International Journal of Agricultural Technology 2025 Vol. 21(1):73-84
Available online http://www.ijat-aatsea.com
ISSN 2630-0192 (Online)

# Utilizing of aerial photography to study the distribution of seaweed in Saphan Hin Park, Mueang District, Phuket Province, Thailand

**Kumlom, T.[1,5], Phewphan, U.[2,5*], Ponganan, N.[3] and Rakasachat, C.[4]**

[1]Environmental Science Program, Science and Technology Faculty, Phuket Rajabhat University, Phuket , Thailand; [2]Innovation for Social and Environmental Management, Mahidol University, Amnatcharoen campus, Amnatcharoen, Thailand; [3]Sirindhorn International Institute of Technology (SIIT), Thammasat University, Thailand; [4]Center of Research and Academic Services, Faculty of Environment, Kasetsart University, Thailand, [5]Faculty of Environment and Resource Studies, Mahidol University, Nakhon Pathom, Thailand.

Kumlom, T., Phewphan, U., Ponganan, N. and Rakasachat, C. (2025). Utilizing of aerial photography to study the distribution of Seaweed in Saphan Hin Park, Mueang District, Phuket Province, Thailand. International Journal of Agricultural Technology 21(1):73-84.

**Abstract** Seaweed is essential in ecosystems for producing oxygen and absorbing carbon dioxide, thereby reducing the greenhouse effect. It also provides habitat and food for various aquatic species and helps mitigate coastal erosion. The periodic surveys identified seaweed was done in four periods in January, April, August, and October covered the areas of 897.96 sq.km, 9,164.26 sq.km, 6,462.12 sq.km, and 14,678.95 sq.km, respectively. For Seaweed lumps, the areas were 30.12 sq.km, 310.54 sq.km, 903.28 sq.km, and 1,552.02 sq.km, respectively. The classification results were invaluable for effective natural resource planning and management. While the overall seaweed distribution remained stable, and some areas showed density changes. The resulting maps highlighted the advantages of using UAV aerial snapshots and MLC techniques for accurately identifying seaweed in shallow waters. The findings are anticipated to serve as a model for monitoring changes to support seaweed conservation and restoration and can be applied to other contexts involving natural resource and environmental management.

**Keywords**: Seaweed distribution, Aerial photograph, UAV, Remote sensing, Saphan Hin Park

## Introduction

Seaweed assemblages are essential to coastal environments. They play a critical role in producing oxygen and absorbing carbon dioxide, which helps mitigate climate change (Lakshani *et al.*, 2024). Seaweed also provides habitat and nourishment for many marine species, enhancing biodiversity and boosting coastal productivity. Furthermore, seaweed stabilizes coastlines, reducing erosion and protecting coastal structures (Matos *et al*., 2024).

* **Corresponding Author:** Phewphan, U.; **Email:** uthaiwan.phe@mahidol.edu

Globally, seaweed is gaining attention for its ecological and economic importance. The global seaweed industry has seen significant growth, driven by the increasing demand for seaweed in food, pharmaceuticals, cosmetics, and biofuels. In 2019, the global seaweed market was valued at approximately USD 10.6 billion and is projected to reach USD 26.1 billion by 2025 (FAO, 2020). This rapid expansion highlights the need for sustainable management practices to balance economic benefits with environmental protection.

However, human activities and climate change pose significant threats to seaweed populations. Global warming and ocean acidification are increasing due to the rising concentrations of greenhouse gases, primarily from industrial activities and deforestation. These changes in the environment adversely affect the growth and distribution of seaweed (Thomsen *et al.,* 2016). Additionally, the degradation of coastal habitats due to pollution, overfishing, and coastal development further exacerbates the decline of seaweed populations (Krumhansl *et al*., 2016). Studies have shown that human-induced changes such as coastal reclamation and aquaculture expansion have led to significant reductions in seaweed habitats (Mamun Abdullah Al *et al*., 2020) (Diruit *et al.,* 2022).

