DTU Library

Submerged aquatic vegetation: overview of monitoring techniques used for identification and determination of spatial distribution in European coastal waters

Lønborg, Christian; Thomasberger, Aris; Staehr, Peter A. U.; Stockmarr, Anders; Sengupta, Sayantan; Rasmussen, Mikkel Lydholm; Nielsen, Lisbeth Tangaa; Hansen, Lars Boye; Timmermann, Karen

Published in:
Integrated Environmental Assessment and Management

Link to article, DOI:
10.1002/ieam.4552

Publication date:
2022

Document Version
Peer reviewed version

Christian Lønborg ORCID iD: 0000-0001-8380-0238

Manuscript title: Submerged aquatic vegetation: overview of monitoring techniques used for identification and determination of spatial distribution in European coastal waters

Submerged aquatic vegetation: overview of monitoring techniques used for identification and determination of spatial distribution in European coastal waters

Christian Lønborg[1*], Aris Thomasberger[2], Peter A.U. Stæhr[3], Anders Stockmarr[4], Sayantan Sengupta[4], Mikkel Lydholm Rasmussen[5], Lisbeth Tangaa Nielsen[5], Lars Boye Hansen[5] and Karen Timmermann[2]

[1]Section for Applied Marine Ecology and Modelling, Department of Bioscience, Aarhus University, Roskilde, Denmark

[2]Section for Coastal Ecology, National Institute of Aquatic Resources, Technical University of Denmark, Kgs. Lyngby, Denmark

[3]Section for Marine Diversity and Experimental Ecology, Department of Bioscience,

Aarhus University, Roskilde, Denmark

[4]Department of Applied Mathematics and Computer Science, Technical University of Denmark, Kgs. Lyngby, Denmark

[5]DHI GRAS, Hørsholm, Denmark

[*]Corresponding author: E-mail: c.lonborg@ecos.au.dk

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/ieam.4552.

EDITOR'S NOTE

This article is part of the special series, "The Future of Marine Environmental Monitoring and Planning." The series will take a sneak peek into the future of marine monitoring where integration of new monitoring technologies with advanced ecosystem modeling will make it possible to estimate real-time ecosystem status, improve model precision, and provide a robust basis for marine environmental assessments.

Acknowledgements

The authors have no conflicts of interest. This study was funded by the Innovation Foundation Denmark as part of the project "SeaStatus – Innovative Technologies for Quantification of Sea Status". Tinna Christensen (Aarhus University) is thanked for making the graphical illustration included in the manuscript. Two anonymous reviewers and the editor are acknowledged for their valuable comments, which increased substantially the quality of the manuscript.

Data Availability Statement: All information used in this manuscript is based on **previous published studies. These studies have been referenced in the text and are listed in the reference list.**

Abstract

Coastal waters are highly productive and diverse ecosystems, often dominated by marine Submerged Aquatic Vegetation (SAV) and strongly affected by a range of human pressures. Due to their important ecosystem functions, both researchers and managers have for decades investigated changes in SAV abundance and growth dynamics to understand linkages to human perturbations. In European coastal waters monitoring of marine SAV communities traditionally combines diver observations and/or video recordings to determine e.g. spatial coverage and species composition. While these techniques provide very useful data, they are rather time consuming, labour intensive and limited in their spatial coverage. In this manuscript, we compare traditional and emerging remote sensing technologies used to monitor marine SAV, which include satellite and occupied aircraft operations, aerial drones and acoustics. We introduce these techniques and identify their main strengths and limitations. Finally, we provide recommendations for researchers and managers to choose the appropriate techniques for future surveys and monitoring programs.

Keywords: Submerged aquatic vegetation, Technology, Observations, Monitoring programs, Remote sensing, Image analysis.

Introduction

Coastal waters are responsible for 18-33% of the ocean primary production despite containing less than 1% of the total ocean volume (Wollast 1998). This high productivity occurs in shallow waters, where light and suitable substrate is available, largely due to dense coverage of submerged aquatic vegetation (SAV; macroalgae and seagrasses) (Duarte and Cebrián 1996).

Besides being highly productive, SAV also influence the overall functioning of coastal ecosystems by: 1) providing food e.g. for herbivorous waterbirds; 2) being shelter and hatching/nursery areas for many animals (e.g. fish); 3) improving water quality by absorbing nutrients; and 4) stabilizing sediments and decreasing hydrodynamic energy, thus increasing sedimentation and water clarity (Cabaço et al. 2013; Nacken and Reise 2000; Polte et al. 2005). Besides these positive functions, some opportunistic ephemeral (e.g. *Ulva lactuca*) and invasive (e.g. *Sargassum muticum*) macrophytes, have been shown to negatively affect the composition of the native flora and fauna, sometimes with severe impacts on ecosystem functioning (e.g.(Salvaterra et al. 2013). Due to their role in the ecosystem, both researchers and managers have for decades been interested in what factors control SAV abundances and species composition.

In coastal waters SAV generally shows rapid response to environmental disturbance, such as eutrophication, and are therefore widely used as indicators of the environmental status (e.g.(Chakraborty et al. 2014; Krause-Jensen et al. 2005; Zalewska and Danowska 2017). While most work has focused on eutrophication related aspects, declining water clarity and increased anoxia (Krause-Jensen et al. 2007a), other factors, such as the removal of suitable substrate, increased physical disturbance (e.g. extreme temperature and salinity), sediment instability as well as increased sediment loading from land (Orth et al. 2006) and diseases (e.g. the wasting disease) also impact SAV abundances and species composition (Short and Wyllie-Echeverria 1996).

In the European Union, monitoring and assessments of the status of marine waters are mainly driven by three legal acts: The Water Framework Directive (WFD), the Marine Strategy Framework Directive (MSFD;(European Commission 2000; 2008) and the Habitat Directive (HD) (European Commission 1992). Overall these directives consider SAV in one way or another, but with partly different purposes. The WFD aims to achieve at least a good ecological status (GEcS) in all European surface waters and SAV is one out of three biological quality elements that should be used to assess ecological status in coastal waters.The MSFD aims to achieve good environmental status (GEnS) by using 11 wide spanning qualitative descriptors, with SAV in this context used as an indicator for several of the descriptors. Two descriptors are in particular relevant, non-indigenous species (Descriptor 2) and eutrophication (Descriptor 5), where the ratio between opportunistic and perennial macroalgae has been proposed as a possible eutrophication indicator. The HD sets standards to assure biodiversity by preserving the natural habitats of flora and fauna, with SAV (e.g. seagrass) being one of the components that should be assessed in order to determine the conservation status. The central role of SAV as an indicator of environmental status impose a need for monitoring as a mean to assess whether targets on improving status are met or not.

Monitoring of marine SAV traditionally uses a combination of diver observations, photos and/or video recordings to determine e.g. spatial coverage and species composition (Duffy et al. 2019). However, these techniques are time consuming, labour intensive and highly limited in their spatial extent. In recent years, technological innovations of remote sensing platforms, sensors and data processing tools have provided new opportunities for improving SAV monitoring (Duffy et al. 2019). Yet, in order for researchers and managers to use the results obtained with these new monitoring techniques, several criteria should be fulfilled. These include that results; 1) should be reproducible, 2) preferably should be comparable and have the same resolution as those obtained previously, and 3) should require the least possible pre-/post treatment. If such criteria are not fulfilled, the obtained data would likely be of limited use.

In this manuscript, we provide an overview of traditional and emerging remote sensing technologies used to monitor marine SAV by introducing their principles and identifying their main strengths and limitations (Table 1, 2 and 3). Technologies that might have the potential, but have not yet been used to map marine SAV, such as mini-remotely operated vehicles (Mini-ROV;(Boavida et al. 2015) are not considered in this manuscript. We believe our review will help guide researchers and managers to choose the appropriate techniques for future SAV surveys and monitoring programs.

Techniques used to monitor SAV

Marine SAV can be found in extensive and continuous beds, but they can also, even within meters, be highly fragmented and occur as small patches (Duarte et al. 2006). Furthermore, significant changes in SAV cover and distribution may occur in exposed locations within days while other, less exposed and stable locations only show significant changes on a seasonal basis. Combined, this spatial and temporal heterogeneity makes the monitoring of SAV a challenging task. Over the past decades, many benthic monitoring programs, such as the Danish marine monitoring program, have shifted from in situ visual field surveys to the use of mainly video based techniques (Figure 1). Moreover, satellite, plane and drone based photogrammetry as well as ship and underwater drone based echo-sounding/acoustic techniques have been suggested as feasible tools for the monitoring of marine SAV (Figure 1; e.g.(Frederiksen et al. 2004; Hossain et al. 2015; Manfreda et al. 2018). Due to differences in spatial resolution, coverage and depth limit, the limitations of each technique has to be carefully considered prior to their application in monitoring programs. Divers and videos are commonly considered the “golden standard” approach, which is used to ground validate the other methods (e.g.(Gumusay et al. 2018). In this manuscript we will therefore evaluate and compare the other techniques to the diver and video approaches. Common for most of these newer techniques is that they create a permanent archive, which can be used for subsequent analysis, which increase reproducibility by decreasing the “diver effects” (Balsby et al. 2013). In addition, they reduce costs by minimizing in-water time, which may constrain underwater visual surveys. However, the post processing steps often bear a heavy workload and/or require advanced post processing algorithms.

When choosing a technique several local factors need to be considered. These include turbidity, water depth, drifting material, waves, cloud cover (causing shadows and light diffusion), fog/rain, or the presence of physical obstacles as they might affect the detection limit and resolution of the methods which in the end will determine the usefulness of the results (Dekker et al. 2006; Kirk 1994; Malthus 2017). In the comparison of the different techniques we will focus on data reproducibility, quality and the amount of pre-/post treatment that is needed. This include spatial coverage and resolution, temporal resolution, detection of the depth limit, weather sensibility and the amount of pre-/post treatment required (Table 1, 2 and 3). Also, the applicability of the methods to assess the most common SAV parameters (i.e. SAV coverage, single species identification and SAV depth limit) is included in the evaluation.

Diver and video-based approaches - The diver survey technique involves a free swimming or towed observer that visually assesses and records specific variables along a predefined transect. A similar approach is used for underwater video-based surveys where instead of an observer, a camera sled, or similar, is towed behind a boat. The spatial resolution of diver and video-based approaches is generally high (mm-cm) but depends on the underwater light regime, which varies depending on changes in the optical properties such as the concentration of phytoplankton, as well as the coloured organic matter, turbidity and light levels (e.g. overcast or dawn/dusk, sun elevation angle and latitude). For the video-based approach, the camera setup and resolution as well as the utilization of additional equipment such as artificial light sources, may also affect performance and reliability. Whereas the video-based method enable permanent recording of observations for reference and quality assurance, the diver based method relies on subjective judgements limiting the reproducibility of the results and introducing diver-specific variation in monitoring results (Balsby et al. 2013).

