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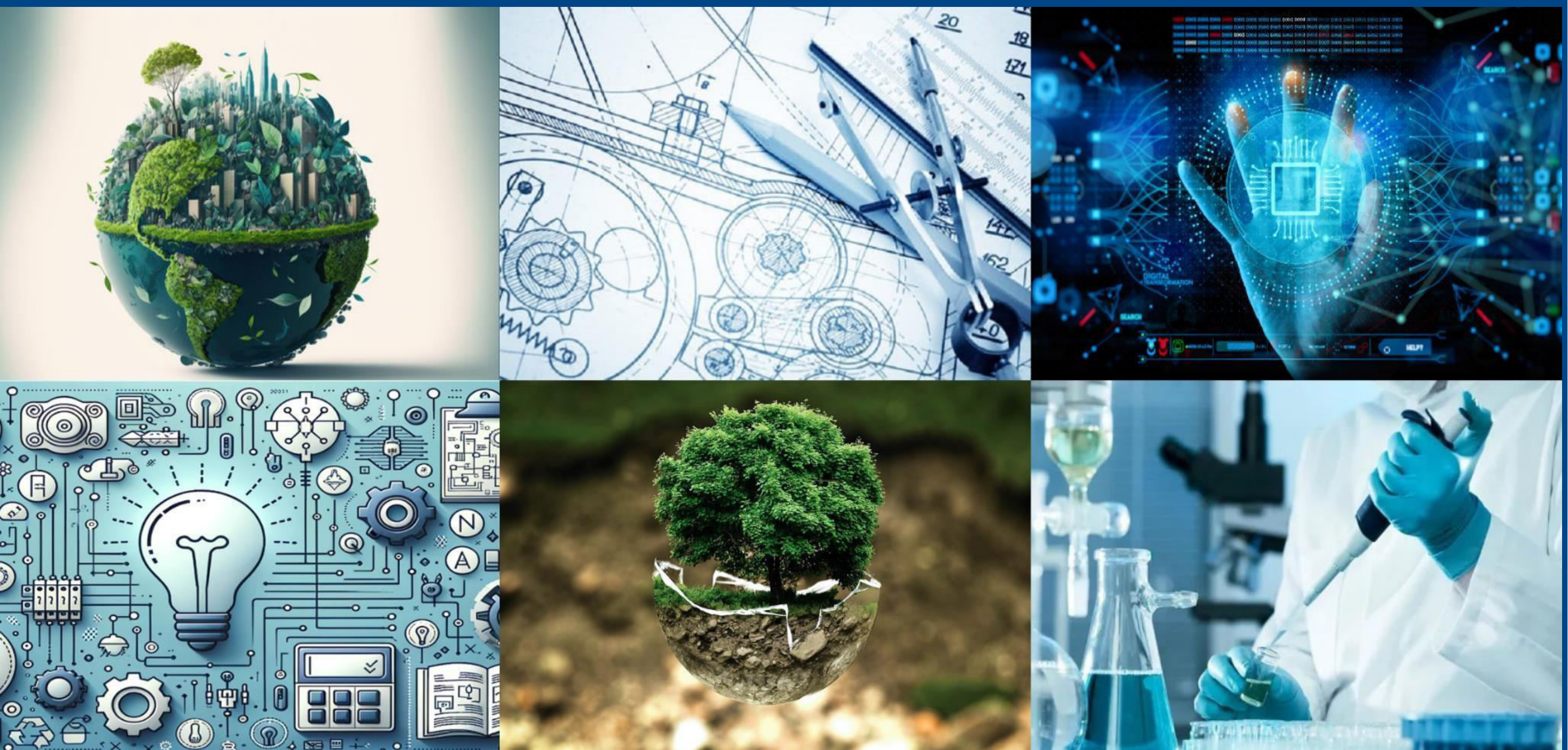

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A Hybrid Approach integrating GIS, Remote Sensing and AI for Monitoring Coastal Macroalgal Diversity: A Review

