction, revealing that each channel has its own unique contribution to the model. Coefficient of determination (R^2), percentage error (%), and percentage accuracy (%) were also used to assess model performance. The results indicated that higher water content corresponds to increased light intensity. The analysis indicated that the visible spectrum outperformed the infrared spectrum in predictive accuracy, with an R^2 value of 0.79 compared to 0.61 for the infrared spectrum. This indicates that the visible light spectrum is more effective in predicting water content in K. alvarezii. The findings underscore the potential of spectral analysis as a reliable method for assessing the physico-chemical properties of seaweeds, advancing the use of optical sensors in aquaculture and environmental monitoring while paving the way for future research.

Keywords: *Multiple Linear Regression, Visible Light, Infrared Light, Instrument, Seaweed*

Introduction

Kappaphycus alvarezii, known as *Eucheuma cottonii*, is a commercially important species of red seaweed found in tropical waters (Rama *et al*., 2018). It is particularly abundant in the Riau Archipelago, including Karimun, Natuna, and Lingga regencies (Ilhamdy *et al*., 2019; Astika *et al*., 2022; Herianto, 2024). The growth and health of this seaweed are highly influenced by environmental factors, especially water availability and water content in its tissues (Sunny, 2017). Due to its high carrageenan content, *K. alvarezii* is a key resource for food, pharmaceutical, and cosmetic industries (Necas and Bartosikova, 2013). Carrageenan, a hydrocolloid extracted from this seaweed, is used as a thickening, stabilizing, and gelling agent in various products, making the seaweed's water content crucial in determining its quality and yield (Aslan *et al*., 2020). The correlation between water content and carrageenan yield is significant because water is an essential solvent in the extraction process of carrageenan from red seaweed Monitoring water content is thus essential for post-harvest processes. However, traditional methods for measuring water content are often invasive, labor-intensive, and time-consuming (Zhang *et al*., 2018).

In light of these challenges, the need for non-destructive, rapid, and reliable methods to assess water content in post harvest of *K. alvarezii* is

*) Corresponding author

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apparent. Spectral analysis using spectrophotometry has emerged as a promising alternative due to its ability to analyze light absorption properties across a wide range of wavelengths. The AS7265x spectroscopy sensor, with its capability to measure UV, visible, and near-infrared spectra, offers a practical solution for such analysis (Daurai *et al*., 2023). This sensor is not only portable and efficient but also capable of detecting light in a range from 410 nm to 940 nm, with a resolution of 25-50 nm (Ams AG, 2018), making it suitable for analyzing the water content in post harvest of *K. alvarezii.* It offers advantages over conventional methods, such as spectro sensors (Stanziola *et al*., 1979) and traditional spectrographs (Allington-Smith and Bland-Hawthorn, 2010), due to its compact size and its ability to measure a wide wavelength range.

The AS7265x sensor needs to be integrated with a microcontroller to obtain data accurately and efficiently. A data acquisition device is an integration of the sensor, microcontroller, and other components, creating a system that can effectively and efficiently capture, store, and display data. The microcontroller acts as the brain of the system, managing operations and interactions between all these components. Several studies have used Arduino (Kusuma *et al*., 2020, 2021, 2023a) and ESP32 (Akbar *et al*., 2023; Kusuma *et al*., 2023a, 2023b). However, Refly and Kusuma, (2022) stated that the ESP32 has lower power consumption than Arduino. Therefore, selecting a microcontroller with low power consumption, such as the ESP32, is crucial to ensure optimal performance of the data acquisition device.

Despite the broad utilization of *K. alvarezii* in various industries, the spectral characterization of its post harvest water content, particularly in the Riau Archipelago, remains under-researched. Present studies have focused on its growth and cultivation in specific regions (Labenua and Aris, 2021; Simatupang *et al*., 2021; Maradhy *et al*., 2022), however, no significant efforts have been made to apply spectral analysis to monitor its water content after harvest for storage or further processes. This gap presents an opportunity to explore the potential use of spectral characterization to assess post harvest water content of *K. alvarezii*, particularly in the Riau Archipelago. Therefore, this study aims to fill this knowledge gap by utilizing the AS7265x spectroscopy sensor. By leveraging the AS7265x spectroscopy sensor, this research is expected to contribute to a better understanding of the relationship between spectral characteristics and water content in *K. alvarezii* in the Riau Archipelago.