In general, divers perceive detail at twice the resolution as modern underwater photo cameras and have a three times larger field of view for the same depth (Bainbridge and Gardner 2016), this suggests that the human eye may be good at identifying known or anticipated targets and generally need fewer samples/runs to scan an area for a specific target (Bainbridge and Gardner 2016). Camera based techniques, depending on camera specifications and optics, can be better than divers at scanning an entire scene or identifying items at the periphery. Some of a video camera's limitations can be counteracted by using several cameras with high resolution and quality optics. Additionally, technologies exists for optical correction under water (Akkaynak and Treibitz 2019) and additionally raw video formats can be used for colour correction and sharpening in post-processing steps. Overall, video-based approaches have several advantages compared to diver-based monitoring (Table 1 and 3). If automated video- based analysis is available this can besides reducing observer bias, also reduce in-water survey time which can constrain underwater visual surveys and allow a permanent data record of observations for reference and quality assurance. Video-based approaches also allow an easy exchange of information and can be used to asses SAV extent and habitat types as well as provide extra information on e.g. extent of epiphytes, occurrence of fauna and impact of bottom trawling. The ability of videos to detect e.g. specific species and/or patches of SAV partly depends on the extend of the surveyed area, image resolution and SAV density. The permanent visual record also allows the re-analysis of earlier obtained photographic material for information previously overlooked, and enables experimentation with new data extraction techniques when they become available. However, the post-survey data processing and extraction are still typically being manually documented and analysed using point annotation software. This is rather time consuming and clearly limits the amount of survey data that can be analysed, but also leads to lags before survey results become available. Additionally, variability in performance among observer in species detection, identification and abundance estimation adds a potential unknown source of bias (Beijbom et al. 2015). However, advances in automated image analysis suggest that a substantial portion of the image-analysis could be automated using machine-learning tools (Sengupta et al. 2020).

Unoccupied Aerial Vehicles (UAVs) - Technological innovations have led to an increase in the use of drones for environmental monitoring (e.g.(Anderson and Gaston 2013; Manfreda et al. 2018). The term drones comprises a wide range of platforms from in-water operating vehicles such as Autonomous Underwater Vehicles (AUVs), Remote Operated Vehicles (ROVs) and Automated Surface Vehicles (ASVs) to aerial platforms, often referred to as Unoccupied Aerial Vehicles (UAVs). While water-based platforms operate in a similar spatial extent as the diver and video-based transect methods, UAVs are able to provide aerial imaging with high spatial (mm-cm) and temporal (on-demand, given adequate environmental conditions) resolution over relatively large areas (depending on flight altitude and UAV platform approx. up to 6 km^2/day) in a cost and time effective manner (Table 1 and 3;(Harvey et al. 2018; Johnston 2019; Ridge and Johnston 2020). UAV platforms can be grouped into three broad categories depending on their design and flight characteristics: 1) multirotor, 2) fixed-wing and 3) transitional (hybrid) (Johnston 2019; Ridge and Johnston 2020; Watts et al. 2012). This variety opens up for a wide range of applications by providing different functionalities in relation to flight performance, endurance, range, payload and control options (Ridge and Johnston 2020; Watts et al. 2012). While fixed-wing UAVs can cover areas larger than 1 km^2 per flight due to efficient aerodynamics and long flight times (~60 minutes), multirotor UAVs have shorter flight times (~30 minutes) and therefore are limited to about 0.2 km^2 per flight. Nonetheless, due to their lower acquisition cost, heavier payload capacity, vertical take-off and landing capability, easy handling and their ability to hover in a fixed position over a point of interest, lightweight (below 25 kg) multirotor UAVs are often the platform of choice when monitoring SAV (e.g.(Duffy et al. 2018a; Kellaris et al. 2019; Nahirnick et al. 2019; Nahirnick et al. 2018).

Most studies on the application of high-resolution, low-altitude aerial photography for SAV monitoring has to date focused mainly on exposed intertidal areas or clear waters, with numerous conducted density coverage mapping and growth dynamic studies from small patches to landscape level (Barrell and Grant 2015; Duffy et al. 2018a; Ventura et al. 2016). More recently, researchers have tested the limits in the application of lightweight multirotor UAV in environmentally more complicated areas with deeper or turbid waters (Nahirnick et al. 2019; Nahirnick et al. 2018).

The UAVs can be equipped with monitoring devices ranging from standard red, green and blue cameras to professional grade arrays of modular passive and active optical sensors ranging from multi- and hyperspectral to compact light detection and ranging (LiDAR) systems allowing for a multitude of mission objectives (Ridge and Johnston 2020). Especially the use of hyperspectral and LiDAR systems is however still limited by their weight, as most lightweight UAVs have a maximum payload capacity of less than 5 kg (Anderson and Gaston 2013). Advances in sensor miniaturization on the other side are likely to counteract these weight limitations in the near future (Anderson and Gaston 2013; Watts et al. 2012).

Positioning and orientation of a UAV and its sensors is generated by an on-board Global Navigation Satellite System (GNSS) positional receiver, which enables direct georeferencing of the collected images with an accuracy of ± 2-10 meters when using a consumer grade platform. If higher precision is needed, spatial accuracy can be brought down to ± 0.02m with the deployment of ground control points (GCPs) at precisely measured and marked locations that are strategically distributed across the study area and therefore subsequently can be used to geometrically correct the location of the collected images (Agüera-Vega et al. 2017; Duffy et al. 2018a). However, deploying GCPs is a labour-intensive task and besides that in environments dominated by water this is not even an option due to the lack of suitable static surfaces. A way of minimizing the need for GCPs while still maintaining accuracy on cm level is the use of UAVs equipped with an on-board high precision multi-frequency multi-constellation GNSS receiver (Teppati et al. 2020). In this way, a UAV's positioning data that is usually only obtained from satellites, is corrected during the flight (RTK) or after the flight (PPK) by correction processes that make use of additional positioning data recorded by a mobile base station (Teppati et al. 2020). Apart from the additional time needed in the field to deploy the base station, higher acquisition cost for UAV and mobile base station need to be taken into consideration when planning a project. The subscription to network RTK correction or Precise Point Positioning (PPP) services on the other hand eliminate the need for a mobile base station by allowing the connection to a network of permanently installed geodetic stations (Teppati et al. 2020), which however comes with the costs of a subscription fee. For aligning and combining single georeferenced images to high-resolution orthomosaics that are needed for quantitative analysis and SAV monitoring, advanced photogrammetric software (e.g. Agisoft or Pix4D) is needed which require adequate skills to use and come with a higher acquisition cost. To obtain non-georeferenced area, perimeter, distribution and coverage measurements as well as counts and shape information of regions of interest, images can be manually processed and analysed in an economic and fast way using free open source (e.g. ImageJ) or low cost (e.g. Adobe Photoshop) pixel-based image-processing software. Methods of Object Based Image Analysis (OBIA) are frequently used for the classification of spectrally difficult to distinguish aquatic habitats (Chabot et al. 2018), including SAV (e.g.(Nahirnick et al. 2019; Nahirnick et al. 2018; Ventura et al. 2018). Despite that OBIA is regarded as a semi-automated approach to digitizing imagery, large amounts of manual effort is needed to process image sets with e.g. different segmentation parameters and the work load for extracting useful information from imagery is often overlooked. However, the recent combination of OBIA with advanced machine learning algorithms is fast developing and promising tool for automated classification of shallow water habitats (Juel et al. 2015).

Several environmental factors including wind, heavy gusts, clouds, ice, and sun angle conditions will alter the quality of images (Casella et al. 2016). Wind speeds of a few m/s

for example will already create ripples at the water surface resulting in optical distortions and irregular light reflections. Together with wind induced movement of SAV, feature detection and matching between images becomes more difficult. While a thick cloud cover lowers the ability to see through the water column, scattered clouds create irregular shadows, leading to changes in illumination of imagery and therefore complicating the classification process (Duffy et al. 2018a). Environment conditions needed to obtain high confidence SAV mapping should at least include a sun angle below 40, cloud cover conditions with consistent reflectance and radiometry characteristics (below 10% or above 90%) and wind speeds of less than 1,4m/s (Nahirnick et al. 2019; Stæhr et al. 2019a).

Light attenuation in the water column lowers the contrast between benthic features, which limits the ability to identify SAV with increasing depth (Dekker et al. 2006). It is therefore that the SAV depth limit is rarely detectable from UAV derived aerial imagery (Table 1 and 3). Events of elevated turbidity levels further decrease the transparency of the water. First case studies have however shown that lightweight multirotor UAVs equipped with submersible camera systems are capable of obtaining close-up point observations of SAV at depths beyond the detection capacity of aerial sensors, enabling a UAV based determination of local SAV depth limit (Table 1, 2 and 3;(Nahirnick et al. 2019; Rasmussen et al. 2020; Stæhr et al. 2019a). The ability todistinguish between SAV genera from lightweight multirotor UAV derived red, green and blue imagery captured at low altitude was already demonstrated (Svane et al. 2016) although e.g. eelgrass can easily be mistaken for sparse macroalgae, especially in areas where they both occur (Table 1;(Nahirnick et al. 2018). The issue of species identification might be tackled by obtaining finer resolution imagery at lower flight altitudes or through the use of hyperspectral sensors to utilize the spectral differences between seagrass and macroalgae (Komárek et al. 2018; O'Neill and Costa 2013). SAV habitat assessments including density coverage mapping and growth dynamics studies have also been successfully conducted using low-altitude aerial photography (Barrell and Grant 2015; Duffy et al. 2018b; Svane et al. 2016). The high spatial resolution lowers the need for extensive ground validation data, compared to low resolution imagery obtained from traditional air- and space-borne remote sensing. Nonetheless, also here efforts are being made to develop methods that allow lightweight multirotor UAVs to collect underwater close up pictures for the validation of aerial images (e.g.(Rasmussen et al. 2020; Stæhr et al. 2019a).

With its capability of SAV monitoring in a cost and time effective way with high spatial and temporal resolution at local scale, UAV technology can fill the gap between point specific field observations and traditional air- and space-borne satellite remote sensing approaches (Manfreda et al. 2018).

Aircraft orthophotos – Aerial orthophotos taken from airplanes or using a UAV are obtained using e.g. digital cameras and have traditionally been used for land surveys and mapping purposes. After collection, the images are geometrically corrected for topographic relief, lens distortion and camera tilt in a process called ortho-rectification. After correction, the images have a uniform scale and can therefore be used for direct measurement of distances, angles, and areas. Orthophotos can be merged and integrated into systems such as a geographic information system (GIS) to produce maps which combine the visual features of an aerial image with the spatial accuracy and consistency of a map.

For monitoring of SAV using aircraft orthophotos, locations within water structures, such as mussel beds and sandbanks, should be excluded from analysis as it is not possible during the analysis to clearly distinguish these from the vegetation (Kendrick et al. 2000). The image quality will also vary depending on changes in tide (high tide vs low tide, springs vs neaps), wave conditions, water depth and clarity as well as sediment types (e.g. bright sand versus dark mud) (Table 1 and 3). Also the amount of sun glint, zenith sun angle as well as cloud cover can influence the image quality by changing the length and position of shadows which can make the identification of SAV beds difficult (Ferguson et al. 1993). Orthophotos should therefore ideally be obtained on sunny days with no cloud cover.

