Enhancing benthic habitat mapping: A review of integrating satellite and side scan sonar data for improved classification accuracy

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ABSTRACT Prevalent challenges persist within remote sensing techniques for benthic habitat mapping. While efforts are being made to improve mapping accuracy through combined remote sensing approaches, the synergistic use of satellite and side-scan sonar datasets to address the inherent limitations of spectral discrimination and geometric distortions in each method remains limited. This review focuses on exploring the latent potential inherent in the complementary properties of both datasets. An analysis of articles from the Scopus databases published between 2010 and 2023 has shown that different data inputs with classification techniques influence the accuracy of coral reef community mapping. The integration of acoustically derived data and/or bathymetric data with satellite imagery can influence mapping results to varying degrees. The addition of acoustic hardness to satellite imagery has unfortunately led to inaccuracies. The contribution of slope derived from bathymetry varies with extraction algorithms; the use of more sophisticated algorithms leads to higher accuracy. Research on classification methods shows that object-based approaches produce different results depending on field conditions, which are consistently better than pixel-based methods, for both satellite spectral and side-scan sonar data. This review not only highlights conceptual discoveries, but also provides recommendations for future research: (1) the need for comparative evaluation of classification algorithms to determine the optimal classifier; and (2) side-scan sonar-derived slope as a forcing factor to improve accuracy. It is also expected that the review will provide valuable insights into data and classification decisions regarding the use of satellite imagery and acoustic data in future coral reef community mapping.

KEYWORDS: Coral reef; Satellite imagery; Side scan sonar; Classification; Borneo
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Review Article

INTRODUCTION

Coral reefs are highly productive and dynamic marine ecosystems that provide habitat and shelter for a wide range of species, including fish, invertebrates, and algae. Yet, many coral reefs are rapidly declining in the wake of increasing anthropogenic pressures and global climate change (Alquezar & Boyd, 2007). Coral-bleaching events are no longer constrained to years with extreme El Niño–Southern Oscillation (ENSO) conditions. The increase in intensity and frequency of ocean acidification and rising sea temperature have hampered the resilience of coral reefs against stresses (Hoegh-Guldberg *et al*., 2017). The duration between each thermal stress event to become shorter, to the extent that there is not enough time for coral communities to recover from their previous disturbance event (Hughes *et al*., 2018). Consequentially, coral reefs are confronting the prospect of ecological collapse, with projections suggesting that as much as 70-90% of these reefs could vanish by the year 2050 (Hooidonk *et al*., 2016).

Accurate information about the geographic distribution, abundance, and overall health of tropical marine resources is crucial for effective ecosystem-based management. This can be achieved by establishing reliable baseline data, such as benthic maps (Singh *et al*., 2021), that play a pivotal role in guiding restoration targets and strategic management plans (Hossain *et al*., 2016). Optical and acoustic remote sensing techniques are invaluable for creating continuous mapped representations of benthic habitats at various scales (Costa & Battista, 2013). Both techniques and their associated methods of data collection vary with regard to their spatial, temporal and, in the case of optical sensors, spectral resolution, and these properties will affect the scale and accuracy of the final habitat map (Reshitnyk *et al.*, 2014).

While passive optical sensors have successfully mapped nearshore benthic habitats, they are subject to environmental conditions such as clouds, sun glints, tides and surface roughness that can obscure or mask target features (Bennett *et al.*, 2020). In contrast, acoustic remote sensing technologies are commonly utilized for mapping subtidal habitats located at greater water depths that passive optical sensors may struggle to effectively capture. These acoustic ground-discrimination systems (AGDS) encompass multi-beam sonar (bin Samsudin, 2020), side scan sonar (Mustajap *et al.*, 2015), and single-beam echosounders (SBES) (Reshitnyk *et al.*, 2014). However, it's important to note that acoustic sensors have limitations when it comes to mapping very shallow areas (less than 0.5 meters) or areas with exposed seafloor.

To address the limitations of optical and acoustic sensing, the integration of data from both sources, particularly through combining side-scan sonar and boat-based sonar with satellite data dating as far back as 2005, has demonstrated improved performance in reef habitat mapping (Bejarano *et al.*, 2010; Karpouzli & Malthus, 2007; Riegl & Purkis, 2005). This progress is facilitated by data fusion, a process that combines information collected from diverse sources, including sensors on satellites, aircraft, and ground-based platforms to enhance data quality and interpretation, resulting in high-resolution representations (Zhang, 2010). Accurate mapping of coral benthic habitats is also closely linked to remote sensing image classifications (Burns *et al.*, 2022), which extract valuable information.

The primary aim of this review is to serve as a comprehensive reference for reef researchers and managers, offering insights into the integration of satellite and sonar datasets. It explores the potential of combining optical and acoustic systems for mapping coral reef communities and assesses the effectiveness of classification techniques in enhancing coral reef community mapping.

MATERIALS AND METHODS

This review compiles and compares data on the integration of satellite imagery and sonar data in coral reef community mapping from peer-reviewed studies published between 2010 and 2023. The data was collected by Scopus for indexed articles (research and review articles), conference papers, book chapters and series. Keywords used to search the database included “benthic”, “habitat”, “satellite”, “sonar”, “seafloor”, morphology”, in combination with "integration", “coral”, “seabed”. A total of 131 publications were selected. In addition, relevant papers were cited according to the year of publication.

In the context of mapping or quantifying the extent of coral reefs using remote sensing technologies, this discussion is organized into three sections. The first section introduces the key remote sensing technologies employed in coral mapping, with a primary focus on satellite and acoustic data sources. The second section explores the potential benefits of integrating parameters derived from both acoustic and satellite sources to enhance mapping accuracy. Finally, the third section delves into the optimal classification techniques to achieve the best mapping results when using each technology individually and in combination.

RESULTS AND DISCUSSION

Analysis of Publication Trends, Types, and Geographic Distribution (2010–2023)

The annual distribution of published articles from 2010 to 2023 (Figure 1) shows clear trends: a growth phase from 2016 to 2018, a stabilisation from 2019 to 2021 and a slight decline in 2022–2023. Between 2010 and 2013, the number of publications fluctuated between 2 and 8, with a notable increase in 2012, followed by a slight decline in 2013. From 2014 to 2016, the number remained constant at 6–8, before declining in 2016.

