Remote Sensing of Environment 240 (2020) 111619

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Remote sensing of shallow waters – A 50 year retrospective and future directions

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ABSTRACT

Technical advancements have widened the limits of remote sensing in mapping shallow water benthic habitats and bathymetry over the last decades. On the other hand, the needs of shallow water remote sensing have pushed instrument development. In this manuscript we provide 50-year retrospective of the developments in the field in terms of both instrumentation and methods. We also show that spectral features characteristic of the main benthic groups in shallow water are consistent from the tropics to sub-arctic regions and from salty to freshwaters. The fundamental limiting factor in both benthic mapping and bathymetry is absorption of light by water molecules. However, spectral absorption by water molecules is the key to bathymetry derivation. Variable backscattering by particles and absorption by dissolved organic matter is a confounding factor for all objectives. The combination of using the spectral and textural characteristics of bottom features and our knowledge about these features have now resulted in the ability to map habitats over large coastal systems. This manuscript has shown that optically shallow water remote sensing has reached levels where the satellite derived bathymetry and habitat maps are accepted by different end users (including the International Maritime Organisation) and are routinely used in ecological studies, monitoring and management of coastal environments.

1. Introduction

The first published study on optically shallow waters appeared in the very first issue of the Remote Sensing of Environment (RSE) in 1969 (Hickman and Hogg, 1969) although it was a LIDAR study, not passive remote sensing that is the main focus of this review. For our purposes here we can define optically shallow waters as those where an effect of the bottom substrate is detectable in the water leaving radiance or reflectance signal. In most cases this means $<$ 20 m deep waters whereas in turbid coastal and inland waters it may mean 1–3 m deep waters.

After the initial paper in 1969 shallow water publications were relatively scarce in the RSE during the following years (Wezernak and Lyzenga, 1975-1976; Jobson et al., 1980; Ackleson and Klemas, 1987). The situation was not much different in other journals and conference publications (Smith et al., 1975; Doak et al., 1980; Lyzenga, 1978, 1981; Jupp et al., 1981, 1985; Jupp and Mayo, 1982; Benny and Dawson, 1983; Kuchler, 1986a, 1986b; Bour et al., 1986; Bour, 1988; Spitzer and Dirks, 1987; Bainbridge and Reichelt, 1988; Philpot, 1988; Nordman et al., 1990).

More rapid developments in the field started towards the end of the last millennium where mainly coral reef remote sensing studies developed fast worldwide (Armstrong, 1993; Ferguson et al., 1993; Luczkovich et al., 1993; Zainal et al., 1993; Mumby et al., 1994, 1997a, 1997b, 1998a, 1998b; Mumby et al., 1999a; Mumby and Harborne, 1999b; Maritorena et al., 1994; Ahmad and Neil, 1994; Jupp et al., 1995; Brotas et al., 1995; LeDrew et al., 1995; Mazel, 1995, 1997, 2000; Peddle et al., 1995; Maritorena, 1996; Morel, 1996; Tassan, 1996; Clark et al., 1997, 2000; Green et al., 1996, 2000, Malthus and George, 1997; Borstad et al., 1997; Knight et al., 1997; Holden and LeDrew, 1997, 1998a, 1998b, 1999; Pratt et al., 1997; Foster-Smith et al., 1998; Holasek et al., 1998; Lee et al., 1998, 1999; Lee and Carder, 2002, Zhang, 1998; Alberotanza et al., 1999; Kutser et al., 2000a, 2000b; Anstee et al., 2000; Hochberg and Atkinson, 2000; Louchard et al., 2000, 2003; Schalles et al., 2000; Wittlinger and Zimmerman, 2000; Zimmerman and Wittlinger, 2000; Stephens et al., 2000; Andrefouet and Payri, 2001; Andréfouët and Riegl, 2004; Andréfouët et al., 2001, 2002, 2003, 2004). Since then, coral reef environments in clear oceanic waters were the primary focus of shallow water remote sensing for a decade or so (Lubin et al., 2001; Elvidge et al., 2004; Hedley and Mumby, 2002, 2003, Mumby et al., 2001, 2004a, 2004b; 2002; 2004; Hedley et al., 2004, 2005, 2009, 2010, 2012a,b, 2016a,b; Minghelli-Roman et al., 2002; Goodman and Ustin, 2002, 2007; Phinn et al., 2001, 2005, 2010; Joice and Phinn, 2002; Joice et al., 2002, 2003, 2004; Roelfsema et al., 2002, 2010, 2013a, 2013b, 2013c; Dierssen

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https://doi.org/10.1016/j.rse.2019.111619
Received 1 April 2019; Received in revised form 18 December 2019; Accepted 20 December 2019

et al., 2003, 2010; Fyfe, 2003; Kutser et al., 2003, 2006a, 2007, 2009; Call et al., 2003; Kutser and Jupp, 2006; Hochberg et al., 2003, 2003, 2003, 2004; Purkis et al., 2002, 2004, 2005, 2008; Stumpf et al., 2003; Yamano and Tamura, 2004; Conger et al., 2006; Mishra et al., 2006; Capolsini et al., 2007; Klonowski et al., 2007: Johansen, 2008; Rowlands et al., 2008; Walker et al., 2008; Soto et al., 2009; Eakin et al., 2010; Knudby et al., 2010) before studies in temperate climate and/or in optically complex coastal and inland waters started to re-emerge more widely (Jupp et al., 1995; Giardino and Zilioli, 2001; Roelfsema et al., 2001; Giardino et al., 2007, 2012, 2014, 2015; Dekker et al., 2005; Kutser et al., 2006b,c,d, 2013; Vahtmäe et al., 2006, 2011, 2012; Vahtmäe and Kutser, 2007, 2013, 2016; Phinn et al., 2008; Cavanaugh et al., 2010a; Casal et al., 2011, 2012, 2013; Brooks et al., 2015; Giardino et al., 2016).

Knowledge about the properties and processes in shallow water areas is critical from many points of view. For example, bathymetry data is needed for navigation safety, planning fish or algae farms and marine protected areas, designing nearshore infrastructure like ports and wind farms. Basically, all marine activities and maritime spatial planning requires depth data. However, hydrographic surveys are expensive and time consuming. There are large areas not accessible by hydrographic ships because of shallowness or other dangers (rocks, moving sand dunes, coral reefs). There are remote places, like many coral reefs and islands, where hydrographic surveys are not feasible due to remoteness and associated costs. And there are dynamic coastal zones, like river deltas, where surveys are needed frequently and this makes having up-to-date nautical charts very expensive. Remote sensing is one of the potential tools to get sufficiently accurate bathymetry maps over such areas. The International Maritime Organisation standards to nautical charts are quite strict and remote sensing based depth maps (satellite derived bathymetry - SDB) do not often meet the requirements. However, there are already nautical charts that contain satellite derived bathymetry. For example, the UK Hydrographic Office published their first SDB based nautical chart (GB2066) of Antigua in 2014 (www.ukho.gov.uk).

Species composition of benthic habitats and shifts in them are important indicators of water quality and ecological state of the shallow water areas (Done, 1992). Seagrasses, the marine flowering plants found in shallow coastal waters globally, are the only rooted marine macrophytes and, as such, are crucial for coastal protection and biodiversity. The shoots emerge from rhizomes, which grow vertically and horizontally, and form extensive “meadows” which provide a habitat for many species of fish and invertebrates, and are significant contributors to water oxygenation. Seagrass meadows have been shown to influence water motion, velocity profiles and turbulent structures, all of which play an important role in sedimentation processes and in general water circulation (Ackerman and Okubo, 1993). In clear lakes, shallow waters are often colonized by macrophytes that play a key role to suppress sediment resuspension, stimulate sedimentary nutrient uptake, and support well-structured food webs and habitat complexity (Strand and Weisner, 2001, and references therein). In turbid lakes, where phytoplankton abundance causes the development of structureless habitats, the restriction of the euphotic zone to the water surface layer triggers the displacement of benthic vegetation and the onset of free-floating and emergent macrophytes (Bolpagni et al., 2013). In turn, positive feedback loop can establish which allow these vegetation forms to self-perpetuate (Scheffer et al., 2003).

Benthic macroalgal communities play similar role in coastal ecosystems like seagrasses. They are essential for many organisms as habitats, mating and nursery grounds, feeding areas and refuge. They also stabilise and protect coastline and their cover and shifts in it are indicators of ecological status of the coastal environments.

Generally, exchange of matter between land and waterbodies takes place in the coastal zone. Benthic algal cover, seagrass beds and coral reefs are critical as processors of land-based fluxes ranging from nutrients to pollutants. Substantial carbon processing takes place in coastal zone. There are carbon budgets for land, but the role of coastal waters in the carbon cycle (e.g. the amount of carbon fixed by benthic habitats) is not known.

Coral reefs, one of the most diverse ecosystems on Earth, are in decline globally (Pandolfi et al., 2003; Bellwood et al., 2004; Hoegh-Guldberg et al., 2007). Climate change, ocean acidification, overfishing and overexploitation of other marine resources, increasing fluxes of soil, nutrients and chemical pollution from land are among the stressor affecting coral reefs. This is not only a threat to biodiversity, but coral reefs have substantial economic value in terms of the ecosystem services they provide to human communities (Costanza et al., 1997). Some coastal communities are highly dependent on reefs for subsistence, either directly through fisheries or indirectly through tourism. Many reefs lie in remote or inaccessible locations, so monitoring by remote sensing is a valuable component of the management toolkit (Hedley et al., 2016b).

Solving many of the above-mentioned problems is not possible without remote sensing as global problems force ecological researchers to perform environmental assessments at temporal and spatial scales that can be difficult to achieve with traditional methods and there exists a gap in scale that can be filled by using satellite images (Giardino and Bartoli, 2009; Hedley et al., 2016b). Hedley et al. (2016b) pointed out three types of issues related to coral reef remote sensing that are applicable to shallow water issues in general. These are: cost related, scale related and focus related. Frequent field surveys are very expensive and cover only small fraction of area actually needed. Moreover, coral reefs and seagrass beds are often located far from research and mapping infrastructure. Many shallow coastal areas are inaccessible for field-based bathymetry surveys and habitat mapping due to shallowness for hydrographic ships, dangerous shallow coral reef structures or rocks. There are very dynamic regions where the shoreline and bottom bathymetry are in constant change and mapping changes in bathymetry with in situ surveys becomes unreasonably expensive. Coral reefs and areas covered with macroalgae are highly heterogenous systems. Field survey programs usually can only provide scattered in time and space information about the benthic habitats. Most conventional monitoring programs are focused on a limited number of biological indicators, but rarely permit to understand drivers of changes occurring in the shallow water areas.

Remote sensing technology provides a multitude of tools that can be used in shallow water remote sensing. There are active and passive sensors on satellite, airborne, ship board and underwater platforms. LIDAR remote sensing has been used in shallow coastal water research since the end of 1960s as was mentioned above. As an example, Wang and Philpot (2007) produced maps of sand, continuous seagrass, and discontinuous seagrass ranging from the depth of 0.8 to 4.3 m from a single LIDAR flightline with limited in situ information. Lidar has been used to characterise shallow water ($<$ 30 m) to produce substrata, biological and canopy structure habitat maps of subtidal coastal environments (Eren et al., 2018; Zavalas et al., 2014; Wang et al., 2019; Tonina et al., 2019). However, the LIDAR equipment is typically and order of magnitude more expensive than passive sensors, requires more effort than passive equipment for flying it over areas with comparable size and hence also for having repeated flights if higher frequency of overpass is needed. In addition, some controlling factors such as water clarity, bed material or surface state might limit the use of LIDAR for multiple applications. Nonetheless, where light penetration is excellent, the combination of LIDAR and passive sensors (multispectral, hyperspectral) recently showed how greatly aids environmental studies as hydrodynamic modelling and ecosystem investigations (Kerfoot et al., 2019).

Some studies (e.g. Renga et al., 2014 and reference herein; Mishra et al., 2014) have instead investigated the use of Synthetic Aperture Radar (SAR) microwave signals. SAR signal cannot penetrate into water deeper than a millimetre, but in some cases it can provide indirect information about seabed morphology through surface wave patterns.

Although SAR bathymetry might cover a wider range of shallow waters irrespectively of the clarity of the water, it can map only seabed features having scale length at least of the same order of magnitude as the peak wavelength of the local swell field can be identified, while limiting factors as image resolution, slicks, waves, fronts, weather condition might limit the exploitation of this technique.

Only visible light can penetrate through the water column and give us information about water depth and benthic habitats. On the other hand, rather than LIDAR, passive remote sensing instruments can be used from different platforms ranging from satellites and aircraft to underwater imaging instruments (Dumke et al., 2018a, 2018b) and laboratory devices to study shallow water bottom types, like corals and algae, (Vahtmäe et al., 2018) at sub-millimetre scale. Therefore, we focus on passive optical remote sensing in this review.

1.1. Progress of shallow water remote sensing due to technological development

In the 1970s and 1980s coral reef and shallow water remote sensing relied on multispectral imagery, since this was the only available technology. The only satellite sensor that was available for shallow water mapping in the 1970s was Landsat. Landsat series satellites were designed for land applications. Their 8-bit radiometric resolution leaves just a few grey-levels for describing the whole range of optical water properties. Therefore, the possible use of Landsat series satellites in optically deep water aquatic environments is limited (Olmanson et al., 2008; Kutser, 2012). However, shallow water areas, and especially coral reefs, are relatively bright targets, compared to optically deep water, making Landsat series satellites usable in habitat and bathymetry mapping (Smith et al., 1975; Doak et al., 1980; Kuchler et al., 1986a,b; Jupp et al., 1981; Jupp and Mayo, 1982; Jupp et al., 1985; Bouvet et al., 2003; Bello-Pineda, 2005; El-Askary et al., 2014; Roelfsema et al., 2018a). Moreover, the long data series from Landsat satellites gives us the only possibility to study long term changes in shallow water environment (Knudby et al., 2010, Lyons et al., 2013) as typically there is no other long time series monitoring data available. The launch of Landsat-8 in 2013 ensures the continuation of the data series, but the improved radiometric resolution (12-bit instead of 8-bit) is beneficial for all aquatic applications (Kovacs et al., 2018).

The first SPOT satellite was launched in 1986. SPOT had only two spectral bands in the visible part of spectrum, compared to the three bands of Landsat. However, it had better spatial resolution. SPOT capabilities were used in coral reef remote sensing since the beginning of the mission (Bour et al., 1986, Bour, 1988, Mumby et al., 1994). Comparative studies showed that Landsat TM performance in coral reef habitat mapping was slightly better than SPOT and SPOT was slightly better than Landsat MSS (Mumby et al., 1997a, 1997b).

Despite the definitely lower spatial resolution, ocean colour radiometers have been also adopted since the previous century to provide shallow water mapping at regional scale (Robinson et al., 2000), with examples making use of the older SeaWiFS used to estimate net primary production in seagrass and benthic algae (Dierssen et al., 2010) or the recent OLCI onboard of Sentinel-3 providing temporal data to identify water quality characteristics and general bathymetry patterns (Caballero et al., 2019).

Hyperspectral airborne sensors (both imaging and non-imaging) were available since the end of 1980s. However, space borne hyperspectral sensors have been, and still are, scarce. The first civil hyperspectral sensor in space was Hyperion on EO-1 satellite that was launched in the end of year 2000 (Ungar et al., 2003). Hyperion had 196 usable spectral bands in 400–2500 nm spectral region, each about 10 nm wide. Thus, it provided spectrally contiguous data for visible and near infrared spectral range with 30 m spectral resolution. Hyperion was primarily designed as a land sensor, but some parts of the Great Barrier Reef were selected as test sites prior to the launch and Hyperion imagery was successfully used in simultaneous mapping of water depth and bottom type using modelled spectral libraries (Kutser et al., 2002; Kutser et al., 2006a, 2006b, 2006c, 2006d). The next hyperspectral sensor on satellite, PRISMA, was launched in March 2019. The first tests are showing encouraging results for bathymetry retrieval as well as for benthic mapping at 30 m resolution, with the potentiality to reach 5 m resolution by fusing data gathered by panchromatic camera with methods similar to those applied to Landsat-8 (Jagalingam and Hedge, 2017).

Hyperspectral spaceborne data was also available for a certain period (2009–2014) and certain geographic areas (51.65°north and south) from the International Space Station (ISS) using HICO imaging spectrometer (Lucke et al., 2011). HICO had spectral coverage of 380–1000 nm, 124 spectral bands and spatial resolution of 100 m. HICO imagery has been used for coastal bathymetry (Garcia et al., 2014a, 2014b) and seagrass mapping (Cho et al., 2014). The following hyperspectral sensor on ISS is DESIS, which is working operationally since March 2019 and will continue at least until the end of 2023. It has a spectral coverage of 400–1000 nm, 235 spectral bands and a 30 m spatial resolution, for variable applications also including shallow water mapping (Alonso et al., 2019).

Many airborne hyperspectral sensors (AISA, AVIRIS, APEX, CASI, HyMap, HySpex, MIVIS, PHILLS, PRISM, etc.) have been used in shallow water habitat and bathymetry mapping. Most of the sensors have 10 nm or better spectral resolution and can be flown with 1 m or smaller pixel sizes. The high spatial resolution is especially useful in very heterogenous environments as it reduces the mixed pixel problem. High spectral resolution, on the other hand, allows to detect features caused by marker pigments increasing the chance to recognise certain benthic habitat types. However, in early years the imaging spectrometers were often used in multispectral mode due to technical limitations of the instruments. The number of spectral bands had to be reduced in order to get smaller pixel size as reading the data from the sensor takes some time and using many spectral bands would have resulted pixels elongated towards the flight direction because plane speed cannot be reduced below certain critical limit. For example, CASI had 288 spectral bands, but it was used with 8–16 spectral bands in coral reef remote sensing (Clark et al., 1997; Mumby et al., 1998a, 1998b). It has to be pointed out that there are very few photons to record from a dark target like water when pixels size is small and spectral resolution is very fine. Fine spatial and spectral resolution creates problems with signal to noise ratio (SNR) of the sensors used. Nevertheless, imaging spectrometry has been offering unique opportunities for its improved capability to map bathymetry, distinguish substrate types like coastal and inland water macrophytes, seagrass and macroalgae in coastal and inland waters, different coral reef habitat types and even map coastal biodiversity (Jupp et al., 1995; Clark et al., 1997; Malthus and George, 1997; Mumby et al., 1997a; Holasek et al., 1998; Alberotanza et al., 1999; Anstee et al., 2000, 2001; Green et al., 2000; Zimmermann and Wittlinger, 2000; Giardino and Zilioli, 2001; Davies et al., 2002; Dierssen et al., 2003; Joyce and Phinn, 2003; Ciraolo et al., 2006, Vahtmäe et al., 2006, 2012; Vahtmäe and Kutser, 2016; Klonowski et al., 2007; Thorhaug et al., 2007; Brando et al., 2009; Hunter et al., 2010; Hamylton, 2011; Casal et al., 2012,2013; Bresciani et al., 2012; Chennu et al., 2013; Herkül et al., 2013; Joyce et al., 2013; Leiper et al., 2014; Uhl et al., 2016; Malthus, 2017; Thompson et al., 2017; Vahtmäe et al., 2019).

Spectral resolution of airborne sensors has improved in recent years. For example, the Portable Remote Imaging Spectrometer (PRISM), offers a spectral resolution of ~3 nm (Mouroulis et al., 2014), and the full resolution has been employed for estimating seagrass canopy density (Hedley et al., 2016a; Hedley et al., 2017) and for coral reef mapping (Thomson et al., 2017). There are also airborne sensors with 2.5 nm resolution, like HySpex (Vahtmäe and Kutser, 2016), however, the spectral features of benthic habitats are usually broader and using such spectral resolution creates also SNR problems. Therefore, the HySpex is usually flown with 5.0 nm resolution in the case of aquatic applications

Fig. 1. Attaching video camera to CSIRO underwater coral reef spectrometer. Typical measurements were carried out without the camera. The study objects were photographed for further identification. Many samples were later taken to the research vessel and reflectance of them was measured in and out of water.