Vasuki Subramanian*

Assistant Professor, PG and Research Department of Zoology, Kunthavai Naacchiyaar Government Arts College for Women (A), Thanjavur, Tamil Nadu, India

*Corresponding author Email: dr.vasukisubramanian@kngac.ac.in

ABSTRACT: Macroalgae or seaweeds play a vital role in intertidal ecosystems, where they are widely studied for their biodiversity and ecological significance. As these zones represent a dynamic interface between marine and terrestrial environments, macroalgae are often used as model systems for understanding ecological processes. This review presents findings on algal communities from various coastal regions. Unlike, traditional studies that mainly focus on biomass and population structure, this approach highlights the integration of UAV-based remote sensing, GIS, and AI with conventional coastal sampling techniques. The paper discusses the advantages and limitations of this combined methodology. By merging these technologies, this review shows a comprehensive, cost-effective, and real-time approach for monitoring coastal seaweed ecosystems. Overall, it highlights the value of an integrated GIS–remote sensing–AI framework for assessing seaweed diversity, promoting sustainable resource management, and supporting conservation planning amid climate change and human-induced pressures.

KEYWORDS: Marine algal communities, GIS, remote sensing, hyperspectral, machine learning, UAV surveying and mapping, spatial distribution.

I. INTRODUCTION

Macroalgae or seaweeds have been used since ancient times as food, mainly by Asian countries, while in Western countries, their main application has been as gelling agents and colloids for the food, pharmaceuticals, and the cosmetic industry. Many species of seaweed are edible and are a good source of proteins, vitamins, minerals, trace elements and dietary fiber. Polyphenols, polysaccharides, and sterols, as well as other bioactive molecules, are mainly responsible for the healthy properties associated with seaweed.

Seaweeds are a valuable component of marine biodiversity that play multiple essential roles in coastal ecology. Seaweeds play a role in marine ecosystem as a primary producer, providing food and habitat for other marine life. They contribute to oxygen production and carbon sequestration, helping to regulate the Earth's climate. Though the uses of seaweeds are immense, a concrete data on distribution and biodiversity is lacking throughout the world. So, the present review focuses on can remote sensing and AI driven technology for filling this gap rather than traditional methods used so far.

II. BIODIVERSITY OF ALGAE

Assessing biodiversity of seaweeds involves combining traditional field methods with modern technological approaches. Each method provides different kinds of data—ranging from species presence to distribution, abundance, and genetic diversity.

Methods Used to Study Seaweed Biodiversity

1.Traditional methods

The traditional methods for studying seaweeds populations frequently involve direct observations and sampling within the seaweed habitat**.** Some of the traditional methods commonly used are:

a. Quadrant Sampling

A quadrat is a square or rectangular frame of a defined size, which is placed randomly within the study area to sample the seaweed population. The number of individuals or the biomass within the quadrat is then recorded to estimate the density and abundance of different seaweed species [1].

b. Line Transects

A line is marked out across the habitat, and researchers walk along the line, observing and counting seaweed individuals or recording the presence or absence of different species at regular intervals. Seaweed samples are collected and examined in the laboratory or field to determining their size, growth stage, and reproductive structures. These traditional methods provide valuable data for understanding seaweed population, but they can be time-consuming and labor intensive.

2. Remote Sensing (RS) and Geographical Information System (GIS)

RS uses sensors to collect data about the Earth's surface without physical contact. This data includes satellites photos, aerial photos etc. Whereas, GIS is a system that performs data management - that is it organizes, analyzes, and visualizes geographic data. GIS can incorporate data from remote sensing, as well as other sources like field surveys, maps, and other databases. Remote sensing offers a valuable approach to studying seaweed populations by providing extensive area observation and prompt data acquisition. Satellites like Sentinel-2, with its high spatial resolution and multispectral capabilities, can be used to monitor seaweed extent, species, and even biomass. These satellites record detailed information across multiple spectral bands, allowing for the identification of seaweed based on its unique reflectance patterns.

a. UAVs (Unmanned Aerial Vehicles)