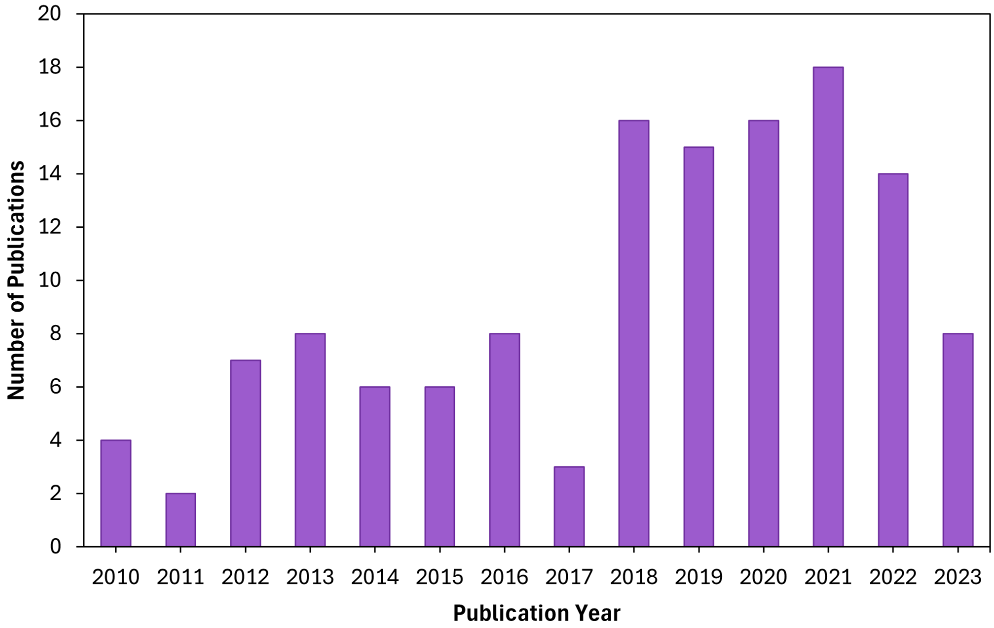

Figure 1. Annual trend of scientific publications (2010–2023).

A strong recovery in 2017 surpassed the 2015 level, reaching 18 articles in 2018, the highest level in this period. From 2019 to 2021, the number of publications stabilised slightly below the 2018 peak, indicating continued productivity. A gradual decline began in 2022, but the publication figures for 2022–2023 remain well above those of 2010–2017, indicating long-term growth. As summarised in Table 1, 79.39% of publications are journal articles, 16.03% are conference proceedings, and the remainder include books (3.05%) and book series (1.53%).

Table 1. Type of publications (2010-2023).

Source type	Number	Percentage
Journal articles	104	79.39%
Conference proceedings	21	16.03%
Book	4	3.05%
Book series	2	1.53%
Total	**131**	**100%**

The 131 publications from 2010–2023 cover various subject areas, all of which were published in English. The leading fields are earth and planetary sciences (79 publications), agricultural and biological sciences (49 publications) and environmental sciences (41 publications), followed by engineering (18 publications) and computer science (13 publications). The remaining publications are spread across multidisciplinary fields, including social sciences, biochemistry, genetics, molecular biology, physics, astronomy, mathematics, materials science, chemistry, decision sciences and energy.

These publications come from 52 countries on all continents (Table 2). The most prolific contributors with more than six publications include the United States (32), Australia (28), Indonesia (14), the United Kingdom (13), France (10), Spain (8), Brazil (7), Germany (7), Malaysia (7) and Italy (6).

Table 2. Number of publications by continent, country, or territory.

Continent (number of publications)	**Country or territory (number of publications (authors))**
Africa (Total 6 publications)	• **Egypt** (3 publications (Abo Elenin *et al.*, 2020; Darweesh *et al.*, 2021; Mohamed *et al.*, 2018)) • **Kenya** (1 publication (McClanahan & Muthiga, 2016)) • **South Africa** (2 publications (Livingstone *et al.*, 2018; Pillay *et al.*, 2021))
Antarctica	• None
Asia (Total 54 publications)	• **China** (5 publications (He *et al.*, 2023; Huang *et al.*, 2022; Ma *et al.*, 2023; Wang *et al.*, 2022; Yang & Yang, 2015)) • **India** (1 publication (Sinner *et al.*, 2023)) • **Indonesia** (14 publications (Agus *et al.*, 2021; Hamidah *et al.*, 2021; Hamsah *et al.*, 2019; Kartikasari *et al.*, 2021; Manessa *et al.*, 2014; Nababan *et al.*, 2021; Nandika *et al.*, 2023; Pramudya *et al.*, 2014; Rozi Nasrul *et al.*, 2021; Setiawan *et al.*, 2022; Solihuddin *et al.*, 2019; Supriyadi *et al.*, 2023; Thalib *et al.*, 2019; Wicaksono, 2016)) • **Iran** (5 publications (Jalali *et al.*, 2018; Kabiri *et al.*, 2020, 2018, 2014, 2013)) • **Israel** (1 publication (van den Bergh *et al.*, 2021)) • **Japan** (5 publications (Manessa *et al.*, 2014; Mohamed *et al.*, 2018; Muslim *et al.*, 2012; Rintoul *et al.*, 2022; Tamondong *et al.*, 2013)) • **Malaysia** (7 publications (Aziz *et al.*, 2014; Grantham *et al.*, 2021; Kabiri *et al.*, 2013; Muslim *et al.*, 2019, 2012; Mustapha *et al.*, 2014; Nababan *et al.*, 2021)) • **Maldives** (1 publication (Andréfouët *et al.*, 2012)) • **Pakistan** (1 publication (Iqbal *et al.*, 2019)) • **Philippines** (5 publications (Foster *et al.*, 2011; Hedley *et al.*, 2016a; Rabi *et al.*, 2015; Sievers *et al.*, 2020; Tamondong *et al.*, 2013)) • **United Arab Emirates** (2 publications (Ben-Romdhane *et al.*, 2016a, 2016b) • **Qatar** (1 publication (Butler *et al.*, 2021)) • **Russian Federation** (1 publication (Priede *et al.*, 2013)) • **Saudi Arabia** (2 publications (Pearman *et al.*, 2018; Roelfsema *et al.*, 2020)) • **Taiwan** (1 publication (Pearman *et al.*, 2018)) • **Viet Nam** (1 publication (Tran *et al.*, 2010)) • **Yemen** (1 publication (Sagheer, 2013))
Europe (Total 69 publications)	• **Belgium** (2 publications (Muller-Karger *et al.*, 2018; Sinner *et al.*, 2023)) • **Bulgaria** (1 publication (Berov *et al.*, 2022)) • **Estonia** (2 publications (Hedley *et al.*, 2018; Kutser *et al.*, 2018)) • **France** (10 publications (Bajjouk *et al.*, 2019; Chami *et al.*, 2019; Collin *et al.*, 2019; Hedley *et al.*, 2018; Le Quilleuc *et al.*, 2022; Minghelli *et al.*, 2021; Nguyen *et al.*, 2021a; Priede *et al.*, 2013; Sinner *et al.*, 2023; van Wynsberge *et al.*, 2012)) • **Germany** (7 publications (Hedley *et al.*, 2016a; Muller-Karger *et al.*, 2018; Roelfsema *et al.*, 2018a, 2020; Solihuddin *et al.*, 2019; Teixeira *et al.*, 2015; Traganos & Reinartz, 2018)) • **Iceland** (1 publication (Priede *et al.*, 2013)) • **Italy** (6 publications (Borfecchia *et al.*, 2019; Collin *et al.*, 2019; Foglini *et al.*, 2018; Hedley *et al.*, 2018; Immordino *et al.*, 2019; Zoffoli *et al.*, 2022)) • **Malta** (1 publication (Micallef *et al.*, 2012))

