

Draft – Discriminating Seagrasses From Green Macroalgae in European Intertidal areas using high resolution multispectral drone imagery – Draft

Simon Oiry^{a,*}, Bede Ffinian Rowe Davies^a, Ana I. Sousa^b, Philippe Rosa^a,
Maria Laura Zoffoli^c, Guillaume Brunier^d, Pierre Gernez^a, Laurent Barillé^a

^a*Institut des Substances et Organismes de la Mer, ISOMer, Nantes Université, UR 2160,
F-44000 Nantes, France,*

^b*CESAM – Centre for Environmental and Marine Studies, Department of Biology,
University of Aveiro, Aveiro, Portugal,*

^c*Consiglio Nazionale delle Ricerche, Istituto di Scienze Marine (CNR-ISMAR), 00133
Rome, Italy,*

^d*BRGM French Geological Survey, Cayenne 97300, French Guiana,*

Abstract

Coastal areas support seagrass meadows, which offer crucial ecosystem services including erosion control and carbon sequestration. However, these areas are increasingly impacted by human activities, leading to habitat fragmentation and seagrass decline. In situ surveys, traditionally performed to monitor these ecosystems face limitations on temporal and spatial coverage, particularly in intertidal zones, prompting the addition of satellite data within monitoring programs. Yet, satellite remote sensing struggles with spatial and spectral resolution, making it difficult to discriminate seagrass from other macrophytes in highly heterogenous meadows. Drone images at a very high spatial resolution offer a promising solution to address challenges related to spatial heterogeneity and intrapixel mixture. This study focuses on using drone acquisitions with a ten spectral band sensor mirroring those of Sentinel-2, for mapping intertidal macrophytes and effectively discriminating between seagrass and green macroalgae. Nine drone flights were conducted at two different altitudes (12m and 120m) across heterogeneous intertidal European habitats in France and Portugal. Low altitude flights were used to train a Deep Learning classifier based on Neural Networks to discriminate among five taxonomic classes of intertidal vegetation: Magnoliopsida (Seagrass), Chlorophyceae (Green macroalgae), Phaeophyceae (Brown algae), Rhodophyceae (Red macroalgae) and benthic Bacillariophyceae (Diatoms). Classification of drone imagery resulted in an overall accuracy of

*Corresponding author
Email address: oiry_simon@gmail.com (Simon Oiry)

94% across all the sites and images, covering a total area of 467 000 m². The model exhibited an accuracy of 96.4% in identifying seagrass. Importantly, seagrass and green algae can be discriminated, although they share the same pigment composition. As the algorithm was developed for a multispectral camera with ten spectral bands in the visible and near-infrared, it could be adapted to the Multi-Spectral Instrument (MSI) onboard Sentinel-2 thus offering promising perspectives for satellite remote sensing of intertidal biodiversity over larger scales.

Keywords: Drone, Remote Sensing, Seagrass, Coastal Ecosystems, Neural Network

1. Introduction

Coastal areas are vital hotspots for marine biodiversity, with intertidal seagrass meadows playing a crucial role at the interface between the land and oceans [1]. Seagrass meadows provide a myriad of ecosystem services to humanity, including carbon sequestration, oxygen production, protection against sea-level rise and coastline erosion, and limitation of eutrophication. They serve as vital habitats for a diverse array of marine and terrestrial species, providing living, breeding, and feeding grounds [2, ; 3, ; 4]. Due to the concentration of human activities in coastal zones, seagrass meadows are directly exposed to and impacted by anthropogenic pressures. Global regression and fragmentation of seagrass meadows are currently observed due to climate change, diseases, urbanization, land reclamation, dredging, competition with alien species, and reduction in water quality [5, ; 6, ; 7, ; 8, ; 9, ; 10, ; 11]. Both habitat fragmentation and reduction, in turn, can severely compromise the effectiveness of ecosystem services provided by seagrass meadows. While improvements in water quality have been recently reported in Europe, allowing an overall recovery of seagrass ecosystems at local scales, many coastal waters worldwide are still subjected to strong eutrophication processes [12, ; 13]. Coastal eutrophication has been associated to excessive accumulation of green macroalgae, so-called green tides [14]. Green tides produce shade and suffocation over seagrass individuals, thus threatening the health of seagrass ecosystems [15].

The importance of seagrass meadows and the variety of ecosystem services they provide have led to the enhancement of both global and regional programs to monitor Essential Oceanic Variable (EOVs) such as seagrass composition [16], as well as Essential Biodiversity Variable (EBVs) such as seagrass taxonomic diversity, species distribution, population abundance, and phenology [17]. Traditionally, indicators of seagrass status have been quantified using *in situ* measurements. However, the acquisition of these measurements in intertidal zones is notoriously challenging. Intertidal seagrass meadows are only partially exposed during low tide and can be situated in difficult-to-reach mudflats, potentially leading to inaccurate and limited estimations with conventional sampling techniques [18]. Satellite observations have been proven effective in complementing

in situ sampling, allowing for the near real-time and consistent retrieval of seagrass EOFs and EBVs over extensive meadows. [13, ; 19, ; 20, ; 21]

While satellite remote sensing (RS) provides temporally consistent observations over large spatial scales, its utilization over intertidal areas is limited by several constraints. Satellite missions with a high temporal resolution (e.g. daily MODIS observation) are limited by a too coarse spatial resolution ($>100\text{m}$) to accurately map patchy seagrass meadows. Missions with a high spatial resolution such as Sentinel-2 (10m) or Landsat8/9 (30m) can be limited by low spectral resolution. The limited number of spectral bands challenges accurate discrimination of seagrass from other co-existing macrophytes. In particular Chlorophyceae (green algae) and marine Magnoliopsida (seagrass) share the same pigment composition [22, ; 23]. Therefore, to someone not specialized in the field, their spectral signatures may appear to be alike [24, ; 25]. Recently, using advanced machine-learning algorithms trained with a large hyperspectral library of more than 300 field reflectance spectra, [24] demonstrated that it was possible to discriminate Magnoliopsida from Chlorophyceae using radiometric data acquired at Sentinel-2's spectral resolution. However the application of this approach to satellite RS remains to be validated. Moreover patches of green algae can develop at small spatial scales that are not observable using non-commercial satellite imagery [26], especially during the initial stage of a green tide.

Drones can potentially fill the data gaps left by satellite RS and *in situ* measurements, due to their ability to provide spatially-explicit observations at very high spatial resolutions (pixel size from mm to cm) while capturing data at multi-spectral resolution [27, ; 28]. The versatility of drones allows for their application across a diverse thematic range, from coastal zone management [29, ; 30, ; 31] to mapping species distribution [32, ; 33, ; 34, ; 35, ; 36]. However, when applied to coastal habitat mapping, most case studies were previously limited to a single flight, restricting the generalizability of their application over wider geographical scales [35, ; 37, ; 38, ; 36]. The present study aimed at analyzing the potential of multispectral drone RS to map intertidal macrophytes over a diverse biogeographical range, with a particular focus on discriminating Magnoliopsida and Chlorophyceae (Seagrass and Green Algae respectively). Ten drone flights were performed over soft-bottom intertidal areas along the Atlantic coastlines of two European countries (France and Portugal), covering a wide range of habitats, from monospecific seagrass meadows to meadows mixed with green, or red macroalgae. A deep learning algorithm was trained and validated for macrophyte discrimination, emphasizing applicability across diverse sites without a loss of prediction accuracy.

