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A review of seagrass detection, mapping and monitoring applications using acoustic systems

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ABSTRACT

Seagrass meadows are key elements of marine ecosystems as they affect the physical, chemical and biological environment and provide habitats for fish and invertebrates. Human activities have caused a deterioration in seagrass which has led to unstable benthic habitats; therefore, to prevent major decline, seagrass distribution must be mapped and monitored. Acoustic systems allow researchers, scientists and decision makers to collect high-resolution datasets such as bathymetry, backscatter and sub-bottom profiles. These systems are able to characterise the properties of the seafloor including plants, sediments and habitats. In this review, we examine seagrass mapping, monitoring and detection applications using acoustic systems in the literature. Although there are various methodologies for data collection, processing, classification and validation, these are limited to certain seagrass species or study areas. Further worldwide research is required to achieve consistent seagrass detection systems with data acquisition, pre-processing, classification and post-processing.

Introduction

Seagrass ecosystems provide ecologically essential functions which influence the physical, chemical and biological environment in coastal waters by producing and exporting organic carbon, regulating carbon dioxide, nutrient cycling, sediment stabilisation, preventing coastal erosion and reducing exposure to the bacterial pathogens of humans, fish and invertebrates (Lamb et al., 2017; Orth et al., 2006). As seagrasses grow, they rise into the reefs, trap sediment, mediate the movement of the waves, clarify the water and protect the beaches from erosion. Thus, the role of seagrass meadows in coastal marine environments is often compared to that of a forest (Boudouresque et al., 2012). These species are large and live for a long time, but they grow slowly (1–6 cm per year) and take a long time to regenerate once harmed (Pergent et al., 2016).

Seagrass and other benthos in the sea ecosystem are under human pressure (Brown, Smith, Lawton, & Anderson, 2011). Fishing, mining, pollution and other human activities damage the seabed ecosystem and reduce the benthic biodiversity. If no precautions are taken, fish and sea products are estimated to dramatically reduce by the middle of the 21st century (Worm et al., 2006), and all the world's oceans are said to be affected (Halpern et al., 2008). According to the studies, only 5–10% of the world's seafloor is mapped (Wright & Heyman, 2008). Therefore, it is

impossible to manage resources effectively and protect ecologically substantial areas. Marine ecosystems must be mapped to determine marine protected areas (MPAs) and manage resources. Due to the limitations of classic surveying techniques, information about benthic habitat's ecologic function and geographic diversity is scarce (Wright & Heyman, 2008). Geological and biological research into the seafloor was carried out in the early part of the 19th century by collecting samples from the bottom of the sea (Eleftheriou, 2013); however, sampling techniques such as grab and trawl cannot characterise biological patterns and processes (Van Rein, Brown, Quinn, & Breen, 2009). These techniques provide detailed information about small areas. However, it is impossible to present biological characteristics of the seafloor on a large scale (Brown et al., 2011).

Benthic mapping and bathymetry derivation (Dekker Arnold et al., 2011; Lyons, Phinn, & Roelfsema, 2011), seagrass biomass and productivity (Hill, Zimmerman, Bissett, Dierssen, & Kohler, 2014), estuarine and coastal water quality estimation (Brando & Dekker, 2003), other coastal features and processes extraction (Klemas, 2012) studies utilising LiDAR, optical and hyperspectral satellite and airborne remote sensing technologies are widely available in the literature. As relatively easy to implement acoustic technologies have rapidly developed and became widespread, it is now possible to quickly derive accurate and high-quality backscatter and

bathymetry information that cannot be derived from optical sensors and to map the physical aspects of marine and coastal areas (Brown & Blondel, 2009; Wright & Heyman, 2008). It is now possible to obtain geomorphological and habitat information for sea bottom-related studies in extensive areas using broad-acoustic beam systems, such as side scan sonar (SSS), ground discriminating single-beam echo-sounders (e.g. RoxAnn, QTC-View, Submerged Aquatic Vegetation Early Warning System [SAVEWS]), multiple narrow-beam swath bathymetry systems, multibeam echosounder (MBES), recreational-grade fish finder SSS, forward-looking sonar (e.g. DIDSON ARIS, EchoPilot FLS, Simrad ForwardScan) and Multispectral MBES (Godet, Fournier, Toupoint, & Olivier, 2009; Wright & Heyman, 2008). By combining these techniques with conventional or remotely operated underwater vehicles (ROV) *in situ* to characterise the geological and biological seafloor characteristics, it is possible to produce thematic seafloor maps for management applications and defining MPAs. High-resolution seafloor mapping has recently become more prevalent as these tools become more affordable, more widely available and are integrated with

Geographic Information System (GIS) (Brown et al., 2011; Mayer, 2006).

In this paper, we review the literature on seagrass mapping, detection and monitoring applications using mainly acoustic systems. There are also studies that benefit from optical and airborne systems in the same manner reviewed by Hossain, Bujang, Zakaria, and Hashim (2015). Therefore, studies using these systems are not covered in this paper.

Principal acoustic technologies for seagrass mapping applications

Seagrasses belong to four families known as Posidoniaceae (9 species), Zosteraceae (24 species), Hydrocharitaceae (25 species) and Cymodoceaceae (18 species), that is, a total of 76 species. The status and trends for these species according to The International Union for Conversation of Nature (IUCN) Red List of Threatened Species (www.iucnredlist.org) are shown in Table 1. The IUCN provides nine types of status description on its red list of species. In Table 1, the species have been given with their status and trends.

Table 1. Status and trends of seagrasses according to the IUCN red list of threatened species.

Family	Genera	Species	Status	Trend	Family	Genera	Species	Status	Trend
Posidoniaceae	*Posidonia*	*Angustifolia*	LC	STA	Hydrocharitaceae	*Enhalus*	*acoroides*	LC	DCR
		Australis	NT	DCR		*Thalassia*	*hemprichii*	LC	STA
		Coriacea	LC	STA			*testudinum*	LC	STA
		Denhartogii	LC	STA		*Halophila*	*australis*	LC	STA
		Kirkmanii	LC	STA			*baillonis*	VU	DCR
		Oceanica	LC	DCR			*beccarii*	VU	DCR
		Ostenfeldii	LC	N/A			*capricorni*	LC	N/A
		Robertsoniae	N/A	N/A			*decipiens*	LC	STA
		Sinuosa	VU	DCR			*engelmannii*	NT	DCR
Zosteraceae	*Phyllospadix*	*Iwatensis*	VU	DCR			*euphlebia*	DD	N/A
		Japonicus	EN	DCR			*gaudichaudii*	N/A	N/A
		Juzepczukii	N/A	N/A			*hawaiiana*	VU	DCR
		Scouleri	LC	STA			*japonica*	N/A	N/A
		Serrulatus	LC	STA			*johnsonii*	LC	INCR
		Torreyi	LC	STA			*major*	N/A	N/A
	Zostera	*Angustifolia*	N/A	N/A			*mikii*	N/A	N/A
		Asiatica	NT	DCR			*minor*	LC	N/A
		Caespitosa	VU	DCR			*nipponica*	NT	DCR
		Capensis	VU	DCR			*okinawensis*	N/A	N/A
		Capricorni	N/A	N/A			*ovalis*	LC	STA
		Caulescens	NT	DCR			*ovata*	LC	STA
		Chilensis	EN	DCR			*spinulosa*	LC	STA
		Geojeensis	EN	DCR			*stipulacea*	LC	STA
		Japonica	LC	INCR			*sulawesii*	DD	N/A
		Marina	LC	DCR			*tricostata*	LC	N/A
		Mucronata	N/A	N/A	*Cymodoceaceae*	*Amphibolis*	*antarctica*	LC	STA
		Muelleri	LC	STA			*griffithii*	LC	STA
		Nigricaulis	LC	DCR		*Cymodocea*	*angustata*	LC	N/A
		Noltii	LC	DCR			*nodosa*	LC	STA
		Novazelandica	N/A	N/A			*rotundata*	LC	STA
		Pacifica	LC	N/A			*serrulata*	LC	STA
		Polychlamys	LC	STA		*Halodule*	*beaudettei*	DD	N/A
		Tasmanica	LC	STA			*bermudensis*	DD	DCR
Cymodoceaceae	*Syringodium*	*Filiforme*	LC	STA			*ciliata*	DD	N/A
		Isoetifolium	LC	STA			*emarginata*	DD	N/A
	Thalassodendron	*Ciliatum*	LC	N/A			*pinifolia*	LC	DCR
		Leptocaule	N/A	N/A			*uninervis*	LC	STA
		Pachyrhizum	LC	N/A			*wrightii*	LC	INCR

LC: least concern; NT: near threatened; VU: vulnerable; EN: endangered; DD: data deficient; DCR: decreasing; INCR: increasing; STA: stable; N/A: information not available) (www.iucnredlist.org).

As can be seen from Figures 1 and 2, seagrass species are widely distributed along temperate and tropical coastlines around the world (Short, Carruthers, Dennison, & Waycott, 2007). Figure 1 shows the estimated distribution map of seagrass along the North and South American coasts. Figure 2 shows the estimated distribution map of seagrass in Europe, Africa, Asia and Australia. Each
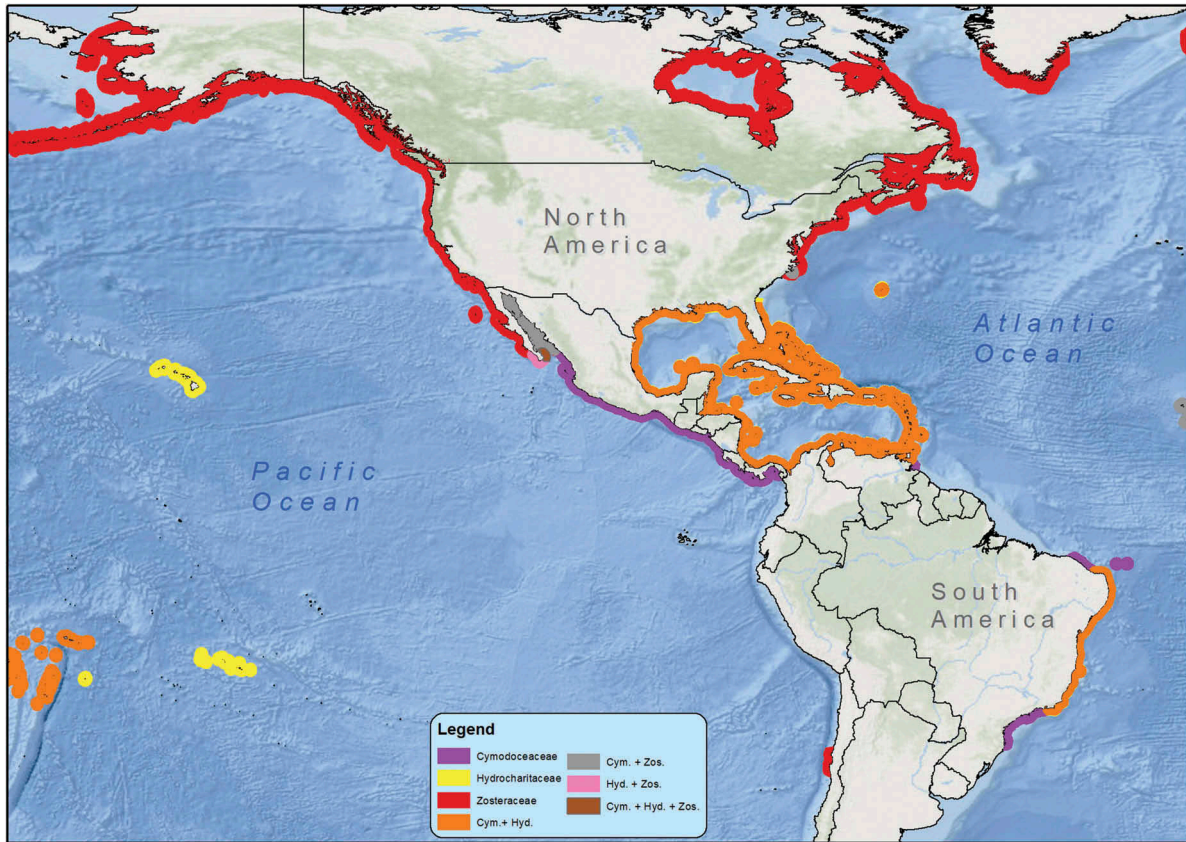