	• **Netherlands** (4 publications (Kabiri *et al.*, 2013; Muller-Karger *et al.*, 2018; Nandika et al., 2023; Polónia *et al.*, 2015)) • **Norway** (3 publications (Foglini *et al.*, 2018; Priede *et al.*, 2013; Sinner *et al.*, 2023)) • **Poland** (2 publications (Priede *et al.*, 2013; Sokołowski *et al.*, 2021)) • **Portugal** (3 publications (Polónia *et al.*, 2015; Priede *et al.*, 2013; Tempera *et al.*, 2012)) • **Spain** (8 publications (Eugenio *et al.*, 2017; Marcello *et al.*, 2018; Mata *et al.*, 2021; Micallef *et al.*, 2012; Parrish *et al.*, 2022; Rajani *et al.*, 2023, 2023; Serrano *et al.*, 2013; Sinner *et al.*, 2023)) • **Sweden** (4 publications (Berov *et al.*, 2022; McLaren *et al.*, 2019; Sinner *et al.*, 2023; Teixeira *et al.*, 2015)) • **Switzerland** (2 publications (Goodman *et al.*, 2020; Grol *et al.*, 2020)) • **United Kingdom** (13 publications (Collin *et al.*, 2019; Craig *et al.*, 2010; Foster *et al.*, 2011; Hedley *et al.*, 2016a, 2018; Micallef *et al.*, 2012; Piechaud *et al.*, 2015; Priede *et al.*, 2013; Sinner *et al.*, 2023; Szostek *et al.*, 2016; Teixeira *et al.*, 2015; Tempera *et al.*, 2012; Townsend *et al.*, 2018))
Oceania (Total 38 publications)	• **Australia** (28 publications (Collings *et al.*, 2020; Doo *et al.*, 2017; Foster *et al.*, 2011; Goodell *et al.*, 2018; Grantham *et al.*, 2021; Grol *et al.*, 2020; Hamylton *et al.*, 2017; Hedley *et al.*, 2016a, 2018; Jalali *et al.*, 2018; Knudby *et al.*, 2011; Kovacs *et al.*, 2022; Livingstone *et al.*, 2018; Lucieer *et al.*, 2013; Mellin *et al.*, 2012; Muller-Karger *et al.*, 2018; Nguyen *et al.*, 2021a; Piggott *et al.*, 2020; Priede *et al.*, 2013; Purkis & Roelfsema, 2015; Roelfsema *et al.*, 2018a; Roelfsema & Phinn, 2009; Roelfsema *et al.*, 2020, 2021; Sievers *et al.*, 2020; Tran *et al.*, 2010; van Wynsberge *et al.*, 2012; Williamson *et al.*, 2021)) • **Fiji** (2 publications (Knudby *et al.*, 2011; Singh *et al.*, 2021b)) • **French Polynesia** (2 publications (Collin *et al.*, 2019; Le Quilleuc *et al.*, 2022)) • **New Caledonia** (3 publications (Andréfouët *et al.*, 2012; Mellin *et al.*, 2012; van Wynsberge *et al.*, 2012)) • **New Zealand** (3 publications (Burns *et al.*, 2022b; Naidu *et al.*, 2018; Townsend *et al.*, 2018))
North America (Total 45 publications)	• **Bermuda** (1 publication (Zeng *et al.*, 2022b)) • **Canada** (4 publications (Knudby *et al.*, 2011; Mellin *et al.*, 2012; Misiuk & Brown, 2022; Reshitnyk *et al.*, 2014b)) • **Dominica** (1 publication (Steine & Willette, 2010)) • **Jamaica** (1 publication (McLaren *et al.*, 2019)) • **Mexico** (2 publications (Arias-González *et al.*, 2012; Cruz-Vázquez *et al.*, 2019)) • **Panama** (1 publication (Pearman *et al.*, 2018)) • **Puerto Rico** (3 publications (Armstrong, 2016; Rintoul *et al.*, 2022; Sotomayor *et al.*, 2016)) • **United States** (32 publications (Butler *et al.*, 2021; Chirayath *et al.*, 2020; Collings *et al.*, 2020; Foster *et al.*, 2011; Fraiola *et al.*, 2023; Goodell *et al.*, 2018; Goodman *et al.*, 2020; Hamylton *et al.*, 2017; Hatcher *et al.*, 2020; Hedley *et al.*, 2016a; Hernández *et al.*, 2020; Le Quilleuc *et al.*, 2022; A. S. Li *et al.*, 2020; Li *et al.*, 2019; J. Li *et al.*, 2020; Lidz & Zawada, 2013; McClanahan & Muthiga, 2016; Muller-Karger *et al.*, 2018; Naidu *et al.*, 2018; Parrish *et al.*, 2022; Pearman *et al.*, 2018; Priede *et al.*, 2013; Purkis & Roelfsema, 2015; Purkis *et al.*, 2019; Reif *et al.*, 2021; Rintoul *et al.*, 2022; Steine & Willette, 2010; van den Bergh *et al.*, 2021; Wei *et al.*, 2018; Wirt *et al.*, 2013; Zeng *et al.*, 2022b; Zoffoli *et al.*, 2022))