2. Material & Methods

2.1. Study sites

Seven study sites distributed between France and Portugal were selected for their relatively extensive intertidal seagrass beds. Two sites were located in

the Gulf of Morbihan (Figure 1 A), France (47.5791°N , 2.8018°W). This gulf covers an area of 115 km^2 and is only connected to the sea through a 900m wide channel. A total of 53 small islands are scattered across the gulf leading to 250 km of shorelines. Patchy seagrass meadows can be found on many of these islands. One of the sites within the gulf was on one its islands (Arz) and the other was located further south on a mainland beach area (Duer). Two other sites were located in Bourgneuf Bay, France (46.9849°N , 2.1488°W). This is a 340 km^2 semi-enclosed macrotidal bay, protected from waves by Noirmoutier Island. Bourgneuf bay hosts a large intertidal seagrass meadow of about 6 km^2 [39]. Within this meadow, the sites observed by drones (L'Epine and Barbatre, Figure 1 B) contained monospecific beds of *Nanozostera noltei* (dwarf eelgrass) with very little mixing with other macrophytes. Three sites were surveyed in the Ria de Aveiro Lagoon in Portugal (40.6887°N , 8.6810°W). The extent of this lagoon is $\sim 80 \text{ km}^2$ with many narrow channels, large salt marshes and many mudflats that uncover at low tide. It is connected to the open sea through a single channel, with a tidal lag between the North and the South of the lagoon. The southernmost site (Gafanha) was a mudflat located in a tributary river of the lagoon whereas the two other sites (Mataducos and Marinha Lanzarote) were situated in the middle of the lagoon and only accessible by boat (Figure 1 C). These Portuguese sites are characterized by a more diverse intertidal vegetation, where patches of seagrass intermingle with red, brown, and green macroalgae.



Figure 1: Location of drone flights in France and Portugal. A: Gulf of Morbihan (Two sites), B: Bourgneuf Bay (Two sites), C: Ria de Aveiro Coastal Lagoon (Three sites). Green areas represents the intertidal zone.

2.2. Field sampling

2.2.1. Drone acquisition

At each location, a DJI Matrice 200 quadcopter drone equipped with a Micasense RedEdge Dual MX multispectral camera was flown to take 1.2 million pixel reflectance photographs with ten spectral bands ranging from the blue to the near infrared (NIR): 444, 475, 531, 560, 650, 668, 705, 717, 740 and 840 nm. To ensure consistent lighting conditions across flight paths, the drone's trajectory was aligned to maintain a solar azimuth angle of 90 degrees. An overlap of 70% and 80% (side and front respectively) between each image was set for each flight. A downwelling light sensor (DLS2) was used to acquire irradiance data concomitantly with the camera measurements. Raw data were calibrated in reflectance using a calibration panel reflective at ~50% provided by the man-

Table 1: List of drone flight, summarising the date, the altitude, and the purpose of each flight. 12 m and 120 m flights have a spatial resolution of 8 and 80 mm respectively.

Country	Site	Name	Altitude	Utility	
France	Gulf of Morbihan	Arz Island	12m	Training	
		Duer	12m	Training	
		Duer	120m	Validation	
	Bourgneuf Bay	Barbâtre	120m	Validation	
		L'Epine	120m	Validation	
	Aveiro Lagoon	Marinha Lanzarote	120m	Validation	
Portugal		Mataducos	120m	Validation	
		Gafanha	120m	Validation	
		Gafanha	12m	Training	

ufacturer. Across all sites, flights were made at two different altitudes : 12 m or/and 120 m. (Table 1).

2.2.2. Ground Control Points

Before each flight, targets used as ground control points were distributed over the study site and georeferenced with a Trimble © Geo XH 6000 differential GPS (dGPS). Ground control points were used to correct georeferencing imprecision of orthomosaics with an horizontal and vertical accuracy of 10cm. A dGPS was also used to georeference quadrats of 0.25 m^2 , which assessed the presence or absence of five key taxonomic classes of intertidal vegetation : Bacillariophyceae (Unicellular benthic diatoms forming biofilms at the sediment surface during low tide), Phaeophyceae (brown macroalgae), Magnoliopsida (dwarf seagrass), Chlorophyceae (green macroalgae) and Rhodophyceae (red macroalgae) (Figure 2). Pictures of each quadrat were uploaded online to the Global Biodiversity Information Facility (GBIF) platform [40], a public open portal to store and share biodiversity data. Each photograph was also processed to estimate the percent cover of each type of vegetation using an image processing software [ImageJ, 41]. Hyperspectral reflectance signatures of each vegetation class were recorded using an ASD FieldSpec HandHeld 2 spectroradiometer, which acquires reflectance between 325 and 1075 nm, with 1 nm of spectral resolution. Hyperspectral signatures served dual purposes: they validate the radiometric calibration of drone data and contribute to error reduction in photo interpretation.

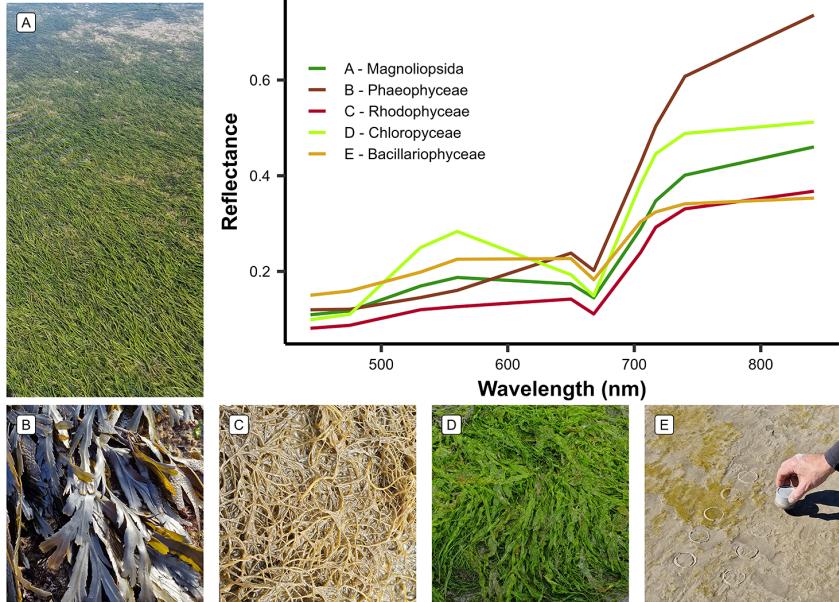


Figure 2: The five taxonomic classes of vegetation used to train the Neural Network model and their raw spectral signatures at the spectral resolution of the Micasense RedEdge Dual MX.

2.3. Drone Processing

A structure-from-motion photogrammetry software [Agisoft Metashape, 42] was used to process images to obtain multispectral orthomosaics of each flight. The process for orthomosaicking was identical for every flight. First, tying key points were detected inside of each image and between overlapping images in order to obtain a sparse point cloud. This cloud was cleaned using reprojection accuracy metric in order to remove noisy points. A dense point cloud was then produced using a structure from motion algorithm. A surface interpolation of this dense point cloud was made to obtain a digital surface model (DSM), used to reconstruct the multispectral ortho-image [43]. Low altitude drone flights produced ortho-images with a very high spatial resolution (8 mm per pixel), making it efficient to visually distinguish between the various types of vegetation. High altitude flights on the other hand allowed to cover large areas and produced images with a pixel size of 80 mm (Table 1).

