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Algorithms applied for monitoring pelagic *Sargassum*

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Massive arrivals of pelagic *Sargassum* to the coasts of several countries in the Atlantic Ocean began in 2011. Monitoring the abundance and distribution of *Sargassum* in the ocean and along the coasts is necessary to understand the phenomena better and develop forecasting products and management protocols. Most *Sargassum* monitoring has been conducted in the open ocean through traditional remote sensing techniques. However, since the most significant ecologic and socioeconomic impacts occur on the coasts, it is necessary to monitor these macroalgae on nearshore waters and beaches. This manuscript reviews the remote sensing algorithms used in *Sargassum* observation reported in the last 17 years in more than sixty high-impact scientific publications. The discussion regarding the evolution of the methodologies used for monitoring these macroalgae allowed us to conclude that the synergy generated by incorporating new disciplines like artificial intelligence and citizen science has positively impacted the development of this field. Additionally, the current state-of-the-art methods, the fundamental challenges, and the directions for future research are also discussed.

KEYWORDS

remote sensing, machine learning, deep learning, citizen science, crowdsourcing

1 Introduction

Since the 1970s, the coastal waters of various regions of the planet have experienced the arrival of large volumes of macroalgae. Some examples include the Green Tides of *Ulva* spp. that affected the North American, Asian, and French coasts (Charlier et al., 2007; Hu et al., 2010a; Xiao et al., 2021) and *Cladophora* sp. as well as *Enteromorpha* in Europe (Charlier et al., 2008). Brown tides of *Sargassum horneri* have also affected various regions of Asia since the 2000s (Wang and Hu, 2016; Qi et al., 2017). More recently, those composed of two holopelagic *Sargassum* species (*S. fluitans* morphotype III and *S. natans* morphotypes I and VIII) began affecting several nations in the tropical Atlantic (Gower et al., 2013; Smetacek and Zingone, 2013; Johns et al., 2020). These two holopelagic species reproduce asexually

by fragmentation and float through their lifecycle (Ortega-Flores et al., 2022). Their distribution and abundance in the Sargasso Sea have been known since the 15th century. Nevertheless, in recent decades they had only occasionally arrived in relatively large numbers along the coasts and beaches of the Caribbean Sea (CS). However, since 2011, pelagic *Sargassum* spp. (herein referred to as *Sargassum*) landings in the Caribbean increased due to the formation of a recurrent Great Atlantic *Sargassum* Belt (GASB), often extending from West Africa to the Gulf of Mexico (Wang et al., 2019). In the open ocean, *Sargassum* constitutes a habitat for more than a hundred species (Anderson, 2007; Rodríguez-Martínez et al., 2019; Uribe-Martínez et al., 2020). Still, its accumulation and decomposition on beaches and in coastal waters result in severe ecologic (Rodríguez-Martínez et al., 2019), economic (Martínez-González, 2019), and human-health related (Resiere et al., 2018) impacts. Despite significant scientific and technological advances in *Sargassum* monitoring, questions such as: What is the extent of *Sargassum* cover along the coast? What is its volume? What is the amount of biomass reaching the beaches? are still being studied. This information is needed to generate better strategies for the appropriate collection, handling, use, and disposal of *Sargassum*. To develop such strategies, we need to know *Sargassum*'s origin, biomass, physiology, biochemical composition, and spatiotemporal dynamics at different scales. Additionally, the legal framework for managing *Sargassum* locally, regionally, and internationally is required.

The first observation of *Sargassum* from space was conducted in 2005 using algorithms developed to detect *Chlorophyll-a* (*Chl-a*) because it can be found in *Sargassum* (Gower et al., 2006). Since then, several remote sensors and algorithms have been developed and evaluated under different conditions to determine the distribution and abundance of *Sargassum* in the ocean (Blondeau-Patissier et al., 2014; Cuevas et al., 2018; Wang and Hu, 2020; Wang and Hu, 2021). Currently, several early warning platforms provide information regarding the presence of *Sargassum* in the open ocean (e.g., SaWS, FIU-NOAA, SAMTOOL). However, these satellite remote sensing methods have certain limitations. For instance, several factors can affect macroalgae measurements from satellite images, including atmospheric moisture, clouds, intense sunglint, water depth and turbidity, and African dust (Wang and Hu, 2016). Satellite imagery pixel sizes also limit the accurate measurement of accumulated *Sargassum* cover area. For example, MODIS imagery may underestimate *Sargassum* coverage by 50%, as small mats (< 2m wide), are not captured (Hu et al., 2021). These limitations can result in disparities between satellite and beach-cast estimated biomass (Rodríguez-Martínez et al., 2022). To date, *in situ* monitoring of *Sargassum* has been limited to relatively small coastal areas due to limited resources to cover larger areas (García-Sánchez et al., 2020; Torres-Conde and Martínez-Daranas, 2020; Rodríguez-Martínez et al., 2022; Torres-Conde, 2022).

The scientific work related to *Sargassum* observation and monitoring has recently increased to study aspects of its biology, ecology, and impact. Nevertheless, it is still necessary to design methodologies that support automatic and scalable quantification of its coverage and biomass (wet and dry) on coasts and beaches. This information will help elaborate early warnings and decision-making for *Sargassum* management, use, and disposal to reduce ecology and

socioeconomic impacts. Due to the adverse effects of *Sargassum* in several countries of the Caribbean, Central America, West Africa, Florida, and Brazil, diverse scientific-based international forums have been created to integrate the existing studies around the areas of knowledge required for studying this phenomenon.

The present review analyzed how *Sargassum* monitoring through satellite remote sensing is being addressed at different spatial-temporal scales. The manuscript is structured in different parts. First, based on information from the Scopus database, a set of manuscripts related to monitoring pelagic *Sargassum* between 1991 and 2023 is presented. Subsequently, we discuss the physical limitations that the Earth's atmosphere imposes on spatial observations and the spectral characteristics of *Sargassum*. In the following sections, we comment on the traditional methods for mapping vegetation, which served as the foundation for designing new, more specific algorithms for observing floating algae. Later, we address reflectance band-ratio, spectral band difference, and bio-optical algorithms, focusing on the algorithms used to identify *Sargassum* in the ocean through satellite imagery. Later we address studies that have applied Machine Learning (ML) algorithms to improve ocean *Sargassum* monitoring. Following, we discuss how *Sargassum* monitoring along the coastline is approached. Finally, we present the discussion section and the conclusions.

2 Materials and methods

The bibliography used in this manuscript was found traditionally, that is, by searching in bibliographic databases. Additionally, specific searches were conducted using Scopus to review existing literature regarding the algorithms used in pelagic *Sargassum* monitoring, which we describe in more detail below.

2.1 Peer-reviewed articles

We reviewed the existing literature on monitoring pelagic *Sargassum* through remote sensing techniques, using Boolean search in the Scopus database, for the period 1991 to date (March 23rd, 2023). We used the keywords “remote sensing” and “pelagic *Sargassum*” ((TITLE-ABS-KEY (remote AND sensing) AND TITLE-ABS-KEY (pelagic AND *Sargassum*)). The search results provided 22 documents (20 research articles, 1 conference paper, and 1 note). Twenty of these documents were published between 2015 and 2023. We repeated the search, replacing the keywords “pelagic *Sargassum*” with “floating *Sargassum*”. In this case, we obtained 37 documents (35 research articles and 2 conference papers). Thirty-one of these documents were published between 2015 and 2023. The second search contains 29 documents that are different from those in the first search. A third search used the keywords “*Sargassum*” and “Deep Learning” yielded 16 documents (13 research articles, 1 conference paper, and 2 conference reviews). Eleven of these documents were new and had not been part of the first two searches. The outcome of these three searches is shown in Figure 1. Peer-review publications related to monitoring *Sargassum* through remote sensing (RS) and deep learning (DL) techniques have increased significantly in the last five years.

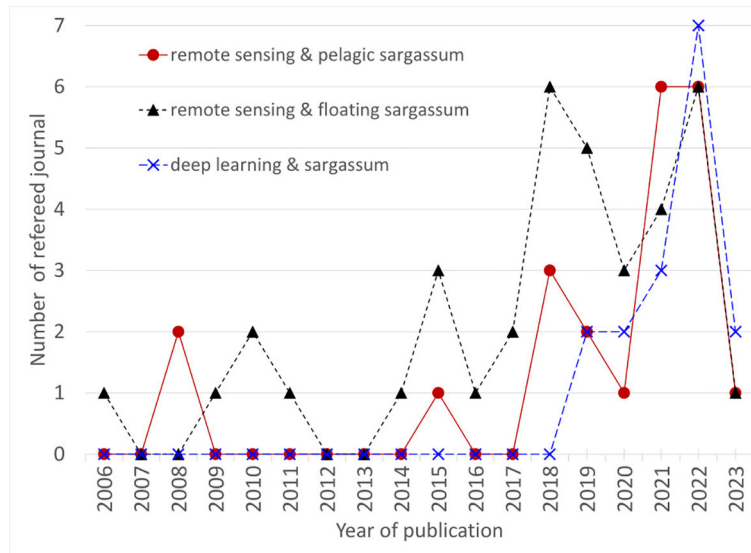


FIGURE 1 Contrasting the findings obtained from 3 peer-reviewed journal searches conducted in Scopus, using the terms “remote sensing” and “pelagic *Sargassum*”; “remote sensing” and “floating *Sargassum*” and “deep learning” and “*Sargassum*” as of March 23rd, 2023. Prior to 2006, no publications were found in the searches.