South America (Total 10 publications)	• **Brazil** (7 publications (Araujo *et al*., 2023; Conti *et al*., 2020; De A. Mazzuco *et al*., 2020; de Azevedo Mazzuco & Fraga Bernardino, 2022; de Oliveira *et al*., 2019; Rocha *et al*., 2020; Zoffoli *et al*., 2022)) • **Chile** (1 publication (Grantham *et al*., 2021)) • **Colombia** (1 publication (Mondragón *et al*., 2010)) • **Venezuela** (1 publication (Muller-Karger *et al*., 2018))

Field Surveys vs. Remote Sensing Technologies

Field surveys and remote sensing are the two main methods for assessing coral cover and health (Dung *et al*., 2023). The former method collects data through in-person measurements and direct observation, thus providing accurate information on coral density, species distribution and colony size. However, field surveys require a considerable time and financial burden for monitoring large areas and are unfriendly to remote regions with limited boat access (Foo & Asner, 2019). These problems are addressed with remote sensing with technological advancement.

Remote sensing is the collection of information about the physical characteristics of a region from a distance by detecting the radiation emitted and reflected from it (Gonzalez-Rivero *et al*., 2020). It is cost and time-efficient for large coverage when identifying coral reefs (Komatsu *et al*., 2019) and provides higher accuracy than local environmental knowledge in estimating habitat distributions (Selgrath *et al*., 2016). In the current era, remote sensing is probably the only technology capable of detecting widespread, often subtle changes or spatially and temporally limited, episodic changes in coral reef exposure to anthropogenic stressors (Hedley *et al*., 2016).

Remote sensing can be categorized in several ways, primarily based on the source and type of energy used. Passive remote sensing relies on naturally occurring energy sources like reflected sunlight or radiated heat (Janga *et al*., 2023). In contrast, active sensing technologies generate their own energy and capture the returning signals from a transmission source (Foo & Asner, 2019).

These two broad categories can be further divided into optical and acoustic remote sensing technologies, depending on the type of energy employed. In coral reefs, optical remote sensing harnesses various ranges of electromagnetic radiation. It gathers crucial information by measuring light interactions within the reef ecosystem. Passive optical sensors, found on satellites, aircraft, or drones, collect data about coral reefs and their surroundings. An example of active optical sensing is LiDAR (Light Detection and Ranging), which measures the time and intensity of emitted return laser pulses. LiDAR is particularly useful for bathymetry measurement in non-navigable areas (Szafarczyk & Toś, 2023).

Conversely, acoustic sensors utilize acoustic waves produced by the compression and expansion of water masses. Passive sensors like hydrophones convert underwater sound into electrical signals. For collecting data on depth, seabed topography, geomorphic zones, and general habitat information, active acoustic sensors such as SONAR (Sound Navigation and Ranging) are deployed from ships. SONAR provides measurements in various environments, ranging from shallow waters to depths exceeding 100 meters (Foo & Asner, 2019).

Remote Sensing Technologies for Coral Reef Community Mapping: Sensors and Limitations

Satellite sensors

Among the available remote sensing technologies, satellite-based multispectral technology stands out as the most mature, thoroughly tested, and well-suited for assessing the general distribution of reef geomorphology and benthic cover (Foo & Asner, 2019). Satellite sensors provide datasets of different qualities depending on the aim and scope of the study.

Multispectral and hyperspectral imaging permits the assessment of habitat characteristics in clear water up to 20 m depth (Foo & Asner, 2019). Despite a lack of clarity, satellite hyperspectral sensors for coastal applications typically provide image data in a much wider range of narrow bands, consisting of more than 20 bands with bandwidths of less than 15 nm in the visible wavelength range (Dierssen *et al.*, 2021). Multispectral sensors, on the other hand, produce images in a limited number of bands with no more than 20 or 30 channels (Nguyen *et al.*, 2021). As hyperspectral remote sensing provides more meaningful information about the environment (Dierssen *et al.*, 2021), it is attracting great interest in quantifying spectral signatures, mapping geomorphic zones and detecting periodic shifts in coral reef habitats (Zeng *et al.*, 2022a).

The freely accessible Landsat satellite with 30 m resolution has provided a long-time series archive since its first launch in 1984. Sentinel 2 sensors are a recent development that provides a similar moderate open-source dataset but with a higher spatial resolution of 10 m in some bands (Hedley *et al.*, 2016). These moderate-resolution satellites, with pixel sizes ranging from 10 to 30 meters, can provide cost-effective solutions for mapping extensive reef areas (Foo & Asner, 2019).

However, in recent years, high-resolution satellite data sources like Ikonos, GeoEye, Quickbird, WorldView 2 and 3, and Pleiades, offering resolutions finer than 10 meters, have become increasingly prevalent and are now a popular choice for detailed habitat-level mapping (Hedley *et al.*, 2016). PlanetScope imagery with a 3 m pixel size, freely available for educational and research purposes, has shown promise for monitoring coral patterns as it is available on a daily basis (Nguyen *et al.*, 2021). It has proven to be particularly beneficial for monitoring coral reefs on small islands, providing a solid scientific basis and reliable information for establishing a more detailed ecological monitoring and management system for coral reefs (Dung *et al.*, 2023).

Despite the rapid advancements in remote sensing technologies, there are certain limitations when it comes to using satellite sensors for coral reef mapping. These limitations include factors like variations in water depth, atmospheric conditions, and the distribution of the Sun's radiation, which constrain the achievable signal-to-noise ratios and the choice of light frequencies suitable for multispectral satellite imaging in aquatic environments (Chirayath & Li, 2019).

Furthermore, a challenge arises from the trade-off between high spatial resolution and high spectral resolution in satellite sensors. The key factor impacting spectral resolution, and consequently enhancing benthic mapping, lies in the number of visible bands and the inclusion of infrared bands (Nguyen *et al.*, 2021). Visible light and infrared bands can penetrate the water column, making them the primary sources of data for extracting information from aquatic environments (Li *et al.*, 2022). This includes crucial data on water depth and benthic habitats (Kutser *et al.*, 2020).