The orthophoto technique can be used to identify objects and study SAV distribution and has been shown to provide reliable percent SAV cover estimates in coastal waters allowing mapping at water depths generally less than 3 m (Table 1 and 2;(Ørberg et al. 2018), with a spatial resolution of meters (Young et al. 2008). The spatial resolution of ortophotos depends on water transparency, but also on the flight altitude, camera resolution and ability to capture light (e.g.

colour and infrared). While the resolution of orthophotos generally do not allow species detection, the possibility to distinguish major vegetation groups (seagrass, macroalgae) seems promising (Table 1, 2 and 3; (Ørberg et al. 2018) but needs further documentation.

An advantage of orthophotos is that in some cases images have repeatedly been obtained over decades, which potentially allows the determination of long-term variability in the distribution of SAV as far back as the 1930s (e.g.(Frederiksen et al. 2004; Larkum and West 1990). However, as early photos were only obtained in black and white, establishing such trends is only possible in regions dominated by sandy substrates with light colouring, which allows enough contrast between the background and plants to clearly detect SAV patches. In order to detect temporal changes there has to be overlap of each orthophoto image over time and these should ideally have been obtained at the same time of year to catch the SAV at an advanced growth state. The interpretation and mapping using recent orthophotos should also be followed up by field reference data to verify the results, with most studies finding reasonable agreement between photos and diver derived coverage estimates (60-80%;(Stæhr et al. 2019b).

An obvious application of orthophotos is the potential to monitor SAV over decadal time scales in shallow waters (less than 5m) and larger areas where a relatively low mapping resolution (m) is sufficient (Table 1 and 3;(Frederiksen et al. 2004; Kendrick et al. 2000). Some of the limitations of the method is that it cannot be used for determining the SAV depth limit which is partly related to insufficient light, reduced contrast between vegetation and sediment at depth, as well as to the patchy SAV growth closer to the depth limit making clear identification difficult (Table 1 and 3). Furthermore, in many cases the availability of historic orthophotos is limited, as water has historically been masked out in the processing partly to reduce storage space (Frederiksen et al. 2004). The method also requires calibration/ground validation in order to separate vegetation from other benthic features such as mussel beds (Ferguson et al. 1993; Frederiksen et al. 2004).

Echo-sounding / acoustic techniques - Acoustic technologies have rapidly developed and become widespread, providing accurate and high-quality backscatter information that enables mapping of bathymetry, geomorphology and benthic habitats such as marine SAV (Brown and Blondel 2009; Wright and Heyman 2008). Acoustic methods for mapping SAV is not limited by light availability and can be used even in turbid waters (Hossain et al. 2015) and for detecting the deepest edge of seagrass beds (Table 1 and 3;(Costello and Kenworthy 2011). Common for all acoustic methods are that they rely heavily on calibration with in situ data (density and canopy height) collected with conventional or remotely operated underwater vehicles to properly characterize the SAV community (Table 3).

The use of echo-sounding techniques for SAV mapping all rely on the specific acoustic impedance difference between gas pockets in the structure of the SAV blades and the surrounding water column (Lyons and Pouliquen 1998; McCarthy and Sabol 2000; Sabol et al. 1997; Warren and Peterson 2007). The specific acoustic impedance difference is a product of the density and speed of sound passing through water and SAV, where seagrasses strongly scatter sound waves. Also the buoyant structure of seagrasses caused by presence of gas within blade tissue makes them more acoustically reflective and thus distinguishable from other benthic features (Sabol and Shafer 2005). The scattering properties of seagrasses can sometimes even obscure the acoustic return signal from the underlying seabed (McCarthy and Sabol 2000; Sabol and Johnson 2002).

Although many applications of acoustic techniques focus on geological features (e.g. sediments and stone reefs) and seagrasses, the techniques have gradually been improved and applied to other seafloor components including macroalgal coverage (Seaman et al. 2000), measurements of oxygen synthesis by seagrasses (Hermand 2004; Hermand et al. 1998) and shellfish abundance estimation (Smith and Greenhawk 1998; Wildish et al. 1998).

Acoustic methods cover a large number of techniques. These can broadly be categorized into Single-beam echo-sounders (SBES), broad-acoustic beam systems, such as side scan sonar (SSS), and multiple narrow-beam swath bathymetry systems, such as multi-beam echo sounder (MBES) (Norton 2019). The SBES collect data only at vertical incidence, providing detail in the along-track and vertical directions, but with no angular discrimination and often has limited across-track coverage (Di Maida et al. 2010; Gumusay et al. 2018). The interpretation of data from SBES systems is well studied and understood. Also SBES systems are usually less expensive compared to other sonar mapping types. The SSS provide high resolution acoustic backscatter images of the seafloor and broad across-track coverage providing a good broadside orientation enabling detailed mapping in shallow waters typically occupied by SAV

(Pasqualini et al. 2010; Pasqualini et al. 1998). The vertical resolution is however reduced by cast shadows thus limiting estimations of canopy height for larger seagrass beds. The MBES collect data along a series of beams arranged in an angular swath across the track of the vessel. Due to the high resolution bathymetry and broad swath imagery with fine angular resolution, MBES have become the standard for most acoustic seabed mapping, including habitat mapping and hydrography (Gumusay et al. 2018).

Processing of acoustic data was originally based on visual interpretation. In recent years there has however, been developed several analytical routines and softwares to automate the processing of acoustic data. For ground discriminating single beam echo-sounders (SSS) these include RoxAnn, QTC-View, SAV Early Warning System (SAVEWS), and the recreational-grade fish finder (SSS) which is a forward looking sonar (e.g. DIDSON ARIS, EchoPilot FLS). As an example, recreational grade SSS has been applied for measuring seagrass cover in shallow environments (Greene et al. 2018).

Applications of acoustic techniques for seagrass mapping are many, and was recently reviewed based on comparison of 91 seagrass related studies (Gumusay et al. 2018). Their main conclusions were that significant improvements in methodologies for data collection, processing, classification and validation have been achieved enabling acquisition of seagrass coverage of areas up to 1400 km^2 (Table 1 and 3). Acoustic techniques so far remain limited to certain seagrass species but are optimal under turbid conditions and enable data on deeper patches. Further research is needed to achieve consistent seagrass detection systems. Despite advances in automated classifications, ground validation data remains essential for verification and assessment of accuracy of the study products. Fortunately, AUV devices now makes it more feasible and practical to collect ground validation data (Gumusay et al. 2018).

Satellite remote sensing - Most studies using passive optical satellite imagery for seagrass mapping have focused on local to regional scales, typically using open and freely available imagery from the Copernicus Sentinel-2 and NASA Landsat 8 missions (e.g. (Dierssen et al. 2019; Fritz et al. 2019; Hogrefe et al. 2014; Xu et al. 2021; Yadav et al. 2017)), which collect data at moderate spatial resolution (10-30 m). Only recently, with the advent of the Sentinel-2 fleet combined with technical developments in cloud-computing and machine learning, large-scale mapping became feasible (e.g.(Huber et al. 2021; Traganos et al. 2018). In addition to the free imagery, several studies have successfully mapped coastal habitats with commercial satellite imagery, providing spatial resolutions down to the sub-meter scale (Table 1; e.g.(Fritz et al. 2017; Marcello et al. 2018; McLaren et al. 2019; Pu and Bell 2017; Roelfsema et al. 2014; Traganos and Reinartz 2018).

The spatial resolution of the satellite imagery is the key factor determining which submerged habitats can be discriminated and thus mapped, as it becomes feasible to identify also smaller patches of vegetation and different macrophyte communities. The data from Sentinel-2 and Landsat 8 imagery is typically limited to identify absence and presence within a given pixel, as long as the macrophyte patch is big and dense enough to cover a large proportion of the pixel (Table 1, 2 and 3). Besides the spatial resolution, the spectral and temporal resolution of the satellite sensor plays also a role for sensing submerged macrophytes. The spectral resolution specifies the number of spectral bands in which a satellite sensor simultaneously measures data in multiple wavelengths of the electromagnetic spectrum. Most optical satellite sensors collect data for visible, near infrared, and short wave infrared spectral bands (i.e. multispectral sensors). For detecting submerged vegetation, the green region of the spectrum is considered optimal, followed by the red and red edge regions (Fyfe 2003; Silva et al. 2008). The green region is particularly important as it provides greater light penetration in waters with higher concentrations of suspended and dissolved material (Kirk 1994). Pigment concentrations and leaf structures in macrophytes are the primary determinants of their reflectance spectra. Additional spectral bands, beyond the red, green and blue bands, can therefore provide important information to discriminate between different habitat classes and benthic communities. However, to achieve an acceptable degree of discrimination at the species level would require hyperspectral data (Dekker et al. 2006; Muller-Karger et al. 2018). Yet, spectral information does not only improve class discrimination, but is also improves the preprocessing of the satellite imagery, such as water column correction, water surface sun and sky glint and atmospheric correction (Giardino et al. 2019).

The satellite’s temporal resolution, i.e., the revisit time of the satellite, is important as a larger archive of images increases the chance of acquiring not only images under ideal environmental conditions with high water clarity but also if there are further constraints on the timing of the mapping, e.g., growing cycle or comparison with other techniques (Table 1 and 3;(Zoffoli et al. 2020). Whereas Sentinel-2 and Landsat 8 satellites have revisit times of 2 to10 times a month, the commercial satellites only acquire images upon request. The revisit interval is 2 to 5 days for Sentinel-2 and 16 days for Landsat 8, with more observations at higher latitudes (Table 1).

Prior to using a satellite image for SAV classification, the spectral signal in the image must be corrected for atmospheric effects, as well as sea surface interactions. Since the method relies on optical imagery, it is susceptible to cloud cover, as the presence of clouds obscures the signal. Moreover, the signal from the sea floor must be detectable and the method therefore requires relative clear waters and shallow depths (approx. the same as the secchi depth; Table 1). High levels of atmospheric dust, large wave activity and sun glint can further reduce the potential for identifying benthic features in an image. As the method is dependent on observations of reflected sunlight, the sun elevation angle at image acquisition time is additionally important, though local environmental factors will typically dominate image selection (Table 1 and 3). The above mentioned effects can be mitigated through careful image selection.

The analysis of optical satellite imagery for SAV mapping is generally based either on visual inspection and interpretation of the imagery by a specialist or by using supervised classification algorithms. Supervised classification schemes, such as gradient boosting schemes, random forests or artificial neural networks, require a relatively large amount of suitable, labelled training data. Typically, training data is created through image interpretation, normally supported by high resolution basemaps, orthophotos, UAV images or similar, where smaller patches of the image are classified and labelled, thereby enabling the generation of training data where distinct characteristic of each class can be found in the satellite imagery. Training data obtained from other survey techniques, such as diver transects and similar, may also be used, but requires that attention is given to minimize differences in spatial resolution and time of acquisition. Using higher resolution imagery as a supporting layer for interpretation assures that small features and texture elements can be properly understood and incorporated into the training dataset. Transferability of the classification models between different images is a topic that needs further research.

To enhance the accuracy of the classification of the satellite image, supporting data layers are estimated and used as additional input features for the classification algorithm.