Monitoring intertidal seaweed is crucial for effective coastal management and conservation strategies. The distribution and abundance of seaweed are influenced by factors such as water temperature, light availability, nutrient levels, and hydrodynamic conditions. Traditional methods like field surveys and satellite imagery often face limitations in spatial resolution and accessibility (Dadon and Oldani, 2017).

The application of an Unmanned Aerial Vehicle (UAV) as a low-cost and flexible tool has revolutionized ecological monitoring. UAV-based aerial photography allows for detailed mapping and tracking of seaweed distribution over vast areas with minimal environmental interference (De Kock *et al.,* 2022). This technology provides accurate, up-to-date information that is crucial for informed decision-making in coastal management. Additionally, the use of multispectral UAV has proven effective in estimating seaweed biomass, as demonstrated in the intertidal zone of Gouqi Island, where multispectral imagery provided precise data on seaweed distribution and biomass (Román *et al.,* 2021).

Seaweed, along with other biomass, contributes to the organic matter in coastal regions, which is vital for carbon stock estimation. Understanding carbon dynamics in these ecosystems is essential. The importance of estimating aboveground carbon stock for effective resource management and climate change mitigation. Their work in Ubon Ratchathani Zoo provides valuable insights into carbon storage, which can be applied to similar coastal studies. (Muangsong *et al*., 2024).

The study aimed to apply UAV or drone technology as a low-cost and flexible tool for monitoring the distribution of seaweed in Saphan Hin Park, Mueang District, Phuket Province, Thailand.

## Materials and methods

### *Study site*

The study site situated in Saphan Hin Public Park, located in the Mueang District of Phuket Province, functions as a significant relaxation space that effectively combines the attraction of nature with urban facilities. The park is located on the southeastern coast of Phuket Island and has a mostly flat landscape, with some areas reaching heights of around 10 meters above sea level. The climate of the region is characterized as a tropical monsoon environment, with temperatures typically falling between the range of 24°C to 32°C. The average annual precipitation in the area amounts to 2,400 mm. (Akkajit *et al.*, 2018). The park boasts a diverse range of flora and fauna, including lush mangrove forests and a wide array of avian and reptilian species. In addition to its ecological significance, Saphan Hin Public Park plays a pivotal role in community life by hosting a wide range of recreational and cultural activities. This makes it a prime place for doing research on urban ecology and implementing environmental management strategies in coastal regions.