(Vahtmäe and Kutser, 2016).

At present, there are no satellite sensors dedicated to coastal and inland water studies (Palmer et al., 2015; Hestir et al., 2015; Mouw et al., 2015). Therefore, shallow water remote sensing community has to use all sensors that show promise. One direction in technical development has been improving the spectral resolution, as was described above. Another option is to use multispectral satellites with high spatial resolution. Optically shallow waters are often spatially very heterogenous. Besides, the relatively low SNR hampering the use high spatial resolution satellites in optically deep waters is not such a problem in the case of relatively bright shallow water targets. Sensors like IKONOS (launched in 1999), QuickBird-2 (2001), WorldView-2 (2009), WorldView-3 and WorldView-4 (2016) have brought the spatial resolution of multispectral data down to 1.24 m and panchromatic imagery down to 0.31 m. Capabilities of these sensors in shallow water remote sensing have been tested widely (Mumby and Edwards, 2002; Andrefouet et al., 2003, 2005; Hochberg et al., 2003; Malthus and Karpouzli, 2003; Purkis, 2005; Mishra et al., 2006; Benfield et al., 2007; Capolsini et al., 2007; Vahtmäe and Kutser, 2007, 2013; Phinn et al., 2008; Lyons et al., 2011; Hedley et al., 2012b, 2016b; Botha et al., 2013, Botha and Brando, 2016; Hamylton et al., 2015).

Wide access to fixed wing and copter drones has made them attractive also for shallow water remote sensing scientists (Joyce et al., 2018). Cheap drones include only photo or video cameras on board. Their imagery is very useful in detail mapping of small areas. However, some specific to water problems have to be taken into account – the flight lines have to be planned trying to minimise glint and it has to be kept in mind that automated mosaicking software cannot cope with homogenous areas (deep water, large sandy areas, etc.). Large drones can fly with hyperspectral sensors weighting several kilograms. However, flying relatively small drones carrying costly instruments above waterbodies may easily result loss of the instrument due to a wind gust or small technical malfunction. Therefore, the wider use of drones, ultralight planes and other small carriers has pushed also instrument developers. For example, hyperspectral sensors weighting below 500 g (Sima et al., 2016) or even below 200 g (Gamaya.com) have been developed.

Wider use of hyperspectral sensors and the need to understand the capabilities of forthcoming satellite sensors forced researchers to measure spectral properties of different benthic habitats. Research groups around the world collected reflectance data of different benthic habitats. Majority of the instrument developments and collection of spectral library of different benthic types took place in tropical and/or coral reef environment (Holden and LeDrew, 1997, 1998a,b, 1999; Mazel, 1997; Holden et al., 2000; Kutser et al., 2000a,b, 2003; Hochberg and Atkinson, 2000; Hochberg et al., 2003a, 2003b; Hochberg and Atkinson, 2003; Zimmermann et al., 2003; Roelfsema et al., 2006; Roelfsema and Phinn, 2012, 2017a,b,c; Hamylton, 2011, Reichstetter et al., 2015; Russel et al., 2015; Roelfsema and Phinn, 2013d; Garcia et al., 2018). However, there were also developments in temperate coastal and inland waters (Penuelas et al., 1993; Alberotanza et al., 1999; Anstee et al., 2000; Stephens et al., 2000; Wittlinger and Zimmermann, 2000; Fyfe, 2003; Dekker et al., 2005; Kutser et al., 2006c,d; Vahtmäe et al., 2006; Bresciani et al., 2012; Casal et al., 2012; Bolpagni et al., 2014: Kotta et al., 2014; Brooks et al., 2015; Fritz et al., 2017, Vahtmäe et al., 2019).

The need in reflectance data pushed also technical development. Earlier studies used regular field spectrometers that were often very bulky. The other option was taking corals and other benthic samples to laboratory or measure their reflectance on the boat or shore immediately after collection. This is a relatively good option used by many authors cited in the previous paragraph. However, this is a destructive method. Therefore, there was need in underwater instruments that allow to collect as many as possible reflectance spectra without damaging the environment and possible effects of taking corals, plants, macroalgae and other benthic habitats out from water.

A diver-operated spectrofluorometer, based on Ocean Optics S2000 spectrometer, was developed by Mazel (1997). It was possible to collect also spectral reflectance with the instrument by measuring light reflected from different targets (coral, sand, seagrasses, etc.) and a Spectralon panel (Lesser and Mobley, 2007).

Fig. 1 shows an early underwater spectrometer built for coral reef studies in CSIRO Marine Research in Australia. The instrument was built and tested in 1999 using two (upwelling radiance and downwelling irradiance) Zeiss MMS-VIS spectrometers (used also by Trios in Ramses spectrometers) and fibre optics to allow shadow-free measurements of coral reef habitat reflectances. The instrument had 60 m cable that allowed relatively free diving around a boat and the collection of reflectance spectra was carried out by the operator in the boat. Three people were needed to measure bottom reflectances – a diver, a snorkeller on the surface who communicated between the diver and computer operator, and the computer operator who was running the software. Development plans of the instrument included replacing the regular laptop and cable system with an underwater touch-screen laptop (a decade before the first iPad) and adding a GPS buoy as well as a camera. Unfortunately, these plans did not materialise.

At the same time Zimmerman et al. (2003) built a diver-operated bio-optical spectroradiometer (DOBBS) using three channel HydroRad (HOBI Labs). DOBBS was placed at the sea bottom and allowed to measure bottom reflectance at different fixed depths.

The complexity of having to communicate with surface support via snorkeler or underwater communication devices, the long cables going from the sensor to the computer in the moving boat (CSIRO system), time consuming measuring process (DOBBS) and the lack of reviewing spectra by the operator under water promoted the need to find independent solutions for fast spectral collection of optical data in a submerged environment.

Rapid developments in both computer and spectrometer technology made it possible to collect reflectance spectra with an independent small setup that can be submerged and operated by a diver or snorkeler. These setups have in common that the operator is able freely move around in the water column to collect spectral signatures, review the results underwater on a monitor and adjust the settings if required without being depended or on communication through other people and/or cables going from boat to diver. Initially, purpose built underwater housing and palmtop software was integrated with small spectrometers (e.g. Ocean Optics 2000). Later, off-the-shelf setups were available that provided the opportunity to have two spectrometers in one housing and simultaneously collect upwelling and downwelling spectral signatures (e.g. Jaz Ocean Optics). In other cases, more high-end spectrometers were created with the same capability as the Jaz but with better signal to noise ratio and stable working condition, built into purpose built underwater housing (e.g. ASD field spec 2). A standard camera (e.g. Lumix, or GoPro) was integrated in the spectrometer system in order to allow later identification of the measured object (Fig. 2).

The main aim of the in situ instruments described above was collecting reflectance spectra of “pure” targets in order to be able to interpret airborne and satellite imagery. Part of instrument development has nowadays moved towards using imaging spectrometers underwater. For example HyperDiver (Chennu et al., 2017) is a diver-operated measuring complex that includes PAR, oxygen, pH, depth sensor and video camera in addition to a hyperspectral imager. Dumke et al. (2018a,b) made a remote operated deep water hyperspectral imager that allows to map seafloor at the depths of several kilometres. On the other hand, unmanned surface vehicles (USV, i.e. floating drones) are also used to collect in situ data. For example, Mogstad et al. (2019) developed a twin hull USV with a push-broom hyperspectral scanner on board that collects underwater radiance with 0.5 cm spatial resolution. This package's weight is around 95 kg and it requires some effort to deploy. There are also more portable systems for collecting shallow water reflectance. For example, Kutser et al. (unpublished) and SurfBee designed an instrument package based on an inflatable board with electric thrusters equipped with Trios Ramses spectrometers (hyperspectral reflectance below our above the water surface), Trios microFlu fluorometers (water quality parameters like Chl-a, CDOM, etc.), sonar and video. This system fits into a backpack and can easily be transported and used by a single person.

Advancements in in situ reflectance measurements capabilities increased the amount of information available about different benthic habitats. This information allowed to study which benthic types can be separated from each other based on their optical signatures and in how deep water it can be done. As was mentioned above, the main focus of collecting hyperspectral reflectance properties of different bottom types was in tropical environments where optical properties coral reef habitats and seagrass beds were studied intensively (Maritorena et al., 1994; Holden and LeDrew, 1997, 1998a, 1999; Kutser et al., 2000a,b, 2003, 2006a; Schalles et al., 2000; Stephens et al., 2000; Zimmerman and Wittlinger, 2000; Lubin et al., 2001; Goodman and Ustin, 2002; Joyce and Phinn, 2002; Fyfe, 2003; Hochberg et al., 2003a,b, 2004; Mumby et al, 2004a, 2004b; Mishra et al., 2005, Roelfsema et al., 2006, Roelfsema and Phinn, 2017a,b,c,d; Leiper et al., 2014. Nevertheless, such measurements took place also in temperate environments and optically more complex coastal and inland waters (Alberotanza et al., 1999; Anstee et al., 2001; Phinn et al., 2001; Dekker et al., 2005; Kutser et al., 2006c; Vahtmäe et al., 2006; Giardino et al. 2007; Villa et al., 2015; Kotta et al., 2014; Vahtmäe et al., 2019). This increased significantly our knowledge about optical properties of different shallow water bottom types in different climate zones and with different water salinities.

Sun-induced fluorescence contributes also towards the formation of spectral signatures of corals (Mazel and Fuchs, 2003). A diver-operated spectrofluorometer (Mazel, 1997) was designed to measure reflectance of corals relative to Spectralon panel while illuminated with blue, white and red LEDs. This device allowed one to understand better the formation of the reflectance signal. However, it allowed also to collect spectral reflectance of different bottom types as was mentioned above (Lesser and Mobley, 2007).

1.2. Spectral signatures of shallow water habitats

The results of the spectral measurements described above showed that optical properties of major bottom types are similar in tropical and temperate as well as freshwater and oceanic environments i.e. the characteristic features in reflectance spectra of major groups, like brown algae, are consistent globally. Fig. 3 illustrates the shape of

Fig. 2. Small independent unit underwater spectrometers in action: ocean optics 2000 (a), Jaz Ocean optics(b), and ASD field spec 2(c), all setup with separate camera on top to capture photo of endmember.

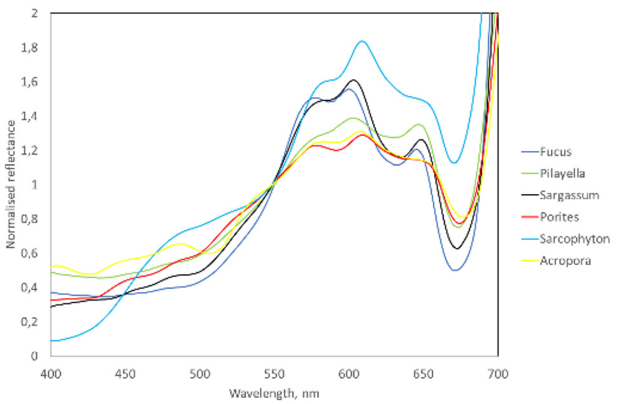

Fig. 3. Reflectance spectra of brown macroalgae (Fucus, Pilayella, Sargassum), corals (Porites, Acropora) and a soft coral (Sarcophyton) collected in the Great Barrier Reef and the Baltic Sea (Kutser et al., 2000a,b, 2006a, Kutser and Jupp, 2006; Vahtmäe et al., 2006). Spectra are normalised to values at 550 nm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

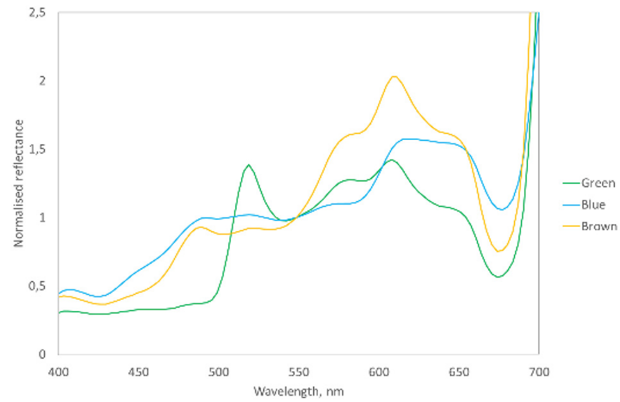

Fig. 4. Reflectance spectra of three different coral reflectance classes – green, blue and classic brown. All three spectra belong to different colonies of plate coral *Acropora hyacinthus* (Kutser et al., 2000a,b; Kutser and Jupp, 2006). Spectra are normalised to values at 550 nm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reflectance spectra of many "brown" benthic types. This includes brown macroalgae (*Fucus vesiculosus, Pilayella* sp. from the Baltic Sea and *Sargassum* from the Great Barrier reef), brownish corals (*Porites sp, Acropora florida*) and a soft coral (*Sarcophyton sp.*) collected in the Great Barrier Reef (Kutser et al., 2000a,b, 2006a,b,c,d; Vahtmäe et al., 2006). Typical features for all of them are the same – a peak at 600–610 nm and two shoulders at around 575 nm and 650 nm (Maritorena et al., 1994; Holden and LeDrew, 1997, 1998a, 1999; Kutser et al., 2000a,b, 2006a; Hochberg et al., 2003,2004; Kutser and Jupp, 2006, Vahtmäe et al., 2006). The results seen in Fig. 3 show that it is nearly impossible to separate different species of brown macroalgae, soft corals and typical brownish corals from each other based on their reflectance spectra. Optical properties of soft and hard corals are determined by microscopic algae (*zooxanthellae*). These symbionts contain pigment peridinin, spectral absorption of which is almost identical to fucoxanthin, present in brown algae (Hedley and Mumby, 2002). Therefore, it is understandable that common yellow/brownish corals are similar to each other and to brown macroalgae.

Coral reflectance may be determined by other pigments and fluorescence besides the optical properties of zooxanthellae (Shibata, 1969; Takabayashi and Hoegh-Guldberg, 1995 Dove et al., 1995, 2001, Mazel, 1995, 1997, 2000; Myers et al., 1999; Salih et al., 2000; Hedley and Mumby, 2002; Mazel and Fuchs, 2003). In that case the reflectance is different from typical brownish corals and brown macroalgae. Hochberg et al. (2004) were able to distinguish two main groups of corals based on their spectral signature – brown and blue. However, Kutser and Jupp (2006) found that there are three main colour types of corals – brown, blue and green. Characteristic spectral features of these three groups can be seen in the Fig. 4. Blue corals don't have the typical peak near 605 nm and two shoulders in their reflectance and green corals have a very distinctive peak around 520 nm besides the 605 nm peak and two shoulders.

Recognising corals at species level by their optical signature is not possible (Kutser and Jupp, 2006; Russell et al., 2016). First of all, some species, like several *Acropora* species, may have all three differently coloured morphs as seen in Fig. 4. It is seen also in the Fig. 3 that brown hard and soft corals, as well as brown macroalgae, are spectrally very similar. Consequently, different colonies of the same species may have as high variability in their reflectance as all corals combined and many species are virtually identical making their recognition even with hyperspectral instrument challenging.

It is also hard to separate green algae and plants from each other. For green algae and many species of seagrass their spectral reflectance is dominated by chlorophyll *a*nd accessory pigments take a minor role. Typically, they have relatively smoothly curved reflectance spectra with a local maximum in green part of spectrum, while the common to all plants high near-infrared signal is masked by water absorption (Kutser et al., 2006a,b,c,d; Vahtmäe et al., 2006; Dekker and Pinnel, 2018). Fig. 5 illustrates normalised to 550 nm reflectances of green algae and plants from Estonian coastal waters of the Baltic Sea (Vahtmäe et al., 2006), Italy (Matta et al., 2014), the Great Barrier Reef (Kutser et al., 2000, 2006) and Palau (Roelfsema, unpublished). It is seen that there is some variability in the red part of spectrum. The lowest values there are by bright green seagrass *Enchalus* while the reddish colony of *Potamogeton perfoliatus* has the highest reflectance in the red part of spectrum. However, water is absorbing light very strongly in the red part of spectrum. Consequently, just a few centimetres or decimetres of water above the plant may make the same *Potamogeton perfoliatus* inseparable from other green plants or macroalgae as we cannot determine whether the change in reflectance was caused by actual variation in target reflectance or just in water depth. It must be noted that the particular *Potamogeton* specimen was more reddish than majority of them in the Baltic Sea. Thus, a more common *Potamogenton* reflectance is even more similar to other species shown in the Fig. 5. There are a few studies where seagrasses or macroalgae have been mapped at species level (Alberotanza et al., 1999), but those are

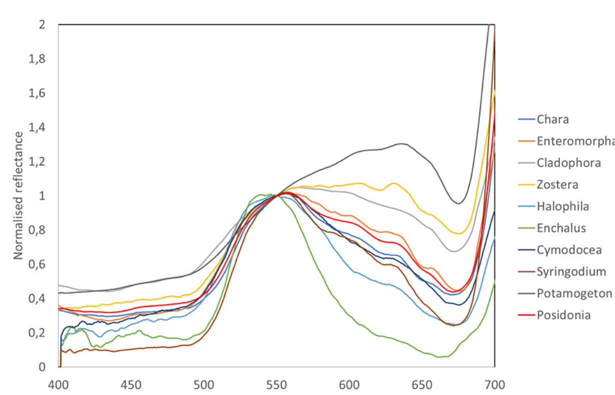

Fig. 5. Reflectance spectra of green algae and plants from the Baltic Sea and Medditerranean as well as coral reefs in Palau. (Vahtmäe et al., 2006; Kutser et al., 2006d; Matta et al., 2014; Roelfsema, unpublished). Spectra are normalised to values at 550 nm. Some noise is aparent in the blue end of the spectrum (< 450 nm) due to low signal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

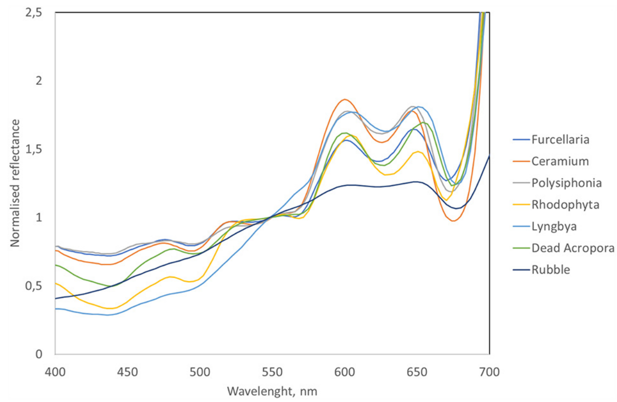

Fig. 6. Reflectance spectra of red algae and cyanobacteria collected in the Baltic Sea and the Great Barrier Reef (Vahtmäe et al., 2006; Kutser et al., 2000a,b, 2006a,d). Spectra are normalised to values at 550 nm. The first three spectra were collected in the Baltic Sea and the last four in the Great Barrier Reef. One of the specimen from the Great Barrier Reef was not identified at species level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

probably some very simplistic cases e.g. the water depth is limited to 1–2 m, the number of algae/plant species is very small and they are growing on bright substrate. Green et al. (1996) pointed out already several decades ago that recognising even monospecific seagrass beds is not possible, and recent hyperspectral work still demonstrates the difficulty to separate seagrass species such as *Thalassia*, *Syringodium* and *Halodule* (Thorhaug et al., 2007; Hedley et al., 2017). Therefore, the current knowledge suggests that green algae, seagrasses and other submerged aquatic plants are hardly separable from each other based on their optical signature (Fig. 5). However, combining spectral signature of seagrass species with textural characteristics of patches of these species when using hyperspectral sensors could be very promising, as empirical work has shown that this could work for shallow (< 3 m) coastal waters (Hedley and Enríquez, 2010; Roelfsema et al., 2014). In the empirical approach seagrass species and cover were mapped over time by differentiating areas with seagrass species based on their texture and colour, using high spatial resolution multispectral imagery and object based analysis techniques (Urbanski et al,. 2010; Roelfsema et al., 2014).