One of the most important supporting input layers is bathymetry, as depth estimates can be used in the classification to account for the effect of the variations of the reflected spectrum caused by variations in water depth (Kirk 1994). The depth can itself be derived from the imagery by using a radiative transfer model to retrieve the reflected spectrum, described as a function of depth, bottom type, backscattering, chlorophyll-a, coloured dissolved organic matter, and the slope of the backscattering function (Malthus 2017). The optimal set of parameters, including the depth, is estimated for each pixel, by minimizing the difference between the observed and the modelled spectrum. Other simpler methods, such as empirical log-ratio methods (Lyzenga 1978), can also be used to derive a bathymetry map for the analysed area using satellite data. Additional variables, such as depth invariant indices, simple convolutions of the spectral bands and additional independent layers, such as maps of exposure estimates, can further be included as input features to the classification algorithm (Huber et al. 2021).

Satellite-based methodologies for mapping and monitoring coastal habitats is developing from a topic predominantly dealt with in research into mature and operational monitoring systems used in practice (Table 2). Using free satellite imagery (e.g., Sentinel-2) to monitor and map aquatic vegetation provides a tool that allows for extensive spatial coverage, but given the limitations of the spatial resolution (10 to 30m; Table 1), the sharp decrease in the benthic signal with increasing water depths (e.g. (Dekker et al. 2006), and many potential noise sources in the imagery, it is not a suitable tool for identifying individual species or for consistently mapping the lower depth limits of seagrasses. However, at shallower water depths (typically above 3 to 5 m), the accurate representation of extents and changes over time gives a perspective on the health and status of the SAV in larger areas and opens up for inclusion of area coverage percentages and how this changes as a supplementary input source for assessment of ecological status of water bodies and for detection of any changes in status at large scale (Table 1 and 3; see e.g.(Hansen et al. 2021).

Discussion

Monitoring of SAV in coastal waters is inherently challenging due to the large patchiness in distribution, abundance and diversity, as well as the dynamic nature of these shallow systems. Most monitoring programs, mainly due to fiscal constraints, have had a strong emphasis on measuring parameters which we “need to know”, and there is therefore “no monitoring without a clear goal” (Carstensen et al. 2011). Commonly SAV monitoring activities address several needs by delivering information on: 1) overall trends in ecosystem status, 2) environmental assessment, and 3) determine impacts of human activities, natural stressors and/or the effectiveness of management actions (e.g. nutrient reductions). While most marine monitoring programs contain some form of SAV monitoring, the specific parameters measured and deduced differ. While some programs focus on determination of vegetation cover, biomass, and density, others focus on estimation of distribution ranges (e.g., depth limit and space distribution), species composition and/or a combination (Krause-Jensen et al. 2005; Krause-Jensen et al. 2007b; Marbà et al. 2012; Patrício et al. 2016). All these aspects vary depending on environmental conditions such as light availability, physical exposure, salinity, nutrient availability (Krause-Jensen et al. 2007a; Krause-Jensen et al. 2007b; Nielsen et al. 2002) and suitable growth substrates (e.g. stones, sandy bottom). As most SAV are present as patches, it also has to be considered if transect or spatial maps are the most appropriate for the purpose of the monitoring program as well as the location of the transects. Therefore to adequately address all these aspects the technique used has to be carefully considered and the desired outcomes need to be prioritized.

Traditionally monitoring of SAV is based on direct field observations and measurements within quadrats or along transects, using divers and/or underwater videos and photos. While these methods are well tested and have high spatial resolution, they also have limitations as they are labour intensive and have a limited spatial coverage (Table 1 and 3). Partly due to these limitation there has been an increased focus on replacing or supplementing these techniques with newer technology. But when substituting old techniques, it should firstly be ensured that the new ones give comparable estimates to the established technique, so that for example time series of important variables can be continued. As outlined in this article all techniques have limitations, so the choice of approach will ultimately depend on the objectives of the monitoring program (Table 1 and 3). Below we will discuss and compare the strengths and weakness of these methods and outline which approach could be used if certain information is warranted (Table 1, 2 and 3). In our comparison we use the diver and video techniques as the "reference" approach to ground validate the other methods. In the comparison we discuss data reproducibility, quality and the amount of pre-/post treatment that is needed.

In the European Union SAV are listed in the Water Framework Directive (WFD) as one of the biological quality elements (BQEs) that should be evaluated when assessing the ecological status of coastal waters, but also the Marine Strategy Framework Directive (MSFD, Directive 2008/56/EC) and Habitat Directive (HD, Directive 92/43/EEC of 21 May 1992) demands indicator-based assessments using SAV. Therefore an important aspect in the implementation of new technologies is if they can be used to determine commonly used indicators such as the key taxonomical units including brown macroalgae (Nielsen et al. 2002) or single species such as *Fucus vesiculosus* and *Zostera marina* (Rinne et al. 2018) and/or the maximum depth limit of certain species (Nielsen et al. 2002).

Currently only divers and videos have the capability to distinguishing single species of SAV and thus determine the relevant indicators (Table 1 and 3). If, however, group level differentiation (e.g. seagrass and macroalgae) is sufficient, UAVs and echosound can also be appropriate alternatives (Table 1 and 3).

However, if the aim is to obtain accurate information on SAV presence/absence, all of the assessed technologies could be used with the main differences being the area covered and spatial resolution as well as the surveying costs (Table 3). Although, neither of the new technologies are able to distinguish single species at present, further development and innovation may improve this.

The spatial distribution including the depth limit of SAV is of high ecological relevance and important as indicator in ecological assessments. The UAVs have proven to be more precise than aircraft orthophotos and/or satellite platforms when information is needed with a resolution at the scale of individual beds and areas below 1 km^2 (Table 1). Contrary, if there is no need for resolving the fine (below m) spatial distribution and considering the sparsely vegetated areas, but the focus is on presence/absence and areal extent of large beds (above m) within km´s, satellite imagery remains a good option (Table 1 and 3; e.g.(Purkis and Roelfsema 2015). But it should also be kept in mind that satellites across heterogeneous areas have issues and often cannot detect changes in presence/absence and areal extent less than 30% (Hossain et al. 2015; Schultz et al. 2015).

Obtaining reliable data for deeper water poses several problems for above water derived monitoring which include reduced light levels and that SAV is often patchy at depth and therefore need several observations to produce solid estimates. As SAV depth limits are often restricted by light availability (Duarte 1991), above water technologies are currently not suitable. Therefore if deeper water SAV monitoring and/or depth limit indictors are important currently only divers, videos and echo-sound techniques can provide reliable data (Table 1 and 3).

The seasonal and exact recurrent timing of SAV monitoring can be another important factor to consider if for example it is desired to capture the same growth stages from year to year and/or opportunistic non-indigenous species need to be identified (Krause-Jensen et al. 2005; Krause-Jensen et al. 2007b; Marbà et al. 2012; Patrício et al. 2016). Recurrent satellite observations are dependent on satellite revisiting time which currently is ranging from 2 to 10 days (Dekker et al. 2006; Muller-Karger et al. 2018). Although factors such as cloud cover, tides etc. may hamper the applicability of satellite images, seasonal monitoring is likely possible (Dekker et al. 2006; Muller-Karger et al. 2018). For UAVs, orthophotos and echo-sounding as well as diver and video-based approaches only extreme meteorological conditions (strong winds/currents) may prevent monitoring and these technologies can provide data with any requested timing and frequency (Table 3; e.g. (Duffy et al. 2019; Duffy et al. 2018b; Nahirnick et al. 2018).

In any study area the prevalent environmental conditions will also influence the reliability and data quality of the different techniques. If the waters are generally turbid, deep and have low contrast sediments it becomes increasingly difficult to discriminate between different bottom features and identify the lower distribution range of SAV using UAVs, orthophotos or satellites (Table 3). But also cloud cover hampers visibility of SAV beneath the water surface, which is problematic for the above water techniques. In such circumstances videos and/or echo-sounding would be the preferred technique for spatial coverage estimates

(Table 3). On the other hand when the waters have high visibility, light sandy bottoms, and SAV are the dominant bottom feature UAVs, orthophotos or satellites provide accurate estimates (Table 3; e.g.(Reise and Kohlus 2007).

The comparability of data obtained with different techniques is also an important aspect, which will depend on the scale and resolution considered. All techniques can as example provide estimate of coverage but the resolution, level of detail and extent of these estimates varies between techniques (Table 1). Most techniques, besides diver and video, do not provide species level information (Table 3).

The legal restrictions in the use of the SAV monitoring techniques vary with method and between countries. As examples the legislation regarding the use of platforms such as UAVs are primarily concerned with safe operation and respecting territorial boundaries. Therefore UAVs must follow all relevant licensing, operational and navigational requirements in the study area. Policymaking is often lagging behind this development and adaptations of existing regulations are still ongoing (Barrell and Grant 2015; Stöcker et al. 2017). In such a transitional period, it is particularly important that UAV operators make themselves aware of the respective current national/local regulations defining technical requirements, human resource requirements, operational limitations and administrative procedures. Regularly updated online sources and databases such as the Global Drone Regulations Database (https://droneregulations.info/) or the European Union co-founded database on national regulatory profiles in member states (https://dronerules.eu/en/professional/regulations) provide brief outlines and links to national UAV regulations and are a good starting point when planning flights in a certain country or region. Contrary to these country specific legal restrictions, the legislation regarding satellite remote sensing is governed by international laws, such as the Outer Space Treaty (United Nations 2018) or various other United Nations resolutions, as satellites do not orbit in the territory of any State and States can therefore collect imagery of one another (Rowan and Kalacska 2021).

Current and future perspectives - Coastal managers must consider the monitoring objectives when deciding on the type of technique and determine whether the trade-off of e.g. reduced costs for coarser spatial resolution is worth the loss in detailed detection (Table 3). But also as different monitoring programs use different assessment indicators to show or evaluate environmental conditions, it is unlikely that one-fit all approach will deliver all the necessary answers. Furthermore, several factors have to be considered such as local logistic and financial situation, which will influence the design of the monitoring program as well as the replication, taxonomic resolution and sampling frequency. As the new technologies mature and algorithms improve, monetary costs as well as the need for manpower will likely decrease (Table 3).

Generally, for all the methods presented here there is a urgent need to standardize the methodologies used to monitor different systems in order to assure that the quality of the data obtained with these platforms is the same (Manfreda et al. 2018). If this is attained, future aerial surveys using techniques such as UAVs equipped with hyperspectral or multispectral sensors could deliver images both within and beyond the visible spectrum, providing an opportunity for spectral differentiation in multi-species beds (Murfitt et al. 2017) and potentially allowing to distinguish bottom vegetation from epiphytes. The combination with other hyper- or multispectral tools could provide information on important environmental factors such as turbidity and sediment flow, as well as surface water chlorophyll a concentrations (Díaz-Delgado et al. 2018; Kislik et al. 2018), which can be vital in explaining the obtained results.

Satellite remote sensing data are priced reasonably cheaply per unit area relative to the cost for e.g. diver and video acquisition (Table 3). Thus, satellite data can many times provide a useful input to coastal zone mapping. The new generation of high spatial resolution and mid-spectral resolution hyperspectral satellites, can deliver high resolution imagery and will allow more feature extraction from satellites (Brando et al. 2009; Lu and Weng 2007).

