Characterization of Intertidal Vegetation on European Coasts Using Multi-Scale Remote Sensing in Response to Natural and Anthropogenic Pressures

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2025-03-11

Abstract

To Be Written

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# Preface

This PhD work was carried out at Nantes University between 2022 and 2024, within the “Remote Sensing, Benthic Ecology and Ecotoxicology” (RSBE²) team of the Institute of Marine Substances and Organisms (ISOMer). This thesis was funded by the Ministry of Research and Higher Education and supervised by the doctoral school “Plant, Animal, Food, Sea, Environment” (VAAME).

## Scientific papers

* Barillé, L., Paterson, I. L. R., **Oiry, S.**, Aris, A., Cook-Cottier, E. J., & Nurdin, N. (2025). Variability of *Kappaphycus alvarezii* cultivation in South-Sulawesi (Indonesia) related to the monsoon shift: Water quality, growth and colour quantification. *Aquaculture Reports*, 40, 102557. https://doi.org/10.1016/j.aqrep.2024.102557
* **Oiry, S.**, Davies, B. F. R., Sousa, A. I., Rosa, P., Zoffoli, M. L., Brunier, G., Gernez, P., & Barillé, L. (2024). Discriminating Seagrasses from Green Macroalgae in European Intertidal Areas Using High-Resolution Multispectral Drone Imagery. *Remote Sensing*, *16*(23), 4383. https://doi.org/10.3390/rs16234383
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* Davies, B. F. R., Gernez, P., Geraud, A., **Oiry, S.**, Rosa, P., Zoffoli, M. L., & Barillé, L. (2023). Multi- and hyperspectral classification of soft-bottom intertidal vegetation using a spectral library for coastal biodiversity remote sensing. *Remote Sensing of Environment*, 290, 113554. https://doi.org/10.1016/j.rse.2023.113554
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* Brunier, G., **Oiry, S.**, Gruet, Y., Dubois, S. F., & Barillé, L. (2022). Topographic Analysis of Intertidal Polychaete Reefs (Sabellaria alveolata) at a Very High Spatial Resolution. *Remote Sensing*, 14(2), 307. https://doi.org/10.3390/rs14020307

## Presentations to International Conferences

* Effect of Marine and Atmospheric Heatwaves on Reflectance and Pigment Composition of Intertidal *Zostera noltei* (February 2025); BioSpace25 - Biodiversity insight from Space, Frascati, Italy; Oral presentation
* Discriminating Seagrasses From Green Macroalgae in European Intertidal Areas using High Resolution Multispectral Drone Imagery (17 - 21 June 2024); Word Seagrass Conference, Napoli, Italy; Poster
* Remote Sensing discrimination of seagrass and green macroalgae: hyperspectral library and drone-mounted multispectral camera (22 - 24 November 2023); EC-ESA Joint Earth System Science Initiative, Frascati, Italy; Poster
* Precision aquaculture drone mapping of the spatial distribution of *Kappaphycus alvarezii* biomass and carrageenan (August 2023); 8th European Phycological Congress, Brest, France ; Oral presentation
* Remote Sensing discrimination of seagrass and green macroalgae: hyperspectral library and drone-mounted multispectral camera (August 2023); 8th European Phycological Congress, Brest, France ; Poster
* Remote Sensing discrimination of seagrass and green macroalgae: hyperspectral library and drone-mounted multispectral camera (23 - 27 may 2022); Living Planet Symposium, Bonn, Germany ; Poster

# 1. Introduction & Overview

## 1.1 General Introduction

Marine coastal zones are among the most densely populated regions globally, serving as critical hubs for economic activity, transportation, and tourism. These areas support diverse ecosystems and provide essential resources. Additionally, they play a pivotal role in global trade and commerce while also offering cultural and recreational value. However, their popularity and utility make them highly vulnerable to environmental pressures such as pollution, habitat destruction, and climate change impacts like sea-level rise and coastal erosion. Effective management and sustainable practices are crucial to preserving their ecological integrity and ensuring long-term viability.