Often, sensors that offer excellent spatial resolution lack the necessary spectral resolution, and vice versa. The inability to simultaneously achieve both high spatial and spectral configurations in single imagery hinders their broader application in discriminating habitat communities at a finer level of detail (Zhang, 2015). This challenge is compounded by the attenuation of energy in the water column as depth increases, leading to misclassifications between dominant species with similar absorption spectra for photosynthetic pigments. For example, habitats dominated by algae may be mistakenly identified as habitats dominated by living corals (Wicaksono *et al.*, 2019).

TRANSACTIONS ON SCIENCE AND TECHNOLOGY

To effectively capture the fine-scale details of coral reef characteristics, spatial resolutions finer than what most satellite-based sensors can provide are required (Foo & Asner, 2019). Consequently, the limitations of spectral data have spurred numerous research efforts in the field of acoustic remote sensing. In fact, from 2018 to 2020, the number of publications utilizing acoustic methods for remote sensing exceeded the number of publications focusing on optical satellites for coral mapping in a review study (Nguyen *et al.*, 2021).

Acoustics side scan sonar sensors

Among all, side scan sonar (SSS) is a commonly used acoustic instrument for locating and investigating marine environments in shallow and deep waters, including coral reefs, seagrass beds and rhodoliths (Zhao *et al.*, 2018). Most modern SSS devices operate at two frequencies, allowing them to image the seabed from a multispectral perspective (Fakiris *et al.*, 2019). It provides backscatter images of the seafloor at a much higher resolution, making them ideal for comprehensive habitat mapping using texture analysis. Higher-resolution side scan sonar produces more detailed sonograms. This increased detail manifests in the textural bands of higher frequencies. Hence, the incorporation of additional frequency bands has the potential to enhance class differentiation and boost classification rates even further (Malthus *et al.*, 2009).

Compared to other hydroacoustic devices, a side scan sonar (SSS) can efficiently survey large areas of the seabed. Unlike multibeam echo sounders (MBES), SSS is not limited to a narrow range of beam angles and can collect data from very high scattering angles, making it more suitable for shallow waters (Fakiris *et al.*, 2019). Recent trends show an upswing in the popularity of side scan sonar as the systems become more affordable, portable and practical in shallow water environments, including rivers and coastal areas (Zhao *et al.*, 2017).

Side scan sonar has been combined with a multibeam echo sounder (MBES) in seabed surveying and mapping. This is due to the ability of MBES to directly measure the three-dimensional geometry of the seabed, resulting in the creation of a bathymetric map (Xie *et al.*, 2022), which is an essential element in creating a comprehensive map of seabed habitat. In contrast, side scan sonar, which is used to obtain detailed images of the seabed due to its high resolution and wide coverage, has been criticised for lacking secondary information such as bathymetry and the angular dependence of returning echoes (bin Samsudin, 2020). This prevents SSS from being accurately corrected for radiometric and geometric artefacts and makes it difficult to study the angular dependence of backscatter for habitat discrimination (Fakiris *et al.*, 2019).

However, it's important to note that the intensity data provided by SSS does contain valuable information related to the seabed slope. Extracting this information is crucial (Xie *et al.*, 2022). Researchers have developed techniques, mainly based on Shape from Shading (SFS), to reconstruct the 3D geometry of seabed components and submerged objects from side scan sonar data (Bikonis *et al.*, 2013). In a recent study, (Xie *et al.*, 2022) successfully reconstructed high-resolution bathymetry using side scan sonar data. They achieved this by utilizing a fully convolutional network to predict both the depth contour and its associated aleatory uncertainty.

A key drawback of sonar technology is its limitation in surveying or navigating through extremely shallow waters where boats cannot safely operate. Using these methods to characterize areas like the reef crest or shallow reef flats may either be impossible or, at best, significantly hindered by factors such as tide levels and sea conditions (Hedley *et al.*, 2016). At a wave height of 1.2 m, the quality of the SSS data was adversely impacted due to the increased presence of air bubbles and debris in the water column, to the extent that post-processing was not able to fully compensate for the data noise

(Capperucci *et al.*, 2020).To maintain the sample conditions, they were transported in a container with vibration isolator (Chong, 2012).

Optimized Use of Various Satellite and Sonar-Derived Datasets

This section focuses on quantifying and harnessing the synergies between different datasets from both satellite and acoustic sources to optimize their usage. By combining multiple image data sets with additional environmental information, it becomes possible to create highly accurate benthic maps (see Table 3).

Table 3. Contribution of satellite and acoustics parameters in benthic habitat mapping. The influence of the types of sensors, band inputs, benthic classes, and classification methods on the overall accuracy are included in the table below.

Authors	Sensors	Band Inputs	Benthic classes	Benthic Classes	Classification methods	Overall accuracy
(Wicaksono *et al.*, 2019)	WorldView-2	Deglint bands	14	• Healthy coral • Intermediate coral • Dead coral • *Halophile ovalis* • *Enhalus acoroides* • *Thalassia hemprichii* • *Enhalus acoroides - Thalassia hemprichii* • *Thalassia hemprichii - Cymodocea rotundata* • *Cymodocea rotundata - Halodule uninervis* • Mixed seagrass • Brown algae • Mixed algae • Sand • Rubble	Random Forest (RF)/ Classification Tree Analysis (CTA) / Support Vector Machine (SVM)	88.01%/ 75.58%/ 75.04
	WorldView-2	Deglint-Bathymetry-Slope	14			87.68%/ 75.25%/ 73.99%
	WorldView-2	DII	14			87.85%/ 77.80%/ 75.98%
	WorldView-2	DII-Bathymetry-Slope	14			88.07%/ 76.82%/ 73.25%
	WorldView-2	PC bands	14			87.88%/ 73.28%/ 73.55
	WorldView-2	PC-Bathymetry-Slope	14			88.29%/ 71.84%/ 73.78
	WorldView-2	All dataset	14		RF/ CTA	88.54%/ 77.17%
(Riegl & Purkis, 2005)	IKONOS-QTCView	Optical - Single- beam sonar data	8	• Dense live coral • Dense dead coral • Sparse coral • Seagrass • Shallow algae • Deep algae • Hardground • Sand	Multi-variate-normal probability density function (depth correction of optical layers	69%