One of the major disadvantages of the video-based approaches is the associated post-survey data processing and extraction, their smaller spatial coverage compared with some other methods (e.g. UAVs and satellites) and the costs involved with boats and personnel (Table 3). Still, these more traditional techniques are suggested as the most feasible for small scale studies where estimates of species composition and depth limit is needed (Table 1 and 3).

A direct consequence of the progress in the use of techniques such as UAVs or satellite remote sensing is that it potentially allows for more imagery to be collected which results in large increase in data volume and complexity. This will increase both the spatial and temporal coverage, resulting in the data being more representative. But on the other hand these new data streams will have a changed quality and will demand new ways of data handling, analysis and reporting. While the human capacity to filter, and analyse data is limited, the advances in machine learning offer new possibilities of addressing these problems. In many cases, machines exceed human precision, for the analyses of complex and heterogeneous data, and they could therefore be used for e.g. pre-screening of videos and for enabling the recording of SAV. There is also strong potential for Artificial Intelligence (AI) to automate detection and allow for improved efficiency for e.g. UAV-based surveys. Some relevant applications of AI are shown for object detection and identification, example face recognition used in video surveillance (Dargan et al. 2019). One study has shown that an absence/presence (seagrass or background) detection is possible based on classification using automated approaches (Bonin-Font et al. 2016; Burguera et al. 2016; Gonzalez-Cid et al. 2017; Massot-Campos et al. 2013), but a recent study also showed how a dataset captured from an AUV could be used to train a Convolutional Neural Network (CNN) model to segment seagrass images (Reus et al. 2018a). Similar CNNs approaches have with high accuracy (order of 90%) been used for identification and classification of plankton (e.g.(Bochinski et al. 2019; Cheng et al. 2019; Cui et al. 2018), similar approaches also could be developed and used for SAV data. Also subfields of machine and deep learning have in other research fields (marine fish detection; e.g.(Salman et al. 2020) been shown as promising tools to treat and automatically analyse the massive data streams from visual monitoring datasets. Visual estimation of SAV using techniques such as underwater videos is a subjective task. Multiple domain experts do not agree necessarily on the same precise estimates of variables such as seagrass cover while evaluating a certain area/video recording. Previous approaches using machine learning to automate SAV estimation tasks (Gonzalez-Cid et al. 2017; Massot-Campos et al. 2013; Reus et al. 2018b; Weidmann et al. 2019) uses model accuracy instead of the bias as the main metric for evaluation. Deep learning approaches have shown to be accurate to a high degree on SAV estimation tasks. Even though model bias can be quantified in a machine-learning framework, it need not translate directly to the perception/subjective bias introduced during the labelling task of the images. A domain expert does pixel wise labelling of SAV images manually to be used to train machine-learning models, which introduce the human bias. But a recent paper introduced a framework through which the subjective bias can be quantified by an empirical value (Akkaynak and Treibitz 2019). Therefore using these new techniques on e.g. video recording could potentially allow rapid species identification and mapping of depth limits, but may also increase the reliability and reproducibility of field-detections. Therefore communication between machine learning and marine scientists should be improved such that both sides become aware of the range of potential applications, limitations and challenges of data use. But it should also be kept in mind that these techniques have their own limits, as they have been shown to have relatively poor analysis performance, both automated and manual, for SAV groups (Beijbom et al. 2015; Gonzalez-Cid et al. 2017), partly due to the variability in vegetation morphology and extent of epiphytes which can make it difficult to differentiate groups such as seagrass from green algae. But also changes in the environmental conditions which impact e.g. each UAV flight can result in different image properties which can be a major obstacle for these automated classification.

For all new techniques a ground-validation of the results is necessary, either from divers or underwater videos or suitable labelled training data to verify the obtained results (Table 3). These ground validation estimations are normally done manually and are very time consuming, but few studies have investigated how to automate these (Moniruzzaman et al. 2019; Reus et al. 2018a).

Emergent technologies offer new possibilities for increasing the spatial coverage of SAV monitoring compared with traditional techniques, but at the cost of decreased level of biological details (Table 3). Technologies such as UVs and echo-sounding can under optimal conditions provide information on SAV presence at group or even species level at medium range areas (m to km´s) whereas satellite images cover the largest monitoring areas (≥ km) but also with lowest level of biological information (Table 3). Hence, no single technology and approach is sufficient to observe all SAV relevant parameters, and the assessed technologies can supplement but not fully replace each other. Future studies should look at how to combine the different technologies. As e.g. UAVs could be suitable for training of satellite based classification models (for training and validation data) and satellite-data could provide a broad overview and also pinpoint areas where finer detail from UAVs is required (such as in areas with inter/intra annual changes). But also rapid technological developments and increase in the use of machine learning will likely overcome many of the current limitations hopefully enabling a more effective use of resources and management of SAV.

Conclusion

A whole range of new exciting technologies exists for the monitoring of marine submerged aquatic vegetation. In this article, we have outlined the capabilities of each of the techniques as well as their main strengths and limitations. As no technology is perfect in all circumstances, the monitoring objectives, data needs and budget should be known before the preferred technic is chosen. We suggest that future studies should combine the different technologies as well as increase the use of machine learning for post processing of the obtained data.

References

Agüera-Vega F, Carvajal-Ramírez F, Martínez-Carricondo P. 2017. Assessment of photogrammetric mapping accuracy based on variation ground control points number using unmanned aerial vehicle. Measurement. 98:221-227.

Akkaynak D, Treibitz T. 2019. Sea-thru: A method for removing water from underwater images. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).1682-1691.

Anderson K, Gaston KJ. 2013. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. Frontiers in Ecology and the Environment. 11(3):138-146.

Bainbridge S, Gardner S. 2016. Comparison of human and camera visual acuity—setting the benchmark for shallow water autonomous imaging platforms. Journal of Marine Science and Engineering. 4(1).

Balsby TJS, Carstensen J, Krause-Jensen D. 2013. Sources of uncertainty in estimation of eelgrass depth limits. Hydrobiologia. 704(1):311-323.

Barrell J, Grant J. 2015. High-resolution, low-altitude aerial photography in physical geography: A case study characterizing eelgrass (*Zostera marina* l.) and blue mussel (*Mytilus edulis* l.) landscape mosaic structure. Progress in Physical Geography. 39:440-459.

Beijbom O, Edmunds PJ, Roelfsema C, Smith J, Kline DI, Neal BP, Dunlap MJ, Moriarty V, Fan TY, Tan CJ et al. 2015. Towards automated annotation of benthic survey images: Variability of human experts and operational modes of automation. PloS one. 10(7):e0130312.

Boavida J, Assis J, Reed J, Serrão EA, Gonçalves JMS. 2015. Comparison of small remotely operated vehicles and diver-operated video of circalittoral benthos. Hydrobiologia. 766(1):247-260.

Bochinski E, Bacha G, Eiselein V, Walles TJW, Nejstgaard JC, Sikora T. 2019. Deep active learning for in situ plankton classification. Pattern recognition and information forensics. p. 5-15.

Bonin-Font F, Massot Campos M, Oliver Codina G. 2016. Towards visual detection, mapping and quantification of *Posidonia oceanica* using a lightweight auv. IFAC-PapersOnLine. 49-23 (2016) 500–505.

Brando VE, Anstee JM, Wettle M, Dekker AG, Phinn SR, Roelfsema C. 2009. A physics based retrieval and quality assessment of bathymetry from suboptimal hyperspectral data. Remote Sensing of Environment. 113(4):755-770.

Brown CJ, Blondel P. 2009. Developments in the application of multibeam sonar backscatter for seafloor habitat mapping. Applied Acoustics. 70(10):1242-1247.

Burguera A, Bonin-Font F, Lisani JL, Petro AB, Oliver G. 2016. Towards automatic visual sea grass detection in underwater areas of ecological interest In 2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA) pp. 1-4.

Cabaço S, Apostolaki ET, García-Marín P, Gruber R, Hernández I, Martínez-Crego B, Mascaró O, Pérez M, Prathep A, Robinson C et al. 2013. Effects of nutrient enrichment on seagrass population dynamics: Evidence and synthesis from the biomass-density relationships. Journal of Ecology. 101(6):1552-1562.

Carstensen J, Dahl K, Henriksen P, Hjorth M, Josefson A, Krause-Jensen D. 2011. 7.08 - coastal monitoring programs. In: Wolanski E, McLusky D, editors. Treatise on estuarine and coastal science. Waltham: Academic Press. p. 175-206.

Casella E, Collin A, Harris D, Ferse S, Bejarano S, Parravicini V, Hench JL, Rovere A. 2016. Mapping coral reefs using consumer-grade drones and structure from motion photogrammetry techniques. Coral Reefs. 36(1):269-275.

Chabot D, Dillon C, Shemrock A, Weissflog N, Sager E. 2018. An object-based image analysis workflow for monitoring shallow-water aquatic vegetation in multispectral drone imagery. ISPRS International Journal of Geo-Information. 7(8).

Chakraborty S, Bhattacharya T, Singh G, Maity JP. 2014. Benthic macroalgae as biological indicators of heavy metal pollution in the marine environments: A biomonitoring approach for pollution assessment. Ecotoxicol Environ Saf. 100:61-68.

Cheng K, Cheng X, Wang Y, Bi H, Benfield MC. 2019. Enhanced convolutional neural network for plankton identification and enumeration. PloS one. 14(7):e0219570.

Costello CT, Kenworthy WJ. 2011. Twelve-year mapping and change analysis of eelgrass (*Zostera marina*) areal abundance in massachusetts (USA) identifies statewide declines. Estuaries and Coasts. 34(2):232-242.

Cui J, Wei B, Wang C, Yu Z, Zheng H, Zheng B, Yang H. 2018. Texture and shape information fusion of convolutional neural network for plankton image classification. in 2018 OCEANS - MTS/IEEE Kobe Techno-Oceans (OTO), Kobe, 2018.pp. 1–5.

Dargan S, Kumar M, Ayyagari MR, Kumar G. 2019. A survey of deep learning and its applications: A new paradigm to machine learning. Archives of Computational Methods in Engineering. 27(4):1071-1092.

Dekker A, Brando V, Anstee J, Fyfe S, Malthus T, Karpouzli E. 2006. Remote sensing of seagrass ecosystems: Use of spaceborne and airborne sensors. Seagrasses: Biology, ecologyand conservation. Dordrecht: Springer Netherlands. p. 347-359.