The searches yielded a total of 62 different documents, which were analyzed using the VosViewer software (Van Eck and Waltman, 2010). The papers with more than 30 citations were chosen for display in Figure 2, which shows the 16 documents, represented by circles and an abbreviated citation of each article for identification purposes. The diameters of the circles demonstrate the normalized number of citations of a document, which is equal to the number of citations the paper has divided by the average number of citations of all the documents published in the same year. The normalization accounts for the fact that older documents have had more time to receive citations than more recent documents. The distance between the two papers in the image

indicates the closeness of the papers in terms of co-citation links. Generally, the closer two papers are to each other, the stronger their relatedness. The most robust co-citation links between papers are represented by lines (Van Eck and Waltman, 2010).

Without being exclusive and to provide a panorama of the benchmark studies related to the remote sensing of *Sargassum*, Table 1 lists the five papers with the highest values in the number of citations, number of links, and normalized number of citations.

The seminal studies of Gower et al. (2006); Hu (2009); Wang and Hu (2016) appear in the first two categories (number of citations and number of links). In contrast, more recent studies appear in the normalized number of citations criterion. The highest

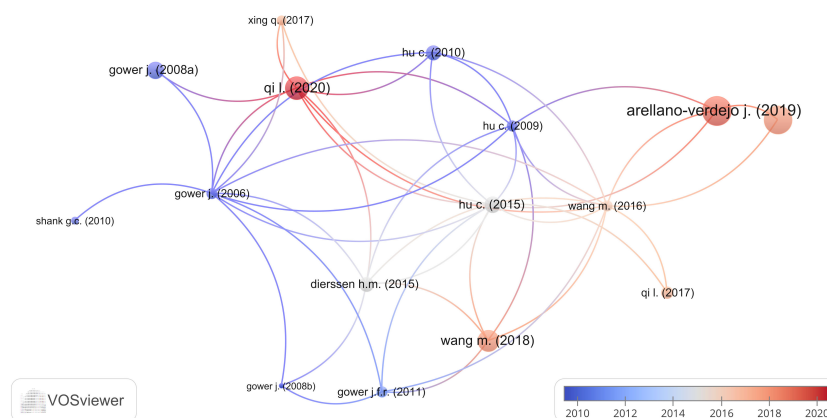


FIGURE 2 Overlay visualization of the most cited peer-reviewed journal publications (16), based on the 62 paper searches in the Scopus database as of March 23, 2023. The circle’s diameters are given by the normalized number of citations of a document (the number of citations of the paper divided by the average number of citations of all documents published in the same year provided by scopus and not only the cites of the documents consulted for the elaboration of the present study). The color scale indicates the time range in years from when the manuscript was published.

TABLE 1 Top five papers according to the highest values in the number of citations, number of links, and normalized number of citations (based on the search conducted in the Scopus database as of March 23, 2023).

	Number of citations	Number of links	Normalized number of citations
1	Hu (2009)	Wang and Hu (2016)	Arellano-Verdejo et al. (2019)
2	Gower et al. (2006)	Hu (2009)	Putman et al. (2018)
3	Wang and Hu (2016)	Hu et al. (2015)	Qi et al. (2020)
4	Gower and King (2011)	Gower et al. (2006)	Wang et al. (2018)
5	Gower et al. (2008)	Gower and King (2011)	Gower et al. (2008)

number of normalized citations corresponds to [Arellano-Verdejo et al. \(2019\)](#). This study applied DL methods to *Sargassum* monitoring for the first time.

Among the papers found in the Scopus database, we have discussed those that have been a significant reference in the observation, monitoring, or quantification of *Sargassum* and have served as an inspiration for the development of new methodologies. We also recognize that, within the limitations of this study, this selection of papers can be debatable, and some relevant studies may not have been considered. However, this study includes the most representative research findings regarding the algorithms used in pelagic *Sargassum* monitoring.

3 Algorithms for *Sargassum* observation

One of the common challenges in satellite remote sensing is overcoming the physical limitations the Earth's atmosphere

imposes on electromagnetic radiation. The radiance of the Earth's surface undergoes several modifications before it reaches the sensor. There is the addition of reflected sun and skylight from the sea surface and scattered light from the intervening atmosphere. Additionally, there is absorption by gasses in the atmosphere. The absorption bands are primarily associated with water vapor (730 nm) and carbon dioxide. Additionally, there is an oxygen absorption band at 687 and 760 nm ([Abbott and Letelier, 1999](#)). [Figure 3](#) shows the transmittance in the top atmosphere between 0.4 and 1.8 micrometers, some wavelengths of the electromagnetic spectrum are almost entirely filtered out; this is an example of the radiation detected by satellite sensors. The graph was produced with specific atmospheric parameters using the modeling program MODTRAN ([Berk et al., 2014](#); [Berk et al., 2015](#)). In conclusion, the solar energy that reaches the Earth's surface is only a fraction of the original incident energy. In the same way, the energy that reaches the satellite sensors is a fraction of that reflected or emitted by the study surface.

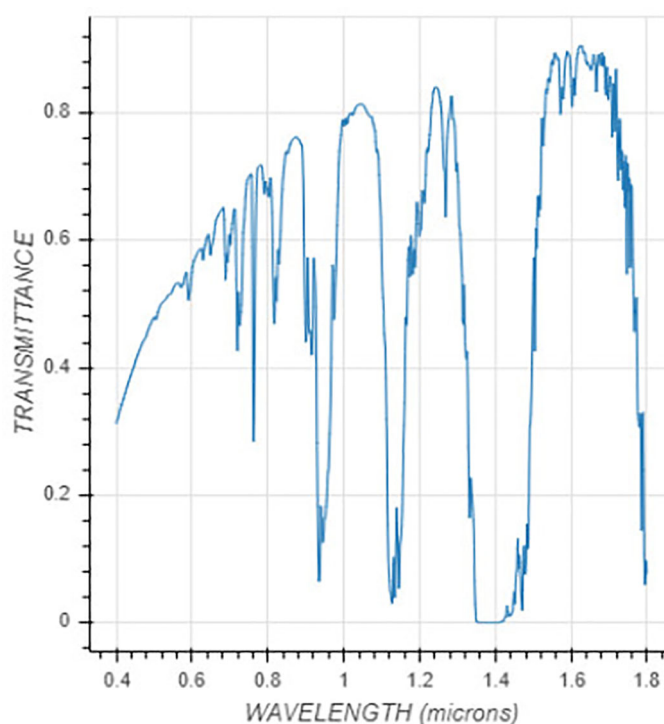


FIGURE 3

The transmittance of the atmosphere, between the sun and the Earth's surface, is calculated using the program MODTRAN. The atmospheric model is "Tropical," and the aerosol model is "Rural," with a visibility of 23km, sensor altitude of 99km, and azimuth of 135°.

Aquatic photosynthetic organisms (i.e., phytoplankton, cyanobacteria, micro and macroalgae) contain different combinations of photosensitive pigments (e.g., chlorophylls, carotenoids, and biliproteins) to produce their food by transforming a fraction of solar energy to biochemical energy (Lazcano-Hernandez et al., 2019). *Sargassum* exhibits unique spectral characteristics between 600 and 650 nm due to the presence of the photopigment *Chlorophyll c* (*Chl_c*) (Hu et al., 2015). Field reflectance measurements suggest that *Sargassum* exhibits a local minimum at approximately 632 nm due to *Chl_c* absorption, generating a unique spectral signature (Figure 4). However, to our knowledge, the sensors used for ocean observation do not discriminate such wavelengths in this spectral range, making analysis of this feature difficult. The observation of pelagic *Sargassum* from space is based on the fact that *Sargassum* when floating on the sea surface, favors the increase of reflectance in the near-infrared (NIR), especially in the red edge (700 to 740 nm), as can be seen in Figure 4. However, monitoring *Sargassum* remains a challenge for several reasons: First, it is constantly moving at the mercy of ocean currents and winds; second, there is a constant presence of clouds in the Caribbean that make it difficult to observe the sea surface; third, *Sargassum* is not the only marine organism that can cause an increase in reflectance in the red edge, organisms such as *Trichodesmium*, *Syringodium*, as well as debris and emulsified oil can also generate this increase. Therefore, from a spectral point of view, the detection of *Sargassum* in the sea is challenging because although the spectral signatures of the different organisms and objects that could be floating in the ocean are different, the spectral resolution of the sensors available for their study does not always allow to distinguish *Sargassum* from other types of organisms or objects (Hu et al., 2015). The study by Hu et al. (2015) also shows typical reflectances for *Sargassum*, *Trichodesmium*, *Ulva prolifera*, emulsified oil, various garbage

materials, and the seagrass *Syringodium*. Another challenge in monitoring *Sargassum* is that the rafts of this macroalgae tend to vary in size, from individual clusters of the order of cm^2 to rafts of hundreds of m^2 (Ody et al., 2019). For this reason, the detection of a raft also depends on the spatial resolution of the sensor used. A study by Hu et al. (2015) suggests that to discriminate *Sargassum* in a pixel of an image, the minimum coverage of *Sargassum* in that pixel must be between 20 and 30% of the pixel (Hu et al., 2015). The phytoplankton absorption coefficient is an essential parameter in ocean color algorithms and is increasingly used to parameterize algal bloom algorithms (Goela et al., 2013). The current challenge is to develop bio-optical algorithms that can take advantage of each organism's particular spectral characteristics to identify its spectral response under actual observation conditions.