It is seen in the Fig. 6 that the shape of reflectance spectra of red algae collected in brackish temperate to sub-Arctic waters of the Baltic Sea (*Furcellaria, Ceramium, Polysiphonia*) are nearly identical to red algae and cyanobacteria reflectance colected in the Great Barrier Reef. It is also seen that the typical doubble peak in reflectance spectra of coral rubble is less distinct than in the case of long time dead plate of *Acropora hyacynthus* covered with thich turf of algae. It is easy to understand as the red turf algae have better conditions for growing on a fixed dead coral rather than continously moving coral rubble. Consequently, the thick algal turf on fixed dead coral has pronounced spectral features while thin film on rubble has only slightly detectable spectral features.

It is also seen that cyanobacterial film (*Lyngbya*) on the sea bottom has reflectance spectra that is nearly identical to red algae. This makes separating these two bottom types nearly impossible based on spectral signatures. The *Lyngbya* reflectance spectrum shown in Fig. 6 was measured above brown film of cyanobacteria. Lyngbya films may also be black, but the shape of their reflectance spectra is identical (Roelfsema et al., 2006; Roelfsema and Phinn, 2012). The only difference is in absolute values of reflectance.

Reflectance spectra of differently coloured corals (Fig. 4) are quite different from dead corals (Fig. 6), typically covered with thinner or thicker film of algae. Thus, it is relatively straighforward to separate live corals from dead corals based on their optical signatures if one has a hyperspectral sensor. However, strong absorption by water molecules makes these difference undetectable already in 2 m deep water (Kutser et al. 2003).

Accurate identification and mapping with satellite and/or airborne imagery requires that each substratum is different from deep water and from other substrata within the study area. Also, the pixel size has to be similar to the size of bottom features mapped. Two complementary studies (Hedley et al., 2012b, Botha et al., 2013) offered a framework to evaluate the sensor and environmental limits to mapping accuracy as a function of the spectral characteristics of the substratum, the depth and composition of the water column, and on the sensor spectral and radiometric resolutions. Sub-pixel spectral mixing is also a primary limiting factor for benthic mapping (Hedley et al., 2012a) raising the need for spatial resolution of ~10 m or less (Hedley et al., 2012a, Hedley et al., 2018a; Giardino et al., 2019).

Strong absorption of light by water itself makes it very difficult to separate different benthic types from each other already in a few meters deep water (Kutser et al., 2003). For instance, Giardino et al. (2007) showed with bio-optical modelling that distinguishing macrophytes beyond 7 m depth is not possible in a clear lake. Nearly similar are the results for optically more complex Baltic Sea (Kutser et al., 2006a,b,c,d; Vahtmäe et al., 2006). Obviously, the maximum depth depends on detail level requested. For example, vegetated bottom can be separated from sand (e.g. only two bottom classes) down to 8–9 m even in the Baltic Sea while separating red algae from brown algae is practically impossible even in 1 m deep water (Kutser et al., 2006a,b,c,d). The situation is slightly better in clear oceanic waters. Kutser et al. (2003) modelled separability of different coral reef bottom types from each other when hyperspectral airborne (HyMap) or satellite (Hyperion) data is available. The main differences between different bottom types occur in the red part of spectrum that is quickly absorbed by water itself. In optically complex waters the blue part of spectrum is absorbed by CDOM and phytoplankton (Fig. 7) and the shorter wavelength range cannot be used in mapping bottom types. In clear oceanic waters light penetrates the deepest in the blue part of spectrum. However, there are very little differences between different benthic types at these wavelengths as is seen in also in Figs. 3–6. So, in both cases absorption by water molecules themselves is a fundamental limiting factor for remote sensing mapping of different benthic types.

On the other hand, the dynamic range of absorption of light by pure water, from being the least in the blue to very strong in the red part of spectrum, is very useful for bathymetry mapping as small changes in water depth have significant impact on the colour of the above-water reflectance. For example, changes in water depth around 10 cm are easy to detect on a bright bottom like sand even in optically complex waters of the Baltic Sea (Vahtmäe and Kutser, 2007). However, the red part of spectrum is relatively quickly absorbed by water molecules, both in

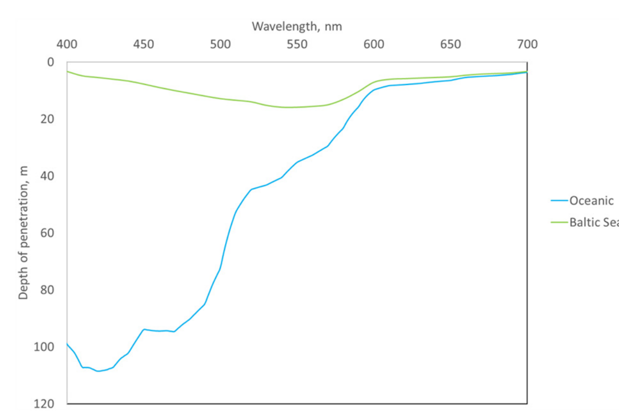

Fig. 7. Spectral depth of penetration of light calculated from the diffuse attenuation coefficient measured in the Great Barrier Reef (Oceanic) and central parts of the Baltic Sea.

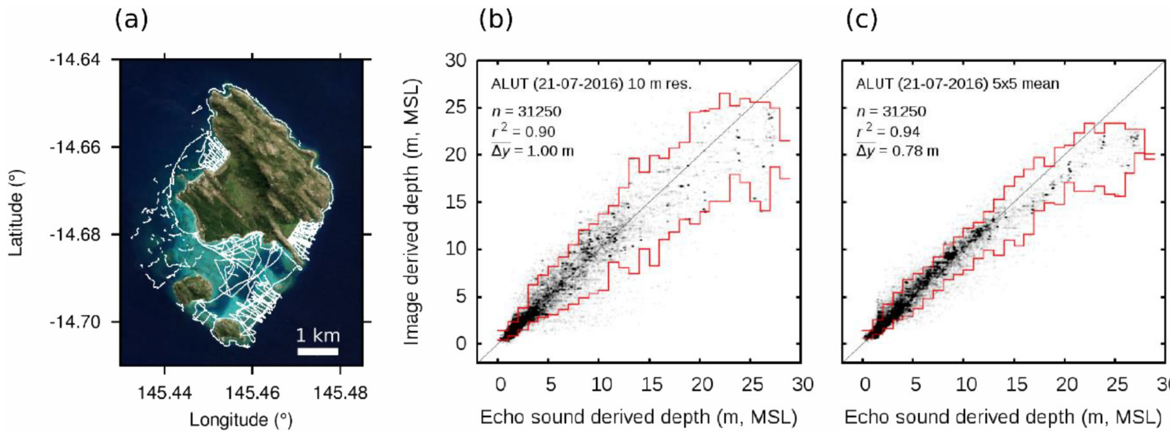

Fig. 8. Bathymetry from semi-analytical ALUT inversion of Sentinel-2 data (bands 1–5) for Lizard Island, Australia (see Hedley et al., 2018a). Location of echo sound data points (a); Results at 10 m resolution show decrease in precision with depth from ~4 m (b); Results spatially filtered, where each pixel becomes the mean of its 5 × 5 neighbourhood (c), shows that pixel-to-pixel noise is a large contribution to reduction in precision, and in this example systematic accuracy decreases from 15 m. Red lines delimit 95% of the points in 1 m x-axis steps. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

clear oceanic and optically complex coastal and inland waters. In deeper water the blue and green part of the spectrum have to be used in depth estimation. Water molecules absorb much less in the blue and green part of spectrum and consequently the change in water depth has to be much larger to cause an equivalent change in reflectance as seen in at red wavelengths for smaller depth variations. In addition, due to the physics of light transmission, the relationship between reflectance and depth is inherently exponential, in that there is progressively less change in reflectance as waters become deeper. Ultimately, approaching the depth of penetration reflectance ceases to change with increasing depth. Consequently, the potential error in depth estimation grows from centimetres to meters as a function of depth. Fig. 7 shows examples of the spectral depth of penetration in the very clearest oceanic waters and in the clearest waters of the relatively CDOM-rich Baltic Sea (occurring in the middle of the sea and in coastal upwellings). It is seen that the differences between the two water types in the red part of spectrum are relatively small. In practice, in the clearest waters over bright (sand) substrates depths of 20 m can be estimated without systematic errors, although pixel-to-pixel noise is large, i.e. reasonable accuracy but low precision (Fig. 8). In CDOM-rich waters depth may not be estimated below a few meters (often just a few decimetres). In waters with very high backscatter (e.g. due to sediment plumes) depth may not be estimable at all. A large component of the loss of precision in deeper waters is pixel-to-pixel noise from sea surface fluctuations (e.g. sun glint), sensor noise, and also potentially from geo-referencing uncertainty. So spatially filtering bathymetry results to lower spatial resolution can increase the precision (Fig. 8c).

Methods used in habitat and bathymetry mapping.

Visual image interpretation was the main benthic habitat mapping method in the analogue imagery (e.g. aerial photography) era where spatial features were delineated manually and labelled with a mapping category. Visual interpretation has not completely gone from interpretation of digital imagery despite being a subjective method, because for shallow water benthic mapping the ability of a knowledgeable user to visually interpret an image is still superior to computational interpretation (although developments in Artificial Intelligence may change this situation). However, digital imagery allows the use of more quantitative methods and also automation of processing to reduce the effort of the operator. Empirical methods were, and still are, widely used in both bathymetry and benthic habitat mapping.

Different supervised and unsupervised image processing methods are often used in habitat mapping. For example, image is classified into as many classes as mathematically possible and then names are given to each class (e.g. sparse seagrass at 1 m depth, coral with some macroalgae, etc.) based on fieldwork results (Green et al., 2000). Another option is carrying out fieldwork and using this data in supervised classification (Kovacs et al., 2018; Roelfsema et al., 2018b). In both cases there is need in as large as possible amount of field data from the exact study site, preferably collected during the sensor overpass. Although potentially precise these methods are effectively limited to application on single scenes and the results are not transferable from image to image and from sensor to sensor. There have been attempts to use a limited number of benthic classes with one particular sensor (Ikonos) in different study sites to get consistent habitat maps (Andrefouet et al., 2003). However, this proved difficult as the benthic habitats are different in different locations, and the extent and complexity of study areas influence these variations as well (Roelfsema et al., 2013a,b; Asner, 2017).

Empirical methods for bathymetry and habitat mapping are quite robust and easy to use. However, they are site specific, sensors specific and require large amount of in situ data, preferably collected during the remote sensing sensor overpass. Moreover, water depth and bottom type cannot be retrieved simultaneously. One of the two has to be known or at least guessed. Physics-based methods using the full reflectance spectrum have to be used in order to avoid shortcomings of the empirical methods. Theoretically, it should be possible to collect a hyperspectral library that contains reflectance spectra of all possible bottom types at all possible water depths and for many optical water types, and then use some spectral matching technique to retrieve water depth and bottom type simultaneously. For example, USGS has created high resolution spectral library for minerals (Kokaly et al., 2017). However, it is easier to use modelling to create such database for shallow waterbodies. The models used may be simpler bio-optical models (Maritorena et al., 1994; Gege, 2004; Gege 2014) or radiative transfer models such as HydroLight (Mobley, 1994). Models that incorporate benthic structural complexity have been devised but as yet have not been used for applied mapping (Hedley, 2008;Hedley and Enríquez, 2010 Hedley et al., 2016a). All models need information about reflectances of different bottom types and these are relatively consistent worldwide as was shown above. Thus, these methods can be applied without the need to carry out fieldwork in a particular study site. The analytical methods can also estimate the optical properties of the water, however what is required is that the possible range of optical properties and bottom reflectances is encompassed in the analysis. In-situ data can be useful to restrict these ranges in order to make the processing faster. If there is no in situ data the ranges can be made conservatively wide but then potential uncertainty arises. Typically, the computations are done hyperspectrally so transferring the methods from one sensor to another just requires convolving the calculation with the spectral response functions of different sensors. Uncertainties are less for sensors with more bands or with good signal to noise ratios, but good results can be obtained from multispectral data such as Sentinel-2 (Hedley et al., 2018a).

Some analytical methods have been based on pre-modelled spectral libraries (Kutser et al. 2002; Kutser et al., 2006a,b,c,d; Mobley et al., 2005; Lesser and Mobley, 2007). The libraries (look-up tables - LUTs) included reflectance spectra of different bottom types at different water depths. There are different methods to select the best matching spectrum from the spectral library. For example, Kutser et al. (2002) and Kutser et al. (2006a,b,c,d) used Spectral Angle Mapper, Mobley et al. (2005) and Lesser and Mobley (2007) used least square distance minimisation. All the authors used HydroLight to create their spectral libraries.

A variety of methods are used to “invert” physics-based models i.e. to find a set of conditions that give rise to the spectral reflectance in each pixel. Brando et al. (2009) used an inversion-optimization method while Lee et al. (1998, 1999) used a nonlinear optimization technique. Hedley et al. (2009) used an adaptive look-up table (ALUT) technique that builds a look-up table evenly distributed in spectral space rather than parameter space, this enables efficient inversion of the Lee et al. model and uncertainty propagation (Hedley et al., 2010, 2012a,b, 2016b, 2017). All analytical methods retrieve water depth and bottom type simultaneously.

The pioneer work of Lee et al. (1998, 1999) and Albert and Mobley (2003) have been further developed in following years in order to include a relative linear mixed distribution of up to three different substrates (e.g. Giardino et al., 2007, 2012; Goodman and Ustin, 2007; Klonowski et al., 2007; McKinna, 2015; Petit et al., 2017). A finer differentiation in water constituents was introduced to retrieve the concentrations of the optically active constituents and to differentiate among phytoplankton types (Brando et al., 2009; Anstee et al., 2010; Gege, 2014). Quality control procedures based on the semi-analytical model and the characteristics of the sensor enable to recognise optically deep from optically shallow waters during the inversion optimization and thus identify automatically pixels where depth retrieval is not accurate (Brando et al., 2009). A comparative study from Dekker et al. (2011) of five different inversion physics-based methods applied to airborne imaging spectrometry all provided accurate retrievals of bathymetry and benthic reflectance in waters < 13 m deep, with homogeneous to heterogeneous benthic or substrate cover. However, it also showed that empirical approaches were relatively accurate as well.

Work on improving and understanding inversion methods continues, with various publications on uncertainty (Jay and Guillaume, 2014, Jay et al., 2018) and efficient processing methods (Garcia et al., 2014a,b, 2015, 2018). Typically, the current physics-based methods use the concept of linear spectral mixing in the bottom reflectance to deal with mixed bottom types. However, the composition of some benthos, especially on coral reefs, is structurally complex. Canopy modelling, as often used in terrestrial remote sensing, is less well developed in shallow water mapping although some work on 3-dimensional optical modelling of coral reef structures (Hedley, 2008, Hedley et al., 2018b, 2018a), and seagrass canopies (Hedley et al., 2010, 2016, 2017; Hedley and Enríquez, 2010) has been done.

Analytical methods have significant advantages compared to the empirical methods – it is possible to retrieve water depth and bottom type simultaneously, there is no need for in situ data from the particular study site, and the methods are easily transferable between sensors. The analytical methods have also two shortcomings – first of all, they take computationally more time than empirical methods. Secondly, the “physically correct” models require high quality input data. This can be very hard to achieve as there are no atmospheric correction methods that provide accurate water reflectances for shallow and/or optically complex coastal waters. A minor error made in atmospheric correction (e.g. when using land remote sensing methods like Sen2cor) may be as big as the whole water leaving signal in waters just a few meters deep. Very bright (e.g. coralline sand, corals in shallow water, etc.) targets are to a certain extent easier objects as the water leaving signal is relatively strong compared to deeper water and the atmospheric correction errors are less crucial. However, the signal drops significantly when the water is deeper than 1–2 m. As a result, the errors in atmospheric correction become as large as the water leaving signal and the outputs of physics based inversion methods may turn unrealistic.

One of the possible options to avoid this problem is using top of atmosphere imagery and top of atmosphere spectral libraries. For example, Kutser et al. (2002) and Kutser et al. (2006a,b,c,d) showed that using the top of atmosphere spectral library (bottom spectra modelled through water with variable depth using HydroLight and then modelling the signal through the atmosphere) produced significantly better water depth and benthic habitat maps than applying the above water spectral library on atmospherically corrected imagery. Large areas of the atmospherically corrected imagery remained unclassified with the conventional workflow (atmospheric correction before image interpretation) as there were no similar spectra in the modelled spectral library. Obviously, the atmosphere properties are also variable and there may be a need to create a spectral library that includes different atmospheric conditions besides different water column properties. However, cloud-free images with good atmospheric transparency are typically chosen for optical remote sensing and therefore, the atmospheric conditions are relatively similar when good images are acquired. Consequently, there may be no need to use many atmospheric conditions in creating the top of atmosphere spectral library. However, such tests have not been made. The results from Kutser et al. (2002) and Kutser et al. (2006a,b,c,d) used Hyperion imagery with contiguous spectra with 10 nm spectral resolution.

Since the last decade the introduction of object-based image analysis (OBIA) has spearheaded new approaches to map and monitor coral reef habitats. OBIA proceeds by initially segmenting the imagery into “objects” using polygons, where the objects represent a group of pixels with specific thematic, spectral and textural properties. Next, objects are assigned to classes on the basis of membership rules (Blaschke, 2010). A variety of studies have now been using OBIA approaches successfully to map seagrass and coral reef habitats (Saul and Purkis, 2015; Urbański et al., 2010, Leon and Woodroffe, 2011, Leon et al., 2012a,b, Phinn et al., 2012, Baumstark et al., 2013, Lyons et al., 2013, Roelfsema et al., 2013a,b, Zhang et al., 2013, Joseph et al. 2015, Wahidin et al., 2015, Selgrath et al., 2016, Teixeira et al., 2016, Xu et al., 2016, Kovacs et al., 2018, Poursanidis et al., 2018, Roelfsema et al., 2018a,b). Recent OBIA approaches have been strengthening the differentiation between habitat classes at various levels by including next to the satellite image also physical attributes such as water depth, slope and wave climate (Roelfsema et al., 2018a,b). These physical attributes are known to influence geomorphic zonation, benthic composition and coral type and therefore, once known for the extent to be mapped, provide the ability to map larger reef systems. This removes the limit of processing single image scenes and can extend to mosaics of tens to hundreds of scenes covering hundreds of reefs. The OBIA approach has now been adapted in large scale habitat mapping programs for the Great Barrier Reef (Roelfsema et al., 2018a,b; Roelfsema et al., 2020; Lyons et al., n.d.) in Australia and for a global coral reef mapping initiative (www.AllenCoralAtlas.org). Both programs use as main input data set, from multi spectral satellite derived surface and bottom reflectance products. The satellite products are also used to derive bathymetry, which then is used to calculate reef slope and model parameters describing the surface wave climate.