Di Maida G, Tomasello A, Luzzu F, Scannavino A, Pirrotta M, Orestano C, Calvo S. 2010. Discriminating between *Posidonia oceanica* meadows and sand

substratum using multibeam sonar. ICES Journal of Marine Science. 68(1):12-19.
Díaz-Delgado R, Cazacu C, Adamescu M. 2018. Rapid assessment of ecological integrity for lter wetland sites by using uav multispectral mapping. Drones. 3(1).
Dierssen HM, Bostrom KJ, Chlus A, Hammerstrom K, Thompson DR, Lee Z. 2019. Pushing the limits of seagrass remote sensing in the turbid waters of elkhorn slough, california. Remote Sensing. 11(14).
Duarte CM. 1991. Seagrass depth limits. Aquatic Botany. 40:363-377.
Duarte CM, Cebrián J. 1996. The fate of marine autotrophic production. Limnology and Oceanography. 41(8):1758-1766.
Duarte CM, Fourqurean JW, Krause-Jensen D, Olesen B. 2006. Dynamics of seagrass stability and change. Seagrasses: Biology, ecologyand conservation. Dordrecht: Springer Netherlands. p. 271-294.
Duffy JE, Benedetti-Cecchi L, Trinanes J, Muller-Karger FE, Ambo-Rappe R, Boström C, Buschmann AH, Byrnes J, Coles RG, Creed J et al. 2019. Toward a coordinated global observing system for seagrasses and marine macroalgae. Frontiers in Marine Science. 6(317).
Duffy JP, Cunliffe AM, DeBell L, Sandbrook C, Wich SA, Shutler JD, Myers-Smith IH, Varela MR, Anderson K, Pettorelli N et al. 2018a. Location, location, location: Considerations when using lightweight drones in challenging environments. Remote Sensing in Ecology and Conservation. 4(1):7-19.
Duffy JP, Pratt L, Anderson K, Land PE, Shutler JD. 2018b. Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone. Estuarine, Coastal and Shelf Science. 200:169-180.
European Commission. 1992. Council Directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and wild fauna and flora (Habitats Directive). Official Journal of the European Communities, 206: 7-50.
European Commission. 2000. Directive 2000/60/EC of the European Parliament and Council of 23 October 2000 establishing a framework for Community action in the field of water policy (Water Framework Directive). Official journal of the European *Communities*, *327*(43): 1-72.
European Commission. 2008. Directive 2008/56/EC of the European Parliament and the Council of 17 June 2008 establishing a framework for community action in the fieldof marine environmental policy (Marine Strategy Framework Directive). fficial journal of the European Union 164 (25.6): 19–40.
Ferguson R, Wood L, Graham D. 1993. Monitoring spatial change in seagrass habitat with aerial photography. Photogrammetric Engineering and Remote Sensing. 59:1033-1038.
Frederiksen M, Krause-Jensen D, Holmer M, Laursen JS. 2004. Long-term changes in area distribution of eelgrass (*Zostera marina*) in danish coastal waters. Aquatic Botany. 78(2):167-181.
Fritz C, Dörnhöfer K, Schneider T, Geist J, Oppelt N. 2017. Mapping submerged aquatic vegetation using rapideye satellite data: The example of lake kummerow (germany). Water. 9(7):510.

Fritz C, Kuhwald K, Schneider T, Geist J, Oppelt N. 2019. Sentinel-2 for mapping the spatio-temporal development of submerged aquatic vegetation at lake starnberg (germany): Mapping the spatial distribution of submerged aquatic vegetation. Journal of Limnology. 78(1).

Fyfe SK. 2003. Spatial and temporal variation in spectral reflectance: Are seagrass species spectrally distinct? Limnology and Oceanography. 48(1part2):464-479.

Giardino C, Brando VE, Gege P, Pinnel N, Hochberg E, Knaeps E, Reusen I, Doerffer R, Bresciani M, Braga F et al. 2019. Imaging spectrometry of inland and coastal waters: State of the art, achievements and perspectives. Surveys in Geophysics. 40(3):401-429.

Gonzalez-Cid Y, Burguera A, Bonin-Font F, Matamoros A. 2017. Machine learning and deep learning strategies to identify posidonia meadows in underwater images. In: OCEANS 2017-Aberdeen IEEE,.pp. 1–5.

Greene A, Rahman AF, Kline R, Rahman MS. 2018. Side scan sonar: A cost-efficient alternative method for measuring seagrass cover in shallow environments. Estuarine, Coastal and Shelf Science. 207:250-258.

Gumusay MU, Bakirman T, Tuney Kizilkaya I, Aykut NO. 2018. A review of seagrass detection, mapping and monitoring applications using acoustic systems. European Journal of Remote Sensing. 52(1):1-29.Hansen LB, Rasmussen ML, Nielsen LT, Huber S, Christensen M. 2021. Monitoring nearshore marine habitats - the values of submerged aquatic vegetation for a healthy and resilient ocean. ECO Magazine.64-67.

Harvey ET, Krause-Jensen D, Stæhr PA, Groom GB, Hansen LB. 2018. Literature review of remote sensing technologies for coastal chlorophyll-a observations and vegetation coverage. Part of restek (brug af remote sensing teknologier til opgørelse af klorofylkoncentrationer og vegetationsudbredelse i danske kystvande) and dce remote sensing in coastal area projects.: Aarhus University, DCE – Danish Centre for Environment and Energy.

Hermand J-P. 2004. Acoustic remote sensing of photosynthetic activity in seagrass beds. In: Seuront L, Strutton PG, editors. Handbook of scaling methods in aquatic ecology: Measurement, analysis, simulation Florida: CRC Press p. 65-96.

Hermand J-P, Nascetti P, Cineli F. 1998. Inversion of acoustic waveguide propagation features to measure oxygen synthesis by *Posidonia oceanica*. Paper presented at: OCEANS'98 Conference Proceedings. Nice, France.

Hogrefe KR, Ward D, Donnelly TF, Dau N. 2014. Establishing a baseline for regional scale monitoring of eelgrass *(Zostera marina*) habitat on the lower alaska peninsula. Remote Sens. 6:12447-12477.

Hossain MS, Bujang JS, Zakaria MH, Hashim M. 2015. The application of remote sensing to seagrass ecosystems: An overview and future research prospects. International Journal of Remote Sensing. 36:61-114.

Huber S, Hansen LB, Nielsen LT, Rasmussen ML, Sølvsteen J, Berglund J, Friesen CPv, Danbolt M, Envall M, Infantes E et al. 2021. Novel approach for large-scale monitoring of submerged aquatic vegetation – a nationwide

example from sweden. Integrated Environmental Assessment and Management. n/a(n/a).
Johnston DW. 2019. Unoccupied aircraft systems in marine science and conservation. Annual review of marine science. 11:439-463.
Juel A, Groom GB, Svenning JC, Ejrnaes R. 2015. Spatial application of random forest models for fine-scale coastal vegetation classification using object based analysis of aerial orthophoto and dem data. International Journal of Applied Earth Observation and Geoinformation. 42:106-114.
Kellaris A, Gil A, Faria J, Amaral R, Moreu-Badia I, Neto A, Yesson C. 2019. Using low-cost drones to monitor heterogeneous submerged seaweed habitats: A case study in the azores. Aquatic Conservation: Marine and Freshwater Ecosystems. 29(11):1909-1922.
Kendrick GA, Hegge BJ, Wyllie A, Davidson A, Lord DA. 2000. Changes in seagrass cover on success and parmelia banks, western australia between 1965 and 1995. Estuarine, Coastal and Shelf Science. 50(3):341-353.
Kirk JTO. 1994. Light and photosynthesis in aquatic ecosystems. Cambridge University Press.
Kislik C, Dronova I, Kelly M. 2018. Uavs in support of algal bloom research: A review of current applications and future opportunities. Drones. 2(4).
Komárek J, Klouček T, Prošek J. 2018. The potential of unmanned aerial systems: A tool towards precision classification of hard-to-distinguish vegetation types? International Journal of Applied Earth Observation and Geoinformation. 71:9-19.
Krause-Jensen D, Carstensen J, Dahl K. 2007a. Total and opportunistic algal cover in relation to environmental variables. Marine Pollution Bulletin 55(1-6):114-125.
Krause-Jensen D, Greve TM, Nielsen K. 2005. Eelgrass as a bioindicator under the european water framework directive. Water Resources Management. 19(1):63-75.
Krause-Jensen D, Middelboe AL, Carstensen J, Dahl K. 2007b. Spatial patterns of macroalgal abundance in relation to eutrophication. Marine Biology. 152(1):25-36.
Larkum AWD, West RJ. 1990. Long-term changes of seagrass meadows in botany bay, australia. Aquatic Botany. 37:55–70.
Lu D, Weng Q. 2007. A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing. 28(5):823-870.
Lyons AP, Pouliquen E. 1998. Measurements of high-frequency acoustic scattering from seabed vegetation. Journal of the Acoustical Society of America. 103:2934.
Lyzenga DR. 1978. Passive remote sensing techniques for mapping water depth and bottom features. Applied Optics. 17:379-383.
Malthus TJ. 2017. Chapter 9 - bio-optical modeling and remote sensing of aquatic macrophytes. In: Mishra DR, Ogashawara I, Gitelson AA, editors. Bio-optical modeling and remote sensing of inland waters. Elsevier. p. 263-308.

Manfreda S, McCabe M, Miller P, Lucas R, Pajuelo Madrigal V, Mallinis G, Ben Dor E, Helman D, Estes L, Ciraolo G et al. 2018. On the use of unmanned aerial systems for environmental monitoring. Remote Sensing. 10(4).

Marbà N, Krause-Jensen D, Alcoverro T, Birk S, Pedersen A, Neto JM, Orfanidis S, Garmendia JM, Muxika I, Borja A et al. 2012. Diversity of european seagrass indicators: Patterns within and across regions. Hydrobiologia. 704(1):265-278.

Marcello J, Eugenio F, Martín J, Marqués F. 2018. Seabed mapping in coastal shallow waters using high resolution multispectral and hyperspectral imagery. Remote Sensing. 10(8):1208.

Massot-Campos M, Oliver-Codina G, Ruano-Amengual L, Miró-Juliá M. 2013. Texture analysis of seabed images: Quantifying the presence of *Posidonia oceanica* at palma bay. In: 2013 MTS/IEEE OCEANS-Bergen IEEE.pp. 1–6.

McCarthy EM, Sabol B. 2000. Acoustic characterization of submerged aquatic vegetation: Military and environmental monitoring applications. Paper presented at: OCEANS 2000 MTS/IEEE Conference and Exhibition. Conference Proceedings (Cat. No.00CH37158), Providence, RI, USA.

McLaren K, McIntyre K, Prospere K. 2019. Using the random forest algorithm to integrate hydroacoustic data with satellite images to improve the mapping of shallow nearshore benthic features in a marine protected area in jamaica. GIScience & Remote Sensing. 56(7):1065-1092.

Moniruzzaman M, Islam SMS, Lavery P, Bennamoun M, Peng Lam CP. 2019. Imaging and classification techniques for seagrass mapping and monitoring: A comprehensive survey. arXiv.1902.11114.

Muller-Karger FE, Hestir E, Ade C, Turpie K, Roberts DA, Siegel D, Miller RJ, Humm D, Izenberg N, Keller M et al. 2018. Satellite sensor requirements for monitoring essential biodiversity variables of coastal ecosystems. Ecological Applications. 28(3):749-760.

Murfitt SL, Allan BM, Bellgrove A, Rattray A, Young MA, Ierodiaconou D. 2017. Applications of unmanned aerial vehicles in intertidal reef monitoring. Sci Rep. 7(1):10259.

Nacken M, Reise K. 2000. Effects of herbivorous birds on intertidal seagrass beds in the northern wadden sea. Helgoland Marine Research. 54:87-94.