					using acoustic z)	
(Karpouzli & Malthus, 2007)	IKONOS	Optical	10	• Sheet corals • Massive and encrusting corals • Dead coral • Green algae • Bedrock & rubble with dense gorgonians • Sand & rubble with some algae • Sand with some algae • Sparse seagrass and algae • Medium density seagrass and algae • Dense seagrass and algae	Distinct Functional Analysis (DFA)	29%
	GeoAcoustics Side scan sonar	Backscatter				34%
	IKONOS-GeoAcoustics Side scan sonar	Optical-Backscatter				52%
(Bejarano *et al.*, 2010)	IKONOS	Optical	4		Unsupervised	56%
	RoxAnn	Acoustic roughness	4		Unsupervised	48%
	RoxAnn	Acoustic hardness	4		Unsupervised	46%
	RoxAnn	Acoustic depth	4		Unsupervised	53%
	RoxAnn	Acoustic roughness, hardness, depth	4		Unsupervised/ Supervised	61%/ 57%
	IKONOS & RoxAnn	Optical and roughness	4	• Unconsolidated *Montastraea* reefs • Consolidated *Montastraea* reefs • Gorgonian plains • Sand patches	Unsupervised/ Supervised	52%/ 54%
	IKONOS & RoxAnn	Optical and hardness	4		Unsupervised/ Supervised	34%/ 50%
	IKONOS & RoxAnn	Optical and depth	4		Unsupervised/ Supervised	54%/ 68%
	IKONOS & RoxAnn	Optical, roughness hardness, depth	4		Unsupervised/ Supervised	59%/ 68%
	IKONOS & RoxAnn	Depth corrected optical	4		Unsupervised/ Supervised	70%/ 60%
	IKONOS & RoxAnn	Depth corrected optical, roughness hardness, depth	4		Unsupervised/ Supervised	70/ 71%

(Zhang *et al.*, 2013)	AVIRIS	MNF transformed hyperspectral image	3	• Hardbottom • Continuous seagrass • Patchy seagrass	RF	80.8%
	National Geophysical Data Centre (NGDC)	MNF transformed hyperspectral image, bathymetry	3	• Hardbottom • Continuous seagrass • Patchy seagrass	RF	87.4%
(Zhang, 2015)	Digital Orthophoto Quarter Quads (DOQQs)	Aerial photography	3	• Hardbottom • Continuous seagrass • Patchy seagrass	RF	63.6%
	AVIRIS, DOQQS, NGDC	Hyperspectral image, aerial photography, bathymetry	3	• Hardbottom • Continuous seagrass • Patchy seagrass	RF	86.3%
	AVIRIS, DOQQS, NGDC	Hyperspectral image, aerial photography, bathymetry	3	• Hardbottom • Continuous seagrass • Patchy seagrass	RF/SVM/k-NN	88.5%/ 82.2%/ 88.5%
	AVIRIS, DOQQS, NGDC	Hyperspectral image, aerial photography, bathymetry	3	• Hardbottom • Continuous seagrass • Patchy seagrass	Ensemble Analysis (RF + SVM + k-NN)	89.6%

Role of bathymetry data

The vertical control of water depth plays a pivotal role in determining the spatial distribution of benthic habitats, primarily because most photosynthetic organisms are limited by depth. Hence, bathymetry is a crucial factor to consider when mapping the spatial distribution of benthic habitats (Wicaksono *et al.*, 2019). Bathymetric maps can be obtained using various methods, including boat-based sonar or echo-sounders, airborne LIDAR systems, or by estimation from optical multispectral or hyperspectral imagery (Hedley *et al.*, 2016).

The integration of bathymetry data and slope – one of the bathymetry derivatives – to enhance benthic habitat mapping has produced contrasting results depending on the type of sensors, bathymetry estimation methods, different input bands and the classification algorithm employed.

In hyperspectral systems alone, the inclusion of bathymetric data does not significantly complement the spectral information from optical imagery to enhance the accuracy of benthic habitat classification (Zhang *et al.*, 2013). However, when aerial photography is added to the same dataset, as observed by (Zhang, 2015), the contribution of bathymetry data becomes statistically significant for the code-level classification of 24 subcategories, but not for the group-level classification, which focuses on broader categories (Eugenio *et al.*, 2015). demonstrated improved benthic habitat classification performance using bathymetry data estimated from WorldView-2. This improvement is likely due to the higher-quality bathymetry obtained through a more complex radiative transfer model (Wicaksono *et al.*, 2019). Similarly, combining bathymetry data from a multibeam echosounder with backscatter data from side scan sonar improves mapping accuracy, increasing it from 21% (SSS BS) to 71% (SSS BS and bathymetry) (Fakiris *et al.*, 2019).

Using the Random Forest (RF) algorithm, (Wicaksono *et al.*, 2019) achieved the highest accuracy, 88.54%, when all deglint, Depth-Invariant Bottom Index (DII) bands, Principal Component Analysis (PCA) bands, bathymetry and slope bands were included in Sentinel 2 imagery for shallow benthic habitat mapping. However, the impact was not significantly pronounced for the incorporation of bathymetry and slope data, with just a slight increment of <1% in accuracy. Interestingly, the inclusion of slope data even led to reduced accuracy when using Classification Tree Analysis (CTA) and Support Vector Machine (SVM) models. These models achieved their highest accuracy—77.80% for CTA and 75.98% for SVM—when only the DII bands were utilized (Wicaksono *et al.*, 2019).

Integration and synergy of satellite and sonar data

To the best of the author's knowledge, the integration of satellite and side scan sonar imagery, despite numerous publications on integration techniques, has been explored in depth by only one study conducted by (Karpouzli & Malthus, 2007), with improvements published in 2009. When IKONOS imagery was combined with side scan sonar imagery for coarse-resolution classification of corals, algae, seagrasses, and bare substrate, the accuracy of benthic coral reef community mapping increased significantly by up to 21% compared to using each sensor individually (Karpouzli & Malthus, 2007).