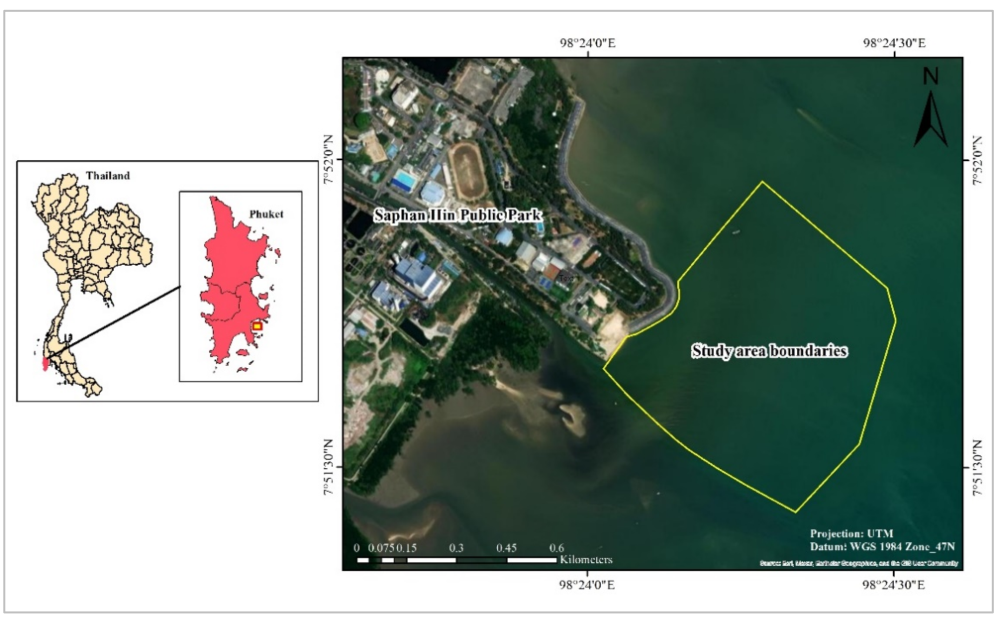


**Figure 1.** The study area in Saphan Hin Public Park, Phuket Province, Thailand

### *UAV data acquisition*

UAV images were collected using a DJI Mavic 3 Pro over a one-year period, with data captured during monitoring cycles in April, August, and October 2023, and January 2024. These time intervals, spaced every 3 to 4 months, were chosen to cover different seasonal conditions. The DJI Mavic 3 Pro was equipped with an RGB camera system, which included a sun incident light sensor and integrated GPS for accurate georeferencing.

Flight plans were designed using the DJI Ground Station Professional application. The UAV operated at a flight altitude of 90 meters, providing a Ground Sample Distance (GSD) suitable for high-resolution analysis. The camera was set to capture nadir photographs, with 70% front overlap and 80% side overlap between images, ensuring seamless stitching during post-processing. To reduce the impact of sun glint, flights were conducted perpendicular to the sun's position during early morning hours. The shooting interval was set to two seconds to maintain continuous image coverage.

### *UAV image processing*

The UAV imagery was processed using PIX4Dmapper following a systematic workflow to ensure high accuracy for scientific analysis. The initial step utilized structure-from-motion (SfM) methods to reconstruct the camera positions and generate a detailed 3D point cloud of the study area. Lens distortion corrections were applied to ensure geometric accuracy.

After aligning the images, bundle adjustment was performed to refine the camera positions and orientations, enhancing the overall precision of the model. Orthomosaics were then generated by stitching the images together, and the resulting outputs were georeferenced using GPS data embedded in the images to accurately map the study area to real-world coordinates.

Radiometric corrections were applied to standardize the images across different flight conditions, using metadata such as sun angle and light conditions during each flight. The corrected orthomosaics were subsequently imported into ArcGIS Pro for spatial analysis. Only datasets collected under favorable conditions, such as good lighting and clear skies, were used to ensure high-quality results. This process ensured reliable data for studying the distribution of seaweed in the area.

### *Image classification*

In this study, a hybrid approach was applied to classify UAV images, combining manual visual interpretation with the Maximum Likelihood

Classification (MLC) algorithm. Initially, UAV imagery was visually inspected to identify key features such as seaweed patches, water bodies, and other relevant elements in the study area. This manual interpretation provided a clear understanding of the scene, ensuring that important features were correctly identified for further automated processing.

MLC method was then used to classify the images. MLC is a widely used supervised classification technique that assigns pixels to the class with the highest probability based on the spectral signatures of the training data (Richards, 2013). Training samples representing different classes such as seaweed, water, and non-vegetated areas—were prepared based on the results from the visual interpretation. These training samples were used to guide the MLC algorithm in classifying the imagery, making use of the spectral and spatial information from the UAV images to map the entire study area.

The combination of manual interpretation and MLC enhanced the accuracy of the classification process. Manual visual interpretation ensured that subtle features were accurately identified, while the MLC algorithm provided a systematic and statistically robust approach to classify the entire area (Mohamed, 2017). The classification results were validated using field data to confirm accuracy and consistency. This hybrid approach demonstrated the effectiveness of combining expert visual analysis with automated classification methods like MLC, particularly for studying complex environmental settings like coastal ecosystems.