Figure 1. Seagrass species estimated distribution in North and South America. (Data Source: IUCN, Map created by T. Bakirman).
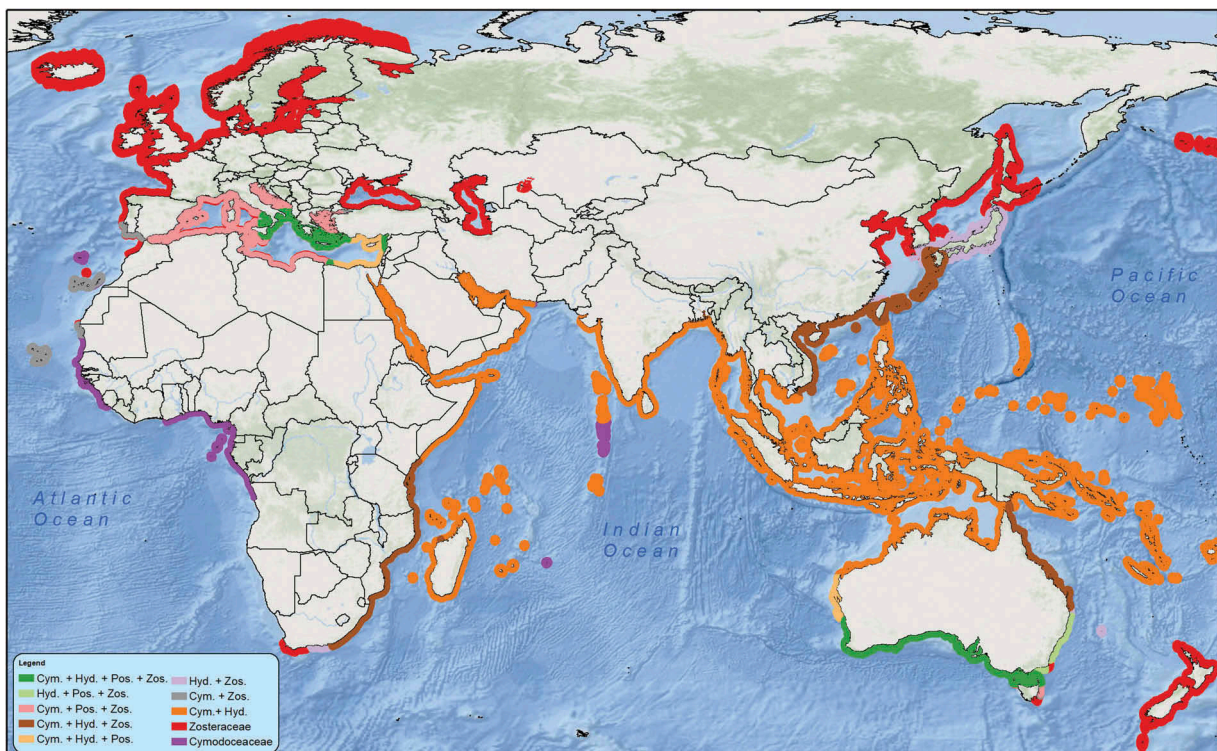

Figure 2. Seagrass species estimated distribution in Europe, Africa, Asia and Australia. (Data Source: IUCN, Map created by T. Bakirman).

geographic distribution data is produced for each species by IUCN based on former scientific studies.

There are many acoustic techniques for seagrass mapping, detection and monitoring applications discussed in the literature. The study by Newton and Stefanon (1975) seems one of the first studies that benefits from acoustic technology for marine biology application. In the study, it is aimed to show the effect of fishery dredging and distribution of *P. oceanica* using SSS. Maceina and Shireman (1980) used a recording fathometer to determine the distribution and biomass of hydrilla (*Hydrilla verticillata*) and American eelgrass (*Vallisneria americana*). Hanley (1982) and Stent and Hanley (1985)'s studies are the first examples of assessing submerged aquatic plant populations in lakes and reservoirs using SBES. However, the observed plant *Elodea canadensis* belongs to inland waters; it has not been classified as a seagrass species. The SAVEWS, which is a compact SBES system, developed by the United States (US) Army Engineer Research and Development Centre. This system was used to map low-density *Halophila, Cymodocea, Syringodium* and *Zostera* in tropical US waters (Lee Long, Roder, McKenzie, & Hundley, 1998). Between 1997 and 1998, seagrass mapping studies have been carried out with Sector Scan Imaging Sonars (SSIS) (Bozzano, Mantovani, Siccardi, & Castellano, 1998; Roberto Bozzano & Siccardi, 1997; Siccardi, Bozzano, & Bono, 1997) and active hydroacoustic methods (Sabol, McCarthy, & Rocha, 1997). The study by Komatsu et al. (2003) conducted in Otsuchi Bay on the Sanriku coast of Japan is the first example of using MBES to map seagrass (*Zostera caulescens*) beds. In 2005, Descamp, Pergent, Ballesta, & Foulquie utilised acoustics telemetry, which is a local underwater positioning system based on an acoustical interferometric scheme, to survey and map *P. oceanica* beds in coastal areas of France. In 2007, Warren and Peterson tried a different approach using an Acoustic Doppler Current Profiler (ADCP) to measure vegetation and canopy height. Lo Iacono et al. (2008) focused on imaging *P. oceanica* meadows by conducting a high-resolution sub-bottom profiler survey along with aerial photogrammetry in the Mediterranean Sea. In 2014, the US Army Engineer Research and Development Centre upgraded SAVEWS with SAVEWS Jr. under the Aquatic Plant Control Research Programme. SAVEWS Jr. uses two frequencies (200 and 800 kHz) to determine the bottom depth and presence/absence of submerged aquatic vegetation (SAV; B. Sabol et al., 2014). In recent years, recreational grade side sonar has become popular for substrate mapping studies in rivers (Buscombe, 2017; Hamill, Buscombe, & Wheaton, 2018). This low-cost technology has also been applied for measuring seagrass cover in shallow environments by Greene, Rahman, Kline, and Rahman (2018).

Even though various methods have been applied in seagrass studies, as the acoustic and sonar technologies have developed it is observed that MBES, SSS and SBES systems are the most common in recent scientific studies. The main technological advances can be summarised as the transition from analogue to digital data acquisition, the ability to record bathymetry along with backscatter with SSS using interferometry and narrower beam angles for MBES systems. Water column data is another innovation to detect objects between the seafloor and sea surface. Recently, multispectral acoustic backscatter, which allows observation of seafloor in multiple frequencies, has been developed. These survey grade systems are easy to implement in any study area. However, they have high marketing prices. Therefore, low-cost systems such as forward-looking sonar (FLS), fish finder sonar and recreational grade SSS have also become widespread.

Discussion

In this paper, we review 91 seagrass related studies which comprise 58 journal articles, 20 conference proceedings, 7 technical notes, 2 books, 3 Ph.D. and 1 MSc. thesis, as listed in Table 2. As it can be seen in Figure 3 which is derived from Table 2, the studies focused on seagrass became highly popular in recent years.

Acoustic instruments

As mentioned in the previous section, various acoustic methods have been used in seagrass related studies. Until 2003, it can be observed that SSS, SBES and other acoustic systems were the most commonly used methods. From 2003, using MBES increased as narrower beam angles for these systems have been exploited which allows production of high-resolution integrated bathymetry and backscatter. A total of 34 studies utilised SSS while SBES has been used in 29 studies and MBES in 24. Sixteen studies examined the capabilities of other systems such as sector scan imaging sonar, acoustic telemetry, or passive acoustics. Note that the total number exceeds 91 since some studies dealt with more than one acoustic system data.

Although standard SSS systems produce visually good backscatter, they cannot collect information about depth. From this view point, four studies examined the possibility of seagrass mapping using a combination of SSS backscatter and SBES depth information (Legrand et al., 2010; McCarthy & Sabol, 2000; Rahnemoonfar & Rahman, 2016; Rahnemoonfar, Yari, Rahman, & Kline, 2017) and five studies dealt with integration of MBES and SSS (Kendrick et al., 2005; Renato et al., 2016; Shono, Komatsu, Sato, Koshinuma, & Tada, 2004; van Rein, Brown, Quinn, Breen, & Schoeman, 2011).

Table 2. Seagrass-related studies listed by their publication year (Recent first – *Full text not available in English, **Full text not available, N/A: Information Not Available).

Study	Acoustic method	Main data	Ancillary data	Seagrass species	Position	Echo Sounder Hardware	Frequency	Ground Truth	Software	Study area size	Study area	Classification method
(Prampolini, Blondel, Foglini, & Madricardo, 2018)	MBES	Backscatter Bathymetry	N/A	P. oceanica	N/A	Kongsberg EM710 SWATHplus-L	70–100 kHz 117 kHz	Grab	CARIS HIPS&SIPS	1400 km²	Malta	TexAn BTM
(Kingon et al., 2018)	SSS	Backscatter Bathymetry	N/A	T. testudinum S. filiforme H. decipiens H. wrightii	N/A	Lowrance HDS-9 Gen 3 StructureScan 3D	455 kHz	N/A	ReefMaster v2	N/A	Trinidad	N/A
(Greene et al., 2018)	SSS	Backscatter	WorldView3 Aerial Imagery	N/A	GPS	Lowrance StructureScan HD	800 kHz	N/A	SonarTRX	8.8 ha	USA	N/A
(Daniel Ierodiaconou et al., 2018)	MBES	Backscatter Bathymetry	N/A	A.antartica Zostera sp.	DGPS	Kongsberg EM2040C	300 kHz	AUV Video	SIS HIPS&SIPS FMGT	N/A	Australia	RF
(M. Rahnemoonfar et al., 2018)	SSS	Backscatter Bathymetry	N/A	N/A	GPS	Lowrance Structure Scan HD LSS-2	200 kHz 800 kHz	Yes	N/A	8.8 ha	USA	Threshold binarization and morp. filtering
(Ferretti et al., 2017)	SBES	Backscatter	N/A	P. oceanica	GPS	ECS400	200 kHz	Video	N/A	N/A	Croatia	DT, SVM Feed Forward NN
(Gérard Pergent et al., 2017)	SSS	Backscatter	UAV	P. oceanica C. nodosa	N/A	Klein 3000	N/A	Video	N/A	20 km	Mediter.	N/A
(M. Rahnemoonfar et al., 2017)	SSS, SBES	Backscatter, Bathymetry	N/A	N/A	GPS	LSS-2 (SSS), Dual Beam (SBES)	455–800 kHz (SSS), 200 kHz (SBES)	Yes	N/A	N/A	USA	Level Set Method
(Castro & Arjona, 2017)*	SSS	Backscatter	N/A	P. oceanica	GPS	Simrad EA400	200 kHz	Video, Scuba	Sonar5-Pro	N/A	Spain	N/A
(Hamana & Komatsu, 2016)	MBES	Bathymetry	N/A	Z. caulescens	DGPS	R2Sonic 2024	380 kHz	Video, Image	QINSy, ArcGIS	N/A	Japan	Threshold based on confidence level
(Renato et al., 2016)	MBES, SSS	Backscatter, Bathymetry	N/A	P. oceanica	DGPS	Reson SeaBat 7125	400 kHz	Video	PDS2000, SonarWiz 6.1, Triton Perspective	N/A	Italy	N/A
(Sonoki et al., 2016)	Split Beam Echo Sounder	Backscatter	Carbon sink and fixation	Z. marina	GPS	Sonic KCE-300	120 kHz	Video	Echoview4.9, ArcGIS	48 ha	Japan	Geostatistical Methods
(Felisberto et al., 2016)	Passive Acoustics	Noise	Dissolved O²	P. oceanica	N/A	N/A	2–7 kHz (Received)	N/A	N/A	N/A	France	N/A
(Maryam Rahnemoonfar & Rahman, 2016)	SSS, SBES	Backscatter	N/A	N/A	GPS	LSS-2, Dual Beam (SBES)	455–800 kHz (SSS), 200 kHz (SBES)	N/A	N/A	N/A	USA	Local standard deviation and morphological operators
(Pribičević et al., 2016)	MBES	Backscatter, Bathymetry	N/A	P. oceanica	RTK GPS	Teledyne Reson SeaBat T20-P	N/A	N/A	CARIS HIPS SIPS 9.0	N/A	Croatia	Normal distribution
(J. Barrell et al., 2015)	SBES	Raw Ping Data	Quickbird	N/A	DGPS	BioSonics DE-X	420 kHz	Video	BioSonics EcoSAV	N/A	Canada	Decision threshold, Binary
(Philippe Blondel, et al.)	MBES	Backscatter, Bathymetry	N/A	P. oceanica, C. nodosa	N/A	Kongsberg EM710	N/A	Grab	HIPS/SIPS, TexAn	13 km²	Malta	TexAn
(Innangi et al., 2015)	MBES	Backscatter, Bathymetry	N/A	P. oceanica	DGPS	Reson SeaBat 8125	455 kHz	Scuba Diving	Isis v. 6.6, DelphMap 2.10, CMST Matlab Toolbox	4 km²	Italy	N/A
(Tecchiato, Collins, Parnum, & Stevens, 2015)	MBES	Backscatter, Bathymetry	N/A	A. griffithii, A. antarctica, S. isoetifolium, Posidonia sp., H. decipiensis, Halophila sp.	N/A	Reson Seabat 8101	240 kHz	Video, Grab	QINSy, QLOUD, CMST Matlab Toolbox	N/A	Australia	Supervised Classification (ArcMap)

(Continued)

Table 2. (Continued).