Marine vegetative habitats in intertidal zones that are exposed at low tide (such as seagrass meadows, microphytobenthos, and macroalgae) are significantly impacted by human activities. Seagrass meadows are under threat due to various anthropogenic activities (Len J. McKenzie et al., 2020a), microphytobenthos are affected by the global decline of intertidal mudflats (N. J. Murray et al., 2019), and areas colonized by macroalgae may be reduced due to the expansion of wild oysters (Le Bris et al., 2016).

These habitats provide vital ecological functions, including coastal erosion protection through root stabilization and sediment trapping (**refs**), mitigation of eutrophication effects by absorbing excess nutrients and improving water quality (**refs**), atmospheric CO2 fixation, contributing to carbon sequestration and combating climate change (**refs**), serving as biodiversity hotspots that support unique flora and fauna, providing feeding, breeding, and nursery grounds for various species. Despite their ecological significance, intertidal zones, particularly mudflats, are challenging to access, and traditional field sampling methods are too time- and labor-intensive to allow repeated observations over large areas. This limitation underscores the need for advanced monitoring technologies to better assess and protect these habitats.

Intertidal habitats, at the interface between marine and terrestrial ecosystems, face significant pressures from both anthropogenic activities and natural forces affecting both realms. Human-induced threats include coastal development, pollution, overfishing, and habitat modification, which degrade these ecosystems and diminish the valuable ecosystem services they provide. Meanwhile, natural factors such as storms, sea-level rise, climatic extreme events and climate change exacerbate these pressures, altering the structure function, and resilience of intertidal habitats. Despite their ecological importance in supporting biodiversity, providing coastal protection, and contributing to nutrient cycling, intertidal habitats remain highly vulnerable. Addressing these challenges requires robust management practices, targeted conservation strategies, and ongoing monitoring to ensure their sustainability and resilience against future pressures.

Regulatory frameworks, such as the Water Framework Directive (WFD) and the Marine Strategy Framework Directive (MSFD), emphasize the need for regular mapping of marine habitats to monitor ecological health. These directives utilize habitat diversity as a bioindicator of coastal and estuarine water quality (Borja et al., 2013; Zoffoli et al., 2021a).

Satellite remote sensing has emerged as a promising tool for studying essential biodiversity variables in these habitats (Pereira et al., 2013a; Skidmore et al., 2015). Remote sensing offers several advantages over in situ sampling: repeated monitoring over large-scale coverage, high-frequency data acquisition, enabling seasonal and phenological studies, reduced costs and logistical challenges compared to field surveys, reconstruction of past conditions when used long time-series.

However, past and current satellite missions lack optimal technical specifications (spatial, spectral, and temporal resolution) for full operational capability (F. Muller-Karger et al., 2018). For some habitats, multispectral resolution may be adequate under certain conditions (Zoffoli et al., 2020a), although risks of classification errors remain. For others, higher spectral resolution is necessary to distinguish taxonomically distinct groups of organisms (S. Fyfe, 2003; Launeau et al., 2018; Méléder et al., 2018). Identification relies partly on the presence of visible absorption bands associated with photosynthetic and accessory pigments, which can be detected and quantified using high-performance liquid chromatography (A. Bargain et al., 2013a; Jesus et al., 2014; Méléder et al., 2005; Méléder et al., 2003).

### Coastal Environment

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### 1.1.2 Concepts of Remote sensing

Remote sensing (RS) defines the ability to retrieve information in a non-invasive way, without direct contact with the target. It relies on the propagation of signals, typically optical, acoustic, or microwave, between the target and the sensor. This technology has been applied in a wide variety of fields, ranging from medical imaging to detect stem cells, to the analysis of the structure of the primordial universe (Aghanim and Dole, 2020; Zhu et al., 2021). Remote sensing provides the basis to Earth observation (EO), where its methodologies facilitate large-scale and long-term data collection. Instruments on satellites, aircraft, and drones provide high-resolution imagery and measurements critical for monitoring environmental changes, mapping natural resources, and assessing land use patterns. These technologies enable systematic data collection over large areas and extended periods, supporting analyses such as deforestation, glacial melting, variations in ocean temperature, and changes in land use.

The following sections examine two complementary approaches used in this study within the field of remote sensing for Earth observation: active and passive remote sensing. Through direct applications on coastal monitoring, these sections will introduce remote sensing methodologies while outlining their respective advantages and challenges.