In other studies, acoustic depth (z) was used to perform water column correction of optical bands for actual depth. (Bejarano *et al.*, 2010) conducted a study to quantify the synergy between optical satellite data (IKONOS) and acoustic (RoxAnn) sensors by calculating the relative contribution of acoustic parameters. A total of eleven layers consisting of six different combinations of acoustic and optical inputs were tested for the accuracy of four benthic classes. When added separately to DII, roughness (E1) and depth (z) had no effect on classification accuracy, but interestingly, acoustic hardness (E2) significantly reduced accuracy. The low E2 contribution is due to the underlying substrate of the coral-dominated ecosystems, which is a carbonate matrix with a fairly homogeneous hardness. Applying supervised classification to depth-corrected optical layers and including E1, E2 and z allowed the greatest improvement in accuracy. Gorgonian plains were easily separated from coral-dominated habitats when either E1 or z were included, but they were acoustically confused with sand patches, resulting in low map accuracy for sand (Bejarano *et al.*, 2010).

Machine Learning Algorithms for Coral Reef Community Classification

Remote sensing image classification is a key process to extract and analyze valuable information (Dhingra & Kumar, 2019) which affects the accuracy of remote sensing special subject information (Zhu *et al.*, 2016). The introduction of machine learning has greatly improved detailed classification for coral reef community mapping (da Silveira *et al.*, 2021). However, as remote sensing circumstances may differ from image to image, a trained algorithm cannot be generalized spatially or temporally to map the benthic composition of the coral reef of a new reef or a new image of a similar reef (Burns *et al.*, 2022).

Machine learning (ML) is a promising empirical technique used for supervised and unsupervised classification and regression of nonlinear systems. They can learn the basic behavior of a system from a set of training data without needing to know the details of the relationships between the data. A large "training data set" of examples is required to cover as much of the system parameter space as possible, and a second random subset of the data must be set aside for fully independent validation. This helps considerably in addressing challenges and problems for which many observations and other data are available but theoretical knowledge is still lacking (Lary *et al.*, 2016), in this case, the coral reef community. Machine learning classifications can be applied to the benthic composition of coral reefs to produce maps of the benthic community using pixel- or object-based image analysis approaches (Burns *et al.*, 2022).

The pixel-based method is a conventional method that has been used for mapping the benthic composition of coral reefs (Wahidin *et al.*, 2015). Pixel-based mapping uses the spectral reflectance characteristics of each pixel to classify it as a benthic component of a benthic assemblage (i.e. corals, algae and sand). This algorithm thus works based on two assumptions. First, each individual pixel must be represented by only one benthic class, where the spatial resolution of the pixel is higher or similar to the target object. Second, the pixels representing each class must have similar spectral reflectance values (Burns *et al.*, 2022).

Although pixel-based image classification can provide results with moderate to high overall accuracy, diverse habitats with high spatial heterogeneity can lead to massing in mixed pixels where one pixel contains members of different benthic groups (Burns *et al.*, 2022). This leads to a "salt-and-pepper effect', where a single pixel is categorized differently from surrounding pixels because information from nearby pixels is not considered in the per-pixel classification (Oktorini *et al.*, 2021). Furthermore, pixel redundancy can occur, i.e. many pixels reflect the same target feature, which is particularly noticeable in high-resolution satellite imagery (< 5 m) (when the spatial resolution is significantly finer than the target objects) (Wicaksono *et al.*, 2019).

Maximum Likelihood Classification (MLC) is the primary pixel-based machine learning technique used for mapping the benthic composition of coral reefs (Burns *et al.*, 2022; Zhang, 2015). Nevertheless, the assumption for a normal distribution of the training dataset as a "requirement" for a good classification is difficult to fulfil in reality, especially with complicated benthic habitat conditions. In satellite imagery, the algorithm has been shown to classify macroalgae in the benthic composition of corals with low overall accuracy (Wicaksono *et al.*, 2019). Likewise, the MLC algorithm consistently produced unsatisfactory results in categorizing coral benthic in acoustic side scan sonar data, with accuracies ranging from 31% to 39% and no regular trends in performance with increasing training size (Ierodiaconou *et al.*, 2011). Thus, the MLC algorithm is used in comparison studies as a control or baseline to determine whether the use of alternative machine learning algorithms improves the accuracy and consistency of the maps produced (Wicaksono *et al.*, 2019).

Several studies have demonstrated significant improvement in the classification results of habitat maps using object-based non-parametric algorithms when multispectral image data is in use (Rusmadi & Hasan, 2020; Zhang, 2015). An object-based classification technique had the ability to increase object segmentation to accommodate fine spatial resolution data (Lu & Weng, 2007) by applying a multi-resolution segmentation algorithm for categorizing pixels to become similar objects into one structure and spectral in one structural, spectral, and additional spatial information like shape, texture, and contextual connection. Nevertheless, this also causes lower classification accuracy due to missing objects when bigger scale is applied (Rusmadi & Hasan, 2020; Wahidin *et al.*, 2015). The scale parameter of OBIA decides the size of the output object and can be difficult to determine because semantically significant regions appear at different scales (Arbiol *et al.*, 2007). Although methods have been developed to determine the ideal scale parameter, in most coral reef benthic mapping work using OBIA, the scale parameter is determined by subjective trial and error (Lyons *et al.*, 2020; Roelfsema *et al.*, 2018).

Object-based SVM, RF and neural networks (NN) are some alternative machine learning algorithms that have shown to be promising at capturing the complex benthic composition and achieving higher accuracy. The classification results vary depending on the existing benthic classes of in-situ conditions (Wicaksono *et al.*, 2019). They have demonstrated the potential to be the best classifier in comparison studies.

SVM uses the model based on maximizing the profit margin and is, therefore, able to produce good results on poor-quality samples without prior estimation of the statistical distribution, even on data with unknown distributions (Eugenio *et al.*, 2015). The accuracy of the classifier often remains constant for satellite imagery, averaging 70% in most published studies (Nguyen *et al.*, 2021). In 2015, SVM was shown to have a higher accuracy of 73% in producing benthic coral habitat maps than Random Tree, Bayesian, k-Nearest Neighbours (k-NN), and Decision Tree (DT) within 7 classes on Landsat 8 OLI satellite imagery (Wahidin *et al.*, 2015). When high-resolution satellite imagery from WorldView-3 is combined with drone imagery, the accuracy of this classifier can reach 93% for 9 different types of benthic habitats (Gray *et al.*, 2018).