Study	Acoustic method	Main data	Ancillary data	Seagrass species	Position	Echo Sounder Hardware	Frequency	Ground Truth	Software	Study area size	Study area	Classification method
(Reshitnyk et al., 2014)	SBES	Backscatter	WorldView-2	*Z. marina*	DGPS	QTC View V	200 kHz	Video	QTC IMPACT	N/A	Canada	PCA, unsupervised Bayesian k-means clustering
(Vandermeulen, 2014)	SSS	Backscatter	N/A	*Z. marina*	DGPS	SportScan	330 kHz	Video	SonarWizMAP	N/A	Canada	Visual
(J. P. Barrell, 2014)	SBES	Raw Ping Data	Quickbird, Aerial Photo.	*Z. marina*	DGPS	BioSonics DE-X	430 kHz	Video	BioSonics EcoSAV v1.2	N/A	Canada	EcoSAV
(J. Barrell & Grant, 2013)	SBES	Raw Ping Data	N/A	*Z. marina*	DGPS	BioSonics DE-X	430 kHz	Video	BioSonics EcoSAV v1.2	N/A	Canada	SAVEWS
(Montefalcone et al., 2013)	SSS	Backscatter	N/A	*P. oceanica*	DGPS	N/A	100 kHz, 190–210 kHz	N/A	GIS	N/A	Italy	N/A
(Munday et al., 2013)	SBES	Raw Ping Data	N/A	N/A	DGPS	BioSonics MX	200 kHz	Video	BioSonics Visual Habitat	N/A	USA	PCA&Clustering
(Micaillef et al., 2012)	MBES	Backscatter, Bathymetry	N/A	N/A	DGPS	Kongsberg EM 3002	300 kHz	ROV, Scuba	HIPS/SIPS, PRISM	28 km²	Malta	Supervised Classification
(Sánchez-Carnero et al., 2012)	SSS	Backscatter	N/A	*P. oceanica*	GPS	Simrad EA400P	200 kHz	Scuba	ArcGIS, R	15 km²	Spain	Based on canopy height
(Hamilton & Parnum, 2011)	MBES	Backscatter, Bathymetry	N/A	N/A	N/A	Reson SeaBat 8125	455 kHz	Grab	Matlab	N/A	Australia	Unsupervised statistical clustering
(Di Maida et al., 2011)	MBES	Backscatter, Bathymetry	N/A	*P. oceanica*	DGPS	Reson SeaBat 8125	455 kHz	Scuba	Reson PDS 2000	N/A	Italy	Classification Tree
(Paul et al., 2011)	SBES	Sediment Imaging Sonar	N/A	*Z. marina, Z. noltii, P. oceanica*	DGPS	Marine Electronics 1640/2640	1.1 MHz	Video, Scuba	N/A	N/A	UK, Italy	Seagrass Index
(Descamp et al., 2011)	Telemetry	Acoustic Interferometry	N/A	*P. oceanica*	GPS	Aqua-Metre D100	N/A	Scuba	ArcGIS 9.3	N/A	France	N/A
(H. van Rein et al., 2011)	SSS, MBES	Backscatter, Bathymetry	N/A	*Z. marina*	DGPS (MBES), GPS(SSS)	EdgeTech Model 272-TD (SSS), Kongsberg EM 3002D (MBES)	100 kHz (SSS), 293 kHz (MBES)	Video	GeoAcoustics GeoPro v4, ArcGIS (SSS), Fledermaus (MBES)	4 km²	UK	N/A
(Collins, Suonpää, & Mallinson, 2010)	SSS	Backscatter	N/A	*Z. marina*	GPS	N/A	800 kHz	Scuba	N/A	N/A	UK	N/A
(De Falco et al., 2010)	MBES	Backscatter, Bathymetry	N/A	*P. oceanica*	GPS	Reson Seabat 8111	100 kHz	Video, Grab	CMST Matlab Toolbox	N/A	Italy	Factor Analysis
(Legrand et al., 2010)	SBES, SSS	Backscatter, Bathymetry	Aerial Photography	N/A	GPS	GeoSwath Plus (SSS), RoxAnn (AGDS)	250 kHz (SSS), 50 kHz (SBES)	Video, Aerial Photo	Idrisi	452 km²	France	Maximum Likelihood
(Plus et al., 2010)	SSS, Split Beam Echo Sounder	Backscatter	Aerial Photography, Chlorophyll a	*Z. marina*	DGPS	GeoSWATH (SSS), Simrad ES60	250 kHz (SSS)	Video	ArcGIS 9.2	22.8 km²	France	N/A
(Chamberlain et al., 2009)	SBES	Bathymetry, Canopy Height and Density	N/A	N/A	DGPS	BioSonics DT 6000	420 kHz	Scuba	EcoSAV	N/A	USA	SAWEVS
(Lefebvre et al., 2009)	SBES	Sediment Imaging Sonar	N/A	*Z. marina*	DGPS	Marine Electronics 1640/2640	1.1 MHz	Video, Scuba	N/A	N/A	UK	Seagrass Index
(Malthus & Karpouzli, 2009)	SSS	Backscatter, Bathymetry	IKONOS	N/A	DGPS	Kongsberg GeoAcoustics DF	100 kHz, 500 kHz	Video	N/A	24 km²	Columbia	Discriminant function analysis

(Continued)

Table 2. (Continued).

Study	Acoustic method	Main data	Ancillary data	Seagrass species	Position	Echo Sounder Hardware	Frequency	Ground Truth	Software	Study area size	Study area	Classification method
(Tseng, 2009)	SBES, Tracor Acoustic Profiler System (TAPS)	Backscatter, Bathymetry	Digital Cameras	P. sinuosa, P. australis	GPS	SIMRAD EQ60 (SBES)	38, 200 kHz (SBES), 265, 420, 700, 1100, 1850 and 3000 kHz (TAPS)	Video	EchoView	N/A	Australia	Waveform Analysis
(Lo Iacono et al., 2008)	Sub-Bottom Profiler	Seismo acoustic records	Aerial Photography	P. oceanica	N/A	Innomar SES-2000	6 kHz	N/A	Innomar-ISE 2.9	N/A	Spain	N/A
(Sagawa et al., 2008)	SSS	Backscatter for Ground Truthing	IKONOS	Z.caulescens, Z. asiatica	N/A	Teledyne SIS-1624	N/A	Video, Scuba	TNT-mips 6.9	N/A	Japan	N/A
(Stevens et al., 2008)	SBES	Bathymetry, Backscatter	N/A	N/A	RTK GPS	Biosonics DT-X	199 kHz, 420 kHz	Video	N/A	N/A	USA	SAVEWS
(Collier & Humber, 2007)	SSS	Backscatter	N/A	N/A	DGPS	Imagenex 858	675 kHz	Video, Scuba	ER-Mapper	N/A	Seychelles	N/A
(D. Ierodiaconou et al., 2007)	MBES	Backscatter, Bathymetry	N/A	N/A	DGPS	Reson Seabat 8101	N/A	Video	ENVI 4.2, ArcGIS 9.1 Benthic Terrain Modeller	25.8 km²	Australia	Automated Decision Tree
(Karpouzli & Malthus, 2007)	SSS	Backscatter, Bathymetry	IKONOS	N/A	N/A	GeoAcoustics	100 kHz, 500 kHz	Yes	N/A	24 km²	Colombia	Discriminant function analysis
(Parnum, 2007)	MBES	Backscatter, Bathymetry	N/A	N/A	GPS	Reson SeaBat 8125	455 kHz	N/A	Matlab	N/A	Australia	Self-Developed Algorithm
(Ryan et al., 2007)	MBES	Bathymetry	Wave Energy, Sediment Data	N/A	N/A	Reson SeaBat 8126	456 kHz	Video	N/A	N/A	Australia	N/A
(B. Sabol et al., 2007)	MBES, SBES	Bathymetry, Canopy Height	N/A	Z. marina	DGPS	Biosonics DT4000 (SBES), Reson SeaBat 8124 (MBES)	420 kHz (SBES), 200 KHz (MBES)	N/A	SAVEWS, Hypack (Survey)	3.25 ha	USA	DSP Algorithm (SAVEWS)
(Warren & Peterson, 2007)	ACDP	Vertical Backscatter Profiles	N/A	Z. marina	GPS	RDI Rio Grande Workhorse	600 kHz	Scuba	N/A	N/A	USA	N/A
(Ardizzone, Belluscio, & Maiorano, 2006)	SSS	Backscatter	N/A	P. oceanica	DGPS	EdgeTech 272 TD	100 kHz	Video	ArcGIS 9.0, ArcView 3.2	N/A	Italy	Visual
(Leriche et al., 2006)	SSS	Backscatter	Aerial Photography	P. oceanica	Handheld GPS	EdgeTech DF 1000	N/A	Scuba	N/A	4 km²	France	Visual
(Montefalcone, Albertelli, Nike Bianchi, Mariani, & Morri, 2006)	SSS	Backscatter	N/A	P. oceanica, C. nodosa	Handheld GPS	Klein 590	100 kHz	Scuba	N/A	N/A	Italy	Visual
(Siwabessy, Parnum, Gavrilov, & McCauley, 2006)	MBES, SBES	Backscatter, Bathymetry	N/A	N/A	N/A	Reson Seabat 8125 (MBES), Simrad EQ-60 (SBES)	455 kHz (MBES)	N/A	N/A	N/A	Australia	Decision Trees
(Descamp et al., 2005)	Acoustic Telemetry	N/A	N/A	P. oceanica	Acoustic Positioner	AQUA-METRE D100	N/A	N/A	GIS	650 ha	France	N/A
(Gavrilov, et al.)	MBES, SBES, TAPS	Backscatter, Bathymetry	N/A	N/A	N/A	Reson SeaBat 8125 (MBES), Simrad EQ60 (SBES)	450 kHz (MBES), 38, 200 kHz (SBES), 265 kHz – 3 kHz (TAPS)	Video, Grab, Stereo Photos	Matlab (MBES), RoxAnn (SBES)	N/A	Australia	E1-E2 (SBES)
(Jordan, Lawler, Halley, & Barrett, 2005)	SBES	Backscatter, Bathymetry	N/A	H.australis, Z. tasmanica, P. australis	DGPS	Simrad EK60	120 kHz	Video	Echoview, SeaBed Mapper 2.4, ArcView 3.2	290 km²	Australia	E1-E2

(Continued)

Table 2. (Continued).