The algorithms developed to observe and assess vegetation on land or *Chl_c*/phytoplankton in deep ocean waters provided the basis for designing new algorithms for monitoring *Sargassum* and other macroalgae. This study will address those used to observe massive *Sargassum* blooms. According to Blondeau-Patissier et al. (2014), RS algorithms for ocean observation can be categorized into four major groups: 1) Reflectance classification algorithms, 2) Reflectance band-ratio algorithms, 3) Spectral band-difference algorithms, and 4) Bio-optical models.

3.1 Traditional methods for vegetation mapping

The Vegetation Indices (VI) are mathematical expressions that have an input of radiometric measurements of the vegetation used to evaluate the temporal and spatial variations of many vegetal biophysical parameters (Liu and Huete, 1995). These indices have been widely applied in RS applications using aerial and satellite

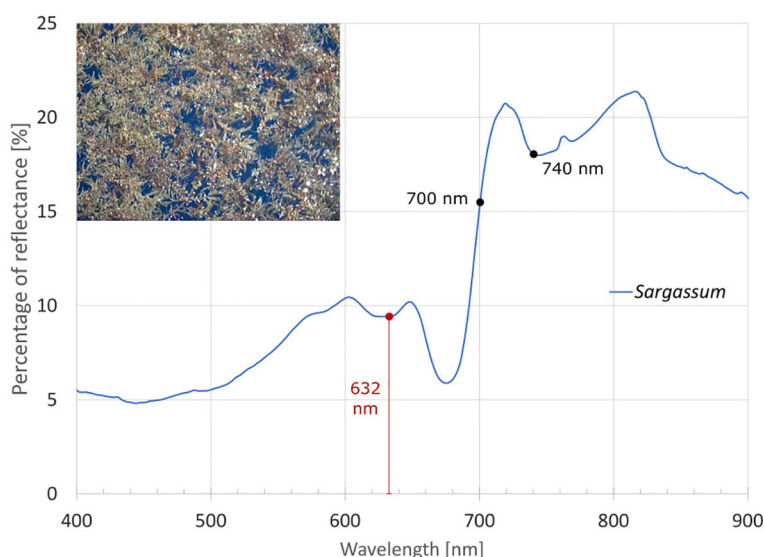


FIGURE 4

Average of several surface reflectance measurements of *Sargassum* floating on the sea surface under natural lighting conditions. Measurements were performed with a field portable spectroradiometer (SVC HR-5112i).

platforms (Xue and Su, 2017). VI are effective algorithms for quantitative and qualitative evaluations of vegetation coverage, vigor, and growth dynamics, among other applications. VI were initially used for land-based observations and provided the basis for marine observations. This study addressed those used to observe massive *Sargassum* blooms.

Between 1972 and 1973, the United States of America developed an experiment to map regional vegetation conditions during the Great Plains growing season (Rouse et al., 1974). Vegetation conditions were measured in vast regions using Multispectral Scanner (MSS) data from the Earth Resources Technology Satellite 1 (ERTS-1, later renamed Landsat-1). The radiance values recorded in ERTS-1 spectral bands 5 (0.6-0.7 μ m) and 7 (0.8-1.1 μ m), corrected for the angle of the sun, were used to calculate the band ratio parameter (BRP), defined as the difference in the ERTS radiance value measured in Bands 5 and 7, divided by their sum, which shows a correlation with the green aboveground biomass in the grasslands (Rouse et al., 1974). The BRP parameter also contributed to the Normalized Difference Vegetation Index (NDVI), which is defined as (Eq. 1):

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \quad (1)$$

Where R_{NIR} and R_{RED} are the reflectance in the near-infrared (NIR) and red bands, respectively. Many applications have utilized NDVI for land coverage/land usage. Several scholars have reported applications of the NDVI concept in studying massive algal blooms (Prangma and Roozkrans, 1989; Kahru et al., 1993; Hu and He, 2008). The NDVI can be used when there is a high contrast between *Sargassum* and the background in the images, and their values can be used as input to other indices to discriminate between *Sargassum* and emulsified oil, garbage, and different types of seaweeds (e.g., *Trichodesmium*, *Syringodium*, and *Ulva*) (Hu et al., 2015). On the other hand Hu (2009) used it as a reference method to compare against a Floating Algae Index (FAI) that he developed to estimate the abundance of *Sargassum* (Hu, 2009). However, it is sensitive to environmental variables and observing conditions (e.g., atmospheric influences, solar/viewing geometry, and sun glint) (Hu, 2009), which makes it difficult for quantitative analyses, because the absolute NDVI values can be changed, manual adjustments are necessary, limiting automation and large spatial-scale applications (Hu and He, 2008; Hu, 2009). Several indexes have been proposed to overcome these issues (Huete et al., 1999), including the Enhanced Vegetation Index (EVI) (Liu and Huete, 1995), which is a feedback-based index that corrects for the interactive canopy background and atmospheric influences by incorporating background adjustment and atmospheric resistance concepts. This enhanced soil and atmosphere-resistant vegetation index is defined in Eq. 2 (Huete et al., 1999):

$$EVI = \frac{G(R_{NIR} - R_{RED})}{R_{NIR} + C_1 R_{RED} - C_2 R_{BLUE} + C_3} \quad (2)$$

Where R_{NIR} , R_{RED} , and R_{BLUE} are the reflectance in the NIR, RED, and BLUE bands, respectively. G is the gain factor to compensate for the aerosol effects, and C_1 , C_2 , and C_3 are the

independent coefficients of the pixels to compensate for the impact of the vegetation background.

Despite efforts, EVI remains sensitive to environmental variables and observation conditions. Therefore, developing more stable algorithms for these conditions is necessary. Also, given the dynamics of the marine environment, the monitoring of *Sargassum* in the sea and its accumulation on beaches requires periodic information to know the moment-to-moment status of the phenomenon, which is often unavailable, making the data provided by algorithms challenging to validate for marine coastal zones.

3.2 Reflectance band-ratio algorithms

Reflectance band-ratio algorithms use spectral bands in the blue and green regions of the visible spectrum to estimate *Chl_a* concentrations in open oceans (Blondeau-Patissier et al., 2014). Examples include NASA's ocean color algorithms, such as the SeaWiFS OC4 (O'Reilly et al., 1998; O'Reilly et al., 2000) and MODIS OC3M (Campbell and Feng, 2005). Most reflectance band-ratio algorithms were designed for global applications in deep ocean waters (Odermatt et al., 2012). Therefore, it is inappropriate to generalize the parameterization of some algorithms to all ocean regions (e.g., Dierssen and Smith (2000); Sathyendranath et al. (2001); Claustre and Maritorena (2003); Volpe et al. (2007)). On the other hand, the use of blue-green spectral bands for specific detection of *Chl-a* in coastal waters is affected by the absorption signal of CDOM and Total Suspended Matter (TSM). Therefore, in coastal waters, the quality of *Chl-a* detection is significantly reduced and is often considered unreliable. A more detailed performance analysis of these algorithms can be found in Blondeau-Patissier et al. (2014).

On the other hand, if appropriate spectral bands are available, it is possible to use the *Sargassum* Index (SI) and the red/green band ratio to identify the presence of *Sargassum* among other species of algae and seagrasses, in which the color green prevails (Dierssen et al., 2015). Hence, the SI is defined as Eq.3:

$$SI = \frac{R_{r3}}{R_{r2}} \quad (3)$$

Where "r3" is the wavelength of a local reflectance peak, and "r2" is the wavelength of a local reflectance trough. Using Portable Remote Imaging Spectrometer (PRISM) images at 1 m resolution, the *Sargassum* Index was used to effectively discriminate *Sargassum* from *Syringodium* seagrass (Dierssen et al., 2015).

The red/green band ratio is defined as Eq.4:

$$RGR = \frac{R_{r3}}{R_{green}} \quad (4)$$

Where "green" has a wavelength near 555 nm. The reason to define this index is to differentiate *Sargassum* from *Trichodesmium* (Cyanobacteria) because they have opposite red/green ratios (Dierssen et al., 2015).

A simple NDVI index can effectively discriminate *Sargassum* from the background in an image with high contrast. However, line depth (LD) and SI are required to enhance NDVI output to differentiate *Sargassum* from *Syringodium* blooms, oil, or garbage. SI can also differentiate *Sargassum* from other floating materials in environments free of emulsified oil and debris (Dierssen et al., 2015). Table 2 shows the steps to discriminate *Sargassum* from other algae and seagrasses or floating materials using PRISM imagery.

