Outlining a methodological pathway to improve the global seagrass map

Book · January 2022

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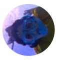

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Photo: Ben Jones

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January 2022

CONTENTS

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Executive summary

Seagrasses are marine flowering plants that inhabit shallow coastal waters globally from the tropics to the Arctic Circle. In the tropics seagrasses often occur as part of an interconnected mosaic of patch types providing shelter and food for diverse species assemblages and many valuable benefits to people. Seagrasses exist in soft sediments that are vulnerable to disturbance from storms and human activities including changes to water quality. It has been estimated that seagrass extent has declined globally since the 1930s and is being lost at a rate of 7% per year. Loss of seagrasses results in a loss of the considerable ecosystem services they provide such as carbon sequestration and storage, fisheries productivity, water filtration and nutrient cycling, protection from erosion and inundation, as well as biocultural importance to many coastal communities.

Seagrass distributions are spatially dynamic at a range of scales and these patterns influence the quality and flow of ecosystem services. Understanding the spatial distribution of seagrasses is critical to the development of conservation planning, the design of restorative actions, monitoring health and mapping ecosystem services. Reliable maps of seagrass extent together with information on seagrass species, biomass and sediments enable basic blue carbon accounting and provide an opportunity for reporting Nationally Determined Contributions (NDCs) under the UN Framework Convention on Climate Change.