2.4. General Workflow

The spectral similarities of the reflectance signatures between intertidal green macrophytes (Magnoliopsida and Chlorophyceae) make their discrimination challenging using simple classification algorithms (Figure 2 F). To overcome this challenge, a deep learning classification method was trained, validated, and applied to each drone flight (Figure 3).

Table 2: Vegetation Classes of the model and the number of pixels used to train and validate each class

Class	Training Pixels	Validation Pixels
Bacillariophyceae	4,475	3,371,920
Chlorophyceae	17,140	6,258,737
Magnoliopsida	221,065	69,079,189
Phaeophyceae	169,936	18,481,141
Rhodophyceae	5,771	3,515,421

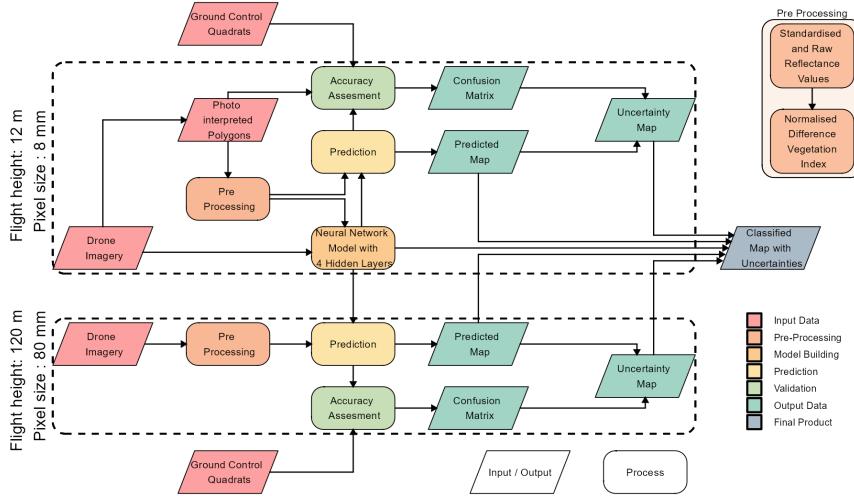


Figure 3: Schematic representation of the workflow. Parallelograms represent input or output data, and rectangles represent Python processing algorithms. The overall workflow of this study is divided into two distinct parts based on the spatial resolution of the drone flights: high-resolution flights (pixel size: 8 mm) were utilized for training and prediction of the Neural Network model, whereas lower-resolution flights (pixel size: 80 mm) were solely employed for prediction purposes. Validation has been performed on both high and low resolution flights.

2.4.1. Training dataset building

A dataset containing photo-interpreted drone reflectance pixels was built to train a Neural Network model. The training pixels were categorized into seven different classes, representing the various habitats encountered at the different study sites: Sediment, Water, Chlorophyceae, Magnoliopsida, Bacillariophyceae, Phaeophyceae and Rhodophyceae. Only low-altitude flights (Table 1) were used

for training because their 8 mm spatial resolution allowed to avoid spectral sub-pixel mixing and to accurately identify vegetation classes. More than 418,000 pixels at 8 mm resolution from the 3 training flights were used to train the model (Table 2). Twenty one variables were used by the model as predictors: the ten raw spectral bands of the Micasense RedEdge Dual MX multispectral camera (ranging from 444 nm to 840 nm), the same ten spectral bands standardized using a min/max transformation (Equation 1 ; [44]) and the Normalized difference vegetation index (NDVI, Equation 2). Standardisation of spectral bands is commonly used to eliminate the scaling differences between spectra and to limit the effect of biomass on the spectra shape [23, ; 24].

$$R_i^*(\lambda) = \frac{R_i(\lambda) - \min(R_i)}{\max(R_i) - \min(R_i)} \quad (1)$$

where $R_i(\lambda)$ is the reflectance at the wavelength (λ) of each individual spectra (i), $\min(R_i)$, and $\max(R_i)$ are the minimum and maximum value of the spectra (i)

$$NDVI = \frac{R(840nm) - R(668nm)}{R(840nm) + R(668nm)} \quad (2)$$

where $R(840nm)$ is the reflectance at 840 nm and $R(668nm)$ is the reflectance at 668 nm.

2.4.2. Model building

A neural network classification model was built using the fastai workflow [45]. This model is composed by 2 hidden layers and have a total of 26 054 trainable parameters. Parameters have been find tune using 12 epoch to minimize the error rate.

2.4.3. Validation

The workflow of this study revolves around two distinct flight heights (12 m and 120 m, Figure 3) where ensuring consistency between reflectances at both heights is crucial. This comparison was conducted at sites where low and high altitude flights overlapped. The low altitude flights were resampled to the same spatial resolution and grid as the high flights using a median resampling method. Reflectance values were then extracted, and a scatterplot was generated. Subsequently, the slope of the linear model and the coefficient of determination (R^2) were computed.

The model was applied to all flights at both 12 and 120 m of altitude. In situ information on georeferenced class type and percent cover collected during each flight was used to assess the model accuracy. These images were used to construct a validation dataset indicating the presence or absence of each class. Additionally to the quadrat-based validation dataset, polygons of each class were photo interpreted in order to increase the number of pixels of the

validation dataset. A total of 536,000 pixels were used to validate the Neural Network classifier. The sites with the lowest and highest number of validation data were Gafanha Low (17316 pixels) and Marinha Lanzarote (159713 pixels), respectively. A confusion matrix, along with precision metrics such as global accuracy, sensitivity, specificity, and Kappa coefficient, was generated for each site. All validation matrices were then aggregated to create an overall matrix.

2.5. Variable Importance

Variable Importance Plots (VIP) serve as a method to identify which predictors are important for predicting a specific class. Out of the twenty one predictors utilized in this study, Variable Importance was computed only for the raw and standardized values of the 10 spectral bands captured by the MicaSense camera. This is achieved by repeatedly predicting the same dataset while randomly shuffling one predictor at a time. The benchmark score obtained after each iteration is then compared to the benchmark score obtained without shuffling any variables. The greater the difference between these two benchmark values, the more important the variable is for the model [46].

2.6. Impact of the percent cover on the prediction

The key aspect of the workflow adopted in the present study is the mapping of specific areas at two different altitudes (12m and 120m), resulting in two distinct resolutions for the same area (8mm and 80mm). The predictions made on the high-resolution flight can be used to estimate the percent cover of each vegetation class for every pixel of the lower resolution flight. Consequently, for each pixel of the high-altitude flights, percent covers of each vegetation class were obtained, and a kernel density plot was generated. This plot provides a visual representation of the behavior of the model in different vegetation percent cover scenarios.

3. Results

3.1. Classification

Each drone flight was used to produce a prediction map, as well as a probability map that indicates the model derived likelihood of the selected class for every pixel. The low-altitude flight conducted in Gafanha, Portugal, represents the site with the highest complexity (Figure 4). Among the five vegetation classes on which the model was trained, four were present on this site, with Chlorophyceae and Rhodophyceae mixed with the seagrass meadow. There was also Bacillariophyceae forming biofilms on parts of sediment surface. Although the seagrass bed was solely composed of *Nanozostera noltei*, various colors of this species could be observed from dark green (corresponding to healthy leaves) to whitish/brown (when leaves were discolored having lost their pigmentation). Regardless of color, Magnoliopsida pixels were accurately predicted by the model.