UAVs, equipped with multispectral or hyperspectral cameras, can be used to collect high-resolution imagery of seaweed communities, particularly in intertidal zones. This allows for detailed assessment of seaweed biomass and growth patterns.

b. Hyperspectral Data

Hyperspectral data, capturing many narrow spectral bands, can provide more detailed information about seaweed species and health. Numerous studies have used hyperspectral data to identify different seaweed species and assess their physiological status.

c. Vegetation Indices

Vegetation indices, like NDVI (Normalized Difference Vegetation Index) or EVI (Enhanced Vegetation Index), can be calculated from multispectral data to quantify seaweed biomass and health.

3. Artificial Intelligence (AI) and Machine Learning (Ml)

Artificial Intelligence, in fact is a broad field of computer science that aims to create intelligent agents that can perform tasks that requires human intelligence. While GIS deals with spatial data and its analysis, AI focuses on developing algorithms and systems that can learn, reason, and make decisions based on data. Machine learning algorithms, such as those used in deep learning models (e.g., UNet, DeepLabv3, SegNet), can be applied to classify and extract seaweed areas from satellite or UAV imagery.

4. Geospatial AI

While GIS and AI have distinct focuses, they are progressively being combined to create new and powerful applications. This convergence is often referred to GeoAI or Geospatial AI, which combines the strengths of both fields. GIS offers the spatial framework and tools to handle and analyze geographic data, while AI contributes the intelligence and algorithms needed to derive insights and support decision-making from that data. GeoAI integrates Geographic Information Systems (GIS) with AI technologies to extract meaningful insights from spatial data. GeoAI models can forecast future scenario's, such as population growth, seaweed biomass, monitoring aquaculture, and mapping natural seaweed beds enabling active planning and mitigation.

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III. ROLE OF GIS, RS AND AI FOR MONITORING COASTAL MACROALGAL DIVERSITY

1.Giant Kelps and Fucus

Giant kelp (Laminariales) is a fast-growing seaweed that forms the base of important ocean ecosystems found across the globe. Kelp forests are found on shallow subtidal rocky reefs in temperate marine regions worldwide. It is well known fact that the kelps serve as foundation species by contributing to primary production and offering complex three-dimensional habitats that support a wide range of ecologically, culturally, and economically significant marine organisms. Kelp forests exhibit high sensitivity to environmental variability and are increasingly threatened by range of stressors operating at both local and global scales. Remote sensing offers a powerful and efficient approach to address the data needs for kelp forest monitoring. Canopy-forming kelp species are especially well suited for identification through airborne, and satellite remote sensing, particularly when multispectral imagery is employed. This capability has supported a long-standing body of research employing remote sensing techniques to track changes in kelp canopy extent and harvestable biomass [2].

Bell et al. [3] and his team analyzed 28 years of data from Landsat satellite images along the California coast to understand the main patterns in kelp growth over time. They compared the amount of chlorophyll a to carbon (Chl\:C ratio) in kelp collected off California with lab and airborne hyperspectral data to create ways to measure kelp health using remote sensing and compared to corresponding laboratory and airborne hyperspectral reflectance data. There findings showed that HyspIRI's detailed spatial, temporal, and spectral data can help us better understand the ecological dynamics and physiological functioning of giant kelp forests. A fully automated method was elucidated to measure giant kelp canopy biomass using image from three different Landsat satellites. A 34-year seasonal data of kelp canopy biomass for about 1,500 kilometers of the California coast, was made is available to the public. The kelp trends were linked to slow, large-scale ocean climate pattern such as the North Pacific Gyre Oscillation [4]. To clearly assess the long-term impacts of climate change on giant kelp, it is prerequisite to have extended and continuous satellite observations that span beyond natural oceanic cycles [5].The degradation or loss of kelp beds is expected to have significant ecological consequences, particularly for subcanopy species such as *Haliotis iris* (pāua) and *Jasus edwardsii* (rock lobster), which depend on the structural complexity of kelp habitats. The decline of these forests may result in altered light penetration and hydrodynamic conditions, further impacting the biodiversity, and functioning of these marine ecosystems. D'Archino, et al. [6] emphasized the effectiveness of machine learning (ML)-based automatic detection methods in accurately identifying macroalgal distributions at species, genus, and group levels.