Given its higher spatial resolution, MSI on Sentinel-2 should be considered as a key bathymetric and benthic mapping satellite; by adding the capacity of revisiting the same area every 5 days it is also relevant for tracking changes. Therefore, in the last years a number of studies have been developed to perform shallow water studies with Sentinel 2, both in lakes (Dörnhöfer et al., 2016; Fritz et al., 2017; Fritz

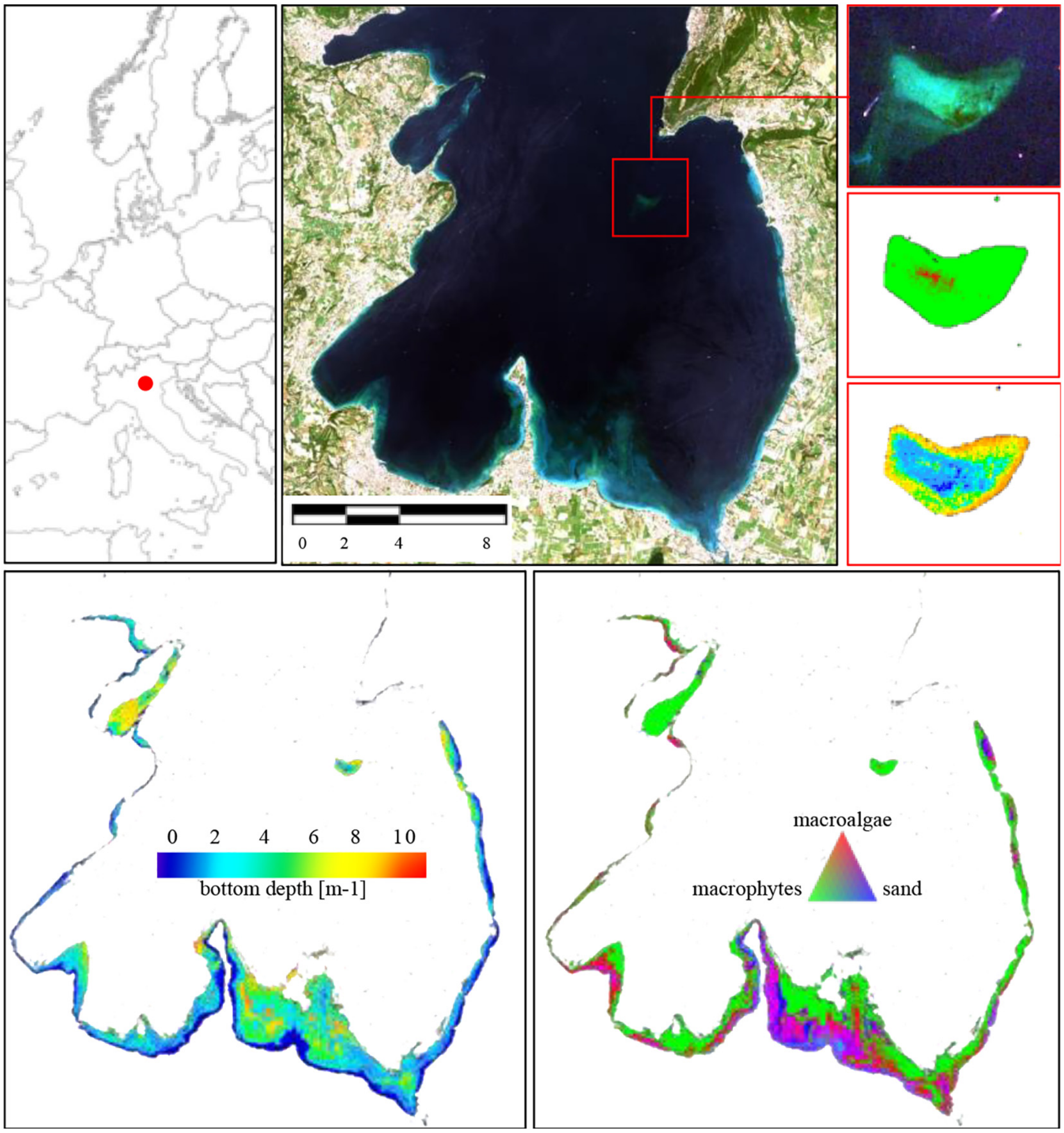

Fig. 9. Sentinel-2 true colour image of southern part of Lake Garda (Italy) acquired on June 2, 2017, with retrieved bottom depth and bottom types using the SWAM analytical model available in SNAP software. The zooms on top right are on Secca del Vo, a pelagic shallow water area colonized by native valuable beds of macrophytes

et al., 2019; Ghirardi et al., 2019), in the Mediterranean Sea (Traganos and Reinartz, 2018; Traganos et al., 2018), and in the tropical reefs (e.g. Hedley et al., 2018a,b; Immordino et al., 2019). Although the well-known risk of environmental conditions, such as sunglint, that could hinder the use of data in during the months around the summer solstice. The results that have been produced so far are demonstrating both the accuracy in bottom depth and in classifying substrate types. For example, Caballero et al. (2019) mapped bathymetry at 10 m with errors of 0.58 m for depths between 0 and 18 m in West Palm Beach, improved to 0.22 m at depths ranging between 0 and 5 m in Key West, in conditions with lower turbidity.

A further example of Sentinel-2 shallow water mapping is given in Fig. 9, that shows the products on bottom depth and substrate type as retrieved from spectral inversion (i.e. a non-linear optimization procedure) of a semi-analytical bio-optical model available in the SNAP (the open-source ESA Sentinel Application Platform). Based on field data, the mean absolute error of depth was 0.34 m while the Pearson correlation coefficient r was 0.92, for depths ranging from 1 to 6 m. The spatial distribution of the three classes of bottom types (i.e. two groups of macrophytes associations and un-colonized substrates) were also comparable to field investigations. Fig. 9 also shows a finer scale mapping for the Secca del Vo, an underwater rock bed reaching close to the surface were shallow waters are colonized by native valuable beds of macrophytes. A high density of biomass was confirmed for this site by field surveys (scuba divers and videos).

Recent work on seagrass species and percentage cover mapping for shallow (< 3 m) water has shown to be successful to semi-automated mapping of these properties using object based analysis of high spatial resolution multi spectral imagery and field data (Roelfsema et al. 2014) (Fig. 10). The same approach is now being applied for coral reef environments as well to present a time series of benthic composition (Roelfsema et al., 2018a).

2. Summary

Evolution of sensor developments has allowed significant improvements in shallow water habitat and bathymetry mapping and vice versa, remote sensing needs have pushed sensor development during the last 50 years. The in situ data collected around the world suggests that there is no major difference between the bottom reflectances

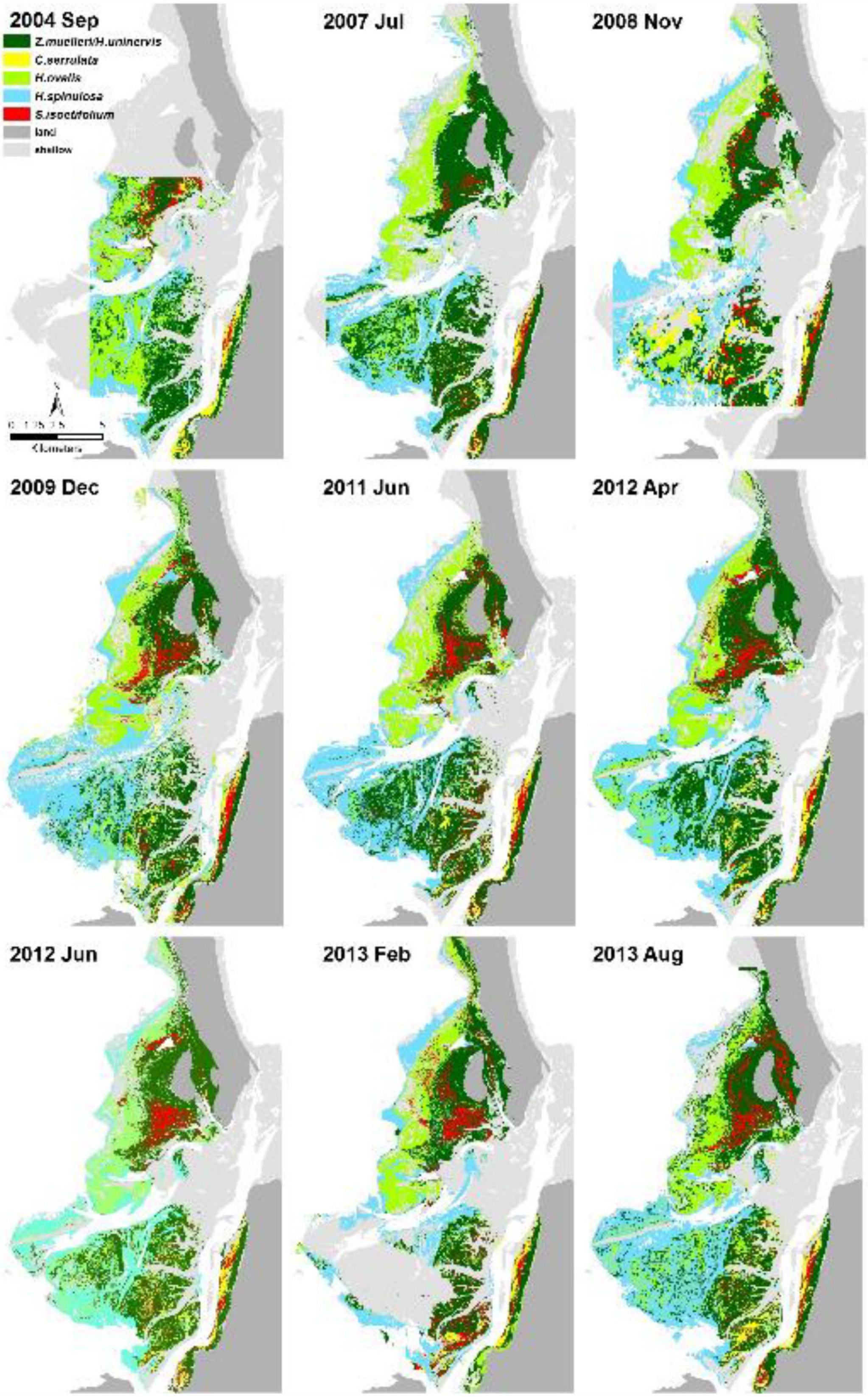

Fig. 10. OBIA-derived maps of dominant seagrass species for the Eastern Banks, Moreton Bay, Australia using high spatial resolution imagery (Roelfsema et al., 2014).

collected in tropical to sub-Arctic regions as well as in oceanic, brackish or freshwaters. The main spectral characteristics of each group remain the same everywhere, and even between groups when pigments are similar.

Bathymetry mapping from airborne and satellite sensors is relatively established (Hamylton et al., 2015; Botha et al., 2016). Higher accuracy can be achieved in waters < 8 m deep (Figs. 7 and 8) where strong absorption by water molecules creates significant changes in water reflectance across the visible wavelengths. The precision drops in deeper waters where shorter wavelengths (blue to green) have to be used and as much larger change in water depth is needed to create change in reflectance that is detectable by remote sensing sensors. In clear oceanic waters SDB works reasonably well down to 20 m. However, per-pixel noise increases with depth, so estimated depths of 20 m are to be interpreted as spatial averages, individual pixels may have errors of up to 5 m (Hedley et al., 2018a). The reliability of satellite derived bathymetry has reached levels where it is already used in production of nautical charts.

There have been significant developments in benthic habitat mapping methodologies during the last 50 years. Empirical methods requiring lots of field data were used in early years while different analytical methods emerged during the last two decades. There are different analytical methods, as was described above, however, there is no single approach that has been adopted as “industry standard”.

The problems in remote sensing habitat mapping are also related to classification schemes. The bottom classes that can be derived in remote sensing are often driven by optical signatures. The classes requested by end users of remote sensing products (biologists, ecologists, coastal managers) use different classification schemes. In some cases the requested classes are not separable from each other based on their optical signature, but integration with eco-geomorphological knowledge could differentiate these classes (Andrefouet et al., 2003; Benfield et al., 2007; Roelfsema et al., 2018c). In some cases remote sensing can even provide more detailed information than the users need (Kutser et al., 2002; Kutser et al., 2006a,b,c,d; Roelfsema et al., 2018c). However, there is no good agreement between the two and this hampers the use of remote sensing. Coastal areas are also highly variable. Therefore, it is nearly impossible to use a consistent benthic classification scheme everywhere. There is obviously a need in accounting for other data besides the spectral signatures of benthic habitats. For example, contextual editing (e.g. taking into account water depth as many species grow only in certain depth range) and object based analysis have been used (Roelfsema et al., 2018c). Different machine learning methods are in their early stages of application in this field (Kotta et al., 2013; Thompson et al., 2017; Parson et al., 2018), but are most probably the way to go as rugosity, structure of different objects, water depth and maybe some other parameters have to be taken into account besides the spectral signature when producing shallow water benthic maps.

2.1. Future directions

It is practically impossible to get depth maps of all coastal areas in the world with sufficient frequency using in situ surveys. Constellations of high spatial resolution satellites already provide plenty of data with high temporal resolution. Thus, it can be expected that use of SDB will widen in the near future. Uptake of the SDB by the hydrographic community is hampered by the challenge of placing SDB products within IHO standards. However, there are discussions how to fit SDB in IHO quality system and some countries have already used SDB in their nautical charts.

Mapping water depth and/or bottom type in coastal and inland waters using remote sensing sensors have typically been one off case studies as acquiring high resolution imagery with high temporal frequency is prohibitably expensive. Frequent availability of free medium-resolution data, like Sentinel-2 MSI imagery with 10 m resolution, opened new possibilities in mapping benthic habitats that were not possible before. For example, coral bleaching may be detectable by remote sensing only in a few days as recovering coral gets darker again and dead coral is overgrown by filamentous algae within a few days (Fang et al., 1995; Hedley et al., 2018a). Density of microalgae on sand in coral reef lagoons is highly variable and depending on weather conditions i.e. sand erosion (Paterson et al., 1998; Decho et al., 2003; Borrego-Acevedo et al., 2014). Spatial resolution and 2–5 day revisit time allows to study such dynamic processes with Sentinel-2 (Hedley et al., 2018a; Skirving et al. 2018).

Launching of constellations of small satellites with very high spatial resolutions (< 5 m) will increase further our chances to move from simple mapping studies to process studies and near real time monitoring (Asner et al., 2017; Li et al., 2019a,b). The data is becoming also more easily accessible as it can be rented instead of purchasing whole scenes.

High spatial resolution remote sensing may provide us indirect information about species richness even if not too many bottom types are recognisable in remote sensing imagery. Herkül et al. (2013) showed that the spatial heterogeneity of remote sensing data is related to species richness of both phyto- and zoobenthos. On the other hand, the accuracy of benthic habitat maps have reached the level when they can be used also in ecology and process studies (Hochberg and Atkinson, 2008; Palandro et al., 2008; Hochberg, 2011, Knudby et al., 2013; Lyons et al., 2015; Gonzales-Rivero et al., 2016; Hamylton et al., 2017; Samper-Villarreal et al. 2018) and management (Jupiter et al., 2013; González-Rivero et al., 2014) including reef restoration (Foo and Asner, 2019). Consequently, it may be feasible to develop indices that describe benthic biodiversity in broader sense not only the presence or absence of a few key species.

Many countries have produced their national carbon budgets. However, these take into account only land-based carbon. Shallow water areas are relatively extensive in many countries. However, the role of benthic habitats in the carbon cycle has not been yet accounted for appropriately (Cavanaugh et al., 2010b; Dierssen et al., 2010; Hill et al., 2014; Ralph et al., 2018; Macreadie et al., 2017).

The Global Climate Observing System has defined Marine Habitat Properties as one of the 54 essential climate variables (ECVs). Coral reefs and seagrass beds are among the required ECV products (https://gcos.wmo.int/en/essential-climate-variables/ecv-factsheets). Thus, it is obvious that most of the studies cited in this review contribute towards monitoring of these two ECV products (Muller-Karger et al., 2018).

The use of hyperspectral optical imagery in aquatic studies has broadened during the recent years. For example, hyperspectral close range imagers have been used to map benthic habitats in deep ocean (Dumke et al., 2018a,2018b) and submillimetre scale imagery collected either in laboratory or in situ (Chennu et al. 2013, n.d.; Barille et al., 2017; Russell and Dierssen, 2015, 2018; Vahtmäe et al., 2018) allows to study physiology of aquatic plants and animals. Thus, the shallow water remote sensing methods can be used also in deep water and in laboratory studies.

From processing and interpretation point of view there are minor differences between data collected from different sensors whether they are in space, plane, drone, just above the water surface (moorings, profiling buys, jetties, ships of opportunity, unmanned autonomous vehicles, remote operated vehicles), close to the ocean floor (unmanned or remote controlled) or are used for submillimetre scale laboratory studies of aquatic flora and fauna in laboratory conditions. Thus, the passive optical remote sensing methods already have very wide range of applications and this will probably broaden in the coming decades.

Author contribution statement

The first draft of the review was prepared by TK. All co-authors provided data, figures and photos as well as participated actively in writing the manuscript.

Declaration of competing interest

The Authors declare no conflict of interests.

Acknowledgements

We would like to acknowledge the anonymous reviewers who reminded us of a few historic details and helped to improve the review. The reflectance data used in this review was collected by the authors while working for different projects in CSIRO, University of Queensland, CNR and Estonian Marine Institute. Funding agencies of these projects are acknowledged in the publications cited in the text. Lizard Island bathymetry data was provided by Sarah Hamylton and Rob Beaman, and the analysis was developed as a part of the European Space Agency project Sen2Coral as part of the SEOM programme (S2 for Land and Water, Coral Reefs). We would like to acknowledge also funding from the Estonian Research Council grant PRG302 and the EU H2020 CoastObs project (Grant agreement: 776348).