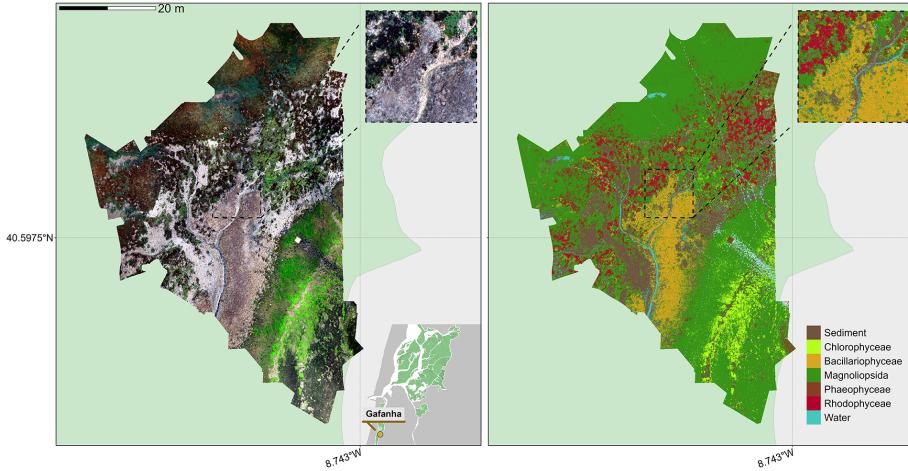


Figure 4: RGB orthomosaic (Left) and Prediction (Right) of the low altitude flight of Gafanha, Portugal. The total extent of this flight was 3000m² with a resolution of 8 mm per pixel. Background colors indicate intertidal area (Light Green) and land area (Light Grey). The zoom covers an area equivalent to a 10-meter Sentinel-2 pixel size.

The high-altitude flight over Gafanha covered a total area of ~1 km² (Figure 5). A channel contouring a small island was masked in the prediction map. Most of the intertidal area was classified as Magnoliopsida by the model, including seagrass patches with discolored leaves. Only a few pixels were classified as Chlorophyceae at this spatial scale. Furthermore, the area that was classified as Bacillariophyceae in the low-altitude flight remained mostly classified as such in the high-altitude flight, though some pixels were classified as Magnoliopsida. Patches of Rhodophyceae were correctly classified. In the northern part of the site and near the land edges, patches of the schorre angiosperm *Spartina* sp. were misclassified, either as Magnoliopsida or as Phaeophyceae.

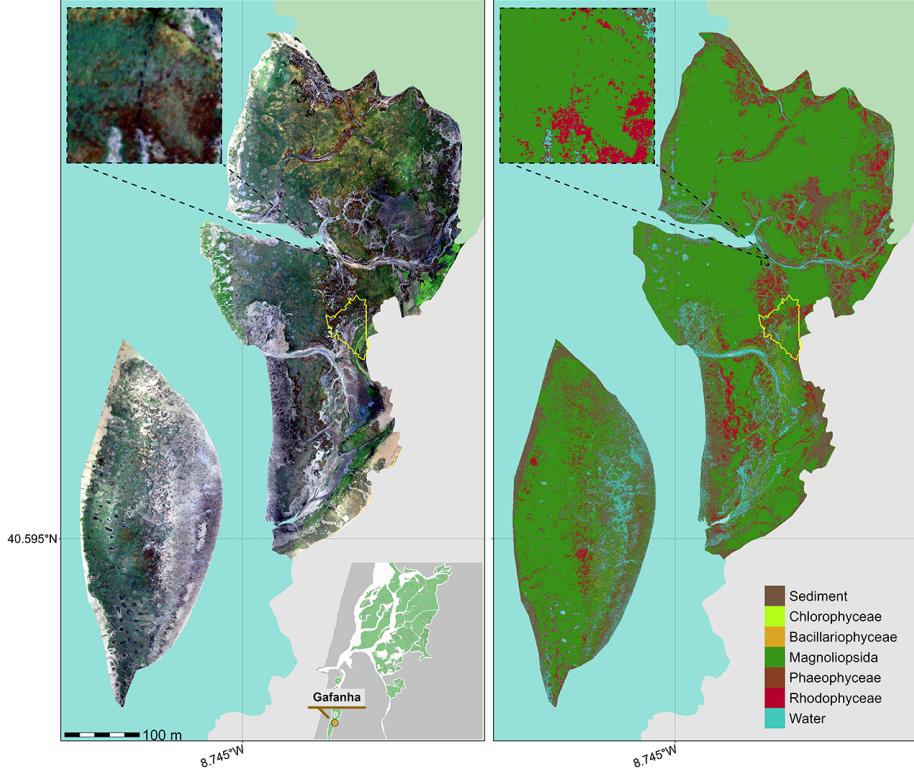


Figure 5: RGB orthomosaic (Left) and Prediction (Right) of the high altitude flight of Gafanha, Portugal. The total extent of this flight was about 1 km² with a resolution of 80 mm per pixel. Background colors indicate intertidal area (Light Green), land area (Light Grey) and water (Light Blue). The yellow outline shows the extent of the low altitude flight of Gafanha presented in Figure 4. The zoom covers an area equivalent to a 10-meter Sentinel-2 pixel size.

Among the high altitude flights, the one acquired over the inner lagoon of the Ria de Aveiro covered the largest area with approximately 1.5 km² (Figure 6). This site was dominated by seagrass and red macroalgae. The classification provided consistent results, with a patchy seagrass meadow mixed with red macroalgae on the eastern part of the site. As shown in the zoom (Figure 6), the edges of the meadow visually appear to be colonised by green macroalgae, which the model agreed with.