#### 1.1.2.1 Active Remote Sensing, Exemple of the LiDAR

Active remote sensing is a technique in which a sensor emits its own energy—typically in the form of electromagnetic radiation—toward a target and measures the energy reflected or backscattered from it. This method allows for the collection of data regardless of natural light conditions, enabling observations during both day and night and through various weather conditions.

The Light Detection and Ranging (LiDAR) sensors emit laser beams in the ultraviolet (UV), visible or infrared (IR) regions of the electromagnetic spectrum. By analyzing the return signal, they can estimate distances to objects or surfaces, detect optically active constituents in water bodies, and assess aerosols in the atmosphere (Jamet et al., 2019; Dionisi et al., 2024).

LiDAR works by emitting a beam of light and measuring the time it takes for the beam to return to the sensor. This process not only calculates distances but also captures the intensity of the returned signal. In terrestrial applications, multiple returns from a single pulse are measured, enabling the mapping of varying objects heights within the same x and y coordinates. This capability allows the creation of precise, three-dimensional representations of the environment, such as mapping tree heights in forests or measuring crop heights in agricultural fields. When ground height cannot be directly measured, LiDAR data can generate a digital surface model (DSM), which represents the uppermost layer of the environment. However, if multiple returns are recorded, it becomes possible to create both a DSM and a digital terrain model (DTM), which represents the ground surface by differentiating between the surface and underlying layers. The difference between DSM and DTM can be used to assess living stock or biomass.

Achieving accuracy in LiDAR measurements is essential due to the high speed of light, approximately 300,000 km/s. Each step of the acquisition process, including the precise timing of the beam’s return and the accurate positioning of the sensor (typically mounted on a drone, aircraft, or satellite), must be meticulously calibrated. The use of Real-Time Kinematic (RTK) positioning ensures that the sensor’s x, y, and z coordinates are consistently accurate. Without these measures, the resulting data may produce a distorted and noisy representation of the mapped surface, rendering it unreliable for analysis.

In coastal environment monitoring, LiDAR systems are classified based on their emitted wavelengths, which determine their performance and application. These systems are categorized into “topographic LiDAR” and “bathymetric LiDAR,” each suited to specific tasks in coastal studies. Topographic LiDAR operates in the near-infrared (NIR) spectrum (approximately 1000 nm) and is used to map terrestrial features, such as beach contours, vegetation density, rocky shores structures and man-made installations. Its ability to generate high-density point clouds stems from efficient operation at lower power. Unlike green LiDAR, NIR LiDAR require less power, making it generally more affordable and compact. These attributes allow topographic LiDAR systems to be easily mounted on drone platforms, offering greater flexibility and accessibility for coastal monitoring. In contrast, bathymetric LiDAR, utilizing green wavelengths (~532 nm), penetrates the water column to reveal submerged landscapes, including coral reefs, seagrass meadows, and shallow seabeds. While this capability is indispensable for underwater mapping, its effectiveness on land is hindered by atmospheric scattering.

The Litto3D® product (SHOM, 2021) provides a high-resolution bathymetric and topographic map in coastal areas, created using LiDAR technologies. During airborne missions, the system captures terrestrial and submerged terrain features with exceptional precision. The topographic LiDAR achieves spatial resolution of 1 m, with vertical accuracy up to 20 cm under optimal conditions, such as minimal atmospheric interference, stable flight paths, and favorable weather. The bathymetric LiDAR maps underwater landscapes to depths of approximately 70 m, depending on water transparency. This dual-mode capability is essential for modeling complex coastal environments, seamlessly integrating terrestrial and marine datasets. The airborne platform enables rapid data acquisition over large areas, overcoming challenges associated with ground-based or shipborne methods. The fusion methodology used by Litto3D® ensures the precise alignment of terrestrial and marine datasets, resolving inconsistencies in elevation data at land-water interfaces. The resulting unified dataset accurately represents coastal environments and supports diverse scientific and practical applications, such as coastal risk assessment and ecological studies. Distributed by the Service Hydrographique et Océanographique de la Marine (SHOM, 2024) and the Institut National de l’Information Géographique et Forestiere (IGN, 2024), this dataset is open-source but currently available only for selected coastal regions in France.