In another study, Gihan et al. [7] examined seaweed distribution and abundance using field investigations with the quadrat method, along with satellite images from the Enhanced Landsat Thematic Mapper (ETM+). In the satellite images, different types of macroalgae appeared mixed together, making them difficult to distinguish. Additionally, the remote sensing data primarily represented general land cover types such as vegetation, bare soil, and water bodies, rather than clearly depicting seaweed on the seafloor.

Fucus is an intertidal brown alga belonging to the order Fucales, commonly found along temperate coasts such as those of the North Atlantic. It plays an important ecological role as both a primary producer and a habitat-forming species in rocky shore ecosystems, offering shelter and food to a variety of marine organisms. An annual monitoring of littoral algae distribution in the bays of the Barents Sea from 2021-2024 was performed using UAV-based remote sensing. An increase in algae biomass was observed and was associated with an increase in summer temperature and water salinity. *Fucus serratus* and *Pelvetia canaliculata* populations remained stable whereas Ulvophycean algae showed seasonal peaks of development with abnormally high biomass in areas of anthropogenic impact, which indicates eutrophication [8].

Subtidal in situ sampling methods are effective, but they are expensive and time-consuming. Because of this, it is difficult to use them regularly for long-term monitoring Hence, more recent techniques, such as remote sensing and advanced imaging techniques, are being used to complement traditional methods and provide more detailed and large-scale assessments of seaweed population [9].

2.Algal Tides and Blooms

Early detection of green macroalgae patches by satellite imagery is of great importance. A study comparing three types of satellite data: CCD images from China's HJ-1A/B satellites, SAR images from ENVISAT, and MODIS images from the TERRA satellite was carried out from massive floating green macroalgae bloom that has occurred for several years repeatedly in the Yellow Sea since 2007 [10]. The CCD data from the HJ-1A/B satellite was given as the best choice for early detection and warning of algae blooms whereas SAR data, showed as a valuable supplementary source, particularly under adverse atmospheric conditions such as cloud cover, fog,, or haze, where optical sensors are less effective.

Zhang et al. [11] found about 2,784 tons of *Ulva prolifera* attached to the rafts and this alga had the same DNA type as the one found in 2013 green algal bloom. These findings gave substantial evidence that the biomass of *Ulva* species thriving on *Pyropia* rafts significantly contributed to the rapid initiation and expansion of the green algal bloom in the Yellow Sea. Xu et al. [12] created a model to estimate algae by using both Sentinel-2A satellite images and drone images. The algae were detected accurately using a method called the Normalized Green-Red Difference Index (NGRDI). Long-term tracking of this algae can help scientists better predict and control green tides in the Yellow Sea. The smaller quantity of algae explained why the green tide in 2017 was not large. Xu et al. [13] utilized three different algorithms that work with RGB (red, green, blue) images developed from quad-rotor UAV equipped with an RGB camera. A notable difference in the maximum value among the red, green, and blue bands in the aerial photos was proven and the difference in the green band, was important for detecting green tide. Among the evaluated indices, the GLI (Green Leaf Index) was found to be the best index for mapping floating green tide on the beach. This highlighted the potential of UAV-based RGB imaging as a reliable, comprehensive, and scientifically sound approach for monitoring floating green tide on seabeaches. In clam farming, sudden algal blooms in shallow waters can pose a serious threat, as they rapidly create anoxic conditions that lead to the death of molluscs. The Goro Lagoon in Northern Italy, a well-known area for clam cultivation, was studied using a MicaSense RedEdge-M multispectral camera mounted on a DJI phantom 3 Professional drone. This approach proved effective for the early detection, mapping, and monitoring of underwater seaweed blooms over time, while radiometric calibration significantly improved the accuracy and reliability of the results [14].