Nahirnick NK, Hunter P, Costa M, Schroeder S, Sharma T. 2019. Benefits and challenges of uas imagery for eelgrass (Zostera marina) mapping in small estuaries of the canadian west coast. Journal of Coastal Research. 35(3).

Nahirnick NK, Reshitnyk L, Campbell M, Hessing-Lewis M, Costa M, Yakimishyn J, Lee L, Horning N, Poursanidis D. 2018. Mapping with confidence; delineating seagrass habitats using unoccupied aerial systems (UAS). Remote Sensing in Ecology and Conservation. 5(2):121-135.

Nielsen SL, Sand-Jensen K, Borum J, Geertz-Hansen O. 2002. Depth colonization of eelgrass (*Zostera marina*) and macroalgae as determined by water transparency in danish coastal waters. Estuaries. 25(5):1025-1032.

Norton AR. 2019. Acoustic methods for mapping and characterizing submerged aquatic vegetation using a multibeam echosounder University of New Hampshire.

O'Neill JD, Costa M. 2013. Mapping eelgrass (*Zostera marina*) in the gulf islands national park reserve of canada using high spatial resolution satellite and airborne imagery. Remote Sensing of Environment. 133:152-167.

Orth RJ, Carruthers TJB, Dennison WC, Duarte CM, Fourqurean JW, Heck KL, Hughes AR, Kendrick GA, Kenworthy WJ, Olyarnik S et al. 2006. A global crisis for seagrass ecosystems. BioScience. 56(12).

Pasqualini V, Clabaut P, Pergent G, Benyoussef L, Pergent-Martini C. 2010. Contribution of side scan sonar to the management of mediterranean littoral ecosystems. International Journal of Remote Sensing. 21(2):367-378.

Pasqualini V, Pergent-Martini C, Clabaut P, Pergent G. 1998. Mapping of *Posidonia oceanica* using aerial photographs and side scan sonar: Application off the island of corsica (france). Estuarine, Coastal and Shelf Science. 47:359-367.

Patrício J, Little S, Mazik K, Papadopoulou K-N, Smith CJ, Teixeira H, Hoffmann H, Uyarra MC, Solaun O, Zenetos A et al. 2016. European marine biodiversity monitoring networks: Strengths, weaknesses, opportunities and threats. Frontiers in Marine Science. 3(161).

Polte P, Schanz A, Asmus H. 2005. The contribution of seagrass beds (*Zostera noltii*) to the function of tidal flats as a juvenile habitat for dominant, mobile epibenthos in the wadden sea. Marine Biology. 147(3):813-822.

Pu R, Bell S. 2017. Mapping seagrass coverage and spatial patterns with high spatial resolution ikonos imagery. International Journal of Applied Earth Observation and Geoinformation. 54:145-158.

Purkis S, Roelfsema C. 2015. Remote sensing of submerged aquatic vegetation and coral reefs. Remote sensing of wetlands. p. 223-242.

Rasmussen MB, Krause-Jensen D, Balsby TJS. 2020. Udvikling og test af dronemetode og interkalibrering af eksisterende metode til undersøgelse af ålegræs og anden vegetation på blød bund (in danish). Aarhus University, DCE – Danish Centre for Environment and Energy.

Reise K, Kohlus J. 2007. Seagrass recovery in the northern wadden sea? Helgoland Marine Research. 62(1):77-84.

Reus G, Möller T, Jäger J, Schultz ST, Kruschel C, Hasenauer J, Wolff V, Fricke-Neuderth K. 2018a. Looking for seagrass: Deep learning for visual coverage estimation. n: 2018 OCEANS-MTS/IEEE Kobe Techno-Oceans (OTO) IEEE,.pp. 1–6.

Ridge JT, Johnston DW. 2020. Unoccupied aircraft systems (UAS) for marine ecosystem restoration. Frontiers in Marine Science. 7.

Rinne H, Korpinen S, Mattila J, Salovius-Laurén S. 2018. Functionality of potential macroalgal indicators in the northern baltic sea. Aquatic Botany. 149:52-60.

Roelfsema CM, Lyons M, Kovacs EM, Maxwell P, Saunders MI, Samper-Villarreal J, Phinn SR. 2014. Multi-temporal mapping of seagrass cover, species and biomass: A semi-automated object based image analysis approach. Remote Sensing of Environment. 150:172-187.

Rowan GSL, Kalacska M. 2021. A review of remote sensing of submerged aquatic vegetation for non-specialists. Remote Sensing. 13(4):623.

Sabol B, Johnson S. 2002. Hydrographic surveying in dense aquatic vegetation: Digital signal processing for improved bottom tracking. Hydro International. 6:7-9.

Sabol B, McCarthy E, Rocha K. 1997. Hydroacoustic basis for detection and characterization of eelgrass (*Zostera marina*). Paper presented at: 4th International Conference Remote Sensing Marine Coastal Environment. Environmental Research Institute of Michigan, Ann Arbor, USA.

Sabol BM, Shafer DJ. 2005. Dredging effects on seagrasses: Case studies from new england and florida. Paper presented at: Proceedings of the Western Dredging Association.

Salman A, Siddiqui SA, Shafait F, Mian A, Shortis MR, Khurshid K, Ulges A, Schwanecke U, Beyan C. 2020. Automatic fish detection in underwater videos by a deep neural network-based hybrid motion learning system. ICES Journal of Marine Science. 77(4):1295-1307.

Salvaterra T, Green DS, Crowe TP, O'Gorman EJ. 2013. Impacts of the invasive alga *Sargassum muticum* on ecosystem functioning and food web structure. Biological Invasions. 15(11):2563-2576.

Schultz ST, Kruschel C, Bakran-Petricioli T, Petricioli D. 2015. Error, power, and blind sentinels: The statistics of seagrass monitoring. PloS one. 10(9):e0138378.

Seaman R, Finkbeiner M, Dorsey Worthy L. 2000. Application of single-beam acoustics to macro-algae bloom management. Paper presented at: OCEANS 2000 MTS/IEEE Conference and Exhibition Conference Proceedings Providence, RI, USA.

Sengupta S, Ersbøll BK, Stockmarr A. 2020. Seagrassdetect: A novel method for the detection of seagrass from unlabelled underwater videos. Ecological Informatics. 57.

Short FT, Wyllie-Echeverria S. 1996. Natural and human-induced disturbance of seagrasses. Environmental Conservation. 23:17–27.

Silva TSF, Costa MPF, Melack JM, Novo EMLM. 2008. Remote sensing of aquatic vegetation: Theory and applications. Environmental Monitoring and Assessment. 140(1):131-145.

Smith GF, Greenhawk KN. 1998. Shellfish benthic habitat assessment in the chesapeake bay: Progress toward integrated technologies for mapping and analysis. Journal of Shellfish Research 17:1433-1437.

Stæhr PA, Groom GB, Krause-Jensen D, Hansen LB, Huber S, Jensen LØ, Rasmussen MB, Upadhyay S, Ørberg SB. 2019a. Use of remote sensing technologies for monitoring chlorophyll a and submerged aquatic vegetation in danish coastal waters. Part of the restek project. Aarhus University, DCE – Danish Centre for Environment and Energy.

Stæhr PA, Göke C, Holbach AM, Krause-Jensen D, Timmermann K, Upadhyay S, Ørberg SB. 2019b. Habitat model of eelgrass in danish coastal waters: Development, validation and management perspectives. Frontiers in Marine Science. 6.

Svane N, Flindt M, Kristensen E, Valdemarsen TB. 2016 Droner – et nyt værdifuldt værktøj til kystnær overvågning (in danish). Vand & Jord. 23:24-28.

Teppati L, L., Chiabrando F, Giulio T, F. 2020. Are measured ground control points still required in uav based large scale mapping? Assessing the positional accuracy of an rtk multi-rotor platform. Int Arch Photogramm Remote Sens Spatial Inf Sci. XLIII-B1-2020:507-514.
Traganos D, Aggarwal B, Poursanidis D, Topouzelis K, Chrysoulakis N, Reinartz P. 2018. Towards global-scale seagrass mapping and monitoring using sentinel-2 on google earth engine: The case study of the aegean and ionian seas. Remote Sensing. 10(8):1227.
Traganos D, Reinartz P. 2018. Interannual change detection of mediterranean seagrasses using rapideye image time series. Frontiers in Plant Science. 9(96).
United Nations OfOSA. 2018. International space law. United Nations.
Ventura D, Bonifazi A, Gravina MF, Belluscio A, Ardizzone G. 2018. Mapping and classification of ecologically sensitive marine habitats using unmanned aerial vehicle (uav) imagery and object-based image analysis (obia). Remote Sensing. 10(9).
Ventura D, Bruno M, Jona Lasinio G, Belluscio A, Ardizzone G. 2016. A low-cost drone based application for identifying and mapping of coastal fish nursery grounds. Estuarine, Coastal and Shelf Science. 171:85-98.
Warren JD, Peterson BJ. 2007. Use of a 600-khz acoustic doppler current profiler to measure estuarine bottom type, relative abundance of submerged aquatic vegetation, and eelgrass canopy height. Estuarine, Coastal and Shelf Science. 72(1-2):53-62.Watts AC, Ambrosia VG, Hinkley EA. 2012. Unmanned aircraft systems in remote sensing and scientific research: Classification and considerations of use. Remote Sensing. 4(6):1671-1692.
Weidmann F, Jäger J, Reus G, Schultz ST, Kruschel C, Wolff V, Fricke-Neuderth K. 2019. A closer look at seagrass meadows: Semantic segmentation for visual coverage estimation. OCEANS 2019 - Marseille.1-6.
Wildish DJ, Fader GBJ, Lawton P, MacDonald AJ. 1998. The acoustic detection and characteristics of sublittoral bivalve reefs in the bay of fundy. Continental Shelf Research. 18:105-113.
Wollast R. 1998. Evaluation and comparison of the global carbon cycle in the coastal zone and in the open ocean. In: Brink KH, Robinson AR, editors. The sea, vol 10, the global coastal ocean: Processes and methods. John Wiley. p. 213–252.
Wright DJ, Heyman WD. 2008. Introduction to the special issue: Marine and coastal gis for geomorphology, habitat mapping, and marine reserves. Marine Geodesy. 31(4):223-230.
Xu S, Xu S, Zhou Y, Yue S, Zhang X, Gu R, Zhang Y, Qiao Y, Liu M. 2021. Long-term changes in the unique and largest seagrass meadows in the bohai sea (china) using satellite (1974–2019) and sonar data: Implication for conservation and restoration. Remote Sensing. 13(5):856.
Yadav S, Yoneda M, Susaki J, Tamura M, Ishikawa K, Yamashiki Y. 2017. A satellite-based assessment of the distribution and biomass of submerged aquatic vegetation in the optically shallow basin of lake biwa. Remote Sensing. 9(9):966.

Young DR, Clinton PJ, Specht DT, DeWitt TH, Lee II H. 2008. Monitoring the expanding distribution of nonindigenous dwarf eelgrass *Zostera japonica* in a pacific northwest USA estuary using high resolution digital aerial orthophotography. Journal of Spatial Science. 53(1):87-97.