Materials and Methods

Design system

The SeaSpec (Seaweed Spectrophotometry) device was developed to capture spectral data from post harvest of *Kappaphycus alvarezii*, allowing for the determination of water content based on spectral characteristics. The design process involved three main stages: (1) electronics design, (2) programming, and (3) mechanical assembly. The main components of the SeaSpec device include the ESP32 microcontroller, which manages data processing, and the AS7265x sensor array, which captures spectral values across 18 channels in the visible and infrared light ranges. The ESP32 transmits the data to a Human-Machine Interface (HMI) Display for real-time visualization and stores the data on a micro SD card for later analysis. All components were integrated into a custom-designed Printed Circuit Board (PCB) to minimize noise and interference, and the device is powered by a 12V 2A adapter to ensure stable performance during long measurement sessions. Figure 1. shows the system architecture, detailing the component integration.

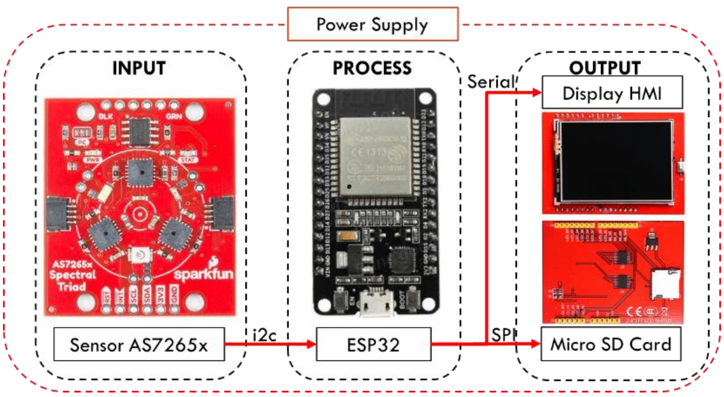

Figure 1. Device system components diagram

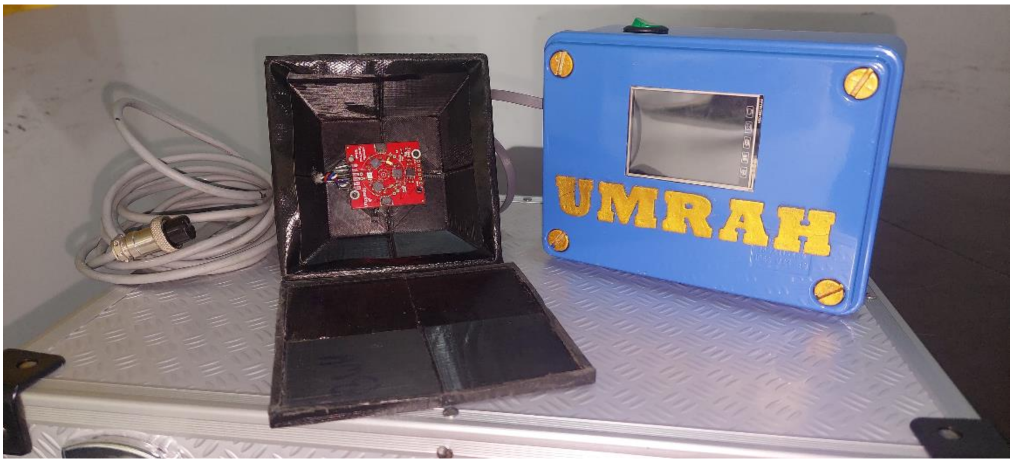

Figure 2. Seaweed Spectral Instrument with a ESP32 inside blue box, TFT display, AS7265x spectral sensor, and black case for seaweed sample measurement.