Nutrient enrichment in estuarine and coastal waters is a primary driver of green tide formation. However, the extent, distribution, and species composition of these blooms can vary greatly even among systems with similar nutrient conditions. Identifying the factors responsible for these variations is crucial for developing and testing explanatory models. In one such study, Bermejo et al. [15] examined the spatial and temporal patterns of biomass distribution of two *Ulva* morphotypes in two Irish estuaries heavily impacted by green tides (wet biomass exceeding 1 kg m^{-2} at peak bloom). The blooms were multi-specific, with tubular forms (*U. prolifera* and *U. compressa*) and laminar forms (*U. rigida*) showing distinct distribution patterns that significantly influenced nutrient and biomass dynamics within the estuary. Such findings improve the accuracy and applicability of remote sensing techniques.

Xiao et al. [16] investigated the relationships among various spectral indices, including the Normalized Difference Vegetation Index (NDVI), Floating Algae Index (FAI), Ratio Vegetation Index (RVI), Enhanced Vegetation Index (EVI), and Ocean Surface Algal Bloom Index (OSABI). The results indicated that EVI, NDVI, and FAI exhibited strong exponential correlations with the biomass per unit area of *Ulva prolifera*. Using the EVI-biomass relationship, a long-term MODIS image series was analyzed to estimate the maximum total biomass of floating *U. prolifera* in the Yellow Sea between 2007 and 2016. Here, the interannual variations in biomass were intricately linked to nutrient inflows from the Sheyang River-Jiangsu Province's largest northern river-and the scale of *Porphyra* aquaculture in the Radial Sand Ridges area. These two factors were identified as the main drivers of the observed variability in *U. prolifera* bloom intensity throughout the study period.

In another study, Jiang et al. [17] employed two distinct methods to estimate algal biomass: one for algae attached to nursery nets (GAAN) and another for algae growing on ropes (GAAR). The GAAN approach utilized drone (UAV) imagery, high-resolution satellite data, and statistical yearbook records, while the GAAR method combined satellite imagery with field-based measurements. Ongoing monitoring of GAAN and GAAR biomass over time yielded valuable quantitative data to support economic forecasting for *Porphyra yezoensis* aquaculture and aided in formulating effective strategies for mitigating green tide events.

Le Gao et al. [18] developed an enhanced deep learning (DL) model for detecting *Ulva prolifera* algae using MODIS and SAR remote sensing data, achieving high detection accuracy. Their analysis revealed that the maximum biological coverage of U. prolifera in 2021 was nearly four times higher than in 2020, a change influenced by both natural and human-driven factors. Additionally, the floating-to-submerged (FS) algae ratio was identified as a reliable indicator for evaluating the vitality and spatial distribution of floating *U. prolifera* blooms.

Geng et al. [19] recommended integrating various types of satellite data with oceanography information and artificial intelligence techniques, such as deep learning to enhance the accuracy and reliability of monitoring and forecasting in

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coastal regions like the Yellow Sea and East China Sea. In these areas, *Ulva prolifera* green tide events have significantly impacted marine ecosystems and the fishing industry. AI-based models for species identification utilize machine learning—especially deep learning—to analyze and categorize images into distinct species. Trained on extensive datasets of labeled images, these models learn to detect patterns and features unique to each species. Compared to traditional identification methods, they provide greater speed, accuracy, and scalability, making them powerful tools for biodiversity assessment, conservation, and scientific research [20].

The rapid growth of harmful algal blooms (HABs) places significant stress on coastal ecosystems. These blooms develop when favorable environmental factors—such as elevated nutrient levels, warm temperatures, and calm water conditions—stimulate excessive algal growth. In general, algal blooms or tides can negatively impact marine environments by reducing oxygen levels, limiting sunlight penetration, and disrupting fisheries and tourism activities. Such studies on the early detection of algal tides and blooms can be of great importance for coastal monitoring and management.