By utilizing this method, the study was able to produce a detailed and accurate classification of seaweed distribution. This provided valuable insights for the monitoring and management of marine ecosystems. The hybrid approach showed the benefits of integrating traditional interpretation methods with supervised classification algorithms, such as MLC, for more precise environmental monitoring.

***Classification accuracy assessment***

The classification accuracy was evaluated using two primary metrics: overall accuracy and the Kappa coefficient. A dataset consisting of 113 ground truth points was used for validation, where each point was labeled as either correctly or incorrectly classified.

**Overall accuracy**

Overall accuracy reflects the percentage of correctly classified points out of the total 113 validation points. It is calculated as:

$$\text{Overall Accuracy} = \frac{\text{Correct Classifications}}{\text{Total Observations}} \text{x100}$$

This metric provides a broad measure of classification performance, indicating the effectiveness of the model in classifying all land cover types (Congalton and Green, 2019). Higher overall accuracy suggests that the classification closely aligns with the reference data, showcasing the model's reliability.

**Kappa coefficient**

The Kappa coefficient is used to measure the agreement between classified data and the actual ground truth while considering the possibility of chance agreement (Singh, and Tyagi, 2021). It compares observed accuracy to expected accuracy under random classification conditions. The formula for calculating Kappa is:

$$\text{K} = \frac{(P_o - P_e)}{(1 - P_e)}$$

Where:

- $P_o$ is the observed agreement, calculated as the proportion of correctly classified points
- $P_e$ is the expected agreement, representing the agreement that could

## Results

### *Seaweed distribution analysis*

This study utilized UAV or drone technology to capture high-resolution images for analyzing seaweed distribution patterns over four different periods combined with field surveys. The integration of UAV data and ground observations enabled the identification of two types of seaweed in the study area: seaweed (general seaweed) and seaweed lumps, as presented in Figure 2. The spatial distribution of these seaweed types in the study area during each observation period is shown in Figure 3.

The results demonstrated significant variations in seaweed distribution over time. During the first observation in April 2023, regular seaweed covered an area of 9,164.26 sq.m., while seaweed lumps occupied 310.54 sq.m.. In the second observation in August 2023, the area of seaweed decreased to 6,462.12 sq.m., while seaweed lumps expanded to 903.28 sq.m.. By the third observation in October 2023, a significant increased in seaweed coverage was recorded, with regular seaweed reaching 14,678.95 sq.m. and seaweed lumps increasing to 1,552.02 sq.m.. However, during the fourth observation in January 2024, a sharp decline in regular seaweed coverage was observed, reducing to only 897.96 sq.m., and no seaweed lumps were detected during this period (Teble 1).


**Figure 2.** (a1) and (a2) represent seaweed, (b1) and (b2) shows seaweed lumps

The variation in seaweed distribution, as illustrated in Figure 3, which highlighted the influence of environmental conditions on the seasonal growth and spatial patterns of seaweed in the study area. This pattern provides essential information for the management and conservation of marine ecosystems.

**Table 1.** seasonal variations in seaweed distribution and total seaweed area across four observation periods

| **Time** | **Area (sq.m.)** | | | |
|---|---|---|---|---|
| | **1st** | **2nd** | **3rd** | **4th** |
| **Date** | April, 2023 | August, 2023 | October, 2023 | January, 2024 |
| Seaweed | 9,164.26 | 6,462.12 | 14,678.95 | 897.96 |
| Seaweed lumps | 310.54 | 903.28 | 1,552.02 | 0 |
| Other's area | 481,587.61 | 483,697.02 | 474,831.44 | 490,161.40 |
| Total Area | 491,062.41 | 491,062.41 | 491,062.41 | 491,059.35 |