The SparkFun Triad Spectroscopy Sensor is an advanced optical device that incorporates three AS7265x spectral sensors (AS72651, AS72652, and AS72653) alongside visible, ultraviolet (UV), and infrared (IR) LEDs. This sensor array is capable of detecting light from 410 nm (UV) to 940 nm (IR) and measures 18 individual light frequencies with a sensitivity of up to 28.6 $nW.cm^{-2}$ and an accuracy of ±12% (SparkFun Electronics, 2018). Its high precision in light measurement makes it particularly suitable for spectral analysis of *Kappaphycus alvarezii*, allowing for detailed examination of its spectral characteristics.

The ESP32 microcontroller was programmed using the Arduino IDE, with custom software written in C to control the sensor array, manage data acquisition, and interface with both the HMI display and the micro SD card for data storage. Libraries specific to the AS7265x sensor were employed to handle the communication between the sensor and the microcontroller. This program ensures efficient and synchronized data acquisition and storage.

The device casing was 3D-printed using PLA/ABS material to ensure lightweight durability. The black chamber, where seaweed samples are placed for scanning, is designed to isolate the sensor from ambient light, improving the accuracy of spectral measurements. The SeaSpec device consists of two main parts: the seaweed scanner, which houses the AS7265x sensor, and the display unit, which contains the electronics and storage components. The design of the scanner's chamber is crucial for preventing light interference during measurements. The display unit and the scanner are connected by a flexible cable, allowing for convenient placement in the field. Figure 2 shows the complete SeaSpec device, including the sensor and black chamber.

Data analysis

Seaweed samples (*K. alvarezii*) were collected from the coastal area of Karimun Islands and weighed in 100-gram increments. The drying process was conducted in an oven at a constant temperature of 40°C. The water content of the seaweed was determined using the moisture ratio method shown in Equation 1, according to Djaeni and Sari (2015). Measurements were taken every 15 min using the developed instrument to record the spectral intensity for each channel.

$$water\ content = \frac{x - x_e}{x_0 - x_e} \quad (1)$$

where x is the water content at the time of sampling, x_e represents the equilibrium water content, and x_0 refers to the initial water content.

The intensity data were categorized into two ranges: visible light and infrared light. Multiple linear regression was applied to the spectral intensity data, using the equation provided in Equation 2. Residual values were calculated to evaluate the accuracy of the model in predicting the water content of the seaweed.

$$y = \beta_1 \times CH_1\ Intensity + \beta_2 \times CH_2\ Intensity + \cdots + \beta_{18} \times CH_{18}\ Intensity + \beta_0 \quad (2)$$

where y represents the predicted water content, β_n are the regression coefficients for each respective channel intensity (CH_n), and β_0 is the intercept.

To further assess model performance, the coefficient of determination (R^2) was calculated for each channel to determine the proportion of variance explained, as shown in Eq. 3. R^2 measures the proportion of variance in the dependent variable explained by the model's independent variables. A comparison of R^2 values between visible and infrared light spectra was conducted to identify the most suitable spectrum for detecting the correlation with water content in *K. alvarezii*.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

where y_i represents the actual observed value of the dependent variable for each data point, while $\hat{y}_i$ denotes the corresponding predicted value obtained from the regression model. The difference between these values, $y_i - \hat{y}_i$, is the residual, which represents the error in the prediction. The term $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ is the sum of squared residuals (also known as the residual sum of squares), quantifying the total error in the model's predictions. The term $\bar{y}$ refers to the mean of the observed values. The difference between the observed values and the mean, $y_i - \bar{y}$, represents the total variation in the data. The sum of squared differences from the mean, $\sum_{i=1}^{n}(y_i - \bar{y})^2$, is called the total sum of squares, measuring the overall variability in the data.