Study	Acoustic method	Main data	Ancillary data	Seagrass species	Position	Echo Sounder Hardware	Frequency	Ground Truth	Software	Study area size	Study area	Classification method
(Kendrick et al., 2005)	SSS, MBES	Backscatter, Bathymetry	Landsat	*P. sinuosa, P. australis, P. angustifolia, P. ostenfeldii, Amphibolis sp., Halophila, Syringodium, Thallasodendron sp.*	DGPS	Edgetech (SSS), Reson SeaBat 8125 (MBES)	100 kHz (SSS), 450 kHz (MBES)	Video	ArcView 3.2	878 km²	Australia	Visual
(B. Riegl et al., 2005)	SBES	Backscatter	Depth Sounder(DS)	N/A	GPS Handheld	QTC View GDS, Suzuki ES 2025 (DS)	200 kHz, 50 kHz	N/A	QTC Impact	N/A	USA	QTC Impact
(B. M. Riegl & Purkis, 2005)	SBES	Backscatter	IKONOS	N/A	DGPS	QTC View GDS	200 kHz, 50 kHz	Video	QTC Impact	10 km²	UAE	Cluster Analysis based on Bayesian Approach (QTC Impact)
(B. Sabol, Shafer, & Lord, 2005)	SBES	Canopy Height	N/A	Z. marina	DGPS	Biosonics DT4000	420 kHz	N/A	SAVEWS	20 ha	USA	DSP Algorithm (SAVEWS)
(Siwabessy, Gavrilov, & Parnum, 2005)	MBES	Backscatter, Bathymetry	N/A	N/A	DGPS	Reson SeaBat 8125	450 kHz	Video	CMST Matlab Toolbox	N/A	Australia	N/A
(Parnum, Siwabessy, & Gavrilov, 2004)	MBES	Backscatter, Bathymetry	N/A	N/A	N/A	Reson SeaBat 8125	450 kHz	Grab	N/A	N/A	Australia	Textural analysis, Angular dependence of acoustic backscatter
(Shono et al., 2004)	MBES, SSS	Backscatter	N/A	Z. caulescens, Z. asiatica	N/A	RESON SeaBat9001 (MBES), Klein SYSTEM3000 (SSS)	455 kHz (MBES), 130–445 kHz (SSS)	N/A	N/A	N/A	N/A	N/A
(Komatsu et al., 2003)	MBES	Bathymetry	N/A	Z. caulescens	DGPS	RESON SeaBat 9001	455 kHz	Scuba	HYPACK	1.8 ha	Japan	Difference in depth
(B. Sabol & Johnson, 2002)	SBES	Canopy Height	N/A	Z. marina	DGPS	Odom EchoTrac 3200 MKII, Biosonics DT4000	200 kHz, 420 kHz	N/A	SAVEWS	3 ha	USA	DSP Algorithm (SAVEWS)
(Bruce M. Sabol, Eddie Melton, Chamberlain, Doering, & Haunert, 2002)	SBES	Canopy Height	N/A	T. testudinum, H. wrightii, S. filiforme	DGPS	Biosonics DT4000	420 kHz	N/A	SAVEWS	N/A	USA	DSP Algorithm (SAVEWS)
(Domico, 2001)	SBES	Canopy Height	N/A	Z. marina	DGPS	Biosonics DT4000	420 kHz	Scuba, ROV	BioSonics EcoSAV	N/A	USA	N/A
(Mulhearn, 2001)	SSS	Backscatter	N/A Aerial Photography	P. australis, Z. capricorni, H. australis	DGPS	Klein 5500	455 kHz	ROV	N/A	N/A	Australia	N/A
(Bruce M. Sabol & Johnston, 2001)	SBES	Canopy Height	N/A	N/A	N/A	Odom EchoTrac 3200 MKII, Biosonics DT4000	200 kHz, 420 kHz	N/A	SAVEWS	18 ha	USA	DSP Algorithm (SAVEWS)
(Schneider, Burczynski, Monteoliva, & Valle, 2001)	Split Beam Echo Sounder	Canopy Height	N/A	Z. marina, Z. Noltii	DGPS	BioSonics DT 6000	208kHz	Yes	BioSonics Visual Acquisition, SAVEWS	4 km²	Spain	BioPlant Software

(Continued)

Table 2. (Continued).

| Study	Acoustic method	Main data	Ancillary data	Seagrass species	Position	Echo Sounder Hardware	Frequency	Ground Truth	Software	Study area size	Study area	Classification method
(McCarthy & Sabol, 2000)	SSS, SBES	Backscatter, Canopy Height	N/A	Z. marina	DGPS	EG&G 272 – Klein 2000 (SSS), Biosonics DT 4000 (SBES)	100–500 kHz (SSS), 420 kHz (SBES)	Video, Scuba	N/A	N/A	N/A	N/A
(Pasqualini et al., 2000)	SSS	Backscatter	N/A	P. oceanica	DGPS	N/A	N/A	Scuba	Multiscope software, version 2.4, Matra Cap System	1400 km	France	Statistical Segmentation Algorithm
(Piazzi, Acunto, & Cinelli, 2000)	SSS	Backscatter	Airborne Teledetection Visible Infrared Scanner	P. oceanica	DGPS	N/A	100–500 kHz	Scuba, ROV	N/A	N/A	Italy	N/A
(Guan, Chamberlain, Sabol, & Doering, 1999)	SBES	Canopy Height	N/A	V. americana	N/A	Biosonics DT 4000	420 kHz	N/A	SAVEWS	N/A	USA	N/A
(A. P. Lyons & Abraham, 1999)	Unknown Acoustic System	Backscatter	N/A	P. oceanica	N/A	N/A	80 kHz	N/A	N/A	N/A	Italy	Statistical Characterisation
(R. Bozzano et al., 1998)	Sector Scan Imaging Sonar	Backscatter	Fluorometer Data	P. oceanica	N/A	Raymarine ST2000	N/A	N/A	N/A	N/A	Italy	N/A
(Lee Long et al., 1998)	Conical Beam, Fan Beam	Backscatter	N/A	H. ovalis, H. pinifolia, H. wtinervis, Z. capricorni, C. Serrulara	DGPS	N/A	420 kHz	Scuba	Surfer	N/A	Australia	Intensity
(A. P. Lyons & Pouliquen, 1998)	SSS, SBES	Backscatter	N/A	P. oceanica	N/A	N/A	30, 50, 80, 90, 110 kHz	N/A	N/A	N/A	Italy Turkey	N/A
(Moreno López et al., 1998)	SSS	Backscatter	N/A	P. oceanica, C.nodosa, Z. marina	N/A	N/A	100 and 500 kHz	Yes	N/A	N/A	N/A	Minimum Distance
(Pasqualini et al., 1998)	SSS	Backscatter	Aerial Photography	P. oceanica	N/A	N/A	N/A	Scuba	N/A	1270 km²	France	N/A
(B. Sabol et al., 1997)**	N/A	N/A	N/A	Z. marina	N/A	N/A	N/A	N/A	N/A	N/A	USA	N/A
(Siccardi et al., 1997)	Imaging Sonar	Backscatter	N/A	P. oceanica	N/A	N/A	1.5–2 MHz	N/A	N/A	N/A	Mediterranean	k-mean, k-NN
(P. A. Siljeström, Rey, & Moreno, 1996)	SSS	Backscatter	N/A	P. oceanica, C.nodosa	DGPS	Klein model 595	100 kHz 500 kHz	N/A	N/A	N/A	Spain	Isodata, Minimum Distance, k-means
(P. Siljeström et al., 1995)	SSS	Backscatter	N/A	P. oceanica	N/A	Klein model 595	100 kHz 500 kHz	N/A	N/A	N/A	Spain	Isodata, Maximum likelihood, Minimum Distance
(Miner, 1993)*	N/A	N/A	N/A	Z. marina	N/A	N/A	N/A	N/A	N/A	20 ha	USA	N/A
(Stent & Hanley, 1985)	SBES	Bathymetry	N/A	E. canadensis	N/A	Seafarer	N/A	N/A	N/A	50 ha	UK	Visual
(Maceina, Shireman, Langeland, & Canfield, 1984)	Fathometer	Bathymetry	N/A	H. verticillata	N/A	Raytheon DE-719	200 kHz	Scuba, Vegetation Sampler	N/A	58.25 km²	USA	Visual
(Colantoni, Gallignani, Fresi, & Cinelli, 1982)	SSS	Backscatter	N/A	P. oceanica	N/A	N/A	N/A	Video, Scuba, ROV	N/A	N/A	Italy	N/A
(Maceina & Shireman, 1980)	Fathometer	Bathymetry	Aerial Photography	V. americana, H. verticillata	N/A	Raytheon DE-719	200 kHz	Buoy	N/A	2.2 km²	USA	N/A
(Newton & Stefanon, 1975)	SSS	Backscatter	N/A	P. oceanica	N/A	EG&G	105 kHz	Buoy	N/A	N/A	Italy	N/A
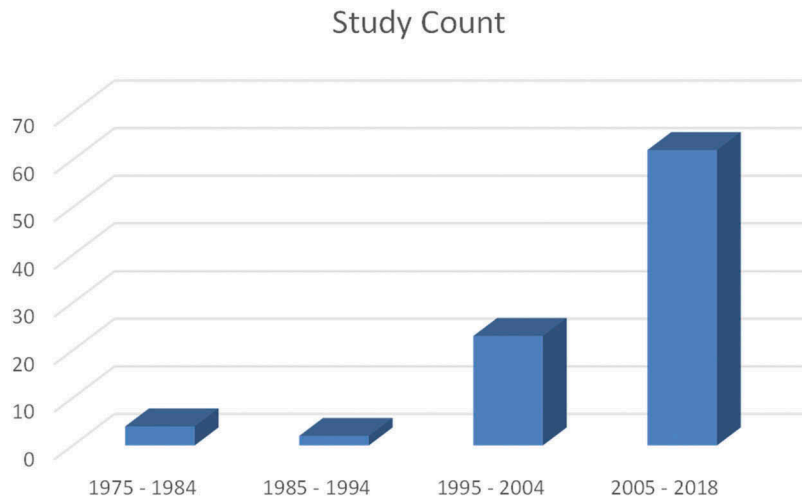
Study Count

Figure 3. Study counts according to years.

Some studies compared the performance of different acoustic methods (B. Sabol, Graves, & Preston, 2007; van Rein et al., 2011), examined manual versus acoustic methods (Chamberlain, Doering, Orlando, & Sabol, 2009) and analysed different MBES backscatter outputs (Innangi et al., 2015). Although acoustic methods provide high-resolution seafloor data, optical satellite images can also be utilised to extract information for wide coverage in shallow areas depending on the water turbidity. Karpouzli and Malthus (2007) focused on integrating SSS with IKONOS while other scientists compared the performance of SBES with IKONOS (B. M. Riegl & Purkis, 2005), WordView-2 (Reshitnyk, Costa, Robinson, & Dearden, 2014) and Quickbird (J. Barrell, Grant, Hanson, & Mahoney, 2015). Aerial photogrammetry is also one of the valid information sources which can be integrated with acoustic data (Legrand et al., 2010; Lo Iacono et al., 2008; Maceina & Shireman, 1980; Mulhearn, 2001; Pasqualini, Pergent-Martini, Clabaut, & Pergent, 1998).

SBES is the most affordable system among survey grade echo sounder solutions. However, gaps can be occurred between survey lines due to working principle geometry of the system. Therefore, it is not feasible to cover huge survey areas. But, these systems are still useful for shallow areas around a couple of meters with dense seagrass. On the other hand, SSS systems provide high-resolution backscatter with wide swath coverage. However, these systems do not acquire co-registered bathymetry. Even though some SSS systems can provide co-acquired bathymetry using interferometry, the measurement principle has limitations (Lurton, 2002). Therefore, SSS bathymetry products are not as accurate as MBES bathymetry. Since SSS systems are used as towfish, position information which is essential for seagrass related studies is computed roughly compared to SBES and MBES systems. Recent technology allows MBES systems to collect highly accurate bathymetry and backscatter by integrating with auxiliary sensors such as gyro and motion sensor. Based on swath angle of the transducer and water depth, they offer wide coverage along survey lines which is generally around 3–4 times of the current water depth. For the same reason, MBES systems are not always the best choice in depths of a couple of meters. One can also prefer to use an SBES system in this scenario due to the high retail prices of MBES systems in the market. Recently recreational grade SSS systems have become widespread due to the same reason. They cost approximately 10% of survey grade SSS. They are extensively utilised by scientists for substrate mapping (Daniel Buscombe, 2017; Buscombe, Grams Paul, & Smith Sean, 2016; Hamill et al., 2018; Hamill, Wheaton, Buscombe, Grams, & Melis, 2017) and benthic habitat mapping (Daniel Buscombe, 2017; Cheek Brandon, Grabowski Timothy, Bean Preston, Groeschel Jillian, & Magnelia Stephan, 2016; Kaeser & Litts, 2010; Kaeser Adam, Litts Thomas, & Tracy, 2013) in river environments. However, this technology has not been widely exploited for seagrass mapping or detection studies except by Greene et al. (2018) and Kingon, Thijs, Robinson, Maharaj, & Garcia (2018). Greene et al. (2018) have constructed a SSS to measure seagrass cover within the Lower Laguna Madre in Texas, USA. Kingon et al. (2018) developed a seagrass mapping system on a budget consisting of a kayak, Lowrance HDS, ReefMaster and Google Earth software. Based on the results of these studies, recreational grade SSS systems are efficient hardware which provides satisfactory data for seagrass-related studies.

FLS systems are generally used recreational activities for safe navigation. They are also utilised for object detection (Galceran, Djapic, Carreras, & Williams, 2012; Hurtós, Palomeras, Carrera, & Carreras, 2017), object segmentation (Banerjee, Ray, Shome, & Sanyal, 2014) and target recognition (Ferreira, Djapic, Micheli, & Caccia, 2014) studies.