References

Ackerman, J.D., Okubo, A., 1993. Reduced Mixing in a Marine Macrophyte Canopy. Funct. Ecol. 7, 305–309.
Ackleson, S.G., Klemas, V., 1987. Remote sensing of sub-merged vegetation in lower Chesapeake Bay: A comparison of Landsat MSS to TM imagery. Remote Sens. Environ. 22, 235–248.
Ahmad, W., Neil, D.T., 1994. An evaluation of Landsat Thematic Mapper (TM) digital data for discriminating coral reef zonation: Heron Reef (GBR). Int. J. Remote Sens. 15, 2583–2597.
Alberotanza, L., Brando, V.E., Ravagnan, G., Zandonella, A., 1999. Hyperspectral aerial images. A valuable tool for submerged vegetation recognition in the Orbetello Lagoons, Italy. Int. J. Remote Sens. 20, 523–533.
Albert, A., Mobley, C., 2003. An analytical model for subsurface irradiance and remote sensing reflectance in deep and shallow case-2 waters. Opt. Express 11, 2873–2890.
Alonso, K., Bachmann, M., Burch, K., Carmona, E., Cerra, D., de los Reyes, R., ... Knodt, U., 2019. Data Products, Quality and Validation of the DLR Earth Sensing Imaging Spectrometer (DESIS). Sensors 19 (20), 4471.
Andrefouet, S., Payri, C., 2001. Scaling-up carbon and carbonate metabolism of coral reefs using in-situ data and remote sensing. Coral Reefs 19, 259–269.
Andréfouët, S., Riegl, B., 2004. Remote sensing: A key tool for interdisciplinary assessment of coral reef processes. Coral Reefs 23, 1–4.
Andréfouët, S., Muller-Karger, F.E., Hochberg, E.J., Hu, C., Carder, K.L., 2001. Change detection in shallow coral reef environments using Landsat 7/ETM+ data. Remote Sens. Environ. 78, 150–162.
Andréfouët, S., Berkelmans, R., Odriozola, L., Done, T., Oliver, J., Muller-Karger, F., 2002. Choosing the appropriate spatial resolution for monitoring coral bleaching events using remote sensing. Coral Reefs 21, 147–154.
Andréfouët, S., Kramer, P., Torres-Pulliza, D., Joyce, K.E., Hochberg, E.J., Garza-Pérez, R., et al., 2003. Multi-site evaluation of IKONOS for classification of tropical coral reef environments. Remote Sens. Environ. 88, 128–143.
Andréfouët, S., Muller-Karger, F.E., Robinson, J.A., Kranenburg, C.J., Torres-Pulliza, D., Spraggins, S., Murch, B., 2004. Global assessment of modern coral reef extent and diversity for regional science and management applications: A view from space. In: Proceedings of the 10th International Coral Reef Symposium, Okinawa, Japan.
Andréfouët, S., Hochberg, E.J., Chevillon, C., Muller-Karger, F.E., Brock, J.C., Hu, C., 2005. Multi-scale remote sensing of coral reefs. In: Har, R.L., Miller, X., Del Castillo, C.E., Mckee, B.A. (Eds.), Remote Sensing of Coastal Aquatic Environments. Springer, Dordrecht, the Netherlands, pp. 297–315.
Anstee, J., Dekker, A., Byrne, G., Daniel, P., Held, A., Miller, J., 2000. Use of hyperspectral imaging for benthic species mapping in South Australian coastal waters. In: 10th Australasian Remote Sensing and Photogrammetry Conference, Adelaide, pp. 1051–1061.
Anstee, J.M., Dekker, A.G., Brando, V., Pinnel, N., Byrne, G., Daniel, P., Held, A., 2001. Hyperspectral imaging for benthic species recognition in shallow coastal waters. In: IGARSS 2001: Scanning the Present and Resolving the Future. Vols 1–7. pp. 2001 Proceedings.
Anstee, J.M., Botha, E.J., Williams, R.J., Dekker, A.G., Brando, V.E., 2010. Optimiszing Classification Accuracy of Estuarine Macrophytes: By Combining Spatial and Physics-Based Image Analysis. IGARSS Proceedings, Honolulu.
Armstrong, R.A., 1993. Remote sensing of submerged vegetation canopies for biomass estimation. Int. J. Remote Sens. 14, 621–627.
Asner, G.P., Martin, R.E., Mascaro, J., 2017. Coral reef atoll assessment in the South China Sea using Planet Dove satellites. Remote Sens. Ecol. Conserv. 3, 57–65.
Bainbridge, S.J., Reichelt, R.E., 1988. An assessment of ground truth methods for coral reef remote sensing data. In: Proceedings of the 6th International Coral Reef Symposium, Townsville, Australia, pp. 439–444.
Barillé, L., Le Bris, A., Méléder, V., Launeau, P., Robin, M., Louvrou, I., Ribeiro, L., 2017. Photosynthetic epibionts and endobionts of Pacific oyster shells from oyster reefs in rocky versus mudflat shores. PLoS ONE 12 (9).
Baumstark, R., Dixon, B., Carlson, P., Palandro, D., Kolasa, K., 2013. Alternative spatially enhanced integrative techniques for mapping seagrass in Florida's marine ecosystem. Int. J. Remote Sens. 34 (4), 1248–1264.
Bello-Pineda, J., Liceaga-Correa, M.A., Hernandez, H., Ponce-Hernandez, R., 2005. Using aerial video to train the supervised classification of Landsat TM imagery for coral reef habitats mapping. Environ. Monit. Assess. 105, 145–164.
Bellwood, D.R., Hughes, T.P., Folke, S., Nyström, M., 2004. Confronting the coral reef crisis. Nature 429, 827–833.
Benfield, S.L., Guzman, H.M., Mair, J.M., Young, J.A.T., 2007. Mapping the distribution of coral reefs and associated sublittoral habitats in Pacific Panama: a comparison of optical satellite sensors and classification methodologies. Int. J. Remote Sens. 28, 5047–5070.
Benny, A.H., Dawson, G.J., 1983. Satellite imagery as an aid to bathymetric charting in the Red Sea. Cartogr. J. 20, 5–17.
Blaschke, T., 2010. Object based image analysis for remote sensing. J. Photogramm. Remote Sens. 65, 2–16.
Bolpagni, R., Bartoli, M., Viaroli, P., 2013. Species and functional plant diversity in a heavily impacted riverscape: implications for threatened hydro-hygrophilous flora conservation. Limnologica 43, 230–238.
Bolpagni, R., Bresciani, M., Laini, A., Pinardi, M., Matta, E., Ampe, E.M., Giardino, C., Viaroli, P., Bartoli, M., 2014. Remote sensing of phytoplankton-macrophyte coexistence in shallow hypereutrophic fluvial lakes. Hydrobiologia 737, 67–76.
Borrego-Acevedo, R., Roelfsema, C.M., Phinn, S.R., Grinham, A.R., 2014. Predicting distribution of microphytobenthos abundance on a reef platform by combining in situ underwater spectrometry and pigment analysis. Remote Sensing Letters 5, 461–470.
Borstad, G., Brown, L., Cross, W., Nallee, M., Wainwright, P., 1997. Towards a management plan for a tropical reef-lagoon system using airborne multispectral imaging and GIS. In: Proceedings of Fourth International Conference on Remote Sensing for Marine and Coastal Environments, Orlando. 2. pp. 605–610.
Botha, E.J., Brando, V.E., Dekker, A.G., 2016. Effects of per-pixel variability on uncertainties in bathymetric retrievals from high-resolution satellite images. Remote Sens. 8, 459.
Botha, E.J., Brando, V.E., Anstee, J.M., Dekker, A.G., Sagar, S., 2013. Increased spectral resolution enhances coral detection under varying water conditions. Remote Sens. Environ. 131, 247–261.
Bour, W., 1988. SPOT images for a coral reef mapping in New Caledonia. A fruitful approach for classic and new topics. In: Proceedings of the 6th International Coral Reef Symposium, Australia, 1988. vol. 2. pp. 445–448.
Bour, W., Loubersac, L., Rual, P., 1986. Thematic mapping of reefs by processing of simulated SPOT satellite data: application to the Trochus niloticus biotope on Tetembia Reef (New Caledonia). Mar. Ecol. Prog. Ser. 34, 243–249.
Bouvet, G., Ferraris, J., Andréfouët, S., 2003. Evaluation of large-scale unsupervised classification of New Caledonia reef ecosystems using Landsat 7 ETM+ imagery. Oceanol. Acta 26, 281–290.
Brando, V.E., Anstee, J.M., Wettle, M., Dekker, A.G., Phinn, S.R., Roelfsema, C., 2009. A physics based retrieval and quality assessment of bathymetry from suboptimal hyperspectral data. Remote Sens. Environ. 113, 755–770.
Bresciani, M., Bolpagni, R., Braga, F., Oggioni, A., Giardino, C., 2012. Retrospective assessment of macrophytic communities in southern Lake Garda (Italy) from in situ and MIVIS (multispectral infrared and visible imaging spectrometer) data. J. Limnol. 71, 180–190.
Brooks, C., Grimm, A., Shuchman, R., Sayers, M., Jessee, N., 2015. A satellite-based multitemporal assessment of the extent of nuisance *Cladophora* and related submerged aquatic vegetation for the Laurentian Great Lakes. Remote Sens. Environ. 157, 58–71.
Brotas, V., Cabrita, T., Serodio, J., Catarino, F., 1995. Spatio-temporal distribution of the microphyto-benthic biomass in intertidal flats of Targus Estuary (Portugal). Hydrobiologia 300/301, 93–104.
Caballero, I., Stumpf, R.P., Meredith, A., 2019. Preliminary assessment of turbidity and chlorophyll impact on bathymetry derived from sentinel-2A and sentinel-3A satellites in South Florida. Remote Sens. 11 (6), 645.
Call, K.A., Hardy, J.T., Wallin, O., 2003. Coral reef habitat discrimination using multivariate spectral analysis and satellite remote sensing. Int. J. Remote Sens. 24, 2627–2639.
Capolsini, P., Andréfouët, S., Rion, C., Payri, C., 2007. A comparison of Landsat ETM+, SPOT HRV, Ikonos, ASTER, and airborne MASTER data for coral reef habitat mapping in South Pacific islands. Can. J. Remote. Sens. 23, 87–200.
Casal, G., Kutser, T., Domínguez-Gómez, J.A., Sánchez-Carnero, N., Freire, J., 2011. Mapping benthic macroalgal communities in the coastal zone using CHRIS-PROBA mode 2 images. Estuarine Coastal and Shelf Science 94, 281–290.
Casal, G., Sanches-Carnero, N., Dominguez-Gomez, J.A., Kutser, T., Freire, J., 2012. Assessment of AHS (Airborne Hyperspectral Scanner) sensor to map macroalgal communities on the Ria de Vigo and Ria de Aldan coast (NW Spain). Mar. Biol. 159, 1997–2013.
Casal, G., Kutser, T., Dominguez-Gomez, J.A., Sanchez-Carnero, N., Freire, J., 2013. Assessment of the hyperspectral sensor CASI-2 for macroalgal discrimination on the Ria de Vigo coast (NW Spain) using field spectroscopy and modelled spectral libraries. Cont. Shelf Res. 55, 129–140.
Cavanaugh, K., Siegel, D.A., Kinlan, B., Reed, D.C., 2010a. Scaling giant kelp field measurements to regional scales using satellite observations. Mar. Ecol. Prog. Ser. 403, 13–27.
Cavanaugh, K., Siegel, D.A., Kinlan, B., Reed, D.C., 2010b. Scaling giant kelp field measurements to regional scales using satellite observations. Mar. Ecol. Prog. Ser. 403, 13–27.
Chennu, A., Färber, P., Volkenborn, N., Al-Najjar, M.A.A., Janssen, F., de Beer, D., Polerecky, L., 2013. Hyperspectral imaging of the microscale distribution and dynamics of microphytobenthos in intertidal sediments. Limnol. Oceanogr. Methods 11,

511–528.
Chennu, A., Färber, P., De'ath, G., de Beer, D., Fabricius, K.E.A., 2017. Diver-operated hyperspectral imaging and topographic surveying system for automated mapping of benthic habitats. Nat. Sci. Rep. 7122.
Cho, H.J., Ogashawara, I., Mishra, D., White, J., 2014. valuating Hyperspectral Imager for the Coastal Ocean (HICO) data for seagrass mapping in Indian River Lagoon, FL. GIScience & Remote Sensing 51, 120–138.
Ciraolo, G., Cox, E., La Loggia, G., Maltese, A., 2006. The classification of submerged vegetation using hyperspectral MIVIS data. Ann. Geophys. (1), 49.
Clark, C.D., Ripley, H.T., Green, E.P., Edwards, A.J., Mumby, P.J., 1997. Mapping and measurement of tropical coastal environments with hyperspectral and high spatial resolution data. Int. J. Remote Sens. 18, 237–242.
Clark, C.D., Mumby, P.J., Chisholm, J.R.M., Jaubert, J., Andrefouet, S., 2000. Spectral discrimination of coral mortality states following a severe bleaching event. Int. J. Remote Sens. 21, 2321–2327.
Conger, C.L., Hochberg, E.J., Fletcher, C.H., Atkinson, M.J., 2006. Decorrelating remote sensing color bands from bathymetry in optically shallow waters. IEEE Trans. Geosci. Remote Sens. 44, 1655–1660.
Costanza, R., dArge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., ONeill, R.V., Paruelo, J., Raskin, R.G., Sutton, P., van den Belt, M., 1997. The value of the world's ecosystem services and natural capital. Nature 387, 253–260.
Davies, C.O., Bowles, J., Leathers, R.A., Korwan, D., Downes, T.V., Snyder, W.A., Rhea, W.J., Chen, W., 2002. Ocean PHILLS hyperspectral imager: design, characterisation and calibration. Opt. Express 10, 210–221.
Decho, A.W., Kawaguchi, T., Allison, M.A., Louchard, E.M., Reid, R.P., Stephens, F.C., Voss, K.J., Wheatcroft, R.A., Taylo, r B.B., 2003. Sediment properties influencing upwelling spectral reflectance signatures: the "biofilm gel effect". Limnol. Oceanogr. 48, 431–443.
Dekker, A., Pinnel, N., 2018. Feasibility Study of an Aquatic Ecosystem Earth Observing System. (CEOS Report, copyright CSIRO, Australia, April 2018).
Dekker, A.G., Brando, V.E., Anstee, J.M., 2005. Retrospective seagrass change detection in a shallow coastal tidal Australian lake. Remote Sens. Environ. 97, 415–433.
Dekker, A.G., Phinn, S.R., Anstee, J., Bissett, P., Brando, V.E., Casey, B., Fearns, P., Hedley, J., Klonowski, W., Lee, Z.P., Lynch, M., 2011. Intercomparison of shallow water bathymetry, hydro-optics, and benthos mapping techniques in Australian and Caribbean coastal environments. Limnol. Oceanogr. Methods 9, 396–425.
Dierssen, H.M., Zimmerman, R.C. Leathers, R.A., Downes, T.V., Davis, C.O (2003) Ocean color remote sensing of seagrass and bathymetry in the Bahamas Banks by high-resolution airborne imagery. Limnol. Oceanogr. 48, 444–455.
Dierssen, H.M., Zimmerman, R.C., Drake, L.A., Burdige, D., 2010. Benthic ecology from space: optics and net primary production in seagrass and benthic algae across the Great Bahama Bank. Mar. Ecol. Prog. Ser. 411, 1–15.
Doak, E., Livisay, J., Lyzenga, D., Ott, J., Polcyn, F., 1980. Evaluation of Water Depth Extraction Techniques Using Landsat and Aircraft Data. Final Report. Defense Mapping Agency, Washington, USA, pp. 1–208.
Done, T., 1992. Phase shifts in coral reef communities and their ecological significance. Hydrobiologia 247, 121–132.
Dörnhöfer, K., Göritz, A., Gege, P., Pflug, B., Oppelt, N., 2016. Water constituents and water depth retrieval from Sentinel-2A—a first evaluation in an oligotrophic lake. Remote Sens. 8 (11), 941.
Dove, S.G., Takabayash,i, M., Hoegh-Guldberg, O., 1995. Isolation and partial characterisation of the pink and blue pigments of Pocilloporid and Acroporid corals. Biol. Bull. 189, 288–297.
Dove, S.G., Hoegh-Guldberg, O., Ranganathan, S., 2001. Major color patterns of reef-building corals are due to a family of GFP-like proteins. Coral Reefs 19, 197–204.
Dumke, I., Purser, A., Macron, Y., Nornes, S.M., Johnsen, G., Ludvigsen, M., 2018a. Underwater hyperspectral imaging as an in situ taxonomic tool for deep-sea megafauna. Nat. Sci. Rep. 8, 12860.
Dumke, I., Nornes, S.M., Purser, A., Marcon, Y., Ludvigsen, M., Ellefmo, S.L., Johnsen, G., Søreide, F., 2018b. First hyperspectral imaging survey of the deep seafloor: high-resolution mapping of manganese nodules. Remote Sens. Environ. 209, 19–30.
Eakin, C.M., Nim, C.J., Brainard, R.E., Aubrecht, C., Elvidge, C., Gledhill, D.K., Muller-Karger, F., Mumby, P.J., Skirving, W.J., Strong, A.E., 2010. Monitoring coral reefs from space. Oceanography 23, 118–133.
El-Askary, H., Abd El-Mawla, S.H., Li, J., El-Hattab, M.M., El-Raey, M., 2014. Change detection of coral reef habitat using Landsat-5 TM, Landsat 7 ETM+ and Landsat 8 OLI data in the Red Sea (Hurghada, Egypt). Int. J. Remote Sens. 35, 2327–2346.
Elvidge, C.D., Dietz, J.B., Berkelmans, R., Andréfouët, S., Skirving, W., Strong, A.E., Tuttle, B.T., 2004. Satellite observation of Keppel Islands (Great Barrier Reef) 2002 coral bleaching using IKONOS data. Coral Reefs 23, 123–132.
Eren, F., Pe'eri, S., Rzhanov, Y., Ward, L., 2018. Bottom characterization by using airborne lidar bathymetry (ALB) waveform features obtained from bottom return residual analysis. Remote Sens. Environ. 206, 260–274.
Fang, L.-S., Liao, C.-W., Liu, M.-C., 1995. Pigment composition in different-colored Scleractinian corals before and during the bleaching process. Zool. Stud. 34, 10–17.
Ferguson, R.L., Wood, L.L., Graham, G.B., 1993. Monitoring spatial change in seagrass habitat with aerial photogra-phy. Photogramm. Eng. Remote. Sens. 59, 1033–1038.
Foo, S.A., Asner, G.P., 2019. Scaling up coral restoration using remote sensing. Front. Mar. Sci. 6, 79.
Foster-Smith, R.L., Davies, J., Sotheran, I., Walton, R., 1998. Is the RoxAnn ground discrimination system a useful tool for remote sensing and mapping of subtidal benthic marine habitats? In: Proceedings of the Canadian Hydrographic Conference: Turning Data into Dollars, Victoria, Canada.
Fritz, C., Schneider, T., Geist, J., 2017. Seasonal variation in spectral response of submerged aquatic macrophytes: A case study at Lake Starnberg (Germany). Water 9, 527. https://doi.org/10.3390/w9070527.
Fritz, C., Kuhwald, K., Schneider, T., Geist, J., Oppelt, N., 2019. Sentinel-2 for mapping the spatio-temporal development of submerged aquatic vegetation at Lake Starnberg (Germany). J. Limnol. https://doi.org/10.4081/jlimnol.2019.1824.
Fyfe, S.K., 2003. Spatial and temporal variation in spectral reflectance: are seagrass species spectrally distinct? Limnol. Oceanogr. 48, 464–479.
Garcia, R.A., McKinna, L.I.W., Hedley, J.D., Fearns, P.R.C.S., 2014a. Improving the optimization solution for a semi-analytical shallow water inversion model in the presence of spectrally correlated noise. Limnol. Oceanogr. Methods 12, 651–669.
Garcia, R.A., Fearns, P.R.C.S., McKinna, L.I.W., 2014b. Detecting trend and seasonal changes in bathymetry derived from HICO imagery: A case study of Shark Bay, Western Australia. Remote Sens. Environ. 147, 186–205.
Garcia, R.A., Hedley, J.D., Tin, H.C., Fearns, P.R.C.S., 2015. Method to analyze the potential of optical remote sensing for benthic habitat mapping. Remote Sens. 7, 1.
Garcia, R.A., Lee, Z.P., Hochberg, E.J., 2018. Hyperspectral shallow water remote sensing with enhanced benthic classifier. Remote Sens. 10, 147.
Gege, P., 2004. The water color simulator WASI: an integrating software tool for analysis and simulation of optical in situ spectra. Comput. Geosci. 30 (5), 523–532.
Gege, P., 2014. WASI-2D: A software tool for regionally optimized analysis of imaging spectrometer data from deep and shallow waters. Comput. Geosci. 62, 208–215.
Ghirardi, N., Bolpagni, R., Bresciani, M., Valerio, G., Pilotti, M., Giardino, C., 2019. Spatiotemporal dynamics of submerged aquatic vegetation in a deep lake from Sentinel-2 data. Water 11 (3), 563 2019.
Giardino, C., Zilioli, E., 2001. Imaging Spectrometry for Submerged Vegetation Mapping in Lake Garda. IGARSS Proceedings, Sydney.
Giardino, C., Bartoli, M., Candiani, G., Bresciani, M., Pellegrini, L., 2007. Recent changes in macrophyte colonisation patterns: an imaging spectrometry-based evaluation of southern Lake Garda (northern Italy). J. Appl. Remote. Sens. 1 (1), 11509.
Giardino, C., Candiani, G., Bresciani, M., Lee, X., Gagliano, S., Pepe, M., 2012. BOMBER: A tool for estimating water quality and bottom properties from remote sensing images. Comput. Geosci. 45, 313–318.
Giardino, G., Brescian, i M., Cazzaniga, I., Schenk, K., Rieger, P., Braga, F., Matta, M., Brando, V.E., 2014. Evaluation of multi-resolution satellite sensors for assessing water quality and bottom depth of Lake Garda. Sensors 14, 24116–24131.
Giardino, C., Bresciani, M., Valentini, E., Gasperini, L., Bolpagn, i R., Brando, V.E., 2015. Airborne hyperspectral data to assess suspended particulate matter and aquatic vegetation in a shallow and turbid lake. Remote Sens. Environ. 157, 48–57.
Giardino, C., Bresciani, M., Fava, F., Matta, E., Brando, V.E., Colombo, R., 2016. Mapping submerged habitats and mangroves of Lampi Island Marine National Park (Myanmar) from in situ and satellite observations. Remote Sens. 8, 2. https://doi.org/10.3390/rs8010002.
Giardino, C., Bartoli, M., 2009. Introduction to the Special issue: "The contribution of remote sensing to the analysis and evaluation of ecological systems at different scales" with a section on AIT-SItE. Rivista Italiana di Telerilevamento 41, 61–63.
Giardino, C., Brando, V.E., Gege, P., Pinnel, N., Hochberg, E., Knaeps, E., Reusen, I., Doerfer, R., Bresciani, M., Braga, F., Foerster, S., Champollion, N., Dekker, A.G., 2019. Imaging Spectrometry of Inland and Coastal Waters: State of the Art, Achievements and Perspectives. Surv. Geophys. 40, 401–429.
González-Rivero, M., Bongaerts, P., Beijbom, O., Pizarro, O., Friedman, A., Rodriguez-Ramirez, A., Upcroft, B., Laffoley, D., Kline, D., Vevers, R., et al., 2014. The Catlin seaview survey—kilometre-scale seascape assessment, and monitoring of coral reef ecosystems. Aquat. Conserv. Mar. Freshwat. Ecosyst. 24, 184–198.
González-Rivero, M., Beijbom, O., Rodriguez-Ramirez, A., Holtrop, T., González-Marrero, Y., Ganase, A., Roelfsema, C., Phinn, S., Hoegh-Guldberg, O., 2016. Scaling up ecological measurements of coral reefs using semi-automated field image collection and analysis. Remote Sens. 8, 30.
Goodman, J.A., Ustin, L., 2002. Underwater spectroscopy: Methods and applications in a coral reef environment. In: Seventh Int. Conf. Remote Sens. Mar. Coast. Environ. Veridian Corp, Arlington, Virginia.
Goodman, J.A., Ustin, S.L., 2007. Classification of benthic composition in a coral reef environment using spectral unmixing. J. Appl. Remote. Sens. 1, 011501.
Green, E.P., Mumby, P.J., Edwards, A.J., Clark, C.D., 1996. A review of remote sensing for the assessment of tropical coastal resources. Coast. Manag. 24, 1–40.
Green, E.P., Mumby, P.J., Edwards, A.J., Clark, C.D., 2000. Remote sensing handbook for tropical coastal management. In: Edwards, A.J. (Ed.), Coastal Management Sourcebooks. 3 UNESCO, Paris (316 pp).
Hamylton, S., 2011. Estimating the coverage of coral reef benthic communities from airborne hyperspectral remote sensing data: multiple discriminant function analysis and linear spectral unmixing. Int. J. Remote Sens. 32, 9673–9690.
Hamylton, S.M., Hedley, J.D., Beaman, R.J., 2015. Derivation of high-resolution bathymetry from multispectral satellite imagery: a comparison of empirical and optimisation methods through geographical error analysis. Remote Sens. 7, 16257–16273.
Hamylton, S.M., Duceb, S., Vila-Concejo, A., Roelfsema, C., Phinn, S.R., Carvalho, R.C., Shaw, E.C., Joyce, K.E., 2017. Estimating regional coral reef calcium carbonate production from remotely sensed seafloor maps. Remote Sens. Environ. 201, 88–98.
Hedley, J.D., 2008. A three-dimensional radiative transfer model for shallow water environments. Opt. Express 16, 21887–21902.
Hedley, J.D., Enríquez, S., 2010. Optical properties of canopies of the tropical seagrass Thalassia testudinum estimated by a three-dimensional radiative transfer model. Limnol. Oceanogr. 55, 1537–1550.
Hedley, J.D., Mumby, P.J., 2002. Biological and remote sensing perspectives of pigmentation in coral reef organisms. Adv. Mar. Biol. 43, 277–317.
Hedley, J.D., Mumby, P.J., 2003. A remote sensing method for resolving depth and subpixel composition of aquatic benthos. Limnol. Oceanogr. 48, 480–488.
Hedley, J.D., Mumby, P.J., Joyce, K.E., Phinn, S.R., 2004. Spectral unmixing of coral reef benthos under ideal conditions. Coral Reefs 23, 60–73.