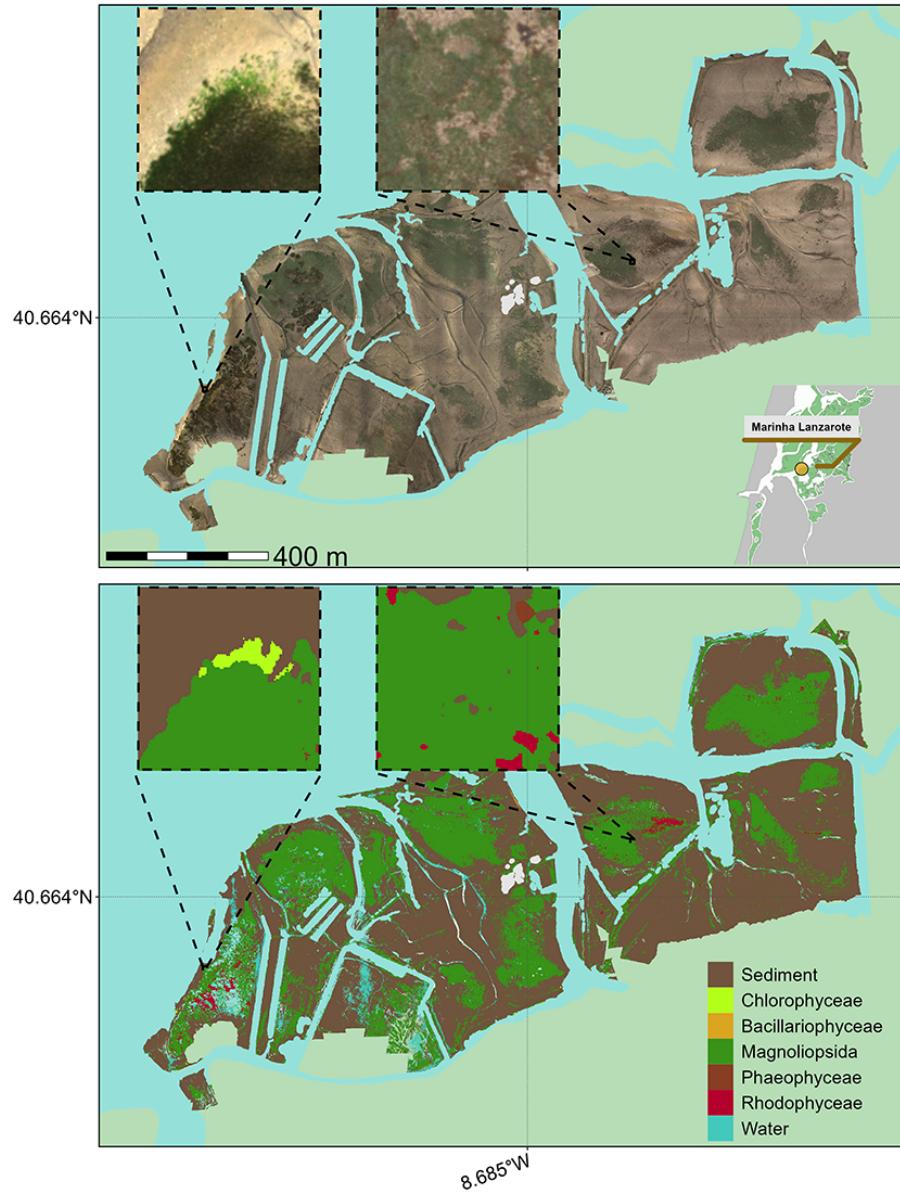


Figure 6: RGB orthomosaic (Top) and Prediction (Bottom) of the flight made in the inner part of Ria de Aveiro Lagoon, Portugal. The total extent of this flight was about 1.5 km^2 with a resolution of 80 mm per pixel. Background colors indicate intertidal area (Light Green), land area (Light Grey) and water (Light Blue). Each cover an area equivalent to a 10 m Sentinel-2 pixel size.

The flight over L'Epine in Noirmoutier Island, France (Figure 7) was conducted

near a dike, which crossed the northern part of the site from west to east. Alongside this dike, Fucale brown algae (*Fucus spp.*, *Ascophyllum nodosum*) were attached to sparse rocks and stranded green algae (*Ulva spp.*) could be observed. Despite the high mixture between Chlorophyceae and Magnoliopsida these two classes were correctly discriminated by the classifier.

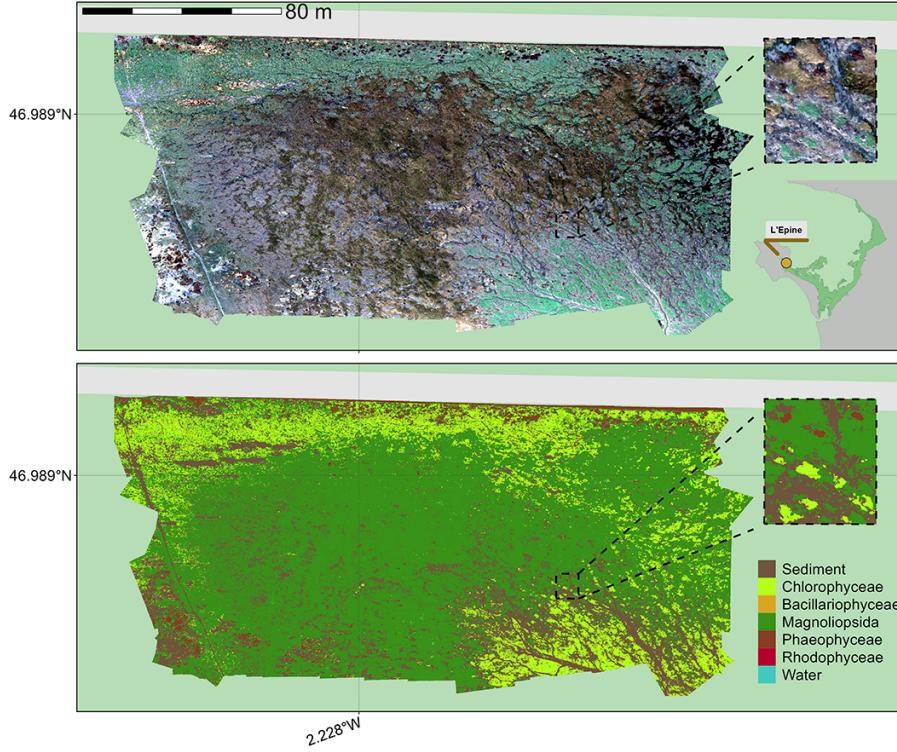


Figure 7: RGB orthomosaic (Top) and Prediction (Bottom) of L'Epine, France. The total extent of this flight was about 28 000 m² with a resolution of 80 mm per pixel. Background colors indicate intertidal area (Light Green) and land area (Light Grey). The zoom covers an area equivalent to a 10-meter Sentinel-2 pixel size.

3.2. Validation

3.2.1. Reflectance comparison between the two different altitudes

In this study, a key innovation lies in the utilization of drone flights at two different altitudes (12m and 120m) for constructing the neural network model. Overall there was a good agreement between the two altitudes (Figure 8).

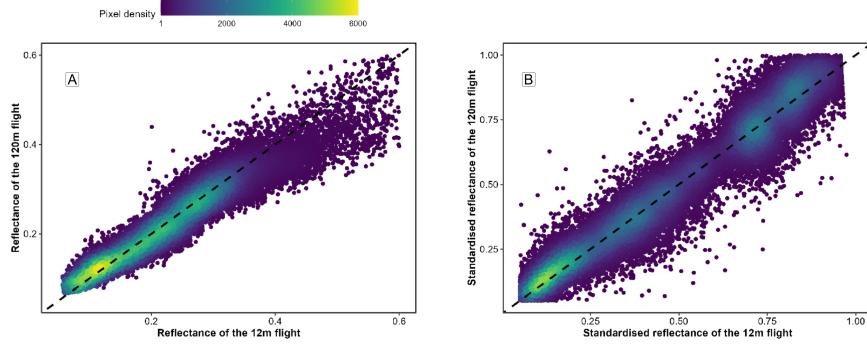


Figure 8: Comparison of reflectance retrieved from both low-altitude and high-altitude flights over a common area. The black dashed line represents a 1 to 1 relationship. Left (A) plots raw data and right (B) plots standardized data (Equation 1).

There was a slight underestimation for raw reflectance values in the high-altitude flight, particularly for higher reflectance values (Figure 8 A). Since both flights were conducted over vegetation areas, the highest reflectance values correspond to the infrared part of the spectrum. This difference is not present when reflectance values have been standardized (Equation 1 ; Figure 8 B).

3.2.2. Neural network classification validation

Model global accuracy was 94.26% with a Kappa coefficient of 0.92 (Figure 9).