However, we have encountered no seagrass-related studies benefits from FLS. On the other hand, a survey grade forward-looking multibeam sonar has been developed within the European MAST III program (COSMOS Project) (Cervenka, 1998). The developed forward-looking multibeam sonar has been applied for seafloor segmentation using angular backscatter responses (Haniotis, Cervenka, Negreira, & Marchal, 2015).

There are also other acoustic methods used by scientist for seagrass applications such as acoustic telemetry (Descamp, Pergent, Ballesta, & Foulquie, 2005), ADCP (Warren & Peterson, 2007), sub-bottom profiler (Lo Iacono et al., 2008), sediment imaging sonar (Lefebvre, Thompson, Collins, & Amos, 2009) and passive acoustics (Felisberto, Rodríguez, Santos, Zabel, & Jesus, 2016).

Frequency

Backscatter data depends on the frequency of the echo transmitted into seafloor by the transducer. The frequency of the transducer directly affects the received dB levels in the backscatter dataset. While some systems offer multiple frequency options for the survey, certain systems only work for a constant frequency.

MBES frequency used in the seagrass applications varies from 100 to 455 kHz. The most used MBES systems are the Teledyne RESON SeaBat series, followed by Kongsberg and R2Sonic. For SBES systems, the frequencies are between 38 and 430 kHz. The most frequently used SBES systems are BioSonics, SIMRAD, QTC and Odom. Some systems also offer split beam options such as the BioSonics DT-X series. SSS systems have a wider frequency range for seagrass mapping applications starting from 100 up to 800 kHz. The most commonly used SSS systems can be summarised as EdgeTech, Klein, EG&G, Imagine and SIMRAD. We have analysed two seagrass-related studies using recreational-grade sonar systems. They both use Lowrance StructureScan HD transducers but with different frequencies as 455 and 800 kHz.

Within the scope of European MAST III program, a forward-looking MBES called COSMOS which transmits signals at 100 kHz has been developed. Haniotis et al. (2015)'s study results show the developed system can also be utilised for seagrass-related applications.

Existing multi-frequency MBES R2Sonic 2026 collects data with 100, 200 and 400 kHz simultaneously. According to Costa (2018), 100 kHz is the most discriminative frequency, and multispectral backscatter may be an effective tool for applications focused soft bottoms. Gaida, Tengku Ali, Snellen, and Simons (2018)'s study shows that the combination of 200 and 400 kHz yields the highest number of acoustic classes while the combination of 100 and 400 kHz provides the highest discrimination performance. There is currently no study in literature focusing on seagrass mapping using multispectral backscatter.

Although there are studies investigating the relationship between used frequency and seagrass in laboratory environment such as Wilson and Dunton (2009), there is no study that applies laboratory results to a real application or investigating this relationship in the field.

Data

Bathymetry and backscatter are the most common acoustic datasets used in seagrass applications. According to a survey conducted by Lucieer et al. (2017), almost 30% of scientists are interested in seagrass applications featuring backscatter data. Most of the seagrass applications take advantage of backscatter data (57 studies) while some use it solely (33 studies). It is also integrated with bathymetry (31 studies), canopy height (2 studies) and fish finder (1 study). Even though applications can be found in the literature based only on bathymetry data (7 studies), backscatter data is mostly used with bathymetry (Lurton & Lamarche, 2015).

One can observe that backscatter is an essential data set for seagrass applications. Recent technology allows MBES systems to acquire better resolution backscatter images by mimicking SSS geometry such as R2Sonic TruePix data which makes it an ideal tool for seagrass applications. In most of the studies, researchers do not give too many details about backscatter pre-processing, and its effects are not investigated deeply. This is a key factor since processes such as time varied gain (TVG) or beam pattern corrections have a huge effect on obtained decibel (dB) levels. There are also some corrections applied by sonar systems. Parnum (2007) investigates beam pattern, saturation and pulse duration MBES system effects on backscatter data. In more recent studies, Lamarche and Lurton (2018) and Schimel et al. (2018) exhaustively analyses MBES backscatter data processing and its effects on data.

Most multibeam systems are monochromatic which operates around a single frequency (Hughes Clarke, 2015). Researchers have investigated various methods to obtain multispectral backscatter for a better seafloor characterization (Brown, Beaudoin, Brissette, & Gazzola, 2017). Hughes Clarke (2015) achieved this aim by mounting a pair of MBES system in the same vessel for data acquisition. Brown et al. (2010) used multiple survey platforms simultaneously during data acquisition for their study. More recently, multispectral acoustic backscatter which allows collecting data using different frequencies simultaneously has been developed. Multispectral data gives more information and

a better insight into the seafloor as each frequency provides distinct outputs and a false colour composite image of backscatter can be created (Brown et al., 2017). R2Sonic launched a multispectral challenge at GeoHab 2017 conference providing a sample data collected via R2Sonic 2026. The researchers have been asked to present their work which focuses on using multispectral backscatter in bottom characterization at GeoHab 2018 conference. In this context, the use of multispectral backscatter was investigated for benthic habitat mapping (Costa, 2018), seabed sediment classification (Gaida et al., 2018), seafloor characterization (Daniel Buscombe, Grams, & Kaplinski, 2018). These studies show that using multiple frequencies provides improved discrimination of the seafloor that can be also applied to seagrass-related studies. Multiple frequencies also allow creating false colour RGB composite images. This may lead to the formation of a vegetation index using band combinations such as Normalized Difference Vegetation Index (NDVI) used in terrestrial studies.

Water column is another output data for echo sounders which collects continuous information from the sea surface to seafloor. A detailed review about water column MBES data applications can be found in Colbo, Ross, Brown, and Weber (2014). They investigated water column MBES data applications in two topics: biological applications, geophysical and oceanographic applications. Biological applications are summarised as fisheries, marine mammals, zooplankton, kelp ecosystems, aquaculture while geophysical and oceanographic applications are mentioned as gas venting, near-surface bubbles, suspended sediment, physical oceanography and wrecks/archaeological oceanography. Although there does not seem any seagrass-related study using water column data, McGonigle, Grabowski, Brown, Weber, and Quinn (2011)'s method can be applied to seagrass mapping studies. The study investigates to identify kelp canopies by benefitting from water column returns of MBES system. One reason for the absence of seagrass studies with water column data can be described as the requirement of huge disk spaces which makes it challenging to collect, process and analyse the data (Gee, Doucet, Parker, Weber, & Beaudoin,

2012). There is currently a working group that aims to develop processing workflows and methodologies for water column data (Lamarche, Le Gonidec, Greinert, Lucieer, & Lurton, 2017).

Positioning

The positioning is a vital component for seagrass mapping as it is for any regular mapping application. However, the position data in seafloor mapping is not as precise as land or navigation applications. Based on the reviewed literature, anything below 1 m to decimeter precision is sufficient for seagrass applications. While most of the studies took advantage of differential GPS (DGPS), two studies used real-time kinematic (RTK) GPS (Pribičević, Ðapo, Kordić, & Pijanović, 2016; Stevens, Lacy, Finlayson, & Gelfenbaum, 2008).

Even though DGPS can provide enough horizontal accuracy, one can also take advantage of GPS tide to improve the vertical accuracy of products using RTK GPS systems. If the study area has dynamic tide changes during the day and nearest tide station is a few kilometres away, resulting data would not be sufficient without GPS tide information.

Seagrass species

There are 76 known species of seagrasses, so species information is as crucial as the final research products in resource management and determining the MPAs.

In 48 studies, the researchers worked on a single species while 19 focused on multiple species. In 23 articles, the authors did not specify significant seagrass species. The most focused seagrass species are *P. oceanica* and *Z. marina* with 33 and 20 studies, respectively (Table 3).

P. oceanica studies are numerous as expected due to it being an essential endemic plant for Mediterranean marine ecosystem. This plant is already near threatened in the Western Mediterranean basin and more information on species distribution, and threats impact in the Eastern and Southern Mediterranean basin is

Table 3. Study count for seagrass species.

Species	Count	Species	Count	Species	Count
P. oceanica	33	*P. sinuosa*	2	*E. canadensis*	1
Z. marina	20	*S. filiforme*	2	*H. ovalis*	1
C. nodosa	5	*T. testudinum*	2	*H. pinifolia*	1
H. australis	4	*V. americana*	2	*H. wtinervis*	1
P. australis	4	*Z. asiatica*	2	*P. angustifolia*	1
Z. caulescens	4	*Z. capricorni*	2	*P. ostenfeldii*	1
A. antarctica	2	*Z. noltii*	2	*S. isoetifolium*	1
H. decipiensis	2	*A. griffithii*	1	*Syringodrum*	1
H. verticillata	2	*Amphibolis* sp.	1	*Thallasodendron* sp.	1
H. wrightii	2	*C. serrulara*	1	*Z. tasmanica*	1

needed. Therefore, *P. oceanica* has been taken under protection by EU legislation, the Bern and Barcelona Conventions and national legislation (EC Council Regulation N° 1967/2006) (Regulation, 2006). There are also national legal frameworks for the protection of *P. oceanica* in Albania, Croatia, France, Italy, Montenegro, Slovenia, Spain and Turkey.

Z. marina is also an essential species of seagrass that is in decline. Even though there have been restoration works in Europe and North America, there is no known national or international legal framework for protecting of this species.

Although seagrass species are distributed around the world, not every species has been considered and investigated deeply. The study distribution map can be seen in Figure 4. Three studies did not specify the study area, and two stated the name of the sea only.

Most of the studies focused on a single area. Some authors tried their approach in multiple areas in the same country. Only two studies focused on multiple areas in different countries (Lyons & Pouliquen, 1998; Paul, Lefebvre, Manca, & Amos, 2011).

In-situ data

Ground truth data is vital for classification of input data, validation of the final product or assessing the conditions of the study area.

While 63 studies met this requirement, 27 studies did not integrate or provide any *in situ* data in their research. Of 63 studies, 46 used the single ground truth collection method, and multiple methods were applied in the rest of the researches. The most preferred ground truth collection methods are underwater video and scuba diving which was used in 38 and 22 studies, respectively (Table 4).

Table 4. Ground truth collection method usage count.

Method	Count
Video	38
Scuba	22
Grab	7
Method not stated	4
Aerial image	2
Buoy	2
Image	2
Vegetation sampler	1

It can be observed that former studies do not include ground truth information because it was not feasible to collect information via scuba diving and grab samples for relatively large study areas. Remotely Operated Vehicle (ROV) (Ferretti et al., 2017) and Autonomous Underwater Vehicle (AUV) (Ierodiaconou et al., 2018) technology have eased this process considerably. *In situ* sampling techniques have been extensively analysed by researchers for seabed habitat mapping (Coggan et al., 2007) and monitoring (Van Rein et al., 2009).

Data classification methods

Classification is a widely used tool for extracting information from images and implemented in seagrass related studies. It is a rapidly developing tool being employed in different marine applications for a long time. In this section, we discuss which classification methods exist, how they have evolved through the years and the future of automated classification techniques focusing mainly on seagrass mapping, detection and monitoring applications but also seafloor characterization studies.