Hedley, J.D., Harborne, A.R., Mumby, P.J., 2005. Simple and robust removal of sun glint for mapping shallow-water benthos. Int. J. Remote Sens. 26, 2107–2112.

Hedley, J.D., Roelfsema, C., Phinn, S.R., 2009. Efficient radiative transfer model inversion for remote sensing applications. Remote Sens. Environ. 113, 2527–2532.

Hedley, J.D., Roelfsema, C., Phinn, S., 2010. Propagating uncertainty through a shallow water mapping algorithm based on radiative transfer model inversion. In: Proceedings of the Ocean Optics XX Conference, Anchorage, AK, USA.

Hedley, J.D., Roelfsema, C., Koetz, B., Phinn, S., 2012a. Capability of the Sentinel 2 mission for tropical coral reef mapping and coral bleaching detection. Remote Sens. Environ. 120, 145–155.

Hedley, J.D., Roelfsema, C.M., Phinn, S.R., Mumby, P.J., 2012b. Environmental and sensor limitations in optical remote sensing of coral reefs: implications for monitoring and sensor design. Remote Sens. 4, 271–302.

Hedley, J.D., Russell, B., Randolph, K., Dierssen, H., 2016a. A physics-based method for the remote sensing of seagrasses. Remote Sens. Environ. 174, 134–147.

Hedley, J.D., Roelfsema, C.M., Chollett, I., Harborne, A.R., Heron, S.F., Weeks, S., Skirving, W.J., Strong, A.E., Eakin, C.M., Christensen, T.R.L., Ticzon, V., Bejerano, S., Mumby, P.J., 2016b. Remote sensing of coral reefs for monitoring and management: a review. Remote Sens. 8, 118–157.

Hedley, J.D., Russell, B., Randolph, K., Pérez-Castro, M.A., Vásquez-Elizondo, R.M., Enríquez, S., Dierssen, H., 2017. Remote sensing of seagrass leaf area index and species: the capability of a model inversion method assessed by sensitivity analysis and hyperspectral data of Florida bay. Front. Mar. Sci. https://doi.org/10.3389/fmars.2017.00362.

Hedley, J.D., Roelfsema, C., Brando, V., Giardino, C., Kutser, T., Phinn, S., Mumby, P.J., Barrilero, O., Laporte, J., Koetz, B., 2018a. Coral reef applications of Sentinel-2: coverage, characteristics, bathymetry and benthic mapping with comparison to Landsat 8. Remote Sens. Environ. 216, 598–614.

Hedley, J.D., Mirhakak, M., Wentworth, A., Dierssen, H.M., 2018b. Influence of three-dimensional coral structures on hyperspectral benthic reflectance and water-leaving reflectance. Appl. Sci. 8, 2688–2708.

Herkül, K., Kotta, J., Kutser, T., Vahtmäe, E., 2013. Relating remotely sensed optical variability to marine benthic biodiversity. PLoS One 8, e55624.

Hestir, E.L., Brando, V.E., Bresciani, M., Giardino, C., Matta, E., Villa, P., Dekker, A.G., 2015. Measuring freshwater aquatic ecosystems: the need for a hyperspectral global mapping satellite mission. Remote Sens. Environ. 167, 181–195.

Hickman, G.D., Hogg, J.E., 1969. Application of an airborne pulsed laser for near shore bathymetric measurements. Remote Sens. Environ. 1, 47–58.

Hill, V.J., Zimmerman, R.C., Bissett, W.P., Dierssen, H., Kohler, D.D., 2014. Evaluating Light Availability, Seagrass Biomass, and Productivity Using Hyperspectral Airborne Remote Sensing in Saint Joseph's Bay, Florida. Estuaries and Coasts, pp. 1–23.

Hochberg, E.J., Atkinson, M.J., 2000. Spectral discrimination of coral reef benthic communities. Coral Reefs 19, 164–171.

Hochberg, E.J., Atkinson, M.J., 2003. Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. Remote Sens. Environ. 85, 174–189.

Hochberg, E.J., Atkinson, M.J., Andréfouët, S., 2003a. Spectral reflectance of coral reef bottom—types and implications for coral reef remote sensing. Remote Sens. Environ. 85, 159–173.

Hochberg, E.J., Andrefouet, S., Tyler, M.R., 2003b. Sea surface correction of high spatial resolution Ikonos images to improve bottom mapping in near-shore environments. IEEE Trans. Geosci. Remote Sens. 41, 1724–1729.

Hochberg, E.J., Atkinson, M.J., Apprill, A., Andréfouët, S., 2004. Spectral reflectance of coral. Coral Reefs 23, 84–95.

Hoegh-Guldberg, O., Mumby, P.J., Hooten, A.J., Steneck, R.S., Greenfield, P., Gomez, E., et al., 2007. Coral reefs under rapid climate change and ocean acidification. Science 318, 1737–1742.

Hochberg, E., Atkinson, M.J., 2008. Coral reef benthic productivity based on optical absorptance and light-use efficiency. Coral Reefs 27, 49–59.

Holasek, R., Portigal, F., Even, D., Johnson, P., Segava, M., Susner, G., Hill, C., 1998. Coral and substrate mapping in Kaneohe Bay, Oahu, Hawaii using the advanced airborne hyperspectral imaging system (AAHIS). In: Proceedings of the Fifth International Conference on Remote Sensing for Marine and Coastal Environment, San Diego. 2. pp. 72–77.

Holden, H., LeDrew, E., 1997. Spectral discrimination of bleached and healthy submerged corals based on principal components analysis. In: Proceedings of the Fourth International Conference on Remote Sensing for Marine and Coastal Environments, Orlando. 1. pp. 177–186.

Holden, H., LeDrew, E., 1998a. Spectral discrimination of healthy and non-healthy corals based on cluster analysis, principal components analysis and derivative spectroscopy. Remote Sens. Environ. 65, 217–224.

Holden, H., LeDrew, E., 1998b. The scientific issues surrounding remote detection of submerged coral ecosystems. Prog. Phys. Geogr. 22, 190–221.

Holden, H., LeDrew, E., 1999. Hyperspectral identification of coral reef features. Int. J. Remote Sens. 20, 2545–2563.

Holden, H., LeDrew, E., Hock, L., Melsheimer, C., 2000. Hyperspectral versus multispectral imaging for submerged coral detection. In: Proceedings of Sixth International Conference on Remote Sensing for Marine and Coastal Environments, Charleston. 1. pp. 186–193.

Hunter, P.D., Gilvear, D.J., Tyler, A.N., Willby, N.J., Kelly, A., 2010. Mapping macrophytic vegetation in shallow lakes using the compact airborne spectrographic imager (CASI). Aquat. Conserv. Mar. Freshwat. Ecosyst. 20 (7), 717–727.

Immordino, F., Barsanti, M., candigliotta, E., Cocito, S., Delbono, I., Peirano, A., 2019. Application of Sentinel-2 multispectral data for habitat mapping of Pacific islands: Palau Republic (Micronesia, Pacific Ocean). Journal of Marine Science and Engineering 7, 316.

Jagalingam, P., Hedge, A.V., 2017. Estimation of bathymetry along the coast of Mangaluru using Landsat-8 imagery. The International Journal of Ocean and Climate Systems 8 (2), 71–83.

Jay, S., Guillaume, M., 2014. A novel maximum likelihood based method for mapping depth and water quality from hyperspectral remote-sensing data. Remote Sens. Environ. 147, 121–132.

Jay, S., Guillaume, M., Chami, M., Minghelli, A., Deville, Y., Lafrance, B., Serfaty, V., 2018. Predicting minimum uncertainties in the inversion of ocean color geophysical parameters based on Cramer-Rao bounds. Opt. Express 26, A1–A18.

Jobson, D.J., Zingmark, R.G., Katzberg, 1980. Remote sensing of benthic microalgal biomass with a tower-mounted multispectral scanner. Remote Sens. Environ. 9, 351–362.

Johansen, K., Roelfsema, C., Phinn, S., 2008. High spatial resolution remote sensing for environmental monitoring and management. J. Spat. Sci. 53, 43–47.

Joseph, F.K., Jennifer, M.C., Lian, P.R., Keith, C.P., 2015. Theory and applications of object-based image analysis and emerging methods in wetland mapping. In: Remote Sensing of Wetlands. CRC Press, pp. 175–194.

Joyce, K.E., Phinn, S.R., 2002. Bi-directional reflectance of corals. Int. J. Remote Sensing 23, 389–394.

Joyce, K.E., Phinn, S.R., 2003. Hyperspectral analysis of chlorophyll content and photosynthetic capacity of coral reef substrates. Limnol. Oceanogr. 48 (1, part 2), 489–496 2003.

Joyce, K., Phinn, S., Roelfsema, C., Neil, D., Dennison, W., 2002. Mapping the southern Great Barrier Reef using Landsat ETM and the Reef Check classification scheme. In: 11th Australasian Remote Sensing & Photogrammetry Conference. Causal Publications, pp. 239–250.

Joyce, K.E., Phinn, S.R., Roelfsema, C.M., Neil, D.T., Dennison, W.C., 2004. Combining Landsat ETM plus and Reef Check classifications for mapping coral reefs: A critical assessment from the southern Great Barrier Reef, Australia. Coral Reefs 23, 21–25.

Joyce, K.E., Phinn, S.R., Roelfsema, C.M., 2013. Live coral cover index testing and application with hyperspectral airborne image data. Remote Sens. 5, 6116–6137.

Joyce, K.E., Duce, S., Leahy, S.M., Leon, J., Maier, S.W., 2018. Principles and practice of acquiring drone-based image data in marine environments. Marine and Freswater Research 70, 952–963.

Jupiter, S., Roelfsema, C.M., Phinn, S.R., 2013. Science and management. In: Goodman, J.A., Phinn, S.R., Purkis, S. (Eds.), Coral Reef Remote Sensing. Springer, Berlin, Germany, pp. 403–427.

Jupp, D.L.B., Mayo, K.K., 1982. The Physical Basis of Remote Sensing of the Great Barrier Reef by Landsat. Workshop on the Remote Sensing of the Great Barrier Reef. James Cook University, Townsville. Australia.

Jupp, D.L.B., Mayo, K.K., Kuchler, D.A., Heggen, S.J., Kendall, S.W., 1981. Remote sensing by Landsat as as support for management of the Great Barrier Reef. In: Proc. Second Australasian Remote Sensing Conference, Canberra, Australia, (9.5.1-9.5.6).

Jupp, D.L.B., Mayo, K.K., Kuchler, D.A., Classen, D.V.R., 1985. Remote sensing for planning and managing the Great Barrier Reef of Australia. Photogrammetria 40, 21–42.

Jupp, D.L.B., Byrne, G.T., Anstee, J.M., McVicar, T.R., McDonald, E.R., Parkin, D., 1995. The use of CASI spectral data to monitor disturbance in shallow areas of Port Phillip Bay. In: Proceedings of International Symposium on Spectral Sensing Research, Melbourne, (9 p., CD-ROM).

Kerfoot, W.C., Hobmeier, M.M., Green, S.A., Yousef, F., Brooks, C.N., Shuchman, R., ... Reif, M., 2019. Coastal Ecosystem Investigations with LiDAR (Light Detection and Ranging) and Bottom Reflectance: Lake Superior Reef Threatened by Migrating Tailings. Remote Sensing 11 (9), 1076.

Klonowski, W.M., Fearns, P.R.C.S., Lynch, M.J., 2007. Retrieving key benthic cover types and bathymetry from hyperspectral imagery. J. Appl. Remote. Sens. 1, 11505.

Knight, D., LeDrew, E., Holden, H., 1997. Mapping submerged corals in Fiji from remote sensing and in situ measurements: applications for integrated coastal management. Ocean & Coastal Management 34, 153–170.

Knudby, A., Newman, C., Shaghude, Y., Muhando, C., 2010. Simple and effective monitoring of historic changes in nearshore environments using the free archive of Landsat imagery. Int. J. Appl. Earth Obs. Geoinform. 12S, S116–S122.

Knudby, A., Jupiter, S., Roelfsema, C., Lyons, M., Phinn, S., 2013. Mapping coral reef resilience indicators using Field and remotely sensed data. Remote Sens. 5, 1311–1334.

Kokaly, R.F., Clark, R.N., Swayze, G.A., Livo, K.E., Hoefen, T.M., Pearson, N.C., Wise, R.A., Benzel, W.M., Lowers, H.A., Driscoll, R.L., Klein, A.J., 2017. USGS Spectral Library Version 7: U.S. Geological Survey Data Series 1035. 61 p. https://doi.org/10.3133/ds1035.

Kotta, J., Kutser, T., Teeveer, K., Vahtmäe, E., Pärnoja, M., 2013. Predicting species cover of marine macrophyte and invertebrate species combining hyperspectral remote sensing, machine learning and regression techniques. PLoS One 8, e63946.

Kotta, J., Remm, K., Vahtmäe, E., Kutser, T., Orav-Kotta, H., 2014. In-air spectral signatures of the Baltic Sea macrophytes and their statistical separability. J. Appl. Remote. Sens. 8, 083634.

Kovacs, E., Roelfsema, C., Lyons, M., Zhao, S., Phinn, S., 2018. Seagrass habitat mapping: how do Landsat 8 OLI, Sentinel-2, ZY-3A, and Worldview-3 perform? Remote Sensing Letters 9 (7), 686–695.

Kuchler, D.A., 1986a. Reef cover and zonation classification system for use with remotely sensed Great Barrier Reef data. In: Great Barrier Reef Marine Park Authority Technical Memorandum GBRMPA-TM-7.

Kuchler, D.A., 1986b. Geomorphological Nomenclature: Reef Cover and Zonation on the Feat Barrier Reef. Great Barrier Reef Marine Park Authority Technical Memorandum GBRMPA-TM-8.

Kutser, T., 2012. The possibility of using the Landsat image archive for monitoring long time trends in coloured dissolved organic matter concentration in lake waters. Remote Sens. Environ. 123, 334–338.