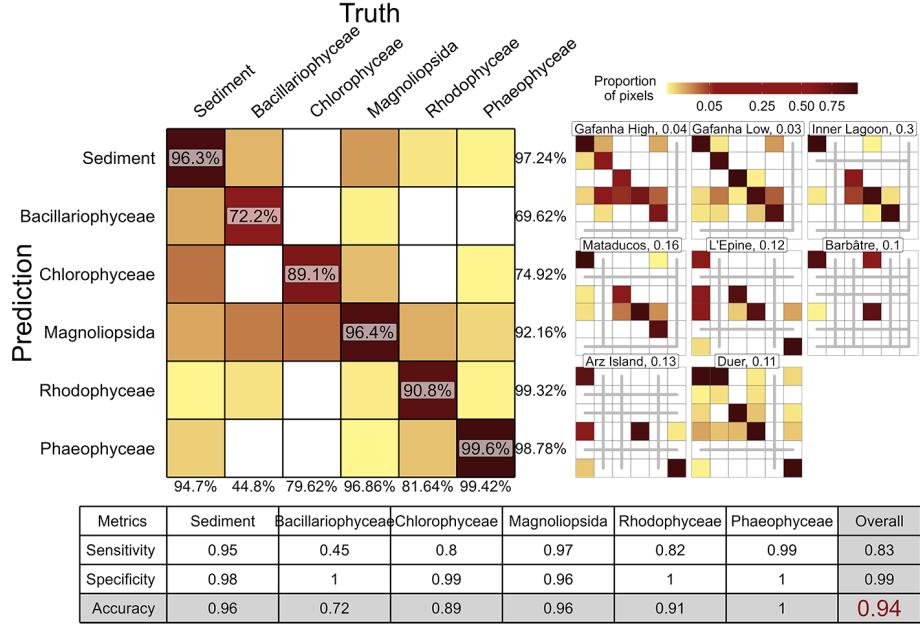


Figure 9: A global confusion matrix on the left is derived from validation data across each flight, while a mosaic of confusion matrices from individual flights is presented on the right. The labels inside the matrices indicate the balanced accuracy for each class. The labels at the bottom of the global matrix indicate the User’s accuracy for each class, and those on the right indicate the Producer’s Accuracy. The values adjacent to the names of each site represent the proportion of total pixels from that site contributing to the overall matrix. Grey lines within the mosaic indicate the absence of validation data for the class at that site. The table at the bottom summarizes the Sensitivity, Specificity, and Accuracy for each class and for the overall model.

The lowest performing site was Gafanha High (global accuracy of 75.45%) whereas Mataducos was the site with the most accurate prediction (global accuracy of 98.05%). Overall, the classes Phaeophyceae, Magnoliopsida, Sediment and Rhodophyceae were correctly classified with a balanced accuracy of 1, 0.96, 0.96 and 0.91 respectively. Bacillariophyceae was the least accurate class (accuracy of 0.72) mainly due to confusion with Magnoliopsida and Sediment.

3.3. Variable importance

The computation of the variable importance made it possible to identify which bands were the most useful for class prediction (Figure 10).

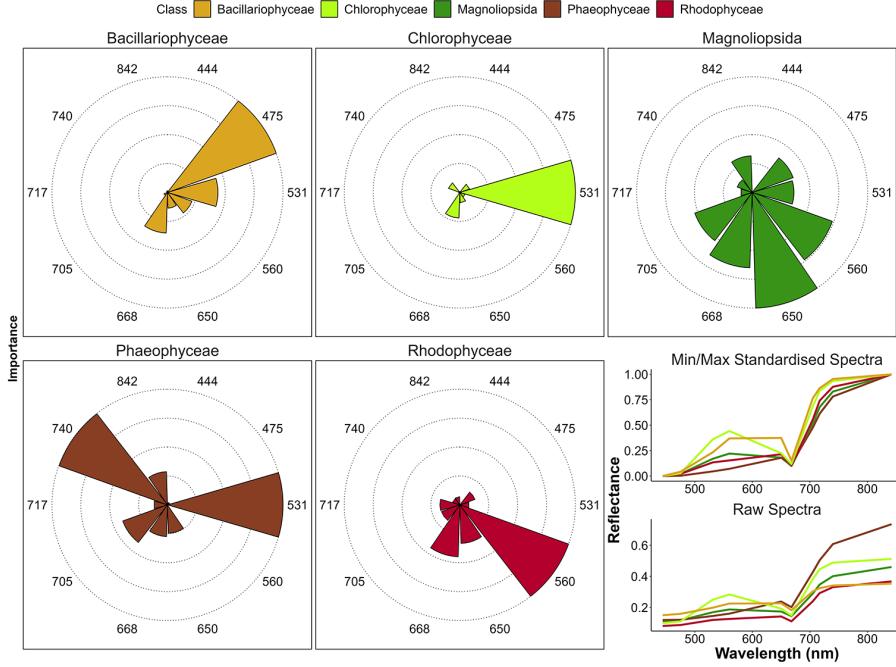


Figure 10: Variable Importance of the Neural Network Classifier for each taxonomic class. The longer the slice, the more important the variable for prediction of each class. The right plot shows the drone raw and standardised reflectance spectra of each class. Each slice represents the VIP of both raw and standardised reflectance combined.

The spectral bands at 444, 717 and 842 nm of the Micasense camera did not provide as important information to discriminate any of the vegetation classes. The band at 531 nm was the only important predictor for the classifier to accurately predict Chlorophyceae. In fact, at this wavelength, the Chlorophyceae spectra showed the highest reflectance among all vegetation classes. The bands at 531 and 740 nm were the most important predictors for Phaeophyceae, corresponding to the lowest reflectance among all classes. Bands at 475 and 560 nm were the most important predictors for Bacillariophyceae and Rhodophyceae, respectively. Four predictors, ranging from the green (560 nm) to the RedEdge (705 nm) bands were important to accurately predict Magnoliopsida.

3.4. Effect of the percent cover on the prediction

Using the very high resolution low altitude flight (8 mm pixels), we determined the minimal percent cover required to correctly classify a given class within the corresponding high altitude flight (Figure 11).