In this study, LiDAR data were utilized in **Chapter 4** using a drone-borne IR LiDAR system. These data were employed to evaluate the elevation and slope of mudflats in French and Spanish estuaries and to map the spatial distribution of an invasive red macroalga, *Gracilaria vermiculophylla*. In **Chapter 5**, the Litto3D product was used along with a water height dataset to assess the emersion time of seagrass meadows in Quiberon, France, during low tide. Since this thesis focuses on intertidal environment mapping, field campaigns were conducted during low tide to ensure optimal conditions for the effective use of IR LiDAR, providing unobstructed access to intertidal zones.

#### 1.1.2.2 Passive Remote Sensing

Passive remote sensing is a method of collecting data about the Earth’s surface or atmosphere by measuring naturally emitted or sunlight-reflected electromagnetic radiation without actively transmitting signals. This technique relies on energy sources external to the instrument, such as sunlight for optical and near-infrared sensors, or Earth’s thermal emissions for thermal infrared sensors.

Passive remote sensing is widely utilized in spaceborne satellite missions and has played a pivotal role in programs developed by major space agencies, including the European Space Agency (ESA) and the National Aeronautics and Space Administration (NASA). For instance, the Sentinel-2 mission, which provides ESA’s highest spatial resolution imagery, employs passive sensors. Data measured by these sensors have been applied to monitor land cover, vegetation dynamics and coastal and inland water environments.

As sunlight enters the Earth’s atmosphere, it interacts with various gases and particles, altering its properties at specific wavelengths. These interactions include scattering, absorption, and refraction. Scattering occurs when atmospheric molecules and aerosols disperse light in different directions, with shorter wavelengths like blue light being more strongly affected. Absorption results from atmospheric constituents such as ozone, water vapor, and carbon dioxide, which absorb energy at specific wavelengths, reducing the intensity of the transmitted light that reaches the Earth’s surface. Refraction occurs as light changes direction and speed while passing through atmospheric layers with varying densities.

When sunlight reaches Earth’s surface, it exhibits several behaviors depending on the surface properties and the angle of incidence. These behaviors include:

* Absorption: The light is absorbed by the surface, converting it into heat or another form of energy. This process varies based on the biogeochemical characteristics of the surface, with darker surfaces typically absorbing more light.
* Transmission: The light passes through the surface, entering a different medium, such as water or transparent materials. The extent of transmission depends on the material’s transparency and refractive index.
* Reflection: The light that was not absorbed or transmitted is redirected back into the sensor. The amount of reflection depends on the surface’s albedo, with bright surfaces like snow reflecting more light compared to darker surfaces such as forests.

Only reflected light can be detected by spaceborne sensors. The most used metric in passive remote sensing to quantify electromagnetic radiation (EMR) is reflectance (R). R is typically measured as the ratio of upwelling radiance (Lu) to downwelling radiance (Ld) (Eq. 1.1). L is defined as the radiant intensity per unit of projected source urea in a specified direction and is expressed in units of W m-2 sr-1. R, however, is dimensionless.

Eq. 1.1

R is defined for each wavelength as a value between 0 and 1. A value of 0 indicates that all light has been absorbed or transmitted by the target, while a value of 1 indicates that all light has been reflected.

R at the Top of Atmosphere (TOA), i.e., the magnitude directly measured by spaceborne or airborne sensors, contains signals originating from both the atmosphere and the Earth’s surface. Therefore, to study targets located on the Earth’s surface, RTOA must undergo atmospheric correction processing to transform it into Bottom of Atmosphere (BOA) R, which represents the intrinsic reflectance properties of the surface target. Precise RBOA is crucial for accurately analyzing surface characteristics and for applications like vegetation monitoring, water quality assessment, and land cover classification.

One of the most basic atmospheric correction methods is the “black pixel” method, which assumes that all the signal retrieved over optically deep waters originates entirely from the atmosphere. This information is then used to correct the reflectance across the entire scene. However, this method requires the presence of optically deep water targets within the scene and assumes uniform aerosol concentrations across the scene. Such assumption may be inaccurate, particularly for satellites with a wide field of view, such as MODIS, where a single image can cover a swath of 2,330 km. Limitations to this technique arise also when the target of study is a water body itself. These limitations highlight the need for more advanced correction techniques that account for spatial variability in atmospheric properties.