King (1967) used echograms to classify five sedimentary bottom types. The echogram classification is
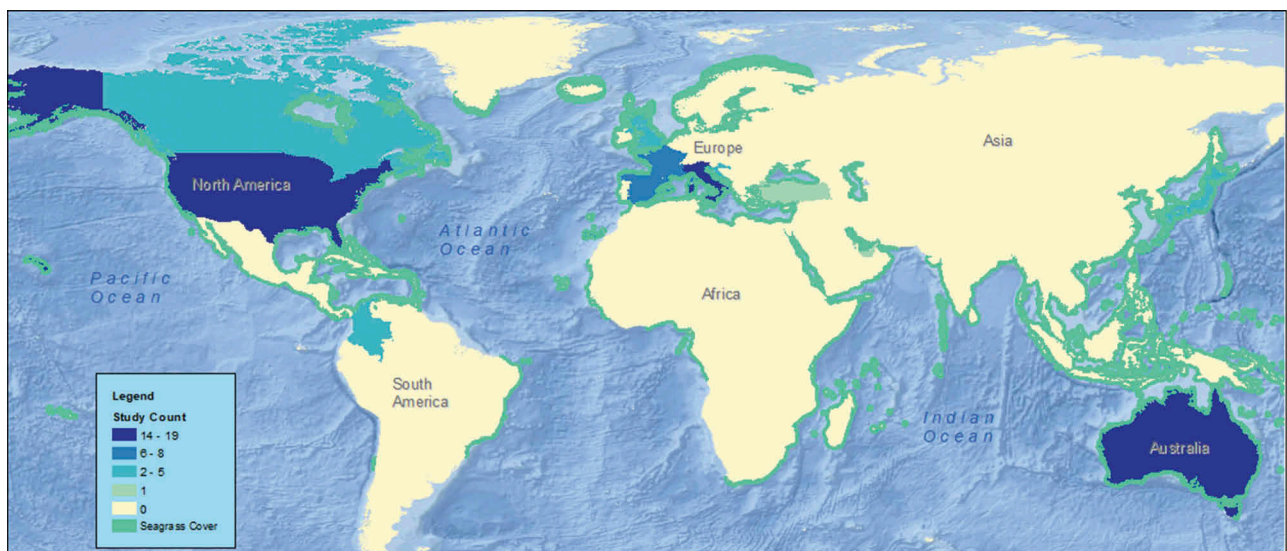

Figure 4. Seagrass study distribution around the world (Map created by T. Bakirman).

based on shape and compaction of the bottom sediment. In 1979, Pace and Dyer used Gray-Level Co-occurrence Matrices (GLCMs) for seafloor characterization and textural analysis of side scan imagery introduced by Haralick, Shanmugam, and Dinstein (1973). They suggest quickly computable 14 grey-tone spatial dependent features calculated based on average spatial relationships between pixels. More grey level features have been proposed by scientists in the following years. For example, Pace and Dyer (1979) exploited 11 features in their study, 8 of which are defined by Haralick (1974) and 3 of which are defined by themselves. They have applied a decision rule model based on Euclidean distance for classification of SSS image. Chivers (1990) and Orlowski (1984) have proposed a method benefits from a measurement of the relationship between energy features using multiple echoes from the bottom to determine sedimentation type which generally known as E1 (roughness) – E2 (hardness) method. Reut, Pace, and Heaton (1985) developed a spectral analysis method that widens system bandwidth and can classify signals scattered from six seabed types. They state that the shape of the probability distribution of the scattered field intensity is related to seafloor roughness and not sensitive to hardness. Pace and Gao (1988) proposes new spectral based features derived from the power spectrum of the backscattered signals using Fourier analysis to discriminate six seabed types. Reed and Hussong (1989) also employed GLCMs for classification of SeaMARC II SSS imagery. They applied principal component analysis (PCA) on 14 features proposed by Haralick (1974). Angular second moment, contrast, entropy and angular inverse difference moment have been determined as most contributing features among all. They also propose a new feature based on the sum of the differences of orthogonal GLCMs which is a measure of the isotopy of the image. They utilised a modified version of unsupervised k-means and supervised minimum distance classification algorithms on SeaMARC II SSS images. In Lurton and Pouliquen (1992)'s approach, signal envelopes have been integrated, normalized, averaged and compared with the theoretical curves for seven sea bottom types. Schiagintweit (1993) presents field results of RoxAnn system which uses E1-E2 method to map five distinct sediments. Hughes Clarke (1994) developed a technique to produce backscatter strength as a function of grazing angle using GLORIA SSS and SeaBeam MBES. They utilise an empirical approach for classification where angular response curves are matched with *in situ* data and matched pairs are then used to deduce the process for other regions without *in situ* data. Stewart, Min, and Marra (1994) have applied a neural-network approach on feature space derived from backscatter. The algorithm focuses on feature selection, training-pattern design and network configuration.

The first automated classification of seagrass study was carried out in 1995 by scanning original SSS images into a digital environment (P. Siljeström, Moreno, & Rey, 1995). The authors applied isodata, maximum likelihood and minimum distance classification algorithms to scanned sonar images to produce a distribution map for *P. oceanica* for their study area. This study can be taken as a pioneer automatic classification approach for seagrass related studies. Before this study, most of the seagrass mapping-related studies were realized by manually or visually measurements from sonar images.

As echo sounders with digital output capability have become widespread and with the development of narrow beam MBES, sonar image classification applications have increased. Hughes Clarke, Mayer, and Wells (1996) have created angular response curves for sediments using EM1000 MBES at 95 kHz. They stated these curves alone are not discriminative enough; however, they would be useful with the combination of textural features such as GLCMs (Reed & Hussong, 1989) and power spectral methods (Pace & Gao, 1988). Dugelay, Graffigne, and Augustin (1996) proposed a semi-automatic mosaic interpretation for low-frequency deep water MBES based on segmentation using a Markov Random Field. The algorithm considers statistical and geometrical properties of the pixels with corrections for the variations of angular backscattered signals as explained by de Moustier and Alexandrou (1991). Siccardi et al. (1997)'s study focused on analysing seabed vegetation in terms of presence-absence and sparse-dense via high frequency 2 MHz sector scan sonar. They extracted features from bathymetry (e.g. mean value, standard deviation, mean deviation, skewness, kurtosis, target range, signal range) and backscatter (e.g. energy, entropy, contrast, homogeneity GLCMs). They applied PCA on feature space and determined 6 features account for 91% of all features. K-means algorithm was exploited for classification of remaining feature space. In studies of Blondel (1999) and Blondel, Parson, and Robigou (1998), only entropy and homogeneity GLCMs are used in a software package called TexAn, which was developed for seafloor characterization. For classification of sediment types, they applied the measurement space guided algorithm, which is stated to have the advantage of not to be biased by the statistical predominance of some regions. In Pasqualini, Clabaut, Pergent, Benyoussef, and Pergent-Martini (2000)'s study, filtering, thresholding and statistical clustering have been applied to segment *P. oceanica* seagrass bed textures. This clustering method is based on statistical properties of pixels and pixel neighbourhood correlation information. In 2001, an Acoustic

Ground Discrimination Systems (AGDS) called SAVEWS was developed by the US Army Engineer Research and Development Centre that works based on bottom tracking (Bruce M. Sabol & Johnston, 2001). The system analyses the data via the U.S. Army Corps of Engineers developed signal processing algorithm. The first step of the algorithm is to detect and track the bottom, and then, the spatial distribution of echo intensity above the determined threshold level is examined above the detected bottom for vegetation (B. M. Sabol & Burczynski, 1998; Sabol, Kasal, & Melton, 1998). The drawback of this method is that system cannot properly track bottom in dense seagrass areas due to the high reflectivity of seagrass depending on its species and density (B. Sabol et al., 1997). The algorithm overcomes this problem by creating a depth histogram with each GPS ping. The system calculates the sharpest rise and the most commonly occurring depth is queried in the histogram with each GPS ping. The latest updated version of this system is called SAVEWS Jr. (B. Sabol et al., 2014). In the same year, Preston, Christney, Bloomer, and Beaudet (2001) demonstrated sediment classification results of QTC Multiview software. The software produces over 130 features such as GLCMs, Fast Fourier Transforms (FFTs), fractal dimension, high order moments, histogram and quantile. Since it would not be sufficient to cluster over 130 features, PCA has been applied to reduce feature space. Finally, k-means method is employed on reduced feature space for classification of the sea bottom. Atallah et al. (2002) used wavelet analysis based on grain size on bathymetric SSS data for seafloor sediment classification. Tęgowski, Gorska, and Klusek (2003) developed an algorithm that uses maxima location in echo envelope series to determine the bottom via 208 kHz BioSonics DT 4200. They have studied a series of echo envelope parameters, such as spectral width and fractal dimension. They have compared vegetated and bare bottom in terms of these parameters. In Komatsu et al. (2003)'s study, seagrass has been distinguished from the bottom using the difference in depth between maximum depth and the sandy bottom. They have used this approach to map the distribution of seagrass and estimate seagrass volume and biomass. In a more recent study, they have used a similar technique to map three categories of relative abundance as dense, sparse and little to no seagrass (Hamana & Komatsu, 2016). Cutter, Rzhanov, and Mayer (2003) have implemented a modified version of local Fourier histograms texture feature classification method to MBES data for automatic seafloor segmentation. A local Fourier transform is calculated for each cell which provides information to characterize the frequencies in the signal. Finally, the classification is utilised by using fuzzy k-means cluster analysis. Dartnell and Gardner

(2004) proposed a two-step empirical technique that exploits both bathymetry and backscatter data to predict seafloor sediments on a pixel by pixel basis. The first step is to apply supervised classification on backscatter based on grain size and ground truths. The results are then used in the latter step as rules for a hierarchical decision tree classification. Collier and Brown (2005) have investigated the correlation of SSS backscatter with grain size distribution using dual frequency (100 and 410 kHz) SSS and 22 sediment grab samples. They processed the raw sonar data and extracted statistical information for comparison with sediment grain size based on appliying empirically derived amplitude grazing angle correction to the acoustic data.

One of the main progress in backscatter processing is the development of the GeoCoder package by Luciano Fonseca from The Centre for Coastal and Ocean Mapping at the University of New Hampshire. GeoCoder is a mosaicking tool that can read backscatter data in multiple formats and apply radiometric and geometric corrections to the data including corrections for beam pattern effects. The package also includes remote estimation of surficial seafloor properties by appliying of an unsupervised Angular Range Analysis (ARA) method which preserves the backscatter angular information to use it for seafloor characterization. The process applies corrections for seafloor slope, beam pattern, TVG, angle varying gain (AVG) and insonification area. Then, four parameters from near range (90°–65°), four parameters from far range (65°–35°), one parameter from outer range (35°–5°) and orthogonal distance parameter from intercept-slope graph are calculated. Finally, the average angular response is compared to density fluid models derived from the Biot theory (Williams, 2001). Although this theory only takes sedimentations into consideration, it cannot be used in seagrass mapping. The GeoCoder package is licensed for most commercial hydrographic software such as Caris, Reson, Fugro, Triton, Hypack, IVS 3D and Chesapeake Technology (Fonseca, Brown, Calder, Mayer, & Rzhanov, 2009; Fonseca & Calder, 2005; Fonseca & Mayer, 2007).

Gavrilov et al. (2005) have measured angular response curves of backscatter at 450 kHz for high and dense seagrass and sand covered seafloor. It is stated that high and dense seagrass depends weakly on the incidence angle. Even though sand backscattering level is relatively low, it decreases considerably with the incidence angle. In his PhD thesis, Parnum (2007) developed a feature space called angle cube which is derived from backscatter. It is created by approximate reconstruction of the angular dependence at each point of the grid using spatial interpolation. Following feature reduction, unsupervised and supervised classification methods have been

applied on remaining feature space combined with bathymetric features (slope, standard deviation, etc.). He applied his technique to multiple study areas with vegetation such as seagrass and rhodolith. Ierodiaconou, Laurenson, Burq, and Reston (2007) used high and low pass filters to backscatter data to obtain three band false colour image. This image was processed along with bathymetry derivatives to create an automated decision tree classification system for benthic habitat mapping. Hamilton (2007) statistically clustered curves using Clustering Large Applications algorithm developed by Kaufman and Rousseeuw (1990). This method was employed in a later study by Hamilton and Parnum (2011) for unsupervised clustering of backscatter curves from across the port and starboard side of the swath for seabed segmentation including seagrass and rhodolith. Lucieer (2007) and Lucieer (2008) proposed an object-oriented hierarchical classification via e-Cognition software to identify reef and sand areas. Erdey-Heydorn (2008) developed an ArcGIS Seabed Characterization Toolbox to investigate benthic habitats. The toolbox includes a supervised texture classification workflow based on SSS mosaic, bathymetry, hillshade and rugosity. Maximum likelihood classifier is applied to these datasets. And finally, classification results are combined with Bathymetry Position Index (BPI) grids to create final habitat maps. Rattray, Ierodiaconou, Laurenson, Burq, and Reston (2009) have used QUEST (Quick Unbiased Efficient Statistical Tree) decision tree classifier (Loh & Shih, 1997) on combined bathymetry and backscatter derivative data to map five benthic biological groups including algae and invertebrates. Fakiris and Papatheodorou (2009) have developed a MATLAB toolbox for acoustic classification of SSS imagery called SonarClass. The toolbox creates five GLCMs, four first-order grey statistics and two 2D Fourier spectrum statistics. Following the employment of a novel feature reduction process on feature space, nearest neighbour classification method is applied to the data. Simons and Snellen (2009) presented a supervised Bayesian seafloor classification method that uses MBES averaged backscatter data per beam at a single angle. As a first step, the algorithm starts with non-linear curve fitting which is fitting a model to the histogram of selected measured backscatter strengths. After determining the probability distribution function for each seafloor type, Bayes decision rule classification is applied to the data. In later years, Alevizos, Snellen, Simons, Siemes, and Greinert (2015) improved this method by utilising a combination of beams simultaneously to obtain the optimal number of classes for unsupervised classification. Preston (2009) have created 132 GLCMs, first- and second-order statistics from backscatter and applied PCA for feature reduction. For clustering