3.3 Spectral band-difference algorithms (Baseline algorithms)

A methodology that has inspired several studies to avoid oxygen absorption at 687 and 760 nm and water vapor absorption at 730 nm is known as the baseline algorithm (Abbott and Letelier, 1999). Gower and co-workers used aircraft-based sensors to test several channels as a baseline for calculating the Fluorescence Line Height algorithm (FLH). They varied the bandwidth and position and eventually developed a simple linear model using three bands (Borstad, 1985), the general form is presented in Eq. 5. The mathematical expression of this algorithm is also known as Spectral Band Difference Algorithm (SBDA).

$$SBDA = R_2 - K(R_1 + (R_3 - R_1) \frac{\lambda_2 - \lambda_1}{\lambda_3 - \lambda_1}) \quad (5)$$

Whereby R_2 is the radiance or reflectance depending on the use of the input data, measured in the peak of λ_2 , R_1 and R_3 are the radiance or reflectance of the baseline wavelengths, λ_1 and λ_3 . Finally, K is a constant (Palmer et al., 2015). The subscripts can be rewritten with the reflectance used according to the study (Eq. 6). Note that the subscripts are generic, and the associated wavelength depends on the index used. For details, see Table 3.

$$SBDA = R_{NIR} - (R_{RED} + (R_{SWIR} - R_{RED}) \frac{\lambda_{NIR} - \lambda_{RED}}{\lambda_{SWIR} - \lambda_{RED}}) \quad (6)$$

To make the expression shorter, it is usually rewritten, as shown in Eq. 7 and 8.

$$SBDA = R_{NIR} - R' \quad (7)$$

Where:

$$R' = R_{RED} + (R_{SWIR} - R_{RED}) \frac{\lambda_{NIR} - \lambda_{RED}}{\lambda_{SWIR} - \lambda_{RED}} \quad (8)$$

All SBDA algorithms discussed in this study are defined as the difference between the reflectance or radiance (R) in the central waveband (λ_2) - which corresponds to the maximum of the red-edge effect -and a linear baseline, drawn between surrounding bands (λ_1 and λ_3 , respectively) (Gower et al., 2005; Hu, 2009; Wang and Hu, 2016). SBDA algorithms take advantage of the fact that absorption tends to vary more rapidly with wavelength than dispersion; two adjacent reflectance spectral bands may have similar backscatter properties but will differ significantly in absorption. Therefore, this absorption can be quantified by spectral difference, which these algorithms seek to take advantage of (Blondeau-Patissier et al., 2014).

The first observation of *Sargassum* from space in 2005 (Gower et al., 2006) was achieved using imagery from the Medium Resolution Imaging Spectrometer (MERIS), on the Envisat satellite launched by the European Space Agency (ESA), and from the Moderate Resolution Imaging Spectroradiometer (MODIS), launched on both the Terra and Aqua satellites by the National Aeronautics and Space Administration (NASA). MERIS imagery was used as input for the Maximum Chlorophyll Index (MCI), and MODIS imagery for the Fluorescence Line Height (FLH) MODIS product. FLH and MCI belong to SBDA algorithms and were the inspiration for the Floating Algae Index (FAI) (Hu, 2009) and the Alternative Floating Algae Index (AFAI) (Wang and Hu, 2016). The SBDA algorithms use band triplets from the visible (VIS), infra-red (IR), near infra-red (NIR) and shortwave infra-red (SWIR) spectral regions (Table 3). The wavelengths are selected depending on the phenomenon monitored to set the index, so the algorithm is sensitive to *Chl-a* fluorescence, *Chl-a* concentration, or surface flowering (Blondeau-Patissier et al., 2014). The features of these algorithms are detailed below.

3.3.1 Fluorescence line height

The Fluorescence Line Height algorithm (FLH) measures the relative amount of radiance leaving the sea surface, presumably resulting from *chlorophyll* fluorescence (Abbott and Letelier, 1999). It is one of the most widely used ocean color SBDA algorithms to quantify solar-induced *chlorophyll* fluorescence. FLH estimates the deviation from the radiance expected for pure water resulting from *chlorophyll* fluorescence through a baseline composed of bands on either side of the high fluorescence wavelength. This increase in radiance (centered at 683 nm for *chlorophyll*) has been observed for decades in light-field ocean measurements. However, the signal is generally weak, even in regions of high *chlorophyll* concentrations.

TABLE 2 Steps to discriminate *Sargassum* from other floating materials and algae using PRISM imagery.

Stage	Steps to discriminate <i>Sargassum</i> from	
	<i>Syringodium</i> , emulsified oil, and garbage	<i>Syringodium</i> , <i>Trichodesmium</i> , and <i>Ulva</i>
1	NDVI $N > 0$ (floating materials)	NDVI > 0 (floating materials)
2	LD $> 2 \times 10^{-3}$ (spectral curvature around 630 nm to rule out the possibility of <i>Syringodium</i> , emulsified oil, and garbage)	SI > 1 (to rule out the possibility of <i>Syringodium</i> and <i>Ulva</i>)
3	RGR > 1 (to rule out the possibility of <i>Trichodesmium</i> , <i>Syringodium</i> , and <i>Ulva</i>)	RGR > 1 (to rule out the possibility of <i>Trichodesmium</i> and <i>Ulva</i>)

TABLE 3 Wavelengths of spectral band difference algorithms used to monitor *Chl-a* fluorescence, *Chl-a* concentration, or surface flowering.

Index	Central λ (nm)			Sensor/Satellite	Use
	Red	NIR	NIR or SWIR		
FLH	665.1	676.7	746.3	MODIS/Terra, Aqua	<i>Chl_a</i>
MCI	681	709	753	MERIS	
FAI	645	859	1240	MODIS/Terra, Aqua	<i>Sargassum</i> /Macroalgae
FAI	655	865	1609	OLI/Landsat	
MFAI	665	833	940	MSI/Sentinel 2 (A&B)	
AFAI	667	748	869	MODIS	

Thus, to measure fluorescence, the signal-to-noise ratio (SNR) was increased for the fluorescence band and the adjacent “baseline” bands at 665.1 nm (band 13) and 746.3 nm (band 15). In the case of MODIS imagery, the fluorescence measurement was adjusted at 676.7 nm (band 14) as a compromise between measuring the fluorescence peak (683 nm) and the presence of an oxygen absorption band at 687 nm (Abbott and Letelier, 1999).

3.3.2 Maximum Chlorophyll Index

The Maximum Chlorophyll Index (MCI) monitors algal blooms in inland waters and in ocean, ranging from low chlorophyll and oligotrophic to optically complex, turbid, and eutrophic conditions (Gower et al., 2006; Binding et al., 2013). The MCI index is used for MERIS imagery at 709 nm to detect a signature of dense surface phytoplankton in bloom conditions. However, in shallow waters, a peak near this wavelength can also indicate the presence of benthic vegetation (Gower et al., 2003). Even though MCI is a versatile tool for monitoring intense surface algal blooms, with chlorophyll concentrations in the 10–300 mg m⁻³ range, this index has limited application when algae biomass is low, as in the case of Lake Ontario (Binding et al., 2013). Thus, the MCI can only be applied to MERIS in the 708.75 nm band because it responds best to strong reflectance in the NIR but not in MODIS and VIIRS, which lack similar bands.

3.3.3 Floating Algae Index

The Floating Algae Index (FAI) is based on the difference between the reflectance at 859 nm (vegetation “red edge”) and a linear baseline between the red band (645 nm) and the short-wave infrared band (1240 or 1640 nm) (Hu, 2009). The wavelengths of these reflectance bands are present in the MODIS sensor. However, the FAI concept can be extended to other satellite platforms because its equation is the same as MODIS FLH (Letelier and Abbott, 1996) and MERIS MCI (Gower et al., 2005), both of which are effective in estimating solar-stimulated chlorophyll-*a* fluorescence (FLH) and to detect intense phytoplankton blooms (MCI). FAI is more tolerant to environmental changes and robust to the influence of CDOM, aerosols, and sun glint because of the use of NIR bands. Nevertheless, similarly to MCI, the FAI is sensitive to turbid waters and shallow depths and is still susceptible to false

positives. Since its release in 2009, the FAI algorithm has been used to study several algae blooms in the ocean. Examples include the monitoring of *Sargassum* in the North Atlantic Ocean and the Gulf of Mexico, *Ulva* (*Enteromorpha*) *prolifera* in the Yellow Sea (Hu et al., 2010a; Hu et al., 2010b), and *Trichodesmium* spp. on the west Florida shelf (Hu et al., 2010a), with support of a multi-sensor hydrocarbon tracking technique (Zhao et al., 2014). Unfortunately, the FAI can confuse clouds, ocean waves, and sun-glint pixels with floating algae (Hu, 2009).

3.3.4 MSI-Modify Floating Algae Index

The spectral bands that the theory indicates are ideal for observing pelagic *Sargassum* from space are not available in all satellite sensors, or technical aspects limit their implementation. This has led to the creation of indexes that use alternative spectral bands. This selection depends on the data sensor (Table 3). Implementing an index is sometimes impossible since the necessary spectral band is unavailable. For instance, the MCI uses a λ_2 centered at 709nm and can be implemented only with data from the MERIS and OLCI sensors (Blondeau-Patissier et al., 2014). Another example is the MSI sensor onboard the Sentinel 2 A&B platforms, which presents parallax effects due to the staggered configuration of the 12 individual detectors concerning the focal plane, resulting in odd or even different angles on the ground. These effects can result in differences in radiometry measured on non-Lambertian surfaces, for example, in the sun’s brightness on sea surfaces (Clerc, 2016). On the other hand, the processing algorithm ensures the co-registration of images acquired by all spectral bands and the ground-level feature detectors. However, objects at higher altitudes, such as airplanes and clouds, cannot be registered correctly, leading to incorrect spectral registration (“rainbow” effect) and discontinuities between the detectors, which causes misalignment of the detector for objects at high altitudes. Considering the effects mentioned above, Ody et al. (2019) proposed using the 940nm band instead of the 1610 nm to calculate the FAI using data from the MSI sensor. This adaptation originated the MSI-Modified Floating Algae Index (MSI-MFAI), which benefits the 10m resolution of the bands at 833 and 665nm. The 940 nm MSI spectral band must be up-sampled to a 10m resolution because it has a native spatial resolution of 60m (Ody et al., 2019).