To address these challenges, sophisticated atmospheric correction algorithms tailored to specific sensors and study areas have been developed. These algorithms account for atmospheric scattering, absorption, and path radiance contributions by leveraging radiative transfer models, auxiliary atmospheric data, and sometimes *in situ* measurements. For example, data of the ESA constellation Sentinel-2 can be processed using Sen2Cor, a correction algorithm designed to produce RBOA by incorporating atmospheric parameters such as water vapor, aerosols, and ozone concentrations. Additionally, some atmospheric correction methods are customized for specific targets, for example, algorithms specifically designed for water bodies, such as POLYMER (Steinmetz et al., 2011) or ACOLITE (Vanhellemont and Ruddick, 2018).

RBOA reflectance provides information regarding light reflected by the target across various wavelengths. This phenomenon, referred to as the spectral signature, is a unique feature of each target type. Spectral signatures contain data about the physical and chemical properties of surfaces, forming the basis for remote sensing applications. By analyzing spectral signatures, scientists can identify and classify surface types, as well as derive insights into environmental changes and land-use dynamics. For example, Chlorophyll-a (Chla), a pigment found in all vegetation cells, plays a key role in shaping the spectral signature of vegetation. Chla absorbs light in specific regions of the electromagnetic spectrum, particularly in the blue region around 440 nm and the red region near 675 nm. Consequently, healthy vegetation exhibits a spectral signature with low R at 440 and 675 nm. Variations in physiological states and vegetation types result in different spectral patterns, enabling their differentiation and monitoring of ecological conditions over time.

Spectral indices are mathematical combinations of reflectance values at specific wavelengths, designed to maximize particular surface characteristics with simple processing. Vegetation indices, for example, leverage the distinct reflectance patterns of photosynthetic pigments. The Normalized Difference Vegetation Index (NDVI) is a widely used index based on the difference between R in the NIR and red regions. It is calculated as:

(Eq. 1.2)

where is the reflectance at 840 nm and is the reflectance at 668 nm.

NDVI values range from -1 to 1, with negative values indicating water and higher positive values corresponding to dense healthy vegetation. While NDVI serves as a proxy for vegetation biomass and photosynthetic activity, its interpretation can be complex in heterogeneous environments, such as areas with mixed vegetation types or substrates. Some studies propose a simple classification of NDVI based on thresholds to differentiate between different types of habitats or vegetation (e.g., Meleder et al., 2003; xxx). While this simple first approximation can be useful for delimitating contrasting types of targets, establishing thresholds depends on specific sensor characteristics and this technique often fails in mapping vegetation types with similar pigment content or highly heterogeneous targets. More sophisticated techniques that utilize a greater amount of spectral information are required in such situations (Oiry and Barillé, 2021).

RBOA can be used to identify key absorption features of chemical compounds of the traget, by applying derivative analysis to the spectral signature. The second derivative of the R is utilized to enhance the detection of subtle vegetal pigment or mineral absorption features. By analyzing the second derivative, these small features are amplified, allowing for more precise identification of pigment presence and estimation of their concentrations. This approach is particularly effective for identifying accessory pigments that have weaker absorption features compared to chlorophyll-a.

Speak about *in situ* spectroradiometry

Finally, a distinction can be made between high-altitude and low-altitude remote sensing. Low-altitude remote sensing refers to the acquisition of spectral images at an altitude of up to 120 m from, in compliance with European regulations on the maximum flight height for Unmanned Aerial Vehicles (UAVs). This contrasts with high-altitude remote sensing, which involves airborne and spaceborne sensors operating at altitudes ranging from tens to hundreds of kilometers. The distinction is important due to significant differences in calibration methods for reflectance measurements, as well as variations in temporal, and above all, spatial resolution.