The R^2 value indicates the proportion of this total variability that is explained by the regression model. A value of R^2=1 means that the model perfectly predicts the observed data, while an R^2 value closer to 0 indicates that the model explains little of the variability. Thus, R^2 provides a measure of the goodness of fit for the regression model (Mendenhall *et al*., 2013).

In addition to the R^2 value, other metrics were incorporated to assess model performance, including Root Mean Square Error (RMSE), percentage error, and percentage accuracy. RMSE was employed to measure the average magnitude of the prediction errors, providing insight into how far the predicted values deviate from the observed data (Chai and Draxler, 2014). A lower RMSE value indicates a more accurate model. The percentage error was calculated to express the deviation of predictions as a proportion of the actual values, offering a relative sense of error magnitude. Finally, percentage accuracy quantified how close the model's predictions were to the true values, with higher percentages indicating better prediction accuracy (Sedha, 2013).

Result and Discussion

Spectral collection of seaweed (K. alvarezii)

The spectral data were collected using the AS7265x sensor, which measures light intensity across 18 channels, each corresponding to a specific wavelength. The list of wavelengths for each channel from 410 nm to 940 nm is provided in Table 1. The seaweed (*K. alvarezii*) samples were weighed to determine their remaining mass after drying, as shown in

Figure 3. Measurements were performed under controlled lighting conditions to minimize external interference.

Figure 3. Seaweed (*K. alvarezii*) being weighed using a scale, displaying the remaining weight after the drying process.

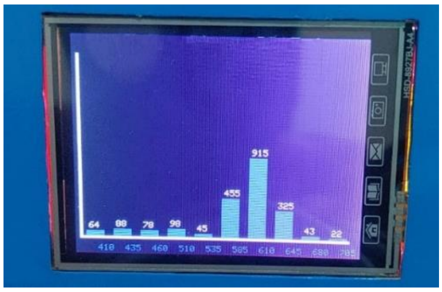

Figure 4. Display of light intensity values measured by the SeaSpec device for each channel, ranging from 410 nm to 705 nm, illustrating the sensor's response across different wavelengths.

Figure 5. Seaweed (*K. alvarezii*) sample placed in the black box containing the AS7265x sensor for spectral measurement.

Table 1. Wavelengths corresponding to each of the 18 channels of the AS7265x sensor used for spectral measurements of the seaweed.

No	Channel Name	Wavelength	Color Spectrum	Spectrum Type
1	Channel A	410nm	Violet	Visible
2	Channel B	435nm	Violet – Blue	Visible
3	Channel C	460nm	Blue	Visible
4	Channel D	485nm	Blue – Green	Visible
5	Channel E	510nm	Green	Visible
6	Channel F	535nm	Green – Yellow	Visible
7	Channel G	560nm	Yellow	Visible
8	Channel H	585nm	Yellow – Orange	Visible
9	Channel R	610nm	Orange	Visible
10	Channel I	645nm	Orange – Red	Visible
11	Channel S	680nm	Red	Visible
12	Channel J	705nm	Deep Red	Visible
13	Channel T	730nm	Near Infrared	Infrared
14	Channel U	760nm	Near Infrared	Infrared
15	Channel V	810nm	Near Infrared	Infrared
16	Channel W	860nm	Near Infrared	Infrared
17	Channel K	900nm	Near Infrared	Infrared
18	Channel L	940nm	Near Infrared	Infrared

The SeaSpec device was used to detect the intensity of each channel, with data displayed on a TFT screen (Figure 4). During measurement, the seaweed was placed inside a black box housing the AS7265x sensor, and the intensity values were recorded (Figure 5). As the seaweed dried, its texture changed, as shown in Figure 6.Thermal transitions during the drying process led to changes in the seaweed's physico-chemical properties, which can affect its color and sorption behavior, thereby impacting the accuracy of spectral measurements (Tolstorebrov *et al*., 2024).

Spectral pattern of K. alvarezii

The spectral data obtained from the AS7265x sensor reveal distinct patterns that correspond to varying water content levels in the seaweed samples. Each channel captures light intensity across specific wavelengths, providing valuable insights into the physiological and biochemical characteristics of *K. alvarezii*. Figure 7 illustrates the intensity values obtained at different water content levels, emphasizing the relationship between moisture content and light absorption properties.