3.3.5 Alternative Floating Algae Index

The Alternative Floating Algae Index (AFAI) was inspired by the same mathematical expression used in the FAI. To eliminate false positives caused by clouds, the AFAI proposes masking the clouds using a new combination of spectral bands ($\lambda_{RED}=667$ nm, $\lambda_{NIR}=748$ nm, and $\lambda_{SWIR}=869$ nm) (Wang and Hu, 2016). Although the 869nm band is in the NIR spectral range, it is still called “SWIR” for consistency (Table 3). In addition to eliminating false positives due to the presence of clouds and solar flares, this proposal improves visual contrast and allows simple interpretation by a wider audience (Wang and Hu, 2016). Although AFAI has a lower spatial resolution (1km) than FAI (250m), the bands used to calculate AFAI have much higher signal-to-noise ratios (SNRs) than those for FAI (Table 3), thus, compensating for the reduction in resolution when detecting small *Sargassum* mats (Hu et al., 2012; Wang and Hu, 2016). The AFAI was applied to MODIS data to generate the first-time distribution and area coverage maps of *Sargassum* in the western central Atlantic region from 2000 to 2015 (Wang and Hu, 2016), obtaining results consistent with those previously reported using MERIS observations up to 2011 (Gower et al., 2013).

Spectral band-difference algorithms have provided the most significant findings in observing these algae and are currently a reference in ocean monitoring. However, their performance in the coastal zone decreases considerably. The FAI is the current benchmark index for *Sargassum* monitoring in the ocean and is used to compute the Satellite-based *Sargassum* Watch System bulletins (SaWS, <https://optics.marine.usf.edu/projects/saws.html>). Nevertheless, several studies seek to improve the results provided by this index, as discussed in the following section.

3.4 Bio-optical algorithms

Bio-optical modeling is an essential tool for understanding the effects of dense algal concentrations on light absorption and backscatter coefficients (Blondeau-Patissier et al., 2014). To bio-optical models have meaningful applications, it is necessary to calibrate them with values from *in situ* measurements of the variables used in the model so that the coefficients used are the most adequate to represent the phenomena under study as accurately as possible. To our knowledge, only the study of Schamberger et al. (2022) sheds light on a bio-optical algorithm specifically designed to detect *Sargassum*. This study adapted the semi-analytical radiative transfer model (Lee et al., 1998), proposed by Desclotres et al. (2021), which included the submerged *Sargassum* in rafts. This model is called *Sargassum* Radiative Transfer (SRT). Like Lee's et al. (1998) model, SRT can simulate surface reflectance using the bio-optical properties of the water column, bottom depth, and bottom composition as inputs (forward model). The model uses the following variables as inputs: *Chl-a*, the concentration of Non-Algal Particles (NAP), the Colored Dissolved Organic Matter (CDOM) absorption coefficient, the seabed reflectance, and the depth (*z*) (Schamberger et al., 2022). These

parameters determine the Inherent Optical Properties (IOP) of the water, such as the absorption ($a(\lambda)$) and backscattering ($bb(\lambda)$) coefficients that are used to model the deep-water reflectance $prsdp(\lambda)$.

4 Machine learning and *Sargassum* observation

The atmosphere imposes limitations on the Earth's observation from space that are challenging to avoid. Several actions have been conducted to overcome these limitations, including developing sensors with better spectral and radiometric characteristics and indices with features that highlight the study object from the background of the images. Concerning *Sargassum* monitoring, filters or masks have been designed to eliminate clouds, cloud shadows, intense reflections of the sun, and others. However, false positives and false negatives persist in most images. In recent years, the development of hardware and software has supported the democratization of ML. Since a decade ago, ML has been employed successfully in various Earth observation studies (Camps-Valls et al., 2021). The first published work that used ML to improve *Sargassum* monitoring using Landsat images was published in 2018 (Cuevas et al., 2018), and the first one using DL in 2019 (Arellano-Verdejo et al., 2019). In 2020, ML steps were incorporated to improve extracting *Sargassum*-associated features in imagery obtained from AFAI (Wang and Hu, 2021). The following section discusses ML and relevant studies where ML has been implemented to improve *Sargassum* observations from satellite imagery.

4.1 Brief presentation of machine learning

In the context of Computer Science, ML is a branch of Artificial Intelligence (AI) (Minsky, 1961) that allows machines to learn without being expressly programmed for it. An ML algorithm can learn from the data (Goodfellow et al., 2016), which is an essential skill for making systems capable of identifying patterns to be able to make predictions. This technology is present in several applications (e.g., content recommendation on streaming platforms, speech recognition from virtual assistants, autonomous cars, search engines, medical diagnoses, or fraud detection). The contribution of ML is the paradigm shift from rule-based programming to autonomous learning from data (Goodfellow et al., 2016). Additionally, ML methods are widely used to extract patterns and insights from the ever-increasing data streams in sensory systems (Camps-Valls et al., 2021). In general terms, ML helps to make a prediction or data grouping based on input data. Prediction problems can be divided into two broad categories: Regression problems, where the variable to be predicted is numerical, and Classification problems, where the variable to be predicted is part of a predefined set of categories. For the training of an algorithm, ideally, a balanced dataset is required, i.e., with homogeneous values of the different elements or variables included in the study case.

A characteristic of ML is that there are metrics for evaluating models and their performance quantitatively, allowing us to know the confidence level of the algorithm in different scenarios. A fraction of the dataset (generally 80%) is used as the training dataset, and the remainder is the test dataset, used to evaluate the algorithm's performance. The ML evaluation metrics depend on the model type (regression or classification). Classification models are applied in *Sargassum* monitoring, and their most straightforward evaluation metric is accuracy, which is the percentage of observations correctly predicted by the model. However, it must be interpreted cautiously, especially if the classes to be predicted are out of balance (Hossin and Sulaiman, 2015).

The confusion matrix is another tool to evaluate and compare models. It compares the actual values of the target variable against the predicted values. The matrix number of rows and columns depends on the number of possible outcomes. There are only two possible outcomes for binary classification, so only two columns and two rows exist. The labels that make up a confusion matrix are true positive (TP), false negative (FN), false positive (FP), and true negative (TN). Additionally, the information from the confusion matrix makes it possible to calculate the following metrics: Precision Eq.9 and Recall Eq.10, as defined below (Hossin and Sulaiman, 2015).

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

Precision and Recall are used to define the metric F1 score as shown in Eq.11

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

4.2 Classical ML algorithms

The metrics above allow us to quantitatively determine the performance of the algorithm used for a particular study and compare different algorithms with each other (Hossin and Sulaiman, 2015). Then, we will describe innovative study cases that use ML techniques to improve the *Sargassum* monitoring in the ocean, the coast, and the beach.

4.2.1 Tree-based models

The study conducted by Cuevas et al. (2018) had two main objectives. First, to understand the spatio-temporal dynamics of pelagic *Sargassum* in the waters of the northern Yucatan Peninsula, Mexico. Second, to extend existing methodological approaches by implementing a low-cost proposal with relatively low computational demand. A Random-Forest type algorithm was designed with inputs defined from the combination of five vegetation indices and two Landsat spectral bands with the potential to contribute to detecting *Sargassum* under supervised classification: NDVI, EVI, FAI, Atmospherically Resistant Vegetation Index (ARVI), Soil Adjusted Vegetation Index (SAVI),

B2 (blue, 0.452–0.512 μm), and B5 (SWIR, 0.851–0.879 μm) were used as inputs of the algorithm.

The classification input was a dataset built with 91 Landsat-8 imagery of the northern Yucatan Peninsula from the years 2014 and 2015. For all classifications, the number of variables in the random subset at each node (m) was set at 3, and the number of trees in the forest (k) at 1,000, with the replacement of samples at each step. Five training zones were included for the other more representative objects present in the scene to provide the classifier with a broader spectral context of each analyzed image and increase the possibilities of correctly classifying *Sargassum*. The results showed that combining vegetation indices in a classification process is a more robust way to detect *Sargassum* in Landsat-8 imagery, improving even those using a single index.

4.2.2 Support vector machine classification

The study conducted by Shin et al. (2021) aimed to detect *Sargassum* distribution along the coast of Jeju Island using the Geostationary Ocean Color Imager-II (GOCI-II) images and a ML model-based on a Support Vector Machine (SVM) and Gentle Adaptive Boosting. The model was trained using the Rayleigh-corrected reflectance image (RhoC) from GOCI-II as input and a “ground truth” of the ground extracted from high-resolution images as output. A *Sargassum* ground truth map was generated from Landsat OLI and Sentinel-2 MSI imagery.

4.3 Algorithms based on deep learning

The democratization of DL has been possible thanks to the availability of large datasets, the advances in hardware and parallelization, computational resources, and community efforts to develop and share codes. This has resulted in an increasing number of people using DL to solve different challenges. Nowadays, DL seems to be consolidating as a widely used scientific research paradigm (Camps-Valls et al., 2021). The vast amount of data about the Earth and its environments, generated by satellite observation platforms and other remote sensors has enabled Earth observation to join the data revolution. The use of DL in Earth Sciences has grown exponentially in recent years because the datasets available offer enormous potential to study terrestrial ecosystems and to address major societal challenges related to emerging issues (e.g., food, water, energy security, and climate change) (Camps-Valls et al., 2021). DL allows the analysis of RS data from another perspective. Below we describe some of the most recent studies incorporating DL to improve *Sargassum* observation.

4.3.1 Artificial Neural Networks approach

The study conducted by Arellano-Verdejo et al. (2019), presented ERISNet, a convolutional and recurrent ANN, to classify pixels into two classes: with and without *Sargassum*. Aqua-MODIS imagery of the coast of Quintana Roo in Mexico was used to build the training, testing, and validation datasets. After the learning process, the designed algorithm achieved 90% probability in its classification capabilities. ERISNet was the first

ANN developed to classify pixels for *Sargassum* observation and provides a novel view to detect the arrival of algal blooms accurately. This study also made the first dataset with MODIS pixels classified as with or without *Sargassum* available.