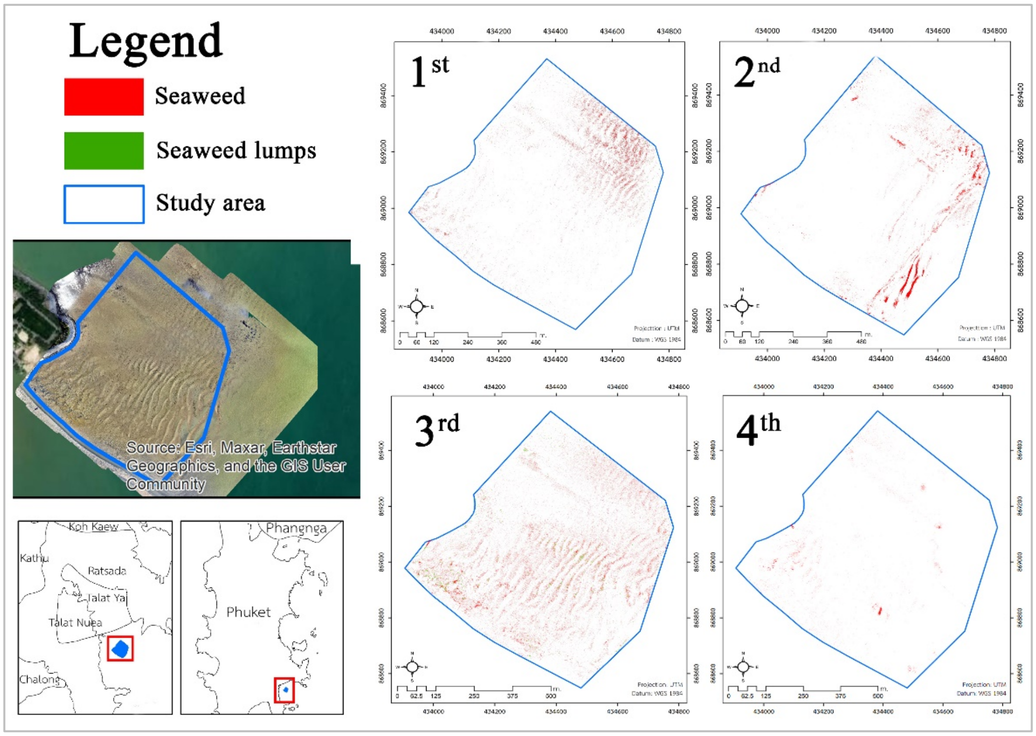


**Figure 3.** Distribution of Seaweed in Saphan Hin Public Park, Phuket Province, Thailand

***Classification accuracy assessment***

The accuracy of the image classification was evaluated using the Overall Accuracy and Kappa Coefficient to measure the performance of the model. The classification achieved an Overall Accuracy of 83.19%, indicating that most of the ground truth points were correctly classified. Out of a total of 113 points, 94 were correctly classified, while 19 were misclassified. The Kappa Coefficient was calculated to be 0.399, indicating a moderate level of agreement between the classified data and the ground truth, beyond what would be expected by chance alone. The Kappa value ranged from -1 to 1, with values closer to 1 showing stronger agreement. Kappa values between 0.6 and 0.8 indicated good agreement, while values above 0.8 represented a near-perfect agreement. These results suggested that the classification model used in this study is reasonably reliable for mapping the target features in the study area. However, there is room for improvement to achieve higher agreement levels.

## Discussion

The results indicated that seaweed distribution in the study area exhibited a clear seasonal pattern, with notable fluctuations in coverage over the year. During the first and second observation periods (April and August 2023), the seaweed coverage decreased, which may be attributed to suboptimal conditions such as lower water temperatures or reduced nutrient availability (Diruit *et al*., 2022; Chayhard *et al.,* 2018b). Conversely, a significant increased in seaweed area was observed in October 2023, reaching its peak during this period. It is suggested that favorable environmental factors, such as increased sunlight and stable water temperatures, supported rapid seaweed growth, a finding consistent with previous studies that highlight the role of temperature and light in seaweed distribution.