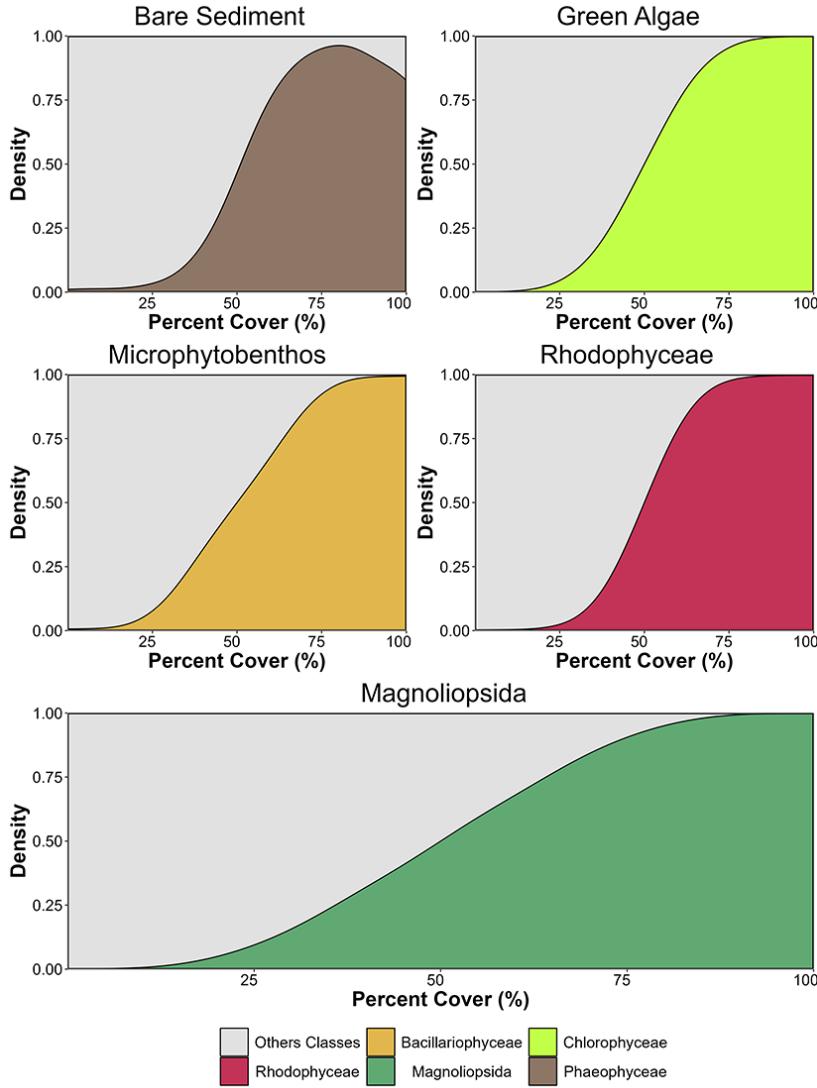


Figure 11: Kernel density plot showing the proportion of pixel well classified based on the percent cover of the class in high altitude flight pixels of Gafanha, Portugal. Each subplot shows all the pixels of the same classes on the high altitude flight. Percent cover of classes was retrieved using the result of the classification of the low altitude flight of Gafanha, Portugal.

When the percent cover of a given class was 100 %, coarser high-flight pixels were well classified for all the classes except for Bare Sediment, which was only well classified 80% of the time. This phenomenon may be attributed to the time gap between the two flights, allowing for microphytobenthos migration to the surface during low tide, consequently altering the model's classification

from bare sediment to Bacillariophyceae. A percent cover of at least 80% was sufficient to have all the pixels of high altitude flights correctly classified, with the exception of Magnoliopsida that required a higher percent cover ($>90\%$) to be well classified. Concerning the probability of each class, the highest percent cover was needed to confidently predict Bacillariophyceae. To predict Chlorophyceae with a model likelihood of 0.85, a percent cover of 93 % was needed, 90 % for Magnoliopsida, 92 % for Rhodophyceae and 97 % for Bacillariophyceae.

4. Discussion

4.1. Vegetation Discrimination

The primary objective of this study was to develop a method for the accurate classification of macrophytes on intertidal mudflats, specifically focusing on distinguishing between Chlorophyceae (green macroalgae) and marine Magnoliopsida (seagrasses) using multispectral drone data. The ability to differentiate between various types of vegetation plays a critical role in ecological monitoring and coastal management [47]. By distinguishing between seagrasses and macroalgae, our approach facilitates targeted conservation strategies, enabling more effective preservation and restoration efforts in coastal ecosystems. The discrimination of seagrasses from green macroalgae presents two main challenges [48, ; 25, ; 49]. First these two macrophytes have a similar pigment composition: chlorophyll-a (common to all vegetation types), chlorophyll-b (an additional photosynthetic pigment), and accessory carotenoids such as zeaxanthin, lutein and neoxanthin (Figure 12). Second, seagrass and green macroalgae frequently co-occur in intertidal areas, and can intermingle within a remote sensing pixel if the spatial resolution is too low. Here, the issue of intra-pixel mixing was resolved thanks to the very high spatial resolution of the drone, and the risk of spectral confusion was avoided thanks to the efficiency of the multispectral classifier. Our results confirm a recent study based on *in situ* radiometry, where it was demonstrated that a radiometer with at least eight spectral bands ranging from 500 to 850 nm and including a green band at 530 nm and a RedEdge band at 730 nm was crucial to accurately discriminate green macrophytes [24].

	Chl-b	Chl-c	Fuco	Zea	Diad	Lut	Neo	PE	PC
Magnoliopsida	Green	Red	Red	Green	Red	Green	Green	Red	Red
Chlorophyceae	Green	Red	Red	Green	Red	Green	Green	Red	Red
Bacillariophy.	Red	Green	Green	Red	Green	Red	Red	Red	Red
Phaeophyceae	Red	Green	Green	Green	Red	Red	Red	Red	Red
Rhodophyceae	Red	Green	Green						
Absorption (nm)	650	636	550	489	496	490	450	566	615

Figure 12: Photosynthetic and carotenoid pigments present (Green) or absent (Red) in each taxonomic class present in the Neural Network Classifier, along with their absorption wavelength measured with spectroradiometer. Chl-b: chlorophyll-b, Chl-c: chlorophyll-c, Fuco: fucoxanthin, Zea: zeaxanthin, Diad: diadinoxanthin, Lut: lutein, Neo: neoxanthin, PE: phycoerythrin, PC: phycocyanin.

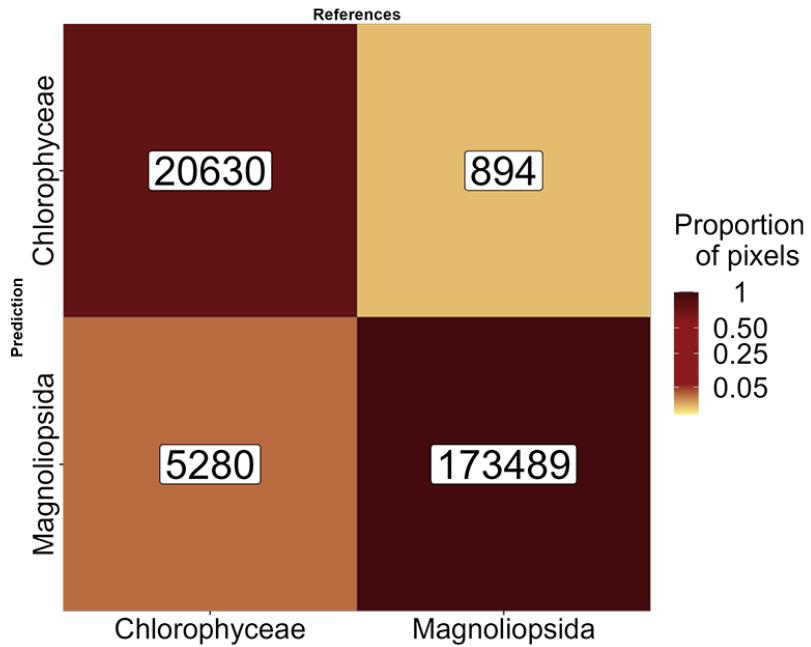


Figure 13: Sample of Figure 9 focusing on green macrophytes. The labels inside the matrix indicate the number of pixels.