4.3.2 Denoising model filtering

A significant challenge for automatically extracting pelagic *Sargassum* information from satellite images is the background noise. Traditionally, noise in VIIRS images is removed using methods such as Gaussian smoothing. However, this methodology cannot be applied in MSI images because the noise patterns are highly variable and attenuate the features, even after local adjustments for optimal performance. MSI images also present relatively large-scale variations in the background, which can result from the image fringe patterns and changes in the optical properties of the water. The study by Wang and Hu (2020) aimed to develop a reliable and fully automatic method for extracting pelagic *Sargassum* features from MSI images using the FAI. The proposal relied on applying a DL model called Trainable Nonlinear Reaction-Diffusion (TNRD) for noise removal. The results show that the proposed model is adequate for image preprocessing and reduces the underlying problems when applying the AF AI index.

4.3.3 UNET image segmentation

The study conducted by Wang and Hu (2021) addressed two main questions. First, how much *Sargassum* had gone undetected in coarse-resolution observations such as MODIS. Second, how would it be possible to fill data gaps in nearshore waters? The authors used a deep convolutional neural network (DCNN) of U-net type to answer these questions and to develop a unified approach to extract *Sargassum* features and quantify its abundance using high-resolution images from multiple sensors (MSI, OLI, WV-2, and PlanetScope/Dove). *Sargassum* biomass density or coverage areas were quantified, while other confounding features (i.e., waves, currents, phytoplankton blooms, clouds, shadows of clouds, or streak noise) were discarded. To design the model, the authors took the feature extraction section of a VGG network to build a U-Net named VGGU-net.

The dataset generated in the study served to train the proposed model. As a result, satisfactory performance was achieved as no apparent noise signal was misidentified as *Sargassum* (false positives), while pixels containing *Sargassum* were mainly detected (few false negatives). Most detection errors (either false positives or false negatives) came from pixels with relatively low biomass densities. Accuracy and recovery rates were high (85%), suggesting that most pixels containing *Sargassum* were detected successfully. The accuracy of *Sargassum* biomass estimated from OLI images was ~92%; from MSI images 90%; from WV-2 images ~98%; and from PlanetScope/Dove images 82%. The study presents beneficial results and statistics; however, the authors omitted to incorporate metrics to evaluate the training performance of their proposed algorithm.

The VGGU-net model showed robust performance even with limited spectral bands, high background variations, and several confounding targets. Another critical advantage of the proposed method was its flexibility. The VGGU-net model can easily adapt to

different types of satellite data or features by adjusting the input layer and optimizing the model parameters.

The study conducted by Zhang et al. (2022) demonstrated the potential of 3m resolution imagery to monitor *Sargassum* on the beaches of Miami and Cancun by employing a U-net-based DL model using Dove images. The model was trained with a dataset of four-band TOA reflectance images and labeled *Sargassum* images. Pixels were roughly delineated to create the labeled *Sargassum* images using NDVI values. The model was applied to the images after local cloud masking of the TOA reflectance. The authors admit that future work is required to improve cloud masking and apply an appropriate atmospheric correction for global applications. The *Sargassum* demonstration clearly shows how valuable high-resolution and high-frequency Dove data are for monitoring dynamic events, such as *Sargassum* inundation. The results show how the *Sargassum* coverage changed quickly, although the results were encouraging, in this case, like in others where ML and DL techniques are employed, the methodologies applied in the datasets used to train the models were not described in depth. It is not clear how the results were evaluated and interpreted since, in most cases, there is no mention of how the authors avoid overtraining and overfitting.

5 Beach monitoring

Monitoring *Sargassum* along the coasts presents challenges to traditional remote sensing because of the heterogeneous characteristics of the shores, which are not evident in the images from most of the sensors that offer open data. An alternative is using very high spatial and temporal resolution data. However, conducting large-scale studies with these inputs is computationally and economically expensive. However, it offers the advantage of monitoring areas of interest with images that provide finer detail. Below is a review of studies that propose alternatives for monitoring *Sargassum* on beaches, what they do, how they do it, their contributions to the state-of-the-art, and their areas of opportunity.

5.1 Network camera systems

In 2021, Rutten et al. (2021) characterized the temporal variation in *Sargassum* found in the reef lagoon in Puerto Morelos, Quintana Roo, Mexico. The study analyzes images taken every hour for approximately 5.2 years (September 2015 to November 2022) to observe the relationship between landings with wave energy, water level, and wind speed. With this information, the authors proposed a model to explain how the natural cleaning process of the *Sargassum* accumulated on the beach occurs. This study used a SVM to classify the images automatically. However, it is necessary to know more details of the algorithm adjustment process to reproduce the experiment; for example, the kernel used, the implication of training the algorithm with an unbalanced dataset, and confusion matrices for different cases. This study contributes to the knowledge about *Sargassum* dynamics and the capacity of the coastal system to remove *Sargassum* naturally on beaches.

5.2 Crowdsourcing and citizen science

Sargassum monitoring on beaches using photographs and videos has also been carried out through various citizen science initiatives, including Crowdsourcing. The increasing use of mobile devices, such as smartphones and tablets, and the infrastructure that interconnects them with the Internet, have made collective participation a vital source for photographs of the presence of *Sargassum* on beaches. Citizen science has recently been used as a methodology to collect field information for the validation and calibration of supervised algorithms for identifying *Sargassum* on the beaches (Arellano-Verdejo and Lazcano-Hernandez, 2020; Iporac et al., 2020). In addition, the study by Putman et al. (2023) suggests the inclusion of wind speed and citizen science data to improve *Sargassum* inundation reports along beaches. This study constructed its dataset by vertically cropping each photograph to remove the sky and then superimposing 50 random points on the image using the Coral Point Count with Excel extensions (CPCe) software (Kohler and Gill, 2006). Each point was classified into six classes (*Sargassum*, sand, sky, water, vegetation, or 'other'). To estimate the relative amount of *Sargassum* present in the photo, a ratio was calculated between the number of *Sargassum* pixels and the sum of sand, water, vegetation, and *Sargassum* points.

The study conducted by Arellano-Verdejo and Lazcano-Hernandez (2021) proposed a methodology for monitoring *Sargassum* on beaches based on Crowdsourcing for capturing geotagged photographs. An application for mobile devices (e.g., smartphones, tablets) was developed so that volunteers could capture and send the photographs to the cloud for storage. A dataset of 2400 photographs (1200 with *Sargassum* and 1200 without) was built to train, test, and validate the classification algorithms. DL algorithms classified the images automatically into two classes (with and without *Sargassum*), and maps were created with GIS to visualize the presence or absence of *Sargassum* on beaches. To accomplish this task, three state-of-the-art CNNs (LeNet-5, AlexNet, and VGG16) were chosen for image classification and compared on their performance to find the most suitable architecture. Each CNNs was adjusted for the classification process to use the new dataset. LeNet-5 was modified to work with RGB images. The last layer of 1,000 categories in the AlexNet and the VGG16 architectures was replaced by a fully-connected layer for two classes (*Sargassum* and non-*Sargassum* images). AlexNet and VGG used augmented data and transferred learning to maximize the generalization capacity of the network for the given dataset. The architecture with the best performance in this study was AlexNet, with an f1 score of 92%. This is a significant result considering that the training was performed with a relatively small set of images (2400). The main contribution of this study is the building of the first dataset of segmented and geotagged images that can be used in other studies. This is important since there is a lack of datasets for studying natural phenomena. Additionally, this study uses the results of the proposed methodology to develop presence/absence maps of *Sargassum* along the beaches.

The study conducted by Santos-Romero et al. (2022) proposed a method to classify images automatically to build adequate datasets

for studies that highlight the presence of *Sargassum* along the beaches. The images were classified into two classes, in-depth linear perspective and no linear perspective. The Transfer Learning technique on three Artificial Neural Networks (ANN's) from the literature (ResNet50, MobileNetv2, and VGG16) was implemented to find the optimal architecture. The study also used the Collective View dataset as input for constructing its training dataset. From that collection, 5,000 pictures were manually selected and classified into two balance classes: 2,500 images with a linear beach perspective and 2,500 images without this perspective. The dataset was divided into two subsets using an 80-20 hold-out scheme (Chollet, 2021). 80% of the data were used for training the model and 20% for its testing. The ANN's performance was assessed with the Accuracy, Precision, and F1 score metrics. A resampling analysis of the F1-Score metric was performed with the Bootstrapping technique, concluding that VGG16 and MobileNetV2 obtained similar results with a confidence interval of 95% between 0.88 and 0.92. Finally, considering both architectures' spatial and temporal complexity, MobileNetV2 was proposed as the most appropriate for classifying images with and without linear perspective in depth. One of the main contributions of this study is the implementation of resampling to analyze the algorithm's performance. Resampling is a statistical technique that allows computing estimates of the variance, bias, and confidence intervals of an estimator, using random subsets of the dataset.