Reflectance calibration methods differ significantly between satellite-based remote sensing and other types of measurement acquisition. For satellite sensors, RBOA estimation relies on pre-launch laboratory calibration and post-launch vicarious calibration, which uses known surface targets or atmospheric correction algorithms to account for sensor degradation, atmospheric effects, and viewing geometry. In contrast, in situ and UAV R measurements require the use of a calibrated reference target with known reflectance properties, conducted near the target area under the same illumination conditions. This method ensures precise ground-truth data, providing high accuracy for R measurements by minimizing the influence of atmospheric scattering and absorption, which are significant factors in satellite-based calibration.

Temporal resolution, defined as the time interval between successive image acquisitions over the same study site, varies significantly between low-altitude and high-altitude sensors. Satellites used for Earth observation, typically placed in low heliosynchronous orbits, acquire data at regular intervals over the same area of the Earth. They are programmed to cross the equator daily at the same time, allowing for seasona studies while ensuring consistent illumination conditions throughout the year. For instance, the Sentinel-2 constellation offers a temporal resolution of 5 days at the equator, which decreases to as little as 3 days at higher latitudes, such as in France. Certain missions, like the Sentinel-3 constellation, achieve even shorter revisit times, providing almost daily images of the same region. In contrast, low-altitude sensors are directly programmed by the user.

Spatial resolution, defined as the ground area represented by a single pixel, differs significantly between low-altitude and high-altitude sensors. Satellite remote sensing can cover vast areas, often spanning millions of km2, and capture data at the scale of entire countries in a single image. The spatial resolution of a sensor is directly influenced by its field of view. While some satellites achieve resolutions as fine as 30 cm per pixel (e.g., Pleiades-Neo), they may struggle to accurately map complex ecosystems. For example, in scenarios involving mixed vegetation types, the inability to capture fine-scale heterogeneity can limit the accuracy of analyses. In such cases, low-altitude remote sensing offers a complementary approach by acquiring millions of pixels over smaller areas, achieving spatial resolutions at the mm-cm scale. This level of detail enables more precise mapping of complex and heterogeneous ecosystems. Overall, there is a trade-off between area coverage, spatial, spectral, and temporal resolutions due to the processing and storage capabilities of sensors. Increasing the area covered by a single image generally results in larger pixel sizes and lower temporal resolution (Figure xx).

A diagram of weather forecasting

Description automatically generated

Figure xx. souce: Jensen

#### 1.1.2.3 Remote Sensing applied to Coastal monitoring

Coastal environments represent highly dynamic and sensitive ecosystems shaped by complex interactions between natural processes and human activities. Remote sensing technologies are crucial for monitoring these regions, providing detailed data on shoreline erosion, habitat degradation, sediment dynamics, and water quality. High-resolution satellite imagery and drone-based platforms facilitate the detection of fine-scale changes in intertidal zones, mangroves, coral reefs, and other critical coastal habitats. These observations enable the quantification of spatial and temporal variations, informing evidence-based strategies for conservation and sustainable management.

EOV EBV

Muller-Karger

## 1.2 Overview

Discriminating between different types of intertidal vegetation using remote sensing poses significant challendes due to overlapping spectral signature in the visible and near-infrared spectral regions caused by similar pigment compositions. This issue is particularly pronounced when comparing green macroalgae and seagrass. In addition to chlorophyll-a, a pigment found in all vegetal cells, both green macroalgae and seagrass share the same accessory pigments such as chlorophyll-b and carotenoids. These shared pigments pronounce analogous reflectance patterns, making it difficult to differentiate between these vegetation types using conventional remote sensing techniques, espacially in heterogenous habitats where these species often co exist.Despite these challenges, advances in spectral resolution and machine learning provide avenues for improved classification.

**Chapter 2** establishes the foundation by presenting a proof-of-concept study that demonstrates the feasibility of distinguising different types of vegetation using remote sensing. It demonstrates that this technique can effectively separate green macroalgae from seagrasses. By employing both multi- and hyperspectral datasets, the study identifies the number of spectral bands and specific wavelengths that maximize classification accuracy, showcasing the potential of remote sensing for detailed habitat mapping.

Building upon the proof of concept, **Chapter 3** focuses on the development of a robust algorithm called DISCOV v1.0, capable of automating the discrimination of green macrophytes in heterogeneous intertidal habitats. Utilizing high-resolution multispectral drone imagery and advanced machine learning techniques, this chapter addresses the spatial complexity of these environments. The algorithm’s validation across diverse geographic and ecological settings ensures its applicability beyond the initial study sites. This advancement underscores the critical role of cutting-edge remote sensing technologies in ecological monitoring.