Meeting these two criteria, the Micasense RedEdge-MX DUAL camera used

in this study, enabled the classifier to achieve 97% of accuracy between these two classes (Figure 13). Even if the pigment composition of green macrophytes is similar, differences in the spectral shape can be observed, with green algae having a higher reflectance peak at 560 nm as well as a higher NIR plateau than seagrass (Figure 2). Such differences were previously attributed to differences in pigments concentration and/or ratios [50], cellular structure as well as in the orientation of the plant over the sediment surface [51, ; 52, ; 53].

The variable importance analysis (Figure 10) identified that the band at 531 nm was the most important for accurately identifying Chlorophyceae. In fact, at this wavelength, Chlorophyceae exhibited the highest reflectance among all other classes, highlighting the difference in carotenoids to chlorophyll-a ratios between seagrasses and green macroalgae [54].

Concerning Phaeophyceae, the thick cell walls of these macroalgae [55] make it more reflective in the infrared part of the spectra [56] whereas the presence of fucoxanthin and zeaxanthin result in a low reflectance in the visible region (Figure 12 ; Figure 10). These two key features have been identified by the Neural Network as the two principal predictors to accurately identify brown algae (Figure 10). Similarly, the presence of phycoerythrin and phycocyanin in Rhodophyceae contribute to the lowest reflectance among all classes in the spectral range from 560 to 615 nm (Figure 10). Indeed the band at 560 nm has been identified as important for identifying this class, likely due to phycoerythrin absorption at this wavelength. Regarding Bacillariophyceae, the VIP analysis (Figure 10) indicated that 475 nm was the most important predictor for this class. Indeed, the reflectance at 475 nm was higher for Bacillariophyceae than for any other vegetation class (Figure 2), very likely due to the low biomass (and associated concentration of blue-absorbing pigments) of microphytobenthos biofilms compared to seagrass and macroalgae.

4.2. Altitude and Temporal Effects on Vegetation Prediction Accuracy

While comparing the reflectance of both altitudes (12 m and 120 m), it was observed that there is an underestimation of the infrared part of the spectra in the high-altitude dataset (Figure 8). Such disparity in infrared reflectance may stem from temporal differences between the flights, possibly resulting in a slightly drier intertidal area and consequently higher infrared reflectance. This disparity poses an issue for the methodology followed in the present study, relying solely on one flight height for training. To address this issue, we employed min/max standardized reflectance spectra as predictors for the model (Equation 1 ; [44]). This approach allowed us to eliminate the slight reflectance difference between the flights (Figure 8 B) and to focus on the shape of the spectra in the visible part of the electromagnetic spectra, where different pigmentation are associated to taxonomic diagnostic features. This was a key feature in building a model that could reliably predict vegetation across geographical sites and seasons. It enabled consistent prediction of vegetation classes across variations in biomass and variability in light conditions [57, ; 58, ; 59].

We found 90 % of seagrass cover is necessary for confident prediction of its presence (Figure 11). This highlights a limitation of the methodology used to construct the training dataset for the model. The dataset used to train our algorithm was composed exclusively of pure pixels, which resulted in the model's reduced confidence when faced with lower percentages of seagrass cover. Also, intertidal seagrasses exhibit marked phenology, with varying pigment composition throughout the year [50, ; 60]. Since the training dataset has been made using well developed seagrass meadows, this model may be less accurate outside of the seasonal seagrass peak of biomass. Further investigation is required to evaluate the accuracy of the method along different periods of the year.

4.3. Towards climate and biodiversity applications

Climate change, global warming, eutrophication, alien and invasive species development, coastal erosion, and sea level rise are expected to continue impacting coastal ecosystems in the future [61; 62, ; 63]. and the demand for meaningful and efficient monitoring of coastal habitats has never been higher[64, ; 65, ; 48]. Our findings, particularly the improved discrimination of seagrass and green macroalgae from other intertidal vegetation classes, highlight the potential of drone-based remote sensing to support diverse applications, from conservation of biodiversity to climate change adaptation strategies.

Because of coastal eutrophication, macroalgal blooms are becoming increasingly common in many regions around the world [66, ; 67]. These blooms can have negative impacts on human health and local economic activities, including human health, fishing and aquaculture, tourism, and recreational activities [68, ; 67]. The first green tide events (i.e. bloom of green macroalgae of the genus *Ulva*) were reported in Brittany, France, back in the 1970s and have since been a concern for local stakeholders and economic activities [69]. Some regions of the world have witnessed an increase in brown macroalgae blooms, predominantly involving algae of the genus *Sargassum* washing along the Caribbean coastlines [70], and more recently *Rugulopteryx okamurae* in southern Europe [34]. Satellite remote sensing has proven to be a valuable tool for mapping the spatial and temporal extent of macroalgal blooms worldwide. However, due to limitations in spatial resolution, it can only effectively map well-developed blooms [71, ; 72, ; 73]. High spatial resolution drone imagery, coupled with an accurate classification algorithm, could be used to map the early stages of macroalgal blooms in areas known to have regular blooms or in new sites. Indeed, this approach could provide early warning alerts to local managers.

Employing traditional sampling methods to monitor coastal ecosystems is time and resource-intensive, and the findings are often difficult to scale-up. Earth Observation can bridge this gap and meet the needs for systematic monitoring coastal ecosystems over large areas [74]. The retrieval of Essential Biodiversity Variables and Essential Ocean Variables through satellite observations has been increasingly common, enabling comprehensive monitoring of entire ecosystems over extended time periods [75, ; 13]. The Water Framework Directive [47] mandates the achievement and maintenance of “good ecological status” for all

European waters, which necessitates a comprehensive understanding and monitoring of aquatic ecosystems, including coastal habitats like seagrass beds [76, ; 77, ; 13].

Effective and efficient monitoring tools are essential for identifying the impacts of human activities and natural changes on coastal ecosystems. On-demand, multispectral drone observations at very high spatial-resolution provide a novel and powerful tool to rapidly and accurately acquire ground truth satellite data. Spatially resolved data are indeed critical for calibrating and validating satellite remote sensing observations, thereby enhancing our capacity to monitor vast coastal areas. A perspective of this work could be to develop a similar classifier for satellite images (e.g. Sentinel-2), and test whether the discrimination between seagrass and green macroalgae is still operational at a coarser spatial resolution. The integration of drone technology facilitates a scalable approach to environmental surveillance, offering significant advancements in the spatial and temporal resolution of data collection. This, in turn, supports the WFD's objectives by enabling more informed and timely management decisions for the conservation and restoration of aquatic ecosystems.

5. Conclusion

The utilization of very high spatial-resolution drone-based remote sensing coupled with machine learning techniques has proven to be an effective method for the discrimination of seagrasses from green macroalgae with a multispectral resolution sensor. Standardized reflectance was incorporated in the Neural Network model allowing for a better discrimination of spectral features related to pigment absorption in the visible. There was a striking difference for the variable of importance to discriminate Magnoliopsida from Chlorophyceae. The latter was essentially identified with the 451 nm spectral band while more spectral bands were needed to identify the former, notably 650, 560, 668, and 705 nm. As the spectral bands of the Micasense RedEdge Dual MX are very similar to those of Sentinel-2, we suggest that multispectral satellite data have the potential to perform this discrimination between green macrophytes. A sentinel-2 algorithm could be developed, using the output of this current workflow as training and validation data. The findings underscore the importance of adopting advanced remote sensing tools in ecological studies and environmental monitoring, providing a foundation for future research and policy implementation aimed at ecosystem conservation and restoration.

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