Random Forest (RF) is a supervised classification ensemble approach that employs several decision trees and chooses training samples and variables at random. Due to its accurate classification results and fast processing times, especially when using high-dimensional remote sensing data, RF algorithms are increasingly used in remote sensing image classification (Belgiu & Drăgu, 2016), and benthic habitat maps with an overall accuracy of 60% to 85% (Ahmed *et al.*, 2021; Lazuardi *et al.*, 2021; Poursanidis *et al.*, 2021; Wicaksono *et al.*, 2019). The performance between SVM and RF classifiers for shallow water benthic mapping did not show significant difference. RF provides more consistent performance in terms of spatial distribution and similarity to field conditions compared to SVM (Lazuardi *et al.*, 2021; Wicaksono *et al.*, 2019). According to (Zhang, 2015), RF outperforms SVM by not more than 7% for 3 classes group-level classification, SVM produced the same accuracy as the RF classifier in identifying hardbottom and continuous seagrass, but yielded a lower accuracy in discriminating patchy seagrass. Another study by (Wicaksono *et al.*, 2019) reported similar findings, while the overall accuracy of RF (71%) lags slightly behind SVM (73%) for 14 classes classification, misclassification of coral reefs and seagrass near the reef crest was evident in SVM results but not in RF results.

The Artificial Neural Network (ANN) is another supervised classifier trained for multilayer feed-forward networks, which is back-propagation. The back-propagation algorithm simultaneously modifies the network weights to reduce the discrepancy between the targets and the computed outputs. The processing is done in the forward direction, starting from the inputs, passing through the hidden layers and finally the output layers (Hassan-Esfahani *et al.*, 2015). ANN is fault tolerance, infinite data correlation, parallel distributed information processing and a self-learning feature. These attributes facilitate ANN as an improved tool for categorizing remote sensing imagery. It was able to outperform MLC with an overall accuracy of 89.55% in coral reef detection using PlanetScope (Dung *et al.*, 2023).

As for its application to acoustic side scan sonar imagery, (Rusmadi & Hasan, 2020) has demonstrated that SVM was the only moderate classifier that achieved the highest accuracy of 81% among the other five algorithms tested, namely k-Nearest Neighbours (k-NN), Random Forest (RF), Decision Tree and Bayes, with accuracy ranging from 45% to 68%. In another work by (Febriawan, 2020), SVM achieved the best overall accuracy (77%) when mapping riverbed habitats using a linear kernel, but using a Gaussian kernel does not seem to be suitable for the classification, providing only 60% accuracy. Similar to satellite imagery, the study showed that SVM can better handle sparse training sets for side scan sonar data (Febriawan, 2020).

Each image classification method has its own set of strengths and weaknesses when it comes to classifying benthic habitats. It is advisable to use a Support Vector Machine (SVM) when dealing with sparse training datasets, opt for a Random Forest (RF) when the in-situ conditions are dominated by seagrass, or consider employing an ensemble approach that combines different algorithms to harness their complementary strengths in classifying various habitats, as demonstrated by (Zhang, 2015).

FUTURE PROSPECTIVE

Ongoing advances in the field of benthic habitat mapping offer promising opportunities to improve research and applications. The following suggestions, listed in Table 4, highlight key strategies that could drive the next phase of progress in benthic habitat mapping.

Table 4. Prospects and strategies in the field of benthic habitat mapping.

Prospects	Strategies
Integration of multi-source data	• Integrate high-resolution satellite imagery with UAV-based surveys to map benthic habitats, incorporating data from both shallow and deeper marine areas. • Utilize high frequency sonar technologies (e.g. multibeam echosounders) for detailed topographic mapping and better delineation of benthic habitats, including identification of seabed features and habitat types. • Use eDNA sampling techniques to assess biodiversity and habitat conditions at small spatial scales to gain molecular insights into benthic community composition. • Improve GIS-based modelling by incorporating environmental variables (e.g. temperature, salinity, substrate composition) to produce more accurate habitat maps and predict future changes in benthic ecosystems. • Establish regional or global databases that integrate habitat mapping, biodiversity data and human impact assessments to support large-scale conservation and restoration initiatives.
Machine learning and artificial intelligence (AI) for data analysis	• Develop AI algorithms to automate benthic habitat classification from multi-source datasets (e.g. sonar data, satellite imagery and field observations) to reduce the labor-intensive manual classification process and improve data processing efficiency. • Use machine learning to predict habitat distribution based on environmental variables to improve the accuracy of habitat maps and enable more effective conservation planning. • Apply convolutional neural networks (CNNs) to sonar and image data to identify complex benthic features such as coral reefs or underwater vegetation that are difficult to recognize manually.
Real-time mapping	• Use autonomous underwater vehicles (AUVs) for real-time, high-resolution habitat mapping, especially in challenging environments where traditional methods are limited (e.g., deep waters or areas with strong currents). • Use continuous monitoring systems to produce real-time benthic habitat maps to improve decision-making processes in the management and conservation of marine resources.
Collaboration and data sharing	• Increase collaboration between research institutions, government agencies and international organizations to facilitate the sharing of data, resources and methods. Such joint efforts can lead to the development of standardized mapping protocols and improved data consistency between regions.

	• Develop open-access databases or platforms to enable seamless sharing of habitat maps and associated data to support informed policy making, conservation planning and education initiatives. • Involve local communities, stakeholders and citizen scientists in data collection to create comprehensive datasets for large, often remote or under-studied regions. • Involve coastal communities in habitat mapping through participatory mapping approaches to raise awareness and promote more effective conservation measures.

CONCLUSION

Advancements in image processing algorithms present significant opportunities for data fusion across various sensors, enhancing coral reef mapping. The ability to extract bathymetry and slope data from side-scan sonar offers considerable potential for optimizing coral mapping. Effective coral reef community mapping relies on integrating diverse datasets and applying appropriate classification techniques to bridge information gaps with precision. While classifier performance depends on study area and data quality, identifying the most effective classification method remains a challenge, particularly for less-explored integration strategies. Combining sonar and satellite data offers a promising direction for future benthic habitat mapping. Object-based detection and classification outperform pixel-based approaches in both satellite and sonar data. Additionally, utilizing Support Vector Machine (SVM) classifiers for poor-quality or limited datasets, Random Forest (RF) for seagrass-dominated reefs, or ensemble classifiers for diverse habitats can improve mapping accuracy.

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