Kutser, T., Jupp, D.L.B., 2006. On the possibility of mapping living corals to the species level based n their optical signatures. Estuar. Coast. Shelf Sci. 69, 607–614.
Kutser, T., Skirving, W., Parslow, J., Done, T., Clementson, L., Wakeford, M., Miller, I., 2000a. Hyperspectral detection of coral reef health. In: Proceedings of 10th Australasian Remote Sensing Conference, Adelaide. CD-ROM 18 pp.
Kutser, T., Parslow, J., Clementson, L., Skirving, W., Done, T., Wakeford, M., Miller, I., 2000b. Hyperspectral detection of coral reef bottom types. In: Proc. of Ocean Optics XV, Monaco, (13 pp., CD-ROM).
Kutser, T., Dekker, A.G., Skirving, W., 2003. Modelling spectral discrimination of Great Barrier Reef benthic communities by remote sensing instruments. Limnology& Oceanography 48, 497–510.
Kutser, T., Miller, I., Jupp, D.L.B., 2002. MAPPING CORAL REEF BENTHIC HABITAT WITH A HYPERSPECTRAL SPACE BORNE SENSOR. Proceedings of the Ocean Optics XVI, Santa Fe, pp. 1–14.
Kutser, T., Miller, I.R., Jupp, D.L.B., 2006a. Mapping coral reef benthic substrates using hyperspectral space-borne images and spectral libraries. Estuar. Coast. Shelf Sci. 70, 449–460.
Kutser, T., Vahtmäe, E., Martin, G., 2006b. Assessing suitability of multispectral satellites for mapping benthic macroalgal cover in turbid coastal waters by means of model simulations. Estuar. Coast. Shelf Sci. 67, 521–529.
Kutser, T., Vahtmäe, E., Metsamaa, L., 2006c. Spectral library of macroalgae and benthic substrates in Estonian coastal waters. Proceedings of the Estonian Academy of Sciences. Biology.Ecology 55, 329–340.
Kutser, T., Vahtmäe, E., Metsamaa, L., 2006d. Spectral library of macroalgae and benthic substrates in Estonian coastal waters. Proceedings of Estonian Academy of Sciences. Biology Ecology 55, 329–340.
Kutser, T., Vahtmäe, E., Roelfsema, C.M., Metsamaa, L., 2007. Photo-library method for mapping seagrass biomass. Estuar. Coast. Shelf Sci. 75, 559–563.
Kutser, T., Vahtmäe, E., Roelfsema, C., Metsamaa, L., 2009. Mapping seagrass biomass with photo-library method. In: Jones, S., Reinke, K. (Eds.), Innovations in Remote Sensing and Photogrammetry. Springer-Verlag, Berlin, pp. 407–415.
Kutser, T., Vahtmäe, E., Paavel, B., Kauer, T., 2013. Removing glint effects from field radiometry data measured in optically complex coastal and inland waters. Remote Sens. Environ. 133, 85–89.
LeDrew, E., Holden, H., Peddle, D., Morrow, J., Murphy, R., Bour, W., 1995. Towards a procedure for mapping coral stressfrom SPOT imagery with in situ optical correction. In: Proceedings of the 3rd Thematic Conference on Remote Sensing of the Marine Coastal Environment. 1. pp. 211–219.
Lee, Z., Carder, K.L., 2002. Effect of spectral band numbers on the retrieval of water column and bottom properties from ocean color data. Appl. Opt. 41, 2191–2201.
Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G., Patch, J.S., 1998. Hyperspectral remote sensing for shallow waters: 1. A semianalytical model. Appl. Opt. 37, 6329–6338.
Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G., Patch, J.S., 1999. Hyperspectral remote sensing for shallow waters: 2. Deriving bottom depths and water properties by optimization. Appl. Opt. 38, 3831–3843.
Leiper, I.A., Phinn, S.R., Roelfsema, C.M., Joyce, K.E., Dekker, A.G., 2014. Mapping coral reef benthos, substrates, and bathymetry, using compact airborne spectrographic imager (CASI) data. Remote Sens. 6, 6423–6445.
Leon, J., Woodroffe, C.D., 2011. Improving the synoptic mapping of coral reef geomorphology using object-based image analysis. Int. J. Geogr. Inf. Sci. 25, 949–969.
Leon, J., Phinn, S.R., Woodroffe, C.D., Hamylton, S., Roelfsema, C.M., Saunders, M., 2012a. Data fusion for mapping coral reef geomorphic zones possibilities and limitations. In: Geographical Object Based Image Analysis Symposium 6–11 May, Rio de Janairo, Brazil.
Leon, J., Phinn, S.R., Woodroffe, C.D., Hamylton, S., Roelfsema, C.M., Saunders, M., 2012b. Data Fusion for Mapping Coral Reef Geomorphic Zones Possibilities and Limitations. Geographical Object Based Image Analysis Symposium 6–11 May, Rio de Janairo , Brazil.
Lesser, M.P., Mobley, C.D., 2007. Bathymetry, water optical properties, and benthic classification of coral reefs using hyperspectral remote sensing imagery. Coral Reefs 26, 819–829.
Li, J., Knapp, D.E., Schill, S.R., Roelfsema, C., Phinn, S., Silman, M., Mascaro, J., Asner, G.P., 2019a. Adaptive bathymetry estimation for shallow coastal waters using Planet Dove satellites. Remote Sens. Environ. 232, 111302. https://doi.org/10.1016/j.rse.2019.111302.
Li, J., Schill, S.R., Knapp, D.E., Asner, G.P., 2019b. Object based mapping of coral reef habitats using Planet Dove satellites. Remote Sens. 11, 1445.
Louchard, E.M., Reid, R.P., Stephens, C.F., Carney, M., 2000. Classification of sediment types and estimation of water depth using spectral libraries. In: Proceedings of Ocean Optics XV, Monaco, CD-ROM.
Louchard, E.M., Reid, R.P., Stephens, F.C., Davis, C.O., Leathers, R.A., Downes, T.V., 2003. Optical remote sensing of benthic habitats and bathymetry in coastal environments at Lee Stocking Island, Bahamas: a comparative spectral classification approach. Limnology & Oceanography 48, 511–521.
Lubin, D., Li, W., Dustan, P., Mazel, C.H., Stamnes, K., 2001. Spectral signatures of coral reefs: features from space. Remote Sens. Environ. 75, 127–137.
Lucke, R.L., Corson, M., McGlothlin, M.R., Butcher, S.D., Wood, D.L., Korwan, D.R., Li, R.R., Snyder, W.A., Davis, C.O., Chen, D.T., 2011. Hyperspectral imager for the Coastal Ocean: instrument description and first images. Appl. Opt. 50, 1501–1516.
Luczkovich, J.J., Wagner, T.W., Michalek, J.L., Stoffle, R.W., 1993. Discrimination of coral reefs, seagrass meadows, and sand bottom types from space: a Dominican Republic case study. Photogramm. Eng. Remote Sens. 59, 385–389.
Lyons, M., Phinn, S., Roelfsema, C., 2011. Integrating Quickbird multi-spectral satellite and field data: mapping bathymetry, seagrass cover, seagrass species and change in Moreton Bay, Australia in 2004 and 2007. Remote Sens. 3, 42–64.
Lyons, M.B., Roelfsema, C.M., Phinn, S.R., 2013. Towards understanding temporal and spatial dynamics of seagrass landscapes using time-series remote sensing. Estuar. Coast. Shelf Sci. 120, 42–53.
Lyons, M., Roelfsema, C.M., Kovacs, E., Samper-Villarreal, J., Saunders, M.I., Maxwell, P., Phinn, S.R., 2015. Rapid monitoring of seagrass biomass using a simple linear modelling approach, in the field and from space. Mar. Ecol. Prog. Ser. 530, 1–14.
Lyons, M., N. Murray, C. Roelfsema, E. Kovacs, R. Borrego, D. Harris, S. R. Phinn, E. Kennedy, G. Asner, J. Li, D. Knapp and Larsen K. (Submitted). Remote sensing as a multiscale, multimodal environmental monitoring system: an example of local to continental scale coral reef habitat mapping. Front. Ecol. Environ.
Lyzenga, D.R., 1978. Passive remote sensing techniques for mapping water depth and bottom features. Appl. Opt. 17, 379–383.
Lyzenga, D.R., 1981. Remote sensing of bottom reflectance and water attenuation parameters in shallow water using aircraft and Landsat data. Int. J. Remote Sens. 2, 71–82.
Macreadie, P.I., Nielsen, D.A., Kelleway, J.J., Atwood, T.B., Seymour, J.R., Petrou, K., Connolly, R.M., Thomson, A.C.G., Trevathan-Tackett, S.M., Ralph, P.J., 2017. Can we manage coastal ecosystems to sequester more blue carbon? Front. Ecol. Environ. 15 (4), 206–213.
Malthus, T., 2017. Bio-optical modelling and remote sensing of aquatic macrophytes. In: Mishra, D.R., Ogashawara, I. (Eds.), Bio-Optival Modelling and Remote Sensing of Inland Waters. Elsevier, Amsterdam, pp. 263–308.
Malthus, T.J.M., George, D.G., 1997. Airborne remote sensing of macrophytes in Cefni Reservoir, Anglesey, UK. Aquat. Bot. 58, 317–332.
Malthus, T., Karpouzli, E., 2003. Integrating field and high spatial resolution satellite-based methods for monitoring shallow submerged aquatic habitats in the Sound of Eriskay, Scotland, UK. Int. J. Remote Sens. 24, 2585–2593.
Maritorena, S., 1996. Remote sensing of water attenuation in coral reefs: a case study in French Polynesia. Int. J. Remote Sens. 17, 155–166.
Maritorena, S., Morel, A., Gentili, B., 1994. Diffuse reflectance of oceanic shallow waters: influence of water depth and bottom albedo. Limnol. Oceanogr. 39, 1689–1703.
Matta, E., Aiello, M., Bresciani, M., Gianinetto, M., Muscanti, M., Giardino, C., 2014. Mapping Posidonia Meadow from High Spatial Resolution Images in the Gulf of Oristano (Italy). IEEEXplorehttps://doi.org/10.1109/IGARSS.2014.6947658.
Mazel, C.H., 1995. Spectral measurements of fluorescence emission in Caribbean Cnidarians. Mar. Ecol. Prog. Ser. 120, 185–191.
Mazel, C.H., 1997. Diver-operated instrument for in-situ measurement for spectral fluorescence of benthic marine organisms and substrates. Opt. Eng. 36, 2612–2617.
Mazel, C.H., 2000. Influence of fluorescence on in situ measurements of shallow seafloor reflectance. In: Proceedings of Ocean Optics XV, Monaco (CD-ROM).
Mazel, C.H., Fuchs, E., 2003. Contribution of fluorescence to the spectral signature and perceived color of corals. Limnol. Oceanogr. 48, 390–401.
McKinna, L.I.W., Fearns, P.R.C., Weeks, S.J., Werdell, P.J., Reichstetter, M., Franz, B.A., Shea, D.M., Feldman, G.C., 2015. A semianalytical ocean color inversion algorithm with explicit water column depth and substrate reflectance parameterization. J. Geophys. Res. Oceans 120, 1741–1770.
Minghelli-Roman, A., Chisholm, J.R.M., Marchioretti, M., Jaubert, J.M., 2002. Discrimination of coral reflectance spectra in the Red Sea. Coral Reefs 21, 307–314.
Mishra, D.R., Narumalani, S., Rundquist, D., Lawson, M., 2005. High-resolution ocean color remote sensing of Benthic habitats: A case study at the Roatan Island, Honduras. IEEE Trans. Geosci. Remote Sens. 43, 1592–1604.
Mishra, D., Narumalani, S., Rundquist, D., Lawson, M., 2006. Benthic habitat mapping in tropical marine environments using QuickBird multispectral data. Photogramm. Eng. Remote. Sens. 72, 1037–1048.
Mishra, M.K., Ganguly, D., Chauhan, P. and Ajai (2014) Estimation of coastal bathymetry using RISAT-1 C-band microwave SAR data. IEEE Geosciences and Remote Sensing Letters, 11, 671–675.
Mobley, C.D., Sundman, L.K., Davis, C., Bowles, J.H., Downes, T.V., Leathers, R.A., Montes, M.J., Bissett, W.P., Kohler, D.D.R., Reid, R.P., et al., 2005. Interpretation of hyperspectral remote-sensing imagery by spectrum matching and look-up tables. Appl. Opt. 44, 3576–3592.
Mobley, C., 1994. Light and water: radiative transfer in natural waters. Academic Press, pp. 592.
Mogstad, A.A., Johnsen, G., Ludvigsen, M., 2019. Shallow-Water Habitat Mapping using Underwater Hyperspectral Imaging from an Unmanned Surface Vehicle: A Pilot Study. Remote Sens. 11, 685.
Morel, Y., 1996. A coral reef lagoon as seen by SPOT. In: Proceedings of the 8th Australasian Remote Sensing Conference, Canberra, pp. 51–62.
Mouroulis, P., Van Gorp, B., Green, R.O., Dierssen, H., Wilson, D.W., Eastwood, M., Loya, F., 2014. Portable remote imaging spectrometer coastal ocean sensor: design, characteristics, and first flight results. Appl. Opt. 53 (7), 1363–1380.
Mouw, C.B., Greb, S., Aurin, D., DiGiacomo, P.M., Lee, Z., Twardowski, M., Binding, C., Hu, C.M., Ma, R.H., Moore, T., Moses, W., Craig, S.E., 2015. Aquatic color radiometry remote sensing of coastal and inland waters: challenges and recommendations for future satellite missions. Remote Sens. Environ. 160, 15–30.
Muller-Karger, F.E., Hestir, E., Ade, C., Turpie, K., Roberts, D.A., Siegel, D., Miller, R.J., Humm, D., Izenberg, N., Keller, M., 2018. Satellite sensor requirements for monitoring essential biodiversity variables of coastal ecosystems. Ecol. Appl. 28, 749–760.
Mumby, P.J., Edwards, A.J., 2002. Mapping marine environments with IKONOS imagery: enhanced spatial resolution can deliver greater thematic accuracy. Remote Sens. Environ. 82, 248–257.
Mumby, P.J., Harborne, A.R., 1999b. Development of a systematic classification scheme of marine habitats to facilitate regional management and mapping of Caribbean coral reefs. Biol. Conserv. 88, 155–163 (A bird's-eye view of the health of coral reefs. Nature 413, 36).
Mumby, P.J., Baker, M.A., Raines, P.S., Ridley, J.M., Phillips, A.T., 1994. The potential of