In **Chapter 4**, the methodology evolves to include red macroalgae, specifically targeting the invasive species *Gracilaria vermiculophylla*. By updating the algorithm in its v2.0, this study extends its application to a different taxonomic group, demonstrating the flexibility and scalability of the approach. Additionally, this chapter integrates LiDAR-based topographical data to examine the relationship between habitat characteristics and macroalgal distribution. The insights gained from mapping and modeling the spatial dynamics of G. vermiculophylla provide valuable implications for managing invasive species and conserving native biodiversity.

Finally, **Chapter 5** examines the physiological impacts of environmental stressors, specifically marine and atmospheric heatwaves, on seagrass reflectance. Through controlled laboratory experiments and field validations, this chapter highlights the spectral responses of *Zostera noltei* under heatwave conditions. Well-established spectral indices such as the NDVI and GLI are employed, and a new index, the Seagrass Heat Shock Index (SHSI), is developed to specifically identify heatwave-impacted seagrasses. These indices provide metrics to detect and quantify stress-induced changes. These findings emphasize the role of remote sensing in assessing the resilience and vulnerability of intertidal ecosystems under climate change.

# 2. Hyperspectral classification of intertidal vegetation for coastal biodiversity

This chapter has been published as a scientific article as: Davies, B.F.R.; Gernez, P.; Geraud, A.; Oiry, S.; Rosa, P.; Zoffoli, M.L.; Barillé, L. 2023. Multi- and hyperspectral classification of soft-bottom intertidal vegetation using a spectral library for coastal biodiversity remote sensing. [Remote Sensing](https://www.researchgate.net/journal/Remote-Sensing-2072-4292?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InByb2ZpbGUiLCJwYWdlIjoicHVibGljYXRpb24iLCJwcmV2aW91c1BhZ2UiOiJwcm9maWxlIiwicG9zaXRpb24iOiJwYWdlSGVhZGVyIn19) of Environment, [290](https://www.sciencedirect.com/journal/remote-sensing-of-environment/vol/290/suppl/C" \o "Go to table of contents for this volume/issue), 113554, DOI: [10.1016/j.rse.2023.113554](http://dx.doi.org/10.1016/j.rse.2023.113554" \t "_blank)

## 2.1 Introduction

## 3. Discriminating Seagrasses from Green Macroalgae in European Intertidal Areas Using High-Resolution Multispectral Drone ImageryThis chapter has been published as a scientific article as: Oiry, S.; Davies, B.F.R.; Sousa, A.I.; Rosa, P.; Zoffoli, M.L.; Brunier, G.; Gernez, P.; Barillé, L. 2024. [Discriminating Seagrasses from Green Macroalgae in European Intertidal Areas Using High-Resolution Multispectral Drone Imagery](https://www.researchgate.net/publication/386131154_Discriminating_Seagrasses_from_Green_Macroalgae_in_European_Intertidal_Areas_Using_High-Resolution_Multispectral_Drone_Imagery?_sg%5B0%5D=voEhgrMRTFUZaVJEo48YCHE9NKGiujRuUjwugUgTjeKgxcCMGwykeZ9mVheJ_ZG0FoLQfaC1ZINyB2k8faRyYse58l4prwQ4TVdg2N6h.12kxgSxTIyhQFpAzF_XLW6gwVV5f-T7H1i-PMmVLRiPT-RGc5iaZ3QU_Pi-Pg07haXkVBddaoEyU48hILVFolg&_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InByb2ZpbGUiLCJwYWdlIjoicHJvZmlsZSIsInBvc2l0aW9uIjoicGFnZUNvbnRlbnQifX0). [Remote Sensing](https://www.researchgate.net/journal/Remote-Sensing-2072-4292?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InByb2ZpbGUiLCJwYWdlIjoicHVibGljYXRpb24iLCJwcmV2aW91c1BhZ2UiOiJwcm9maWxlIiwicG9zaXRpb24iOiJwYWdlSGVhZGVyIn19), 16(23):4383, DOI: 10.3390/rs162343833.1 Introduction