80 km^2 multibeam survey data of Stanton Banks, Mahalanobis distance method was used. Lucieer and Lucieer (2009) applied fuzzy clustering algorithm (FCM) which is an extension of unsupervised k-means or isodata method and fuzzy maximum likelihood estimation clustering for seafloor classification. FCM provides similar results to k-means and isodata and also contains information class membership and classification uncertainty. Marsh and Brown (2009) have employed an artificial neural network (ANN) model called self-organizing map (SOM) (Kohonen, 1990) to classify MBES backscatter and bathymetry. SOM can effectively create a low-dimensional representation of high-dimensional input signals. The architecture has been applied based on normalized backscatter strength and bathymetric beam-level data. In the mentioned study, SOM was evaluated by comparing with other classification methods such as isodata, learning vector quantisation and competitive neural network. It has been observed that SOM is an efficient method for classifying MBES data with high accuracy. De Falco et al. (2010) investigated relationship between multibeam backscatter, sediment grain size, and *P. oceanica* seagrass distribution. The most important finding related to seagrass mapping in this study is that the acoustic response of seagrass is mainly linked to the leaf canopy rather than the substrate it is growing on. Ierodiaconou, Monk, Rattray, Laurenson, and Versace (2011) compared three automated classification techniques for predicting benthic biological communities using the same training and evaluation datasets. The three classification methods were QUEST, CRUISE (Classification Rule with Unbiased Interaction Selection and Estimation) (Kim & Loh, 2001) and maximum likelihood. According to the results, the QUEST method provided better results than other methods. While CRUISE method still provides an overall accuracy close to QUEST, maximum likelihood method produced poor results with the maximum overall accuracy of 39%. Lucieer and Lamarche (2011) utilised unsupervised FCM to sediment samples to identify most appropriate class count and their spatial cores. FCM results are used as training samples for classification of MBES imagery using object-based image analysis (OBIA). The MBES backscatter and bathymetry have been segmented into smaller objects using Definiens Developer v8.0 software. After the creation of object features (GLCM entropy and correlation), nearest neighbour supervised classification was applied and four sediment classes were obtained. Micallef et al. (2012) proposed a multi-method GIS-based geomorphometric and textural analytical technique to map habitat distribution using high-resolution MBES data. The method starts by classifying the seabed into morphological zones and features based on morphometric derivatives

(e.g. slope gradient, profile curvature), BPI and geomorphometric mapping. Then the area is divided into two zones as unvegetated and seagrass covered areas based on roughness estimation. Unvegetated areas were classified into sedimentation using maximum likelihood classifier on entropy, homogeneity and backscatter intensity. Seagrass covered areas were classified into seagrass on sand and gravel and seagrass on sand using maximum likelihood classier on bathymetry data. Finally, morphology and composition results were combined to produce a habitat distribution map of the study area. Sánchez-Carnero, Rodríguez-Pérez, Couñago, Aceña, and Freire (2012) used vertically oriented SSS to detect and map *P. oceanica* meadows. They used acoustic data saved as RAW files integrated with GPS data in NMEA format. After bottom detection, the first meter above the bottom is considered to have possible plants of interest. In that range, intensities higher than the determined threshold is estimated as vegetation. Using Scuba diving data as ground truth, the detection method's accuracy is calculated as 72%. Hasan, Ierodiaconou, and Monk (2012) combined angular response classification and backscatter image segmentation for benthic biological habitat mapping. Angular response curves have been classified using QUEST decision tree along with ground truth data. Backscatter image was converted into a pseudo colour image. The image was segmented using mean-shift technique via Edge Detection and Image Segmentation (EDISON) tool based on five-dimensional feature space (R, G, B, X, Y). The segmented polygons centroids were calculated, and nearest neighbour algorithm was exploited to assign predicted class information from angular curves to polygons. This method was utilised to map distributions of invertebrates, red and brown algae. Rzhanov, Fonseca, and Mayer (2012) benefit from angular response data to label over segmented backscatter image mosaic. This labelling process is conducted by constructing a catalogue. They propose three methods for automatic catalogue construction. The first approach is using quasi-random sampling of the physical parameter space such as acoustic impedance, roughness, etc. The second approach benefits from backscatter strength versus grazing angle histogram. The third approach is based on coarse segmentation of backscatter mosaic into segment expected in the catalogue. Brown, Sameoto, and Smith (2012) derived six features from MBES data. Bathymetry, slope, curvatures and three principal components of QTC textural features are used for CLUSTER procedure in Idrisi software. This procedure uses a histogram peak technique of cluster analysis based on a maximum of seven layers. Hasan, Ierodiaconou, and Laurenson (2012) compared performances of maximum likelihood classifier, QUEST, random forest and support

vector machine (SVM) in classifying MBES backscatter data. For biota classification, SVM and random forest have provided the highest overall accuracy with 84.8% and 83.8%, respectively. The same methods resulted in high overall accuracies for substratum with 82.6% and 83%. Lucieer, Hill, Barrett, and Nichol (2013) investigated methods to derive accurate spatial products for shallow coastal water through MBES data classification methods and segmentation scales along with autonomous underwater vehicle images. They employed 12 bathymetry and 6 backscatter derivatives. MBES data was segmented in two different scales (30 and 60) to investigate the influence of segment size on classification accuracy. The segmented images were classified using classification trees, random forests and k-nearest neighbour for substratum, rugosity and sponge cover individually. Random forest with 30 segmentation scale provided the highest overall accuracy for classification of substratum and rugosity, while k-nearest neighbour with both segmentation scale performed best for sponge classification with same overall accuracy value. Huang, Siwabessy, Nichol, Anderson, and Brooke (2013) tested seven feature analysis approaches for classification of MBES backscatter angular response curves to map seabed cover types. The multibeam swath was split into port and starboard sides, and the angular response curves with 1° bin were generated between 4° and 51° incidence angles using 97 seabed samples. They propose 7 feature analysis methods that produce 4 to 48 variables for classification. Supervised classification process with seven sediment classes was executed using the Probability Neural Network (Specht, 1990) in DTREG software. Diesing et al. (2014) evaluated OBIA and machine learning (random forest) techniques for classifying MBES data to map seabed sediments. OBIA and random forest classification processes were executed on backscatter and bathymetry derivatives. A pixel-by-pixel comparison of classification results was carried out with the Map Comparison Kit software (Visser & de Nijs, 2006). Random forest method outperformed OBIA with an overall accuracy of 76%, while overall accuracy for OBIA was 67%. Stephens and Diesing (2014) evaluated six supervised classification techniques for MBES and grain size data. These techniques are classification trees (CT), SVM, k-NN, neural networks (NN), random forest (RF) and naive bayes (NB). After creating secondary acoustic features from backscatter and bathymetry, classifiers were trained using different input features. First training data consists of solely bathymetry and backscatter. Second training data consists of features from results of feature reduction process. Final training data covers all of the input features. NB technique with second training data (NB2) outperformed other methods with other

training datasets. In a later study, they took their work to another step. Instead of comparing different classification techniques, they combined best performing classification results according to balanced error rate (Diesing & Stephens, 2015). They created a three model combination (NB2, RF2, CT1) and five model combination (NB2, RF2, CT1, NN1, SVM1). The five model ensemble outperformed three of the five component models (RF2, NN1, SVM1). Additionally, the authors propose a novel measure of confidence based on agreement and accuracy. Calvert, Strong, Service, McGonigle, and Quinn (2015) evaluated maximum likelihood supervised classification and iso cluster unsupervised classification on three MBES datasets, namely backscatter, backscatter with bathymetry and derivatives, bathymetry and derivatives. Buscombe et al. (2016) proposed a new algorithm that uses spectral analysis on echograms for automated riverbed sediment classification using low-cost SSS. The routine estimates average lengthscales of acoustic fluctuation in signals from echograms which are statistical representations that integrate with attributes of bed texture. These are calculated by using a Morlet Wavelet Transform and removal of bias caused by varying sonar geometry. In another study, this method was integrated into open source and freely available a software package called PyHum which also offers data processing and correction tools (Buscombe, 2017). Rahnemoonfar and Rahman (2016) proposed an automatic method to detect seagrass potholes using SSS images. They applied mathematical morphology technique and calculated standard deviation to enhance the image and identify the pothole patterns. Same authors developed another process to detect seagrass potholes in sonar images (Rahnemoonfar et al., 2017). This process starts with image enhancement consisting of adaptive thresholding and wavelet noise removal. Finally, level set method is applied to detect boundaries of potholes. In Rahnemoonfar, Rahman, Kline, and Greene (2018), they applied slightly different image enhancement and seagrass pattern identification steps. Sonar image is enhanced by applying adaptive histogram equalization, top hat filter, and Gaussian adaptive thresholding. Then, seagrass patterns are identified by executing binarization by optimum threshold and filling up holes and extracting potholes by using closing morphological filtering. Montereale Gavazzi et al. (2016) compared textural analysis (TexAn), Jenks Optimization, maximum likelihood, OBIA (e-Cognition) and manual classification methods for seabed mapping using MBES and ground truth data. They identified SAV, bare muddy bottom and sponges. According to their results, pixel based method provides higher accuracies and accuracy measure depend highly on the number of classes. Herkül, Peterson, and Paekivi (2017) used the

mathematical models of RF and generalized additive models on MBES data to map seabed substrate. Statistics are calculated from bathymetry, backscatter, slope, and GLCM textural features. These statistics are independent variables in models created in R statistical software package to map distributions of the hard and soft substrate, Mytilus and hydrozoa. It is stated that most dominant variables in models are mean depth and mean backscatter statistics. Ferretti et al. (2017) used different classification techniques to map *P. oceanica* distribution via ROV equipped with SBES and video recorder. NN, decision trees and SVM were applied on acoustic data, and all methods provided high accuracies in *P. oceanica* detection. Buscombe, Grams, and Kaplinski (2017) proposed a method which focuses on strengthening the relationship between backscatter and sediment composition using MBES to map a canyon river consisting of sand, gravel, cobbles, boulders and SAV. The method starts with the removal of beam scale and spectral filtering of suprabeam scale topographic effects in backscatter. The results show that the high pass component associated with bed forms topography or vegetation and the low past component associated with sediment patches. Finally, coherent scales between backscatter and topography are analysed using cospectra. Hamill et al. (2018) used linear least squares and GMM (2 models) for automated segmentation of bed textures using recreational-grade SSS. In this study, SSS imagery is used to derive first order statics and GLCM textures. GMM results seem more promising for applications in areas consisting of similar sedimentary environments. Turner, Babcock, Hovey, and Kendrick (2018) investigated efficiency of single classifiers against model ensembles for seabed substratum maps. The model ensemble is constituted from RF, CT and NB where each classifier votes for each point. Then, substratum is classified based on the majority of voting. If no class can provide the majority, the point is classified based on the vote of the best performing classifier (in this case RF). It is stated that even though model ensembles provide better accuracy, it is not always required unless single classifier performance is poorer than expected. Ierodiaconou et al. (2018) analysed combination of pixel-based (PB) and OBIA of MBES data for habitat mapping including seagrass and macro algae in shallow waters. PB and OBIA derivatives were created and used as predictors in RF modelling. Although OBIA results have overall accuracy higher than PB approach, a combined model approach outperformed OBIA and PB methods alone. Lacharité, Brown, and Gazzola (2018) aimed to create a single habitat map from four non-overlapping surveys via 4 MBES with different frequencies. They proposed a classification technique for bathymetry and uncalibrated

backscatter which consist of segmentation with OBIA and classification using supervised nearest neighbour algorithm. Since backscatter depends directly on the frequency, this classification workflow was applied to each survey separately, and then combined to create a seamless benthic habitat map. Buscombe et al. (2018) compared GMM and CRF probabilistic models for seafloor classification using multispectral backscatter against monospectral backscatter. According to study results, both approaches performed better with multispectral backscatter compared to each monospectral backscatter frequency alone (100, 200, 400 kHz). Additionally, comparing two methods based on multispectral backscatter, CRF provided a higher average classification accuracy. Gaida et al. (2018) proposed an extension of the Bayesian method for seafloor sediment classification using multispectral backscatter data. Results indicate that use of multispectral backscatter leads to improved discrimination between different sediment types. Costa (2018) employed regression trees to classify seven benthic habitats. The results of this study show that multispectral backscatter is more suitable for soft bottom applications.