5.3 Beach image processing approach

The study by Valentini and Balouin (2020) used a SOLARCAM system for beach monitoring, to compute the semantic segmentation of the imagery, the following was carried out: 1) the image was partitioned in superpixels using the sticky-edge adhesive algorithm; 2) the pre-trained CNN MobileNet-V2 classified the superpixels; and 3) semantic image segmentation was performed through fully connected Conditional Random Field (CRF). The segmented classes were algae, anthropic structure, seafoam and swash, sand, sky, vegetation, and seawater. According to the F1 score metric, the performance of the proposed methodology related to the presence of *Sargassum* reached a maximum of 90%. At publication, this study was the first to apply the semantic segmentation technique to beach monitoring. The proposal is scalable and would only need to integrate the results into a map for visualization.

Balado et al. (2021) applied a semantic segmentation technique to classify imagery of five macroalgal species (*Bifurcaria bifurcata* Linnaeus, *Cystoseira tamariscifolia* (Hudson) Papenfuss, *Sargassum muticum* (Yendo) Fensholt, *Sacchoriza polyschides* (Lightfoot) Batters, and *Codium* spp). The study used data augmentation to build the high-resolution dataset to retrain three CNNs and compare their performance (Mobilnet-V2, Resnet 18, and Xception). The framework used in this study was DeepLabV3 in Matlab. In total, 130 images were labeled and distributed: 90 images for training, 10 for validation, and 30 for testing. This paper shares the hyperparameters used in the learning process of the algorithm

(optimization method, learning rate, momentum, L2 regularization, max epochs, and batch size), which are useful for conducting a replica of the study and is information that has usually been omitted in papers. This is one of the pioneering applications of semantic segmentation to differentiate five species of macroalgae.

To improve the results of this type of study, many ground images are required, as well as a good segmentation of the training dataset. On the other hand, geospatial metadata is required to apply the algorithm in the elaboration of maps or other useable products in decision-making. To implement this proposal in aerial images, new datasets are needed to train, test, and validate the algorithm. Additionally, the number of classes required for segmentation needs to be analyzed since UAV-acquired imagery includes information that does not appear in ground images.

In 2022, [Arellano-Verdejo et al. \(2022\)](#), used the collection of geotagged photographs of [Arellano-Verdejo and Lazcano-Hernandez \(2021\)](#) to apply a semantic segmentation technique to propose a new mapping methodology for estimating *Sargassum* coverage on beaches. Implementing the semantic segmentation image technique requires several steps, one of which is to build a dataset consisting of pairs of pictures (source and segmented). To achieve image segmentation, two stages are required: image translation and subsequent segmentation. Image translation was carried out using the Pix2Pix architecture, and segmentation was performed using the k-means algorithm. All images in the dataset were segmented into three classes (*Sargassum*, sand, and others). If all the *Sargassum* observed in the photographs lies on the beach, the total beach area was confirmed by *Sargassum* and beach pixels. With this criterion, the *Sargassum* coverage percentage over the beach on every picture was calculated for each segmented photograph. The number of photographs available for the study zone allowed statistically reliable mapping of the percentage of *Sargassum* coverage from the segmented images. As an element of validation of the proposed methodology, an orthophoto generated by a UAV flight of the study area was used for one of the photographic sampling dates. The main contributions of this study were the generation of the first geotagged and segmented image dataset for *Sargassum* monitoring for the study area (Mahahual, Quintana Roo, Mexico), and the design of a methodology to generate maps of *Sargassum* coverage on beaches, which provides more information than maps of the presence/absence of *Sargassum*. One challenge of the methodology is the need for a constant flow of images for map creation. This situation is generally not possible since society's participation rate is overall low.

6 Discussion

The observation and monitoring of pelagic *Sargassum* landings poses several challenges. Regarding remote sensing capabilities, it requires information at the synoptic scale for oceanic observations, and at the human scale for coastal and beach monitoring, i.e. scale that can be directly visible, touchable and appreciable by the human body and its environment ([Long and Ye, 2016](#)). Understanding the dynamics of this phenomenon requires daily fine spatial resolution

data and short revisit times. Nevertheless, satellite images have several limitations, because of the nature of the interaction of light with the earth's atmosphere (e.g., absorption, refraction, reflection); the elements and biodiversity in the observation areas (e.g., clouds, cloud remnants, reflections, waves, other species of algae and sea grasses, and floating objects); and the technical limitations of the satellites' platform and sensors. Although several platforms have a resolution of less than one meter at present, it is not economically feasible for most academic groups to carry out long-term monitoring with this type of image. Therefore, exploring the possibility of complementing observations with images from citizen science, and geostationary platforms such as GOES is relevant. Another challenge is that AQUA and TERRA platforms are at the end of their useful life. These platforms are important for the observation of the *Sargassum* as they provide daily information at a synoptic scale through MODIS sensor.

The challenges presented by *in situ* beach monitoring are also diverse due to the extensive areas with *Sargassum* which are not always feasible to visit; there is a lack of infrastructure and electricity services needed for the installation of a monitoring network and greater and better internet connectivity; the data capture through citizen science is minimal; and there is a need for the consolidation of platforms for the exchange of beach-level information, as well as those that exist for satellite imagery. Legislation is also an issue to consider in the design of monitoring systems on beaches. If they are located within protected areas, the construction of infrastructure can be prohibited or must follow a rigorous process to be authorized. Additionally, in the case of installing a camera system for monitoring *Sargassum* on the beach, we must consider the costs of maintenance and surveillance to maximize the useful life of the equipment and avoid looting.

The current academic challenge is generating methodologies that allow obtaining as much information as possible from freely available satellite images or under other information-gathering schemes (e.g., to create low-cost solutions from the most affordable inputs).

6.1 Brief evolution of *Sargassum* observation

The evolution of *Sargassum* observation and study approaches can be summarized chronologically, methodologically, by area, and by scale.

6.1.1 Chronological approach

Sargassum observations in the CS can be classified into two stages: before and after 2018. Before 2018, *Sargassum* oceanic observations were carried out using ocean color sensors (i.e. MODIS, MERIS) and algorithms (i.e. FLH, MCI). After 2018, monitoring *Sargassum* on coasts and beaches became necessary due to the environmental and socioeconomic impacts it provokes. False positives (FP) were minimized with FAI and AFAI indices since the first observations of *Sargassum* in images were obtained with MERIS and MODIS sensors. However, this did not solve the

problem entirely because FPs are more accentuated in coastal areas due to the diversity of elements compared to those in the open sea, where the surface is homogeneous. To overcome this challenge, ML algorithms were incorporated to remove the background noise from the satellite images and make *Sargassum* identification easier.

The challenges caused by *Sargassum* landings in 2018, coincided with the democratization of ML, which refers to the accessibility of software, libraries, and computing resources needed for its implementation. For example, in 2015, Google made the Open-Source Neural Networks library – Keras – available to any user, which can run on Tensor Flow, Microsoft Cognitive Toolkit, or Theano. Keras was designed to experiment DL networks relatively easily, being user-friendly, modular, and extensible extensible (Chollet, 2021). In this context, ERISNet was published in 2019 (Arellano-Verdejo et al., 2019). At that time, the state-of-the-art indicated that observing *Sargassum* in coastal areas with MODIS imagery was impossible due to the difficulty of discriminating it from other near-shore elements.

6.1.2 Methodological approach

Since 2005, *Sargassum* observation in the open ocean has been conducted using several baseline-type indices (MCI, FLH, FAI, AFAI) that share the same mathematical expression but different suits of spectral bands to set the image background to improve the observation of floating algae. From a methodological point of view, there has been no real innovation in applying these indices to observe *Sargassum*. From 2018 onwards, studies began to be published where they implemented image processing and ML techniques to improve the images before applying ocean color indexes. Incorporating these techniques suggests a new stage in the observation and monitoring of *Sargassum*; however, the process is still in the initial phase. In this context, *Sargassum*'s observation can be classified into the two methodological approaches described below.

The initial observations of *Sargassum* from space employed indices designed to observe *Chl a* in the open sea. MCI and FLH indices were first used in 2005. Later, in 2009, the FAI was published and became the benchmark until the AFAI was published in 2016. These techniques share the same mathematical expression; the difference lies in the bands selected to calculate the index. Due to the nature of the indices, no methodologies or statistical metrics have been used to assess their performance, except for *in situ* validation. The second methodological stage incorporated ML techniques to improve the results provided by the indices. The first study incorporating ML for *Sargassum* detection in the sea was published in 2018 (Cuevas et al., 2018). ML had already been used to analyze satellite data and images with excellent results (Camps-Valls et al., 2021). ML techniques were either incorporated at some stage of the methodology to improve the discrimination of *Sargassum* offered by the existent indices or used from scratch to design new techniques. The first study incorporating DL for *Sargassum* detection in the sea was published in 2019 (Arellano-Verdejo et al., 2019).

6.1.3 Study area approach

Sargassum monitoring can be conducted in oceanic, coastal, and beach environments. Oceanic monitoring began in 2005 using

traditional indices and algorithms and was improved using ML techniques from 2018 onwards. Coastal monitoring was improved using high-resolution satellite imagery and ML to minimize false positives and improve the generation of value-added products from satellite inputs. Although field data collection has always been carried out to validate satellite data, *Sargassum* monitoring on beaches began improving in 2018 by installing cameras along the coast and through Citizen Science. Data becomes in inputs for computer vision techniques (Álvarez-Carranza and Lazcano-Hernandez, 2019; Arellano-Verdejo and Lazcano-Hernandez, 2020). This information allowed to train ANNs to be capable of classifying photographs with/without *Sargassum* (Arellano-Verdejo and Lazcano-Hernandez, 2021), segmenting *Sargassum* in snapshots (Arellano-Verdejo et al., 2022) and classifying beach perspective in photographs (Santos-Romero et al., 2022), allowing the creation of *Sargassum* coverage maps using photographs at the beach level.