Zalewska T, Danowska B. 2017. Marine environment status assessment based on macrophytobenthic plants as bio-indicators of heavy metals pollution. Marine Pollution Bulletin 118(1-2):281-288.

Zoffoli ML, Gernez P, Rosa P, Le Bris A, Brando VE, Barillé A-L, Harin N, Peters S, Poser K, Spaias L et al. 2020. Sentinel-2 remote sensing of *zostera noltei*-dominated intertidal seagrass meadows. Remote Sensing of Environment. 251.

Ørberg SB, Groom GB, Kjeldgaard A, Carstensen J, Rasmussen MB, Clausen P, Krause-Jensen D. 2018. Kortlægning af ålegræsenge med ortofotos - muligheder og begrænsninger (in danish). Aarhus Universitet, DCE – Nationalt Center for Miljø og Energi.

Figure legends

Figure 1. Graphical representation of current methods (Diver, video, unoccupied Aerial vehicles (UAVs), aircraft orthophotos, echo-sounding/acoustic techniques, satellite remote sensing) used to monitor submerged aquatic vegetation in coastal waters. The drawing is an artistic illustration and thus are not to scale.

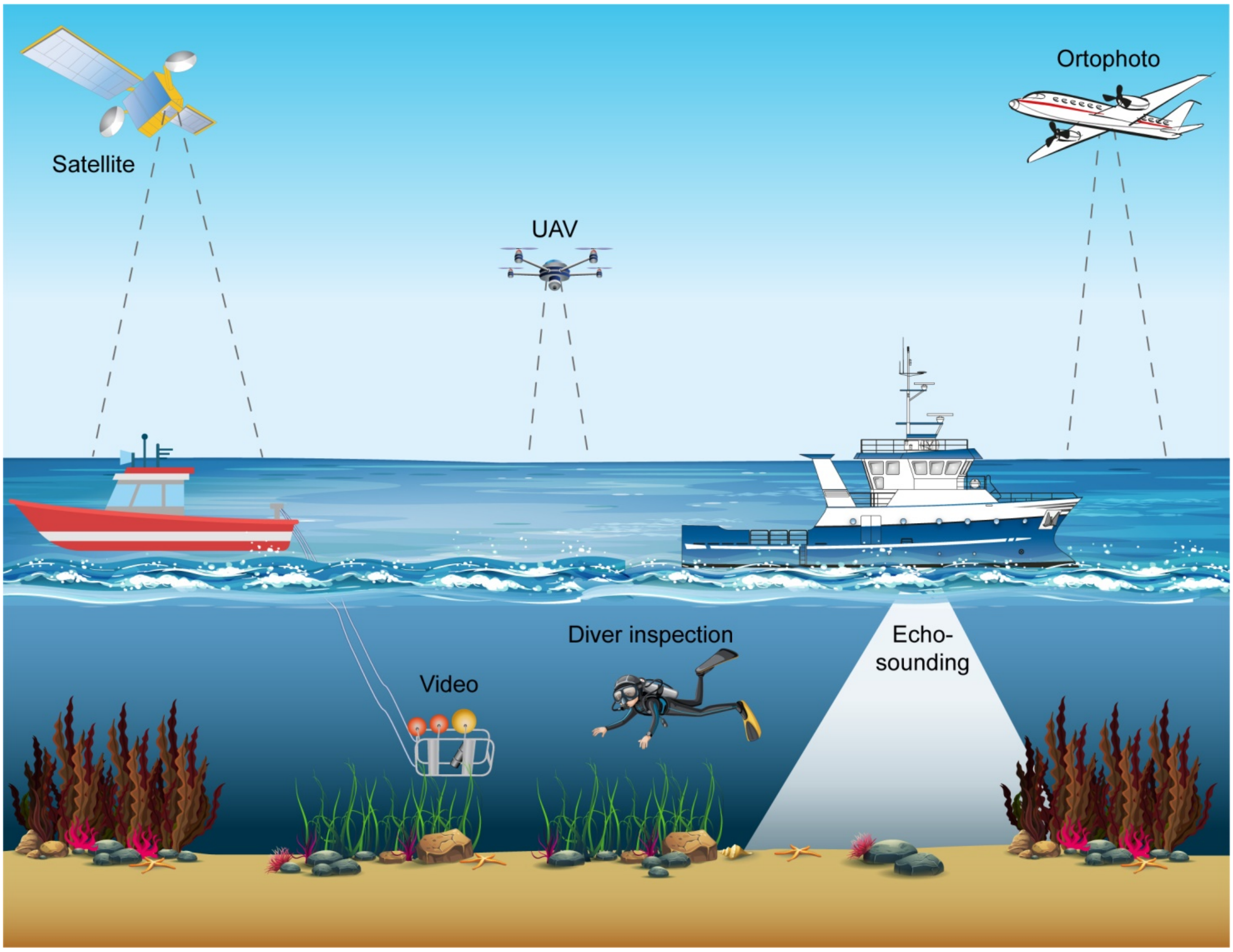

Table 1. Overview of the capabilities of the techniques used to monitor marine submerged aquatic vegetation. Pre-/post-processing, temporal resolution, spatial coverage and resolution, as well as if the method can detect species composition, vegetation coverage and depth limits are described. The sensitivity of the method to weather conditions is also shown.

Method	Pre-/Post-processing	Temporal resolution	Spatial coverage	Spatial resolution	Species composition	Coverage of vegetation	Depth limit	Weather sensitivity
Diver	Visual inspection	On-demand	Transect	High (cm-m)	Yes	Yes	Yes	Yes
Video/Photo	Visual inspection Semi-automatic Automatic	On-demand	Transect	High (cm-m)	Yes	Yes	Yes	Yes
Drone	Image interpretation Semi-automatic – automatic	On-demand	Small	High (cm-cm)	Yes	Yes	Probably – more research needed	Medium
Ortophoto	Image interpretation Visual inspection Semi-automatic	Yearly or less	Large	Medium (m-km)	No	Yes	No-maps down to approx. 5 m	Medium
Echo sounding	Visual inspection Semi-automatic Automatic	Yearly	0.1 to 1000 km^2	10 to 100 cm	No Seagrass/ macroalgae	Yes	Yes	Low
Satellite remote sensing	Image interpretation Pixel-based classification Semi-automatic	New imagery acquired between 1 to 16	Small-Large	0.3 to 30m	No	Yes	Area dependent, sometimes yes, in other	High

Auxiliary datalayers	days/ on demand		areas, no

Table 2. Summary of the main application and scale at which the methods used to monitor marine submerged aquatic vegetation can detect. The references are examples, a more detailed list of relevant references can be found in the supplement material.

Method	Application	Application type (Research/monitoring/other)	Scale (local/regional/national/global)	References
Diver	· Species composition · Vegetation coverage · Vegetation depth limit	Research/Monitoring	Local	(Balsby et al. 2013)
Video	· Species composition · Vegetation coverage · Vegetation depth limit	Research/Monitoring	Local	(Balsby et al. 2013; Marbà et al. 2012)
Drone	· Species composition · Vegetation coverage · Vegetation depth limit	Research/Monitoring	Local	(Duffy et al. 2018a; Duffy et al. 2018b; Nahirnick et al. 2019; Nahirnick et al. 2018; Ridge and Johnston 2020)

Orthophotos	· Vegetation coverage	Research	Local/Regional/ National	(Frederiksen et al. 2004; Kendrick et al. 2000)
Echo sounding	· Species composition · Vegetation coverage	Research/Monitoring	Local and regional	(McCarthy and Sabol 2000; Norton 2019; Pasqualini et al. 2010; Pasqualini et al. 1998; Sabol et al. 1997)
Satellite remote sensing	· Vegetation coverage · Large-scale intra-/interannual variation	Research/monitoring	Regional to global	(Hossain et al. 2015; Malthus 2017; Rowan and Kalacska 2021; Traganos et al. 2018)

Table 3. Overview of some of the main benefits and limitations, as well as estimated financial costs for developed countries and time demand of the summarized methods used to monitor marine submerged aquatic vegetation.

Method	Benefits	Limitations	Financial costs - time demand
Diver	• High temporal resolution and accuracy • Low weather dependance compared with other technics • Detection at species level • Detection of depth limit • Can provide information on additional variables (e.g. epiphyte coverage)	• Low spatial coverage • Low reproducibillity due to e.g. diver to diver dependence of observations	• High financial cost/time demand for monitoring • Low financial cost/time demand for post processing
Video	• High temporal resolution (on demand) • High resolution for small area • Detection at species level • Detection of depth limit • Low weather dependance compared with other technics • Can provide information on additional variables (e.g. epiphyte	• Low spatial coverage • Post processing has high time and costs demands	• High financial cost/time demand for monitoring • Medium financial cost/time demand for post processing

	coverage)		
Drone	• High spatial resolution (mm to cm) • High temporal resolution • Labor, cost and time efficient data collection • Versatile application in relation to sensor (e.g. red, green and blue;, hyperspectral) • High spatial accuracy • Good repeatability through data collection, processing and analysis automation • Can quickly collect data on different spatial scales by adjusting flight altitude	• Spatial coverage • Weather dependent • High data processing effort • UAV pilot license needed • Obtaining flight permit for certain areas • Labor intensive ground validation • No detection at species level • No detection of depth limit	• Medium financial cost/time demand for monitoring • Medium financial cost/time demand for post processing
Orthophotos	• High spatial coverage • Creates permeant record which can be reanalyzed • Good reproducibility	• Only detection at wide group level • Low temporal resolution • Image collection often not with SAV focus and is	• Low financial cost/time demand for monitoring • High financial cost/time demand for post processing

		dependent on other subject fields • Post processing has high time and costs demands • Weather and tide (high tide vs low tide, springs vs neaps) dependent • No detection at species level • No detection of depth limit • Requires good ground validation	
	• Moderate spatial coverage	• Only detection at group level (e.g. Seagrass vs. macroalgae)	• Low financial cost/time demand for monitoring
	• Potential high temporal resolution	• Post processing has high financial cost and is time demanding	• High financial cost/time demand for post processing
Echo sounding	• Moderate weather dependence	• Requires good ground validation	
	• Permeant record which can be reanalyzed	• Some methods require high technical expertise	
	• Not reliant on water depth and turbidity	• No detection at species level	
	• Can detect depth limit		
	• Good reproducibility		
Satellite remote sensing	• Potential for large scale	• High resolution at	• Low financial cost/time demand for monitoring

		smaller scale	
	• Repeated, systematic data acquisition	• High resolution	• High financial cost/time demand for post processing
	• Access to historic remote sensing data	• Weather-dependent	
	• Access to information globally	• Optically deep waters; waters with little contrast between substrate and benthic vegetation; epiphytic growth can obscure plant signal	
	• In some cases free and open data (e.g. Sentinel-3)	• High resolution restricted and with financial costs	
	• Applicable in quantitative analyses	• Spatial resolution of free RS data	
	• Efficient and cost effective data processing	• No detection at species level	
	• Consistent and comparable data	• Limited use when sparse and patchy plant growth	
	• Repeatable and transferable method	• No detection of depth limit	