3.Application in Marine Aquaculture

UAV-based spectral imaging is widely used for high-throughput phenotyping in terrestrial crops, grasslands, and forests, its application in marine aquaculture remains largely unexplored. Also**,** GIS serves as an effective tool for identifying potential coastal sites suitable for seaweed cultivation. Flavo et al. [21] applied GIS combined with multi-criteria evaluation (MCE) to determine the most suitable areas for cultivating the seaweed *Gracilaria birdiae* (Gracilariales, Rhodophyta) along the coast of Rio Grande do Norte State, Brazil. Siddiqui and Zaidi [22] assessed the performance of two satellite sensors—high- resolution WorldView-2 (WV-2) and medium-resolution Landsat 8—in mapping seaweed resources along the coastal waters of Karachi, Pakistan. Their findings revealed that Landsat 8 overestimated the seaweed coverage to 71.28 hectares (0.7128 km^2), mainly due to spectral mixing between seaweed and adjacent water pixels. In contrast, the high-resolution WV-2 imagery proved more effective and accurate for delineating seaweed patches.

Siddiqui et al. [23] utilized the near-infrared (NIR) and shortwave-infrared (SWIR) spectral bands from Landsat 8 satellite imagery and developed a novel remote sensing-based Seaweed Enhancing Index (SEI). In addition to this SEI, the Normalized Difference Vegetation Index (NDVI) and the Floating Algae Index (FAI) were also employed to map seaweed in the coastal waters near Karachi, Pakistan. The SEI showed mapping accuracy equal to or superior to that of NDVI for detecting seaweed. *Pyropia*, an economically valuable genus of red macroalgae, has been cultivated along East Asian coasts for over 300 years. Therefore, developing fast and efficient methods to estimate seaweed growth would greatly benefit both aquaculture and research. Che et al. [24] utilized UAV-based multispectral imaging to monitor *Pyropia yezoensis* cultivation in the northern region of Haizhou Bay, located along the Yellow Sea coast.

Indonesia ranks among the world's top seaweed producers, particularly for species such as *Kappaphycus alvarezii*, *Eucheuma denticulatum*, and *Gracilaria*. Seaweed aquaculture is a vital part of the nation's coastal economy, supporting the livelihoods of thousands of small-scale farmers. However, the Indonesian government and seaweed industry often struggle with the lack of reliable data on potential harvest yields. Pratama and Albasri [25] addressed this issue by estimating the harvest potential of *Kappaphycus alvarezii* using a supervised classification method applied to WorldView-2 satellite imagery. Their analysis, validated with field data, achieved an accuracy of 79.05%. The satellite-based estimation indicated a potential yield of approximately 531.26 tons of dry seaweed, with a variation of about ±250.29 tons. *Neopyropia* is a red seaweed that is widely farmed in East Asia and has economic value. Generally, in red algae, phycobilisomes and chlorophyll-a (Chla) are crucial for photosynthetic activity. The amounts and ratios of three pigments-phycoerythrin (PE), phycocyanin (PC), and allophycocyanin (APC)-along with Chla, can be used to judge the quality of the seaweed. Hence, Che et al. [26] used hyperspectral imaging that can rapidly and non-destructively estimate pigment levels in *Neopyropia*. Using a specialized camera to capture images across wavelengths from 400 to 1000 nanometers, the researchers analyzed the data with two machine learning techniques: partial least squares regression (PLSR) and support vector machine regression (SVR).

Recent progress in the use of satellite remote sensing imagery has greatly improved the inventory and management of aquaculture areas. To bridge existing gaps, Zhu et al. [27] made important early contributions toward integrating remote sensing technologies into aquaculture monitoring. Their research supported the advancement of high-quality aquaculture practices, promoted the sustainable use of marine resources, and contributed to the protection and enhancement of the marine ecological environment. Jin et al. [28] utilized high-resolution (3- meter) satellite imagery from PlanetScope to map seaweed farms along China's coastline. They applied an object-based classification technique, which enabled the

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precise identification of 129,494 hectares of seaweed farms with an overall accuracy of 95.70% and a KAPPA coefficient of 0.912. Based on these results, they produced a detailed seaweed farm distribution map for China's coastal waters covering the period from 2018 to 2019.