By January 2024, a sharp decline in seaweed coverage was recorded, with no seaweed lumps observed. This reduction may be linked to environmental stressors such as higher wave energy, cold water temperatures, and potential nutrient depletion (Taddia *et al*., 2020; Chayhard *et al*., 2018b). These findings aligned with previous research that demonstrated the impact of seasonal variations on seaweed biomass and distribution in coastal environments (Chen *et al*., 2023).

Although this study effectively mapped the seaweed distribution using UAV imagery, a gap remains in understanding the long-term effects of environmental changes on different seaweed species. Previous studies have focused primarily on short-term monitoring and specific seasonal observations (Waqas *et al*., 2024).; Chayhard *et al*., 2018a). Therefore, integrating continuous, long-term UAV monitoring with additional environmental parameters, such as water quality and nutrient levels, would provide a more comprehensive understanding of the factors driving seaweed dynamics over extended periods.

The UAV-based monitoring approach proved effective in distinguishing two types of seaweed: regular seaweed and seaweed lumps. The use of high-resolution imagery enabled detailed spatial analysis, allowing for the identification of small-scale variations that are often missed in satellite imagery (Nurdin *et al.,* 2023). Moreover, the classification accuracy, with an Overall Accuracy of 83.19% and a moderate Kappa Coefficient of 0.399, suggests that while the methodology is reliable, there is still room for improvement. Incorporating more advanced classification techniques, such as machine learning models, could further enhance accuracy and reduce classification errors (Chen *et al*., 2023; Chayhard *et al*., 2018a).

Overall, the study demonstrated the effectiveness of UAV technology for environmental monitoring and the potential to integrate UAV data with traditional field surveys for a more detailed understanding of coastal ecosystems. This combined approach offers a powerful tool for the sustainable management of marine resources, contributing to improved monitoring strategies and more accurate assessments of seaweed ecosystems.


## Acknowledgements

The authors would like to express their sincere gratitude to Phuket Rajabhat University for providing research funding and to Mahidol University, Amnat Charoen Campus, for their support in providing the necessary equipment for the field survey. This research was also supported by funding from the National Research Council of Thailand (NRCT). This research would not have been possible without their invaluable assistance and support.


## References


Akkajit, P., Jaileak, K., Suteersak, T. and Prueksakorn, K. (2018). Assessment of heavy metals in sediment at Saphan Hin, Phuket. Chemical Engineering Transactions, 63:301-306.

Chayhard, S., Manthachitra, V., Nualchawee, K. and Buranapratheprat, A. (2018a). Application of unmanned aerial vehicle to estimate seagrass biomass in Kung Kraben Bay, Chanthaburi province, Thailand. International Journal of Agricultural Technology, 14:1107-1114.

Chayhard, S., Manthachitra, V., Nualchawee, K. and Buranapratheprat, A. (2018b). Multi-temporal mapping of seagrass distribution by using integrated remote sensing data in Kung Kraben Bay, Chanthaburi Province, Thailand. International Journal of Agricultural Technology, 14:161-170.

Chen, J., Wang, K., Zhao, X., Cheng, X., Zhang, S., Chen, J. and Li, X. (2023). Satellite imagery-estimated intertidal seaweed biomass using UAV as an intermediary. Remote Sensing, 15:4428.

Congalton, R. G. and Green, K. (2019). Assessing the accuracy of remotely sensed data: Principles and practices (3rd ed.). CRC Press. Retried from https://doi.org/10.1201/9780429052729

Dadon, J. R. and Oldani, J. I. (2017). Interjurisdictional coastal management in metropolitan areas. Ocean & Coastal Management, 148:260-271.

De Kock, M. E., Pohůnek, V. and Hejcmanová, P. (2022). Semi-automated detection of ungulates using UAV imagery and reflective spectrometry. Journal of Environmental Management, 320:115807.

Diruit, W., Le Bris, A., Bajjouk, T., Richier, S., Helias, M., Burel, T. and Ar Gall, E. (2022). Seaweed habitats on the shore: Characterization through hyperspectral UAV imagery and field sampling. Remote Sensing, 14:3124.