6.1.4 Study scale approach

MERIS, MODIS, and VIIRS have been the most widely used sensors for *Sargassum* studies and monitoring at the synoptic and mesoscale space scales. In 2012, the Envisat mission ended, making MODIS and VIIRS the only sensors available when writing this manuscript. The MODIS sensor obtains 250-1000 meter resolution images with an average of a 2-day revisit period. By combining data from both satellites, daily images can be obtained. Unlike MODIS, the LANDSAT platform obtains images with a better spatial scale (15-30 m), but the revisit period is 16 days. On the other hand, the Sentinel 2A (launched June 2015) and Sentinel 2B (March 2017) satellites provide images with a spatial resolution of 10-60 m and a revisit period of 10 days (or five days if images from both satellites are used). The platforms mentioned above offer free access to several databases collections highly used by the scientific community. However, the databases of images with higher spatial and temporal resolutions considered the ideal input for *Sargassum* monitoring are costly¹. For those who cannot afford them, the alternative has been using aerial and ground photographs and videos.

6.2 Research gaps

Different platforms provide information on *Sargassum* biomass in the ocean, coastal waters, and beaches. However, ideally, they should provide consolidated information for all environments. The only source of periodic reports on the distribution and abundance of *Sargassum* in the Atlantic Ocean is the Satellite-based *Sargassum* Watch System (SaWS) from the Optical Oceanography Laboratory of the University of South Florida². Most countries affected by

1 <https://www.planet.com/our-constellations> <https://www.planet.com/our-constellations>

2 <https://optics.marine.usf.edu/projects/saws.html> <https://optics.marine.usf.edu/projects/saws.html>

Sargassum in the Greater Caribbean rely on this information to estimate landing volumes and develop management strategies. Nevertheless, adequate measurements of *Sargassum* coverage and biomass in coastal waters and on beaches are needed to understand spatial and temporal variability in landings, both within and between countries, and to feed numerical prediction models. Thus, to improve *Sargassum*'s understanding and management, the current geoportals and information sources must evolve into hybrid *Sargassum* monitoring observation and survey systems.

Sargassum monitoring in coastal waters faces several challenges. In the CS, the shallow oligotrophic waters and enormous ecological diversity result in a wide variety of colors, making it difficult to correctly identify the elements in a scene. Thus, monitoring coastal areas requires images with a sharp spatial resolution (1 m) and high revisit periods, preferably once a day. Although satellite platforms that offer very high spatial resolution images do exist³, they are economically inaccessible for most researchers in the region.

A significant research gap has been quantifying *Sargassum* landing volumes because *in situ* measurements are difficult and time-consuming (Rodríguez-Martínez et al., 2022). The computer vision algorithms for the classification and semantic segmentation of *Sargassum* in photographs collected by citizen science are a step towards developing beach monitoring scalable techniques. Nevertheless, methods to discriminate *Sargassum* from other types of macroalgae or seagrasses are still needed to reduce false positives and avoid overestimating *Sargassum* landing volumes. The main challenge of monitoring techniques based on citizen science is for society to adopt them. The platforms based on data and images captured by the voluntary participation of citizens depend on a constant flow of data to produce value-added products. Also, for these platforms to be successful and use their total capacity, they should be run and promoted by the institutions in charge of *Sargassum* management. To date, most of the information available consists of photographs and isolated data records in different formats and with little or no knowledge of metadata.

Incorporating ML methodologies in the *Sargassum* observation process has contributed to minimizing the background noise in the satellite images, thereby reducing the number of false positives and negatives (Wang and Hu, 2020; Wang and Hu, 2021). However, it requires being more rigorous in its implementation, and evaluation. There are well-defined steps in ML that must be followed to successfully implement an algorithm. However, they have either not been followed or have not been discussed in the studies. For example, the supervised classification algorithms applied for *Sargassum* monitoring, requires balanced datasets with thousands of images for training stage (training, testing, and validation). However, most of the studies that employ ML algorithms, lack a detailed explanation about the characteristics of the dataset and about the hyperparameters settings. There is also a need to implement confusion matrices to analyses algorithm performance and implement metrics (F1 score, IoU), to assess with more detail

the algorithm performance. Table 4 shows the general aspects expected to be described in any study using supervised classification algorithms.

6.3 Potential developments in the field

Regarding the application of high-resolution satellite imagery for monitoring *Sargassum* on the coast and beaches also has potential. Although its implementation may be economically costly, its application may be feasible for observing strategic study areas. On the other hand, the development of methodologies using inputs from geostationary satellite platforms is also pending.

Regarding citizen participation in monitoring proposals, an action that we consider essential for gathering data is the coordination and periodic participation of several sectors of the citizenry to serve their purpose.

Regarding the application of ML in the monitoring of *Sargassum* we consider is still in the initial stage, their potential has not been used yet, and improvements will help to obtain more information from satellite imagery. The current challenges are adequately implementing image processing and computer vision techniques to eliminate noise in the images regardless of their scale and to later ingest the image to the preferred index to detect *Sargassum* with the least possible error. We believe that designs from scratch are needed for *Sargassum* discrimination. On the other hand, DL are not always necessary, image processing and computer vision techniques in some cases may be sufficient for the *Sargassum* discrimination in an image.

A common feature in studies that use ML as a methodology to enhance *Sargassum* contrast in images is the use of the UNet architecture, which is a convolutional neural network developed for biomedical image segmentation at the Department of Informatics of the University of Freiburg (Ronneberger et al., 2015). One of the main features of this architecture is that it offers useful image translations from small training data sets (i.e., hundreds of images). This feature has allowed its application to address problems where data is scarce. Such is the case of *Sargassum* observation and monitoring, where the UNet has been used as an architecture base to improve *Sargassum* observations in oceans, coasts, and beaches.

Another challenge is the design of hybrid systems that incorporate information at different scales and environments to improve our understanding of the *Sargassum* phenomenon and the development of better strategies for its management, valorization, and disposal.

7 Conclusions

Ecological and social challenges caused by the enormous quantities of *Sargassum* arriving at beaches in most of the countries located in the CS, particularly since the year 2018 and to date, have generated the necessity of enhancing *Sargassum* monitoring onshore and nearshore to support the management

³ <https://www.planet.com/our-constellations>
<https://www.planet.com/our-constellations>

TABLE 4 Steps for the implementation of supervised classification algorithms.

1	Dataset design
	- Dataset construction
	- Construction of the subsets for the training, testing, and validation stages
	- Assessment of the advantages and disadvantages of the final dataset and how it will impact the performance of the algorithm
2	Design of the algorithm or selection of the architecture to be reused
	- Setting of hyperparameters
3	Training algorithm
	- Analysis of the learning process and accumulated error
	- Hyperparameter readjustment
	- Training until the optimal learning rate is achieved
4	Algorithm testing and validation
	- Compute confusion matrices
	- Compute metrics to know the algorithm performance
	- Analysis of different cases (best, worst, average, outliers)

and disposal of *Sargassum*. However, the methodologies used for monitoring *Sargassum* in the open sea are not useful on coasts and beaches due to various physical and biological factors. Thus, other areas of knowledge, such as computer science and citizen science, have been incorporated to contribute to the improvement of the results, at different scales, obtained using the traditional RS indices.

Currently, the benchmarks for *Sargassum* monitoring in the open ocean are the FAI and AFAI indexes inspired by the MCI and FLH indices. These four indices only differ in the input spectral bands that feed the equation. All the indices used for *Sargassum* monitoring, observe objects that contrast with the ocean surface. Therefore, what is observed could possibly be *Sargassum* or another type of algae (*Syringodium*, *Trichodesmium*, or *Ulva*) or object (garbage or emulsified oil). To address this challenge, the study conducted by Dierssen et al. (2015) proposes *Sargassum* discrimination in two different scenarios, the first step is to apply the NDVI index and then the LD, SI, or RGR indices, as appropriate. This methodology was implemented with high-resolution PRISM images.

From an image processing perspective, the main elements to be discriminated in an image to observe *Sargassum* can be grouped in two cases: 1) low-frequency elements, such as clouds and their shadows and even terra firma; and 2) high-frequency elements, such as wave crests and coastal zone heterogeneity. Buffers or masks can be used to overcome the drawbacks of low-frequency elements. To deal with high-frequency elements, various filtering techniques can be used. Despite advances in image processing, its application in the observation and monitoring of *Sargassum* is still at an early stage.

Computer vision techniques, implemented for several years in other areas of knowledge with excellent results, were incorporated in *Sargassum* monitoring until 2018. However, there are challenges to its proper implementation, for instance, there is a lack of information on the construction of the dataset and the criteria used to create the training, testing, and validation subsets; also, to

evaluate the performance of algorithms, it is necessary to incorporate confusion matrices, performance evaluation metrics, and resampling techniques in case that the training dataset is a sample and not the whole population.

One of the main challenges in observing *Sargassum* in satellite images is background noise discrimination from the images to successfully apply a RS index. Recent proposals for *Sargassum* observation have focused on using various ML techniques to perform background noise removal. This means that ML has been applied only in the preprocessing of the images, therefore, ML designs implemented from scratch are needed.

Author contributions

HL-H and JA-V contributed to the conception and design of the study. HL-H performed the initial research and organized the peer-reviewed literature. HL-H performed the statistical analysis. HL-H and JA-V wrote the first draft of the manuscript. HL-H, JA-V, and RR-M evaluated and discussed sections of the manuscript for improvement. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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