At 18.60% water content, the detected light intensity is relatively low across all wavelengths, with average values lower than in the other conditions. The 63.50% condition demonstrates a significant increase in intensity, particularly at 810 nm and 900 nm, where sharp spikes are observed. At 100% water content, intensity values peak, displaying a pattern similar to the 63.50% condition but with slight increases at 810 nm and 900 nm. This indicates that higher water content correlates with increased light intensity, especially at specific wavelengths around 810 nm and 900 nm, which represent the highest measurements across all conditions.

The accuracy of light intensity measurements by the AS7265x sensor is evident in its ability to detect changes in intensity for colors with high reflectance in specific spectral ranges. This result aligns with the study by (Daurai *et al*., 2023), which states that this sensor has high sensitivity to visible and UV light. Furthermore, the sensor's ability to detect increased intensity in the red and infrared spectrum within the 660-680 nm range. is also consistent with Mathanna *et al.* (2020).

Multiple linear regression for estimating water content

A multiple linear regression model was applied to assess the contribution of each spectral channel to the water content of *K. alvarezii* in the visible and infrared light spectra. The multiple linear regression formulas for the visible and infrared spectra are shown in the equations below.

Visible Spectra:

$$y=0.17\times CH_1 - 0.56\times CH_2 + 0.17\times CH_3 - 1.81\times CH_4+1.56\times CH_5 -1.62\times CH_6 - 4.68\times CH_7 + 0.8\times CH_8 - 0.78\times CH_9 + 0.48\times CH_{10} + 0.32\times CH_{11} + 5.82\times CH_{12} + 17.52 \quad (4)$$

Infrared Spectra:

$$y=1.08 \times CH_{13} - 0.44 \times CH_{14} - 0.13 \times CH_{15} + 0.01 \times CH_{17} + 0.04 \times CH_{18} + 17.41 \quad (5)$$

The visible spectrum in this study ranges from 410 nm to 705 nm, encompassing the violet, blue, green, yellow, orange, and red wavelengths (Channels Ch_A to Ch_J). The infrared spectrum spans 730 nm to 940 nm, covering the near-infrared wavelengths (Channels Ch_T to Ch_L). These ranges correspond to the specific spectral channels of the AS7265X sensor used in the experiment.

Based on the results of the multiple linear regression analysis, differences in the contributions of the visible and infrared spectral channels to the dependent variable (water content) were observed. For example, Channel Ch_E (Channel No. 5) in the visible spectrum, with a positive regression coefficient of 1.56, indicates a significant positive influence on the prediction of water content. In contrast, channel Ch_D (Channel No. 4), with a negative coefficient of -1.81, contributes negatively, suggesting that an increase in intensity in this channel actually decreases the value of the dependent variable. These findings align with the research conducted by Birth, (2020), which demonstrated that channels in the visible spectrum, particularly around the green and yellow wavelengths, have a substantial impact on the characterization of water content-based materials.

Meanwhile, the infrared spectrum channels show more varied patterns. For instance, Channel Ch_T (Channel No. 13) has a positive coefficient (1.08), indicating a positive contribution to water content prediction. However, other infrared channels, such as Ch_U (Channel No. 14) and Ch_V (Channel No. 15), contribute negatively, with coefficients of -0.44 and -0.13, respectively. This is consistent with the findings of Williams, (2009), which suggest that while the infrared spectrum can provide information about water content, certain channels in the near-infrared range often exhibit weaker signals in materials with low water content, reducing the accuracy of the predictions.

Table 2. Accuracy Test Results for Visible and Infrared Light Spectra

Spektrum	R^2	RMSE(% water content)	Percentage Error (%)	Percentage Accuracy (%)
Visible Light	0.79	8.5	19.31	80.69
Infrared	0.61	14.29	33.16	66.84

Figure 6. Changes in seaweed (*K. alvarezii*) texture during the drying process.