Tonion and Pirotti [29] applied a supervised classification approach, training a computer model using known data to identify seaweed. Their analysis utilized spectral indices derived from Sentinel-2 satellite imagery and employed a machine learning algorithm known as Random Forest (RF). Various versions of the RF model were tested to evaluate their effectiveness in monitoring seaweed distribution along Ireland's west coast. The RF models performed exceptionally well, producing minimal errors, and confirming that machine learning (ML) is a reliable and effective method for predicting seaweed presence. It can help people who need a smart and quick way to monitor seaweed biomass in coastal areas.

Chen et al. [30] developed a high-precision monitoring framework by integrating Otsu thresholding with random forest classification, implemented within the Google Earth Engine platform using 10-meter resolution Sentinel-2 imagery. This methodology was applied to examine the spatiotemporal dynamics of seaweed cultivation across the Korean Peninsula over the period from 2017 to 2023. By integrating spectral characteristics, seaweed phenological patterns, and field-based cultivation practices, they could effectively distinguish the dominant cultivated species—laver (*Pyropia*) and kelp (*Saccharina* and *Undaria*). Kumlom et al. [31] employed a hybrid methodological framework that integrated traditional image interpretation techniques with supervised classification algorithms, including Maximum Likelihood Classification (MLC), to enhance the spatial distribution of seaweed in Saphan Hin Park, Mueang District, Phuket Province, Thailand. These approaches both RS and AI collectively demonstrated greater potential for advancing macroalgal breeding, phenomics research, and aquaculture management. By improving monitoring and providing more accurate assessments of seaweed ecosystems, they support sustainable aquaculture practices. Given the low investment and high economic returns of seaweed farming, such methods contribute significantly to marine resource management, economic growth, and food security.

4.Monitoring of Invasive Seaweed Species

Invasive seaweeds are non-native marine algae that establish and spread quickly in new environments, often outcompeting native species. Their ability to withstand a broad range of environmental conditions enables them to dominate coastal ecosystems and disrupt natural community structures and ecological functions. Notable examples include *Asparagopsis armata*, *Caulerpa taxifolia*, and *Sargassum muticum*. Several studies have documented biodiversity shifts and the ecological consequences of seaweed invasions in marine ecosystems. One such study on the Azorean coasts evaluated the use of high-resolution drone imagery to map complex seaweed habitats, focusing on the invasive and commercially valuable species *Asparagopsis armata*. *Asparagopsis* is a filamentous red alga (Rhodophyta) of great taxonomic and biodiversity significance. Using support-vector machine, random forest, and artificial neural network algorithms, researchers developed predictive models to estimate seaweed cover. This approach offered large-scale insights into both the ecological benefits and invasive impacts of the species (Kellaris et al. [32].

5.AI-Driven Detection of Halogenated Compounds in Marine Macroalgae

Volatile hydrocarbons are low molecular weight compounds naturally released by some macroalgae during metabolic and defense activities. Although research is still developing, their distinct chemical profiles offer promising potential for identifying seaweeds in their natural environments. Different seaweed species emit unique volatile organic compounds (VOCs), such as ethylene, isoprene, and short-chain alkanes or alkenes, creating chemical "fingerprints" useful for identification. Green algae such as *Ulva, Caulerpa*, *Halimeda*, and *Codium*; red algae such as *Asparagopsis*, *Laurencia*, and *Plocamium*; and brown algae such as *Laminaria*, *Macrocystis pyrifera, Fucus*, *Ascophyllum nodosum*, and *Sargassum* produce a wide range of halogenated compounds, including halogenated sesquiterpenes, bromoform, dibromochloromethane, tribromomethane, methyl iodide (CH_3I), molecular iodine (I_2), and various brominated hydrocarbons.