Review of developed classification techniques for seabed mapping shows that pre-processing of acoustic data has a strong effect on classification accuracy and results. This is relatively straightforward for bathymetry processing since guidelines for data processing and minimum standards have been determined by The International Hydrographic Organization (Iho, 2008). However, since backscatter is under the influence of frequency, navigation, sonar geometry, seafloor characteristics, etc., it is more complex to specify workflows for all scenarios. Therefore, in most studies, processing of the backscatter data is site or application specific. There are also corrections during data acquisition applied by the sonar itself which are not always clear enough to researchers. Considering mentioned factors, Backscatter Working Group (BSWG) within GeoHab have published guidelines and recommendations for backscatter processing (Lurton & Lamarche, 2015). We will not further discuss the processing of backscatter data here, as this topic extensively analysed recently by researchers in terms of MBES backscatter (Lamarche & Lurton, 2018; Schimel et al., 2018), recreational grade SSS backscatter (Buscombe, 2017) and comparison of MBES and SSS (Le Bas & Huvenne, 2009).

Automated classification of seagrass distribution can be performed using signal-based and image-based classification methods. Signal-based methods deals with echograms (SBES), sonograms (SSS) and angular response curves (MBES). Single beam AGDSs such as SAVEWS, RoxAnn and QTC View exploit unsupervised signal-based methods. These methods are based on bottom tracking (Sabol & Johnston, 2001), roughness-hardness (Gavrilov et al., 2005) and

Bayesian cluster analysis (B. Riegl, Moyer, Morris, Virnstein, & Dodge, 2005), respectively. There are also studies dealing with supervised classification of raw SBES data using clustering (Munday, Moore, & Burczynski, 2013) and machine learning techniques (Ferretti et al., 2017). According to reviewed studies, it can be said that, due to point based data acquisition geometry of SBES, researchers have shifted to swath systems which provide more coverage.

Employment of signal-based methods on SSS data is not investigated widely for seagrass mapping applications (Karpouzli & Malthus, 2007; Sánchez-Carnero et al., 2012). Angular response curves are found to be useful to discriminate different seafloor types (Hughes Clarke, 1994). Since SSS cannot provide integrated bathymetry with backscatter, it cannot be used for angular response analysis due to lack of geometrical information (Brown et al., 2011).

With the capability of high-resolution simultaneous bathymetry and backscatter data acquisition, MBES is efficient hardware for this analysis. Gavrilov et al. (2005) created angular response curves based on incidence angle for seagrass using MBES at 450 kHz. Studies indicate that angular response curves are efficient features to map seagrass distributions (De Falco et al., 2010; Hamilton & Parnum, 2011; Parnum, 2007) and both unsupervised and supervised classification methods can discriminate seagrass patches successfully (Parnum, 2007).

Image-based methods which generally employed to swath systems deal with raster data of bathymetry, backscatter and derivatives. SSS is an adequate system for geological and geophysical mapping (Brown & Collier, 2008). Despite image-based methods on SSS are utilised in seagrass mapping studies (Legrand et al., 2010; Moreno López, Rey Salgado, & Siljeström, 1998; Pasqualini et al., 2000; Siljeström et al., 1995), SSS is not used in machine learning methods due to lack of bathymetry data.

Processed MBES data consist of regular gridded bathymetry and angle independent mosaicked backscatter imagery. Workflows of image-based methods generally start with feature extraction since it is not feasible to perform classification only with these two datasets. There are several derivatives of bathymetry and backscatter used in image-based seabed classification studies (Diesing, Mitchell, & Stephens, 2016). The most common bathymetry derivatives can be summarized as slope, aspect (northness and eastness), standard deviation, BPI, rugosity, and curvature. Bathymetry derivatives can be used solely for morphological segmentation. However, this is not the case generally for seagrass mapping as this process requires textural features with the exception of methods based on depth range (Hamana & Komatsu, 2016; Komatsu et al., 2003; Sabol et al., 2007) and roughness estimation (Micallef et al., 2012). The most

common backscatter derivatives can be summarized as GLCM, ARA, Hue-Saturation-Intensity (HSI), FFT and Moran's I. We observed there is no common accepted agreement on selection of appropriate features which are the best for seagrass mapping. For example, Ierodiaconou et al. (2018) preferred to use HSI to create false colour backscatter image, while Blondel, Prampolini, and Foglini (2015) used GLCM Homogeneity and Energy. Feature extraction process is generally followed by feature selection as it is not practical to use all calculated derivatives in classification due to computational time and accuracy. The objective of feature selection is to determine the most contributing data sets and eliminate inferiors. This is achieved by feature reduction (or dimensionality reduction) of feature space algorithms such as PCA.

Image-based classification methods for seagrass mapping using MBES data can be grouped as (i) unsupervised or supervised, and (ii) pixel-based or object-based classification. Whilst the application of sediment mapping via MBES is widely carried out using OBIA (Lacharité et al., 2018), machine learning (Turner et al., 2018), supervised and unsupervised classification (Calvert et al., 2015), combined approach (Diesing & Stephens, 2015) and statistical learning (Herkül et al., 2017), applications of these methods for seagrass mapping is limited. Ierodiaconou et al. (2007) applied automated decision trees on backscatter and bathymetry derivatives. Di Maida et al. (2011) exploited statistical decision trees to discriminate seagrass meadows. Blondel et al. (2015) used unsupervised k-means clustering on GLCM homogeneity and energy. Ierodiaconou et al. (2018) combined PB and OBIA using RF for improved classification accuracy. While unsupervised methods do not require input data except class number for classification, *in situ* data is still needed for labelling or validation. Recently, Calvert et al. (2015) evaluated supervised and unsupervised classification methods for benthic habitat mapping. However, main interest seems shifted to machine learning methods and model ensembles of multiple methods. This is also the case in seagrass mapping applications, yet the evaluation of supervised and unsupervised machine learning methods such as SVM and SOM for seagrass mapping remains unexplored to date.

Multispectral backscatter can be a milestone that will shift benthic habitat mapping studies to a higher level. The ability to collect data with multiple frequencies simultaneously better discriminates seabed characteristics (Daniel Buscombe et al., 2018; Costa, 2018; Gaida et al., 2018). There is no study to date dealing with this recent technology for seagrass mapping application. Since multiple backscatters allow to create false colour images which include different information in each band, this may ease the process to adapt terrestrial remote sensing methods to image-based seabed classification. Besides this, using false colour images, various indices like NDVI can be created for better discrimination of seagrass and other SAV.

Another approach can be the use of each backscatter individually to extract derivatives from backscatter at different frequencies. This method can be evaluated to indicate which frequency contributes the most for seagrass detection, as Costa (2018) demonstrated for sediments.

Conclusions

Anthropogenic effects such as fishing, trawling, coastal infrastructures threaten marine ecosystems and reduce benthic biodiversity. Seagrasses are an indispensable heritage of marine ecosystem and considerably fragile to these activities since they habitat generally in shallow coastal zones (Duarte, 1991). Therefore, it is critical to map the distribution of seagrass to make policies and determine MPAs. From this perspective, if seagrasses are protected, then the biodiversity-related with seagrass will also be protected (Harris & Baker, 2012). There are several methods for benthic habitat and seagrass mapping. In this paper, we examine 91 studies related to seagrass mapping, monitoring, and detection using acoustic systems under the 12 headings in Table 2, from which, these conclusions are stated:

- Various methods of seagrass mapping were used by researchers in the literature. Recently, most studies have focused on either MBES, SSS or SBES and using MBES increased after 2003 due to hardware developments (narrow beam angles) that allows it to acquire high-resolution backscatter integrated with bathymetry. The development of multispectral MBES opened a new perspective and provided a more discriminative dataset for researchers. The pioneer studies encourage us that this recent technology can be implemented to seagrass studies to obtain promising and reliable results. Recreational grade SSS systems have also become quite popular in recent years as an alternative to survey grade system which is employed to habitat mapping studies due to their cost effectivity even though they do not provide high-resolution products as survey grade systems. Consequently, the choice of the acoustic device can vary depending on the size of study area, study area depth, budget concerns and mapping strategy (automatic or manual).
- It is a widely known fact that backscatter and bathymetry is the most common dataset for seagrass mapping. Multispectral backscatter would also be a perfect addition to these core

datasets in the future. Since this data set consists of multiple bands, it can be used by applying different image processing techniques, the accuracy of seagrass classification can be increased. Beside this, it is a fact that the creation of different band combinations from false colour images can obviously improve visual interpretation capability for manual studies. One can also expect to come across seagrass studies dealing with MBES water column data. This can be explained by the need for high computing power and hard disk space for collecting, storing and processing of water column data.

- There is no common agreement on which frequency is the best for discriminating seagrass. According to the studies, seagrass backscatter depends highly on leaf canopy rather than the substrate it is grown on.

- Most studies obtained position information using DGPS provides one decimetre to a metre accuracy is an acceptable level for most underwater studies. According to the progress of the current studies, in the future, RTK GPS systems can take an important place. Especially in small study areas, in terms of the reliability and usability of data products, proper resource management and determination of MPAs must be implemented using high accuracy GPS solutions such as RTK GPS. Researchers can also take advantage of GPS tide information to improve vertical accuracy using high accuracy GPS solution especially in study areas with dynamic tide changes.

- Researchers frequently focused on two seagrass species in their studies; P. oceanica and Z. marina. If we examine the seagrass study distribution map in Figure 4, the study areas are concentrated in the USA, Australia and Italy. P. oceanica is an endemic plant that forms the Mediterranean ecosystem, prevents coastal erosion and regulates carbon dioxide absorption on land and in the sea. This species has a long life span while its growth rate and regeneration is slow. Even though it is protected by EU legislation, the Bern and Barcelona Conventions and national legislation (Regulation, 2006), it is in decline. Even it is already in a "Near Threatened" state in the Western Mediterranean basin, it is believed this species will be in a vulnerable state unless threats are reduced. Therefore, to protect the future of P. oceanica in the Mediterranean region, more information on species distribution, and the impact of the threats in the Eastern and Southern Mediterranean basin is needed. Z. marina which extends into the Arctic in Alaska, Canada, Greenland and northern Europe and into the tropics in Baja California and Mexico is found in the north Atlantic and the North Pacific and in the Mediterranean and Black Seas. Even though there have been protection and rehabilitation efforts since the 1940s in Europe and North America, it is still declining in these areas. Additionally, the current global population trend of Z. marina is decreasing.

- In terms of the reliability, validation and accuracy of the study products, ground truth data are essential. Therefore, as it has been integrated into most of the studies, ground truth is a must-have dataset for future work, especially for automatic classification. It is now more feasible and practical to collect ground truth data using technological ROV and AUV devices.

- Different freeware (SonarScope, PyHum) and commercial software (HIPS&SIPS, FMGT, Hypack, SonarWiz) are used in the seagrass-related studies for surveying, post-processing and classification. The processing of backscatter data is a key factor as different software for the same dataset can produce different dB levels. BSWG have published guidelines and recommendations for backscatter data acquisition and processing. As this report suggests, hardware-related uncertainties in backscatter measurements must be reduced by constructors.

- Although only 31 studies out of 91 reported study area size, this information is important to understand the applicability of the proposed method for wider coverage areas. Largest and smallest study areas are reported as 1400 km^2 and 1.8 ha, respectively.

- Various benthic habitat and seagrass classification methods have been reviewed. This can be performed by signal-based methods using echograms, sonograms, angular response curves and image-based methods using backscatter and bathymetry raster data. Signal-based methods are widely integrated into AGDS based on bottom tracking and MBES based on angular response curves. Image-based methods are mostly exploited in swath systems. MBES is more preferred than SSS in image-based classification applications since MBES allows to create more derivatives for feature extraction. It can be clearly said that the seagrass classification related studies have been evolved from semi-automatic approaches to machine learning and model ensemble methods. Additionally, use of recent technology, multispectral backscatter can ease the process to adapt terrestrial remote sensing methods to image-based seabed classification which would slightly close the gap between terrestrial and marine remote sensing.

Seagrass mapping, detecting and monitoring studies have increased in recent years. Developments in

machine learning technologies such as deep learning can bring more efficient results and open a new perspective. The use of open acoustic data can allow creating success deep learning architectures and seagrass classification problem can be solved easily. In this context, we conducted a MBES (R2Sonic 2024) survey in a 5 km^2 study area in Gulluk Bay, Turkey, to investigate performances of different segmentation algorithms such as Mean-Shift, Iterative Simple Linear Clustering, Whale Optimization, SVM, ANN, Fuzzy Segmentation and the effects of backscatter corrections for seagrass (*P. oceanica*) mapping. This work aims to be a step towards a better understanding of MBES backscatter processing and classification. At the end of this study, we plan to share obtained results as labelled data for future deep learning studies.

Sustainable monitoring of marine ecosystem requires policies for controlling and supervising of human activities which need to be realized urgently to protect the marine ecosystem to save the future of benthic habitat.

Disclosure statement

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