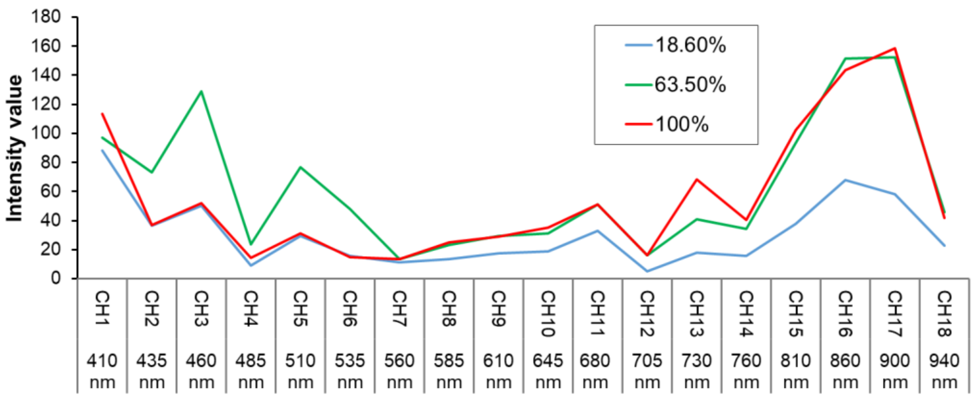

Figure 7. Light intensity values measured for each channel at a specific water content level.

The accuracy tests, including the coefficient of determination (R^2) and Root Mean Square Error (RMSE), were performed separately for these spectral ranges. As shown in Table 2, the visible light spectrum (410–705 nm) demonstrated better performance compared to the infrared spectrum. With an R^2 value of 0.79, the regression model based on the visible spectrum was able to explain 79% of the variation in water content. This R^2 value reflects the collective contribution of all spectral channels in the visible range used in the model, rather than the impact of any single channel. This indicates a relatively high prediction accuracy of the multiple linear regression model for the visible spectrum, as also noted by Baranoski *et al.* (2016), which suggests that wavelengths in the visible spectrum are more effective in predicting physical parameters like water content in biomass materials. This suggests that while the visible spectrum as a whole demonstrated strong predictive power, specific wavelengths, particularly in the green region (*e.g.*, 510 nm), were more influential in determining water content.

In contrast, the infrared spectrum (730 nm – 940 nm) only explained 61% of the variation in water content (R^2=0.61), with a higher RMSE (14.29%), indicating greater prediction error compared to the visible light spectrum. These results align with the findings of Mathanna *et al*. (2020), which state that while the infrared spectrum is useful for water content analysis, it is often more influenced by signal variability, particularly in non-homogeneous materials. Although these findings suggest that the visible spectrum is more reliable for water content analysis in this context, it is essential to acknowledge the inherent potential of the near-infrared region for water detection due to its strong sensitivity to H_2O chemical bonds. However, the observed signal variability in the infrared spectrum underscores the need for further investigation into the interaction between near-infrared wavelengths and the molecular characteristics of water to better understand its predictive potential.

Conclusion

The study successfully utilized the AS7265x sensor to analyze the spectral characteristics of harvested seaweed, *Kappaphycus alvarezii*, revealing significant correlations between water content and light intensity across various wavelengths. The findings indicate that higher moisture levels enhance light absorption, particularly in the near-infrared spectrum around 810 nm and 900 nm. Multiple linear regression analysis further highlighted the distinct contributions of visible and infrared spectral channels, demonstrating that the visible spectrum is more effective for predicting water content, with an R^2 value of 0.79 compared to 0.61 for the infrared spectrum. This underscores the importance of utilizing visible wavelengths for accurate water content analysis in seaweed and potentially other biomass materials. Overall, the results emphasize the reliability of spectral analysis in assessing the physico-chemical properties of seaweeds, paving the way for enhanced applications in agriculture, aquaculture, and environmental monitoring.

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