SPOT panchromativ imagery as a tool for mapping coral reefs. In: Proc. of the Second Thematic Conference on Remote Sensing for Marine and Coastal Environments. New Orleans, USA.
Mumby, P.J., Green, E.P., Edwards, A.J., Clark, C.D., 1997a. Measurement of seagrass standing crop using satellite and digital airborne remote sensing. Mar. Ecol. Prog. Ser. 159, 51–60.
Mumby, P.J., Green, E.P., Edwards, A.J., Clark, C.D., 1997b. Coral reef habitat-mapping: how much detail can remote sensing provide? Mar. Biol. 130, 193–202.
Mumby, P.J., Green, E.P., Clark, C.D., Edwards, A.J., 1998a. Digital analysis of multispectral airborne imagery of coral reefs. Coral Reefs (1), 59–69.
Mumby, P.J., Clark, C.D., Green, E.P., Edwards, A.J., 1998b. Benefits of water column correction and contextual editing for mapping coral reefs. Int. J. Remote Sens. 19, 203–210.
Mumby, P.J., Green, E.P., Edwards, A.J., Clark, C.D., 1999a. The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. J. Environ. Manag. 55, 157–166.
Mumby, P.J., Chisholm, J.R.M., Clark, C.D., Hedley, J.D., Jaubert, J., 2001. A bird's-eye view of the health of coral reefs. Nature 413, 36.
Mumby, P.J., Hedley, J.D., Chisholm, J.R.M., Clark, C.D., Ripley, H., Jaubert, J., 2004a. The cover of living and dead corals from airborne remote sensing. Coral Reefs 23, 171–183.
Mumby, P.J., Skirving, W., Strong, A.E., Hardy, J.T., LeDrew, E.F., Hochberg, E.J., Stumpf, R.P., David, L.T., 2004b. Remote sensing of coral reefs and their physical environment. Mar. Pollut. Bull. 48, 219–228.
Myers, M.-R., Hardy, J.T., Mazel, C.H., Dustan, P., 1999. Optical spectra and pigmentation of Caribbean reef corals and macroalgae. Coral Reefs 18, 179–186.
Nordman, M.E., Wood, L., Michalek, J.L., Christy, J., 1990. Water depth extraction from Landsat-5 imagery. In: Proceedings of the 23rd International Symposium on Remote Sensing of the Environment, pp. 1129–1139.
Olmanson, L.G., Bauer, M.E., Brezonik, P.L., 2008. A 20-year Landsat water clarity census of Minnesota's 10 000 lakes. Remote Sens. Environ. 112, 4086–4097.
Palandro, D.A., Andréfouët, S., Hu, C., Hallock, P., Muller-Karger, F., Dustan, P., Callahan, M.K., Kranenburg, C., Beaver, C.R., 2008. Quantification of two decades of shallow-water coral reef habitat decline in the Florida keys National Marine Sanctuary using Landsat data (1984–2002). Remote Sens. Environ. 112, 3388–3399.
Palmer, S., Kutser, T., Hunter, P., 2015. Remote sensing of inland waters: challenges, progress and future directions. Remote Sens. Environ. 157, 1–8.
Pandolfi, J.M., Bradbury, R.H., Sala, E., Hughes, T.P., Bjorndal, K.A., Cooke, R.G., McArdle, D., McClenachan, L., Newman, M.J.H., Paredes, G., et al., 2003. Global trajectories of the long-term decline of coral reef ecosystems. Science 301, 955–958.
Parsons, M., Bratanov, D., Gaston, K.J., Gonzalez, F., 2018. UAVs, Hyperspectral remote sensing, and machine learning revolutionizing reef monitoring. Sensors 18, 2026.
Paterson, D.M., Wiltshire, K.H., Miles, A., Blackburn, J., Davidson, I., Yates, M.G., McGrorty, S., Eastwood, J.A., 1998. Microbiological mediation of spectral reflectance from intertidal cohesive sediments. Limnol. Oceanogr. 48, 1207–1221.
Peddle, D.R., LeDrew, E.F., Holden, H.M., 1995. Spectral mixture analysis of coral reef abundance from satellite imagery and in situ ocean spectra, Savusavu Bay, Fiji. In: Proceedings of the 3rd Thematic Conference on Remote Sens-Ing of the Marine Coastal Envirnoment. V. 2. pp. 563–575.
Penuelas, J., Gamon, J., Griffin, K., Field, C., 1993. Assessing community type, plant biomass, pigment composition, and photosynthetic efficiency of aquatic vegetation from spectral reflectance. Rem. Sens. Environ. 46, 110–118.
Petit, T., Bajjouk, T., Mouquet, P., Rochette, S., Vozel, B., Delacourt, C., 2017. Hyperspectral remote sensing of coral reefs by semi-analytical model inversion–comparison of different inversion setups. Remote Sens. Environ. 190, 348–365.
Philpot, W.D., 1988. Bathymetric mapping with passive multi-spectral imagery. Appl. Opt. 28, 1569–1578.
Phinn, S., Scarth, P., Roelfsema, C., Dennison, B., 2001. Approaches for monitoring benthic and water column biophysical properties in Australian coastal environments. In: Proceedings of IGARSS'01, Sydney, Australia. CD-ROM.
Phinn, S.R., Dekker, A.G., Brando, V.E., Roelfsema, C.M., 2005. Mapping water quality and substrate cover in optically complex coastal and reef waters: an integrated approach. Mar. Pollut. Bull. 51, 459–469.
Phinn, S., Roelfsema, C., Dekker, A., Brando, V., Anstee, J., 2008. Mapping seagrass species, cover and biomass in shallow waters: an assessment of satellite multi-spectral and airborne hyper-spectral imaging systems in Moreton Bay (Australia). Remote Sens. Environ. 112, 3413–3425.
Phinn, S.R., Roelfsema, C.M., Stumpf, R., 2010. Remote sensing: discerning the promise from the reality. In: Longstaff, B.J., Carruthers, T.J.B., Dennison, W.C., Lookingbill, T.R., Hawkey, J.M., Thomas, J.E., Wicks, E.C., Woerner, J. (Eds.), Integrating and Applying Science: A Handbook for Effective Coastal Ecosystem Assessment. IAN Press, Cambridge, Maryland.
Phinn, S.R., Roelfsema, C.M., Mumby, P.J., 2012. Multi-scale, object-based image analysis for mapping geomorphic and ecological zones on coral reefs. Int. J. Remote Sens. 33, 3768–3797.
Poursanidis, D., Topouzelis, K., Chrysoulakis, N., 2018. Mapping coastal marine habitats and delineating the deep limits of the Neptune's seagrass meadows using very high resolution Earth observation data. Int. J. Remote Sens. 1–18.
Pratt, P., Carder, K.L., Costello, D.K., 1997. Remote sensing reflectance algorithms developed to correct underwater coral imagery for the effects of optical thickness to assist in benthic classification. In: Proceedings of the Fourth International Conference on Remote Sensing for Marine and Coastal Environment, Orlando. 2. pp. 449–457.
Purkis, S.J., 2005. A "reef-up" approach to classifying coral habitats from IKONOS imagery. IEEE Trans. Geosci. Remote Sens. 43, 1375–1390.
Purkis, S.J., Pasterkamp, R., 2004. Integrating in-situ reef-top reflectance spectra with Landsat TM imagery to aid shallow-tropical benthic habitat mapping. Coral Reefs 23, 5–20.
Purkis, S.J., Kenter, A.M., Oikonomou, E.K., Robinson, I.S., 2002. High-resolution ground verification, cluster analysis and optical model of reef substrate coverage on Landsat TM imagery (Red Sea, Egypt). Int. J. Remote Sens. 23, 1677–1698.
Purkis, S.J., Graham, N.A.J., Riegl, B.M., 2008. Predictability of reef fish diversity and abundance using remote sensing data in Diego Garcia (Chagos Archipelago). Coral Reefs 27, 167–178.
Ralph, P.J., Crosswell, J.R., Cannard, T., Steven, A.D., 2018. Estimating seagrass blue carbon and policy implications: The Australian perspective. In: Seagrasses of Australia. Springer, Cham, pp. 743–758.
Reichstetter, M., Fearns, P.R.C.S., Weeks, S.J., McKinna, L.I.W., Roelfsema, C., Furnas, M., 2015. Bottom reflectance in ocean color satellite remote sensing for coral reef environments. Remote Sens. 7, 16756–16777.
Renga, A., Rufino, G., D'Errico, M., Moccia, A., Boccia, V., Graziano, M.D., ... Zoffoli, S., 2014. SAR bathymetry in the Tyrrhenian Sea by COSMO-SkyMed data: A novel approach. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 7 (7), 2834–2847.
Robinson, J.A., Feldman, G.C., Kuring, N., Franz, B., Green, E., Noordeloos, M., Stumpf, R.P., 2000. Data fusion in coral reef mapping: working at multiple scales with SeaWiFS and astronaut photography. In: Proc. of the Sixth Intl. Conference on Remote Sensing for Marine and Coastal Environments (Charleston, South Carolina, 1-3 May 2000). 2. Veridian ERIM International, Ann Arbor MI, pp. 473–483.
Roelfsema, C., Phinn, S., 2010. Integrating field data with high spatial resolution multispectral satellite imagery for calibration and validation of coral reef benthic community maps. J. Appl. Remote. Sens. 4, 043527. https://doi.org/10.1117/1.3430107.
Roelfsema, C.M., Phinn, S.R., 2012. Spectral Reflectance Library of Selected Biotic and Abiotic Coral Reef Features in Heron Reef. Centre for Remote Sensing & Spatial Information Science, School of Geography, Planning & Environmental Management, University of Queensland, Brisbane, Australia, PANGAEA. https://doi.org/10.1594/PANGAEA.804589.
Roelfsema, C.M., Phinn, S.R., 2013c. Validation. In: Goodman, J., Purkis, S., Phinn, S.R. (Eds.), Coral Reef Remote Sensing: A Guide for Multi-Level Sensing Mapping and Assessment. Springer, Berlin, Germany, pp. 365–375.
Roelfsema, C.M., Phinn, S.R., 2013d. Spectral reflectance library of selected biotic and abiotic coral reef features in Glovers Reef, Belize. In: Biophysical Remote Sensing Group, Centre for Spatial Environmental Research. University of Queensland, Australia. https://doi.org/10.1594/PANGAEA.824861. PANGAEA.
Roelfsema, C.M., Phinn, S.R., 2017a. Spectral Reflectance Library of Healthy and Bleached Corals in the Keppel Islands, Great Barrier Reef. PANGAEAhttps://doi.org/10.1594/PANGAEA.872507.
Roelfsema, C.M., Phinn, S.R., 2017b. Spectral Reflectance Library of Corals and Benthic Features in the Cook Islands (Aitutaki). PANGAEAhttps://doi.org/10.1594/PANGAEA.872505.
Roelfsema, C.M., Phinn, S.R., 2017c. Spectral Reflectance Library of Healthy Corals, Bleached Corals and Other Benthic Features in Fiji. PANGAEAhttps://doi.org/10.1594/PANGAEA.872506.
Roelfsema, C., Dennison, B., Phinn, S., Dekker, A., Brando, V., 2001. Remote sensing of cyanobacterial bloom (Lyngbia majuscula) in Moreton Bay, Australia. In: Proceedings of IGARSS'01. CD-ROM, Sydney, Australia.
Roelfsema, C.M., Dennison, W.C., Phinn, S.R., 2002. Spatial distribution of benthic microalgae on coral reefs deter-mined by remote sensing. Coral Reefs 21, 264–274.
Roelfsema, C.M., Phinn, S.R., Dennison, W.C., Dekker, A.G., Brando, V.E., 2006. Monitoring toxic cyano-bacteria Lyngbya. majuscula in Moreton Bay, Australia by integrating satellite image data and field mapping. Harmful Algae 5 (1), 45–56.
Roelfsema, C.M., Phinn, S.R., Jupiter, S., Comley, J., Albert, S., 2013a. Mapping coral reefs at reef to reef-system scales, (10 s–1000 s km^2) using object-based image analysis. Int. J. Remote Sens. 34, 6367–6388.
Roelfsema, C.M., Kovacs, E., Phinn, S.R., Lyons, M., Saunders, M., Maxwell, P., 2013b. Challenges of remote sensing for quantifying changes in large complex seagrass environments. Estuar. Coast. Shelf Sci. 133, 161–171.
Roelfsema, C.M., Lyons, M., Kovacs, E.M., Maxwell, P., Saunders, M.I., Samper-Villarreal, J., Phinn, S.R., 2014. Multi-temporal mapping of seagrass cover, species and biomass: A semi-automated object based image analysis approach. Remote Sens. Environ. 150, 172–187.
Roelfsema, C., Kovacs, E., Ortiz, J.C., Phinn, S., Mumby, P., Callaghan, D., Ronan, M., Wolf, N., Hamylton, S., Wettle, M., 2018a. Coral reef habitat mapping: a combination of object-based image analysis and ecological modelling. Remote Sens. Environ. 208, 27–41.
Roelfsema, C., Kovacs, E., Roos, P., Terzano, D., Lyons, M., Phinn, S., 2018b. Use of a semi-automated object based analysis to map benthic composition, Heron Reef, Southern Great Barrier Reef. Remote Sensing Letters 9, 324–333.
Roelfsema, C., Kovacs, E., Ortiz, J.C., Phinn, S., Mumby, P.J., Callaghan, D., Ronan, M., Wolf, N., Hamylton, S., Wettle, M., 2018c. Characterise Geomorphic Zonation and Benthic Habitat Type in the Southern Great Barrier Reef (GBR) through Ecological Modelling and Remote Sensing.
Roelfsema, C., Kovacs, E., Ortiz, J.C., Callaghan, D., Hock, K., Mongin, M., Johansen, K., Mumby, P.J., Wettle, M., Ronan, M., Kennedy, E., Phinn, S., 2020. (in press). New Habitat Maps to Enhance Monitoring and Management of the Great Barrier Reef. Coral Reefs.
Rowlands, G.P., Purkis, S.J., Riegl, B.M., 2008. The 2005 coral-bleaching event, Roatan (Honduras): use of pseudo-invariant features (PIFs) in satellite assessments. J. Spat. Sci. 53, 99–112.
Russell, B.J., Dierssen, H.M., 2015. Use of hyperspectral imagery to assess cryptic color matching in Sargassum associated crabs. PLoS One 10 (9), e0136260.
Russell, B.J., Dierssen, H.M., 2018. Color change in the Sargassum crab, Portunus sayi:

response to diel illumination cycle and background albedo. Mar. Biol. 165, 28.
Russell, B.J., Dierssen, H.M., LaJeunesse, T.C., Hoadley, K.D., Warner, M.E., Kemp, D.W., Bateman, T.G., 2015. Spectral reflectance of Palauan reef-building coral with different symbionts in response to elevated temperature. Remote Sens. 8, 164.
Russell, B.J., Dierssen, H.M., LaJeunesse, T.C., Hoadley, K.D., Warner, M.E., Kemp, D.W., Bateman, T.G., 2016. Spectral reflectance of Palauan reef-building coral with different symbionts in response to elevated temperature. Remote Sens. 8, 164.
Salih, A., Larkum, A., Cox, G., Kühl, M., Hoegh-Guldberg, O., 2000. Fluorescent pigments in coral are photoprotective. Nature 408, 850–853.
Samper-Villarrea, L.J., Mumby, P.J., Saunders, M.I., Roelfsema, C., Lovelock, C.E., 2018. Seagrass organic carbon stocks show minimal variation over short time scales in a heterogeneous subtropical seascape. Estuar. Coasts 41, 1732–1743.
Saul, S., Purkis, S., 2015. Semi-automated object-based classification of coral reef habitat using discrete choice models. Remote Sens. 7, 15810.
Schalles, J.F., Rudquist, D.C., Gitelson, A., Keck, J., 2000. Close range, hyperspectral reflectance measurements of healthy Indo-Pacific and Caribbean corals. In: Proceedings of the Sixth International Conference on Remote Sensing for Marine and Coastal Environments, Charleston. 1. pp. 431–440.
Scheffer, M., Szabo, S., Gragnani, A., van Nes, E.H., Rinaldi, S., Kautsky, N., Norberg, J., Roijackers, R.M.M., Franken, R.J.M., 2003. Floating plant dominance as a stable state. Proc. Natl. Acad. Sci. U. S. A. 100, 4040–4045.
Selgrath, J.C., Roelfsema, C., Gergel, S.E., Vincent, A.C.J., 2016. Mapping for coral reef conservation: comparing the value of participatory and remote sensing approaches. Ecosphare 7, e01235.
Shibata, K., 1969. Pigments and UV-absorbing substance in corals and blue-green alga living in the Great Barrier Reef. Plant & Cell Physiology 10, 325–335.
Sima, A.A., Baeck, P., Nuyts, D., elalieux, S., Livens, S., Blommaert, J., Delauré, B., Boonen, M., 2016. Compact hyperspectral imaging system (COSI) for small remotely piloted Aircraft systems (RPAS) – System overview and the first performance evaluation results. In: Proceedings of XXIII ISPRS Congress, Prague, Czech Republic.
Skirving, W., Enríquez, S., Hedley, J.D., Dove, S., Eakin, C.M., Mason, R.A.B., De La Cour, J.L., Liu, G., Hoegh-Guldberg, O., Strong, A.E., Mumby, P.J., Iglesias-Prieto, R., 2018. Remote sensing of coral bleaching using temperature and light: Progress towards an operational algorithm. Remote Sens. 10, 18.
Smith, V.E., Rogers, R.H., Reed, L.E., 1975. Automated mapping and inventory of Great Barrier Reef zonation with Landsat data. In: Ocean 75 Conference Record. Institute of Electrical and Electronics Engineers, Inc, New York.
Soto, I., Andréfouët, S., Hu, C., Müller-Karger, F.E., Wall, C.C., Sheng, J., Hatcher, B.G., 2009. Physical connectivity in the Mesoamerican Barrier Reef System inferred from 9 years of ocean colour observations. Coral Reefs 28, 415–425.
Spitzer, D., Dirks, R.W.J., 1987. Bottom influence on the reflectance of the sea. Int. J. Remote Sens. (3), 279–290.
Stephens, F.C., Louchard, E.M., Brand, L.E., Reid, R.P., 2000. Effects of microalgal communities on radiance reflectance of carbonate sediments in optically shallow marine environments. In: Proceedings of Ocean Optics XV, Monaco (CD-ROM).
Strand, J.A., Weisner, S., 2001. Dynamics of submerged macrophyte populations in response to biomanipulation. Freshw. Biol. 46, 1397–1408.
Stumpf, R.P., Holderied, K., Sinclair, M., 2003. Determination of water depth with high-resolution satellite imagery over variable bottom types. Limnol. Oceanogr. 48, 547–556.
Takabayashi, M., Hoegh-Guldberg, O., 1995. Ecological and physiological differences between two colour morphs of the coral Pocillopora damicornis. Mar. Biol. 123, 705–714.
Tassan, S., 1996. Modified Lyzenga's method for macroalgae detection in water with non-uniform composition. Int. J. Remote Sens. 17, 1601–1607.
Teixeira, L., Hedley, J., Shapiro, A., Barker, K., 2016. Comparison of two independent mapping exercises in the Primeiras and Segundas Archipelago, Mozambique. Remote Sens. 8 (1), 52.
Thompson, D.R., Hochberg, E.J., Asner, G.P., Green, R.O., Knapp, D.E., Gai, B.C., Garcia, R., Gierach, M., Lee, Z.P., Maritorena, S., Fick, R., 2017. Airborne mapping of benthic reflectance spectra with Bayesian linear mixtures. Remote Sens. Environ. 200, 18–30.
Thorhaug, A., Richardson, A.D., Berlyn, G.P., 2007. Spectral reflectance of the seagrasses: Thalassia testudinum, Halodule wrightii, Syringodium filiforme and five marine algae. Int. J. Remote Sens. 28, 1487–1501.
Tonina, D., McKean, J.A., Benjankar, R.M., Wright, C.W., Goode, J.R., Chen, Q.W., Reeder, W.J., Carmichael, R.A., Edmondson, M.R., 2019. Mapping river bathymetries: evaluating topobathymetric LiDAR survey. Earth Surf. Process. Landf. 44, 507–520.
Traganos, D., Reinartz, P., 2018. Mapping Mediterranean seagrasses with Sentinel-2 imagery. Mar. Pollut. Bull. 134, 197–209.
Traganos, D., Aggarwal, B., Poursanidis, D., Topouzelis, K., Chrysoulakis, N., Reinartz, P., 2018. Towards global-scale seagrass mapping and monitoring using Sentinel-2 on Google Earth Engine: the case study of the Aegean and Ionian seas. Remote Sens. 10 (8), 1227.
Uhl, F., Bartsch, I., Oppelt, N., 2016. Submerged Kelp detection with hyperspectral data. Remote Sens. 8, 487.
Ungar, S.G., Pearlman, J.S., Mendenhall, J.A., Reuter, D., 2003. Overview of the Earth Observing One (EO1) mission. IEEE Transactions in Geoscience and Remote Sensing 41, 1149–1159.
Urbański, J.A., Mazur, A., Janas, U., 2010. Object-oriented classification of QuickBird data for mappingseagrass spatial structure. International Journal of Oceanography and Hydrobiology 38 (1), 27–43.
Vahtmäe, E., Kutser, T., 2007. Mapping bottom type and water depth in shallow coastal waters with satellite remote sensing. J. Coast. Res. SI50, 185–189.
Vahtmäe, E., Kutser, T., 2013. Classifying the Baltic Sea shallow water habitats using image-based and spectral library methods. Remote Sens. 5, 2451–2474.
Vahtmäe, E., Kutser, T., 2016. Airborne mapping of shallow water bathymetry in the optically complex waters of the Baltic Sea. J. Appl. Remote. Sens. 10, 025012.
Vahtmäe, E., Kutser, T., Martin, G., Kotta, J., 2006. Feasibility of hyperspectral remote sensing for mapping benthic macroalgal cover in turbid coastal waters. Remote Sens. Environ. 101, 342–351.
Vahtmäe, E., Kutser, T., Kotta, J., Pärnoja, M., 2011. Detecting patterns and changes in a complex benthic environment of the Baltic Sea. J. Appl. Remote. Sens. 5, 53559–1–53559–18.
Vahtmäe, E., Kutser, T., Kotta, J., Pärnoja, M., Möller, T., Lennuk, L., 2012. Mapping Baltic Sea shallow water environments with airborne remote sensing. Oceanology 52, 803–809.
Vahtmäe, E., Kotta, J., Orav-Kotta, H., Kotta, I., Pärnoja, M., Kutser, T., 2018. Predicting macroalgal pigments (chlorophyll a, chlorophyll b, chlorophyll a + b, carotenoids) in various environmental conditions using high-resolution hyperspectral radiometers. Int. J. Remote Sens. 39, 5716–5738.
Vahtmäe, E., Paavel, B., Kutser, T., 2020. How much benthic information can be retrieved with hyperspectral sensor from the optically complex coastal waters? J. Appl. Remote Sens. 14 (1). https://doi.org/10.1117/1.JRS.14.016504.
Villa, P., Bresciani, M., Bolpagni, R., Pinardi, M., Giardino, C., 2015. A rule-based approach for mapping macrophyte communities using multi-temporal aquatic vegetation indices. Remote Sens. Environ. 171, 218–233.
Wahidin, N., Siregar, V.P., Nababan, B., Jaya, I., Wouthuyzen, S., 2015. Object-based image analysis for coral reef benthic habitat mapping with several classification algorithms. Procedia Environ. Sci. 24 (Supplement C), 222–227.
Walker, B.K., Riegl, B., Dodge, R.E., 2008. Mapping coral reef habitats in southeast Florida using a combined technique approach. J. Coast. Res. 5, 1138–1150.
Wang, C.K., Philpot, W.D., 2007. Using airborne bathymetric lidar to detect bottom type variation in shallow waters. Remote Sens. Environ. 106 (1), 123–135.
Wang, L., Liu, H.X., Su, H.B., Wang, J., 2019. Bathymetry retrieval from optical images with spatially distributed support vector machines. GISScience and Remote Sensing 56, 232–337.
Wezernak, C.T., Lyzenga, D.R., 1975-1976. Analysis of *Cladophora* distribution in Lake Ontario using remote sensing. Remote Sens. Environ. 4, 37–38.
Wittlinger, S.K., Zimmerman, R.C., 2000. Hyperspectral remote sensing of subtidal macroalgal assemblages in optically shallow waters. In: Proceedings of Ocean Optics XV, Monaco, CD-ROM.
Xu, J., Zhao, J., Li, F., Wang, L., Song, D., Wen, S., Wang, F., Gao, N., 2016. Object-based image analysis for mapping geomorphic zones of coral reefs in the Xisha Islands, China. Acta Oceanol. Sin. 35 (12), 19–27.
Yamano, H., Tamura, M., 2004. Detection limits of coral reef bleaching by satellite remote sensing: simulation and data analysis. Remote Sens. Environ. 90, 86–103.
Zainal, A.J.M., Dalby, D.H., Robinson, I.S., 1993. Monitoring marine ecological changes on the east coast of Bahrain with Landsat TM. Photogramm. Eng. Remote. Sens. 59, 415–421.
Zavalas, R., Ierodiaconou, D., Ryan, D., Rattray, A., Monk, J., 2014. Habitat classification of temperate marine macroalgal communities using bathymetric LiDAR. Remote Sens. 6 (3), 2154–2175.
Zhang, X., 1998. On the estimation of biomass of submerged vegetation using Landsat thematic mapper (TM) imagery: A case study of the Honghu, PR China. International Journal of Remote Sensing 19 (1), 11–20.
Zhang, C., Selch, D., Xie, Z., Roberts, C., Cooper, H., Chen, G., 2013. Object-based benthic habitat mapping in the Florida keys from hyperspectral imagery. Estuar. Coast. Shelf Sci. 134, 88–97.
Zimmerman, R.C., 2003. A bio-optical model of irradiance distribution and photosynthesis in seagrass canopies. Limnol. Oceanogr. 48, 568–585.
Zimmerman, R.C., Wittlinger, S.K., 2000. Hyperspectral remote sensing of submerged aquatic vegetation in optically shallow waters. In: Proceedings of Ocean Optics XV, Monaco, CD-ROM.