Advances in technology now allow in-field detection of VOCs without sample collection. In mixed-species areas, VOC analysis helps distinguish seaweeds by their emission patterns, even under challenging conditions like turbidity. Integrating VOC data with AI and remote sensing further improves the accuracy and scalability of seaweed biodiversity monitoring.

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6.AI Monitoring and Other Roles

AI plays an important role in seaweed biodiversity by enabling automated identification, mapping, and monitoring of species using satellite, drone, and underwater images. It helps detect changes in seaweed habitats, assess threats such as pollution or climate change, and support sustainable management practices. Louime and Raza [33] examined methane emissions from seaweed, particularly *Sargassum.* Using a Convolutional Neural Network (CNN)- a type of machine learning model-along with the PANDAS tool for data handling and analysis, they developed a computer model capable of accurately predicting these emissions. The model achieved high predictive precision with minimal error. This methodology provides important insights into methane release from *Sargassum* and contributes to designing more effective environmental management strategies to reduce such emissions.

Detecting foreign objects in seaweed is crucial for ensuring food safety and maintaining product quality. Traditional visual inspections are time-consuming, inconsistent, and ineffective for large volumes. Therefore, reliable automated detection methods are needed to improve efficiency and consumer trust. Zhang et al. [34] classified six types of seaweed impurities: sand sticks, shells, discolored seaweed, grass, worm shells, and mixed contaminants. They created a dataset of 1,204 images to train and test their detection model. The model's performance was compared with three pre-trained architectures—YOLOv8, ResNet, and MobileNet. YOLOv8 showed the highest accuracy at 98.86%, outperforming the others. An Android application was also developed to integrate the deep learning model for real-time detection and practical use.

Ice-ice disease in seaweeds is a common bacterial infection that causes whitening, softening, and breaking of the algal thallus. It usually affects *Kappaphycus* and *Eucheuma* species and is triggered by environmental stress such as temperature changes, salinity fluctuations, or pollution, leading to reduced growth and yield. Such bacterial outbreaks can destroy entire seaweed farms within days. To tackle this problem, Xia [35] investigated the microbiota in seaweed cultivation systems, integrating low-cost underwater imaging with machine learning to detect diseases early and prevent large-scale damage.

IV. CONCLUSION

This review clearly shows, remote sensing, particularly hyperspectral imaging, has become a powerful tool for identifying seaweed species in complex coastal habitats. Seaweeds show unique spectral signatures based on pigment composition, structure, and reflectance, allowing classification across visible and near-infrared wavelengths. For instance, green algae (e.g., *Ulva* spp.) exhibit peak reflectance in the green band, whereas brown algae (e.g., *Sargassum* spp.) and red algae (e.g., *Gracilaria* spp.) are characterized by differential absorption in blue, red, and shortwave infrared regions. Techniques like spectral unmixing and machine learning reduce interference from associated fauna and background noise, while high-resolution UAV and satellite imagery capture canopy complexity. Together, these methods enable non-invasive, large-scale, species-level monitoring, supporting biodiversity assessment and resource management.

Each method used for assessing seaweed biodiversity—traditional techniques, remote sensing, GIS, and AI—offers unique strengths and faces specific limitations. Traditional approaches allow direct observation, specimen collection, and precise species identification. Remote sensing provides broad spatial coverage and enables efficient, repeatable monitoring, while GIS facilitates spatial mapping, pattern analysis, and data integration. AI improves classification, uncovers hidden patterns, and enhances accuracy through automated learning. However, traditional methods are time-consuming and labor-intensive; remote sensing is constrained by turbidity, spatial resolution, and depth penetration; GIS relies on accurate input data; and AI requires high-quality training datasets, extensive validation, and technically complex setup procedures.

Thus, the most effective approach is a hybrid framework combining AI, remote sensing, GIS, and field validation which offers a robust and scalable method for accurately monitoring seaweed biodiversity and supporting marine ecosystem management. Although this review focuses specifically on studies related to seaweeds, it does not claim to be fully comprehensive of all the published literature on this broad subject. Considerable further research is still required to enhance its practical applications.

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