FAO (2020). The global status of seaweed production, trade, and utilization. Food and Agriculture Organization of the United Nations. Retried from https://doi.org/10.4060/ca9229en

Krumhansl, K. A., Okamoto, D. K., Rassweiler, A., Novak, M., Bolton, J. J., Cavanaugh, K. C. and and Byrnes, J. E. K. (2016). Global patterns of kelp forest change over the past half-century. Proceedings of the National Academy of Sciences, 113:13785-13790.

Lakshani, M. M. T. B., Thilakarathna, M. K. S., Kumarasinghe, D. C. H. S. and Jayasooriya, R. G. P. T. (2024). Role of seaweed as a biofertilizer. In The Role of Seaweeds in Blue Bioeconomy (pp. 292-311). Bentham Science Publishers. https://doi.org/10.2174/9789815223644124010017

Mamun Abdullah Al, Akhtar, A., Rahman, M. F., Kamal, A. H. M., Karim, N. U. and Hassan, M. L. (2020). Habitat structure and diversity patterns of seaweeds in the coastal waters of Saint Martin's Island, Bay of Bengal, Bangladesh. Regional Studies in Marine Science, 33:100959.

Matos, J., Cardoso, C., Serralheiro, M. L., Bandarra, N. M. and Afonso, C. (2024). Seaweed bioactives potential as nutraceuticals and functional ingredients: A review. Journal of Food Composition and Analysis, 133:106453.

Mohamed, M. A. (2017). Monitoring of temporal and spatial changes of land use and land cover in metropolitan regions through remote sensing and GIS. Natural Resources, 8:353-369.

Muangsong, C., Phewphan, U., Kongsombat, P., Meengoen, N., Thongdeephan, T., Chanhom, D. and Pumijumnong, N. (2024). Estimation of aboveground carbon stock in service area of Ubon Ratchathani Zoo, Ubon Ratchathani province, Northeastern Thailand. International Journal of Agricultural Technology, 20:197-212.

Nurdin, N., Alevizos, E., Syamsuddin, R., Asis, H., Zainuddin, E. N., Aris, A., Oiry, S., Brunier, G., Komatsu, T. and Barillé, L. (2023). Precision Aquaculture Drone Mapping of the Spatial Distribution of Kappaphycus alvarezii Biomass and Carrageenan. Remote Sensing, 15(14), Article 14. https://doi.org/10.3390/rs15143674

Richards, J. A. (2013). Remote sensing digital image analysis (5th ed.). Springer-Verlag. Retried from https://doi.org/10.1007/978-3-642-30062-2

Román, A., Tovar-Sánchez, A., Olivé, I. and Navarro, G. (2021). Using a UAV-mounted multispectral camera for the monitoring of marine macrophytes. Frontiers in Marine Science, 8. https://doi.org/10.3389/fmars.2021.722698

Singh, M. and Tyagi, K. D. (2021). Pixel-based classification for Landsat 8 OLI multispectral satellite images using deep learning neural network. Remote Sensing Applications: Society and Environment, 24:100645.

Thomsen, M. S., Wernberg, T., South, P. M. and Schiel, D. R. (2016). Non-native seaweeds drive changes in marine coastal communities around the world. In Z.-M. Hu & C. Fraser (Eds.), Seaweed phylogeography: Adaptation and evolution of seaweeds under environmental change. Springer Netherlands, pp.147-185.

Taddia, Y., Russo, P., Lovo, S. and Pellegrinelli, A. (2020). Multispectral UAV monitoring of submerged seaweed in shallow water. Applied Geomatics, 12:19-34.

Waqas, M. A., Hashemi, F., Mogensen, L. and Knudsen, M. T. (2024). Environmental performance of seaweed cultivation and use in different industries: A systematic review. Sustainable Production and Consumption, 48:123-142.

(Received: 30 September 2024, Revised: 9 January 2025, Accepted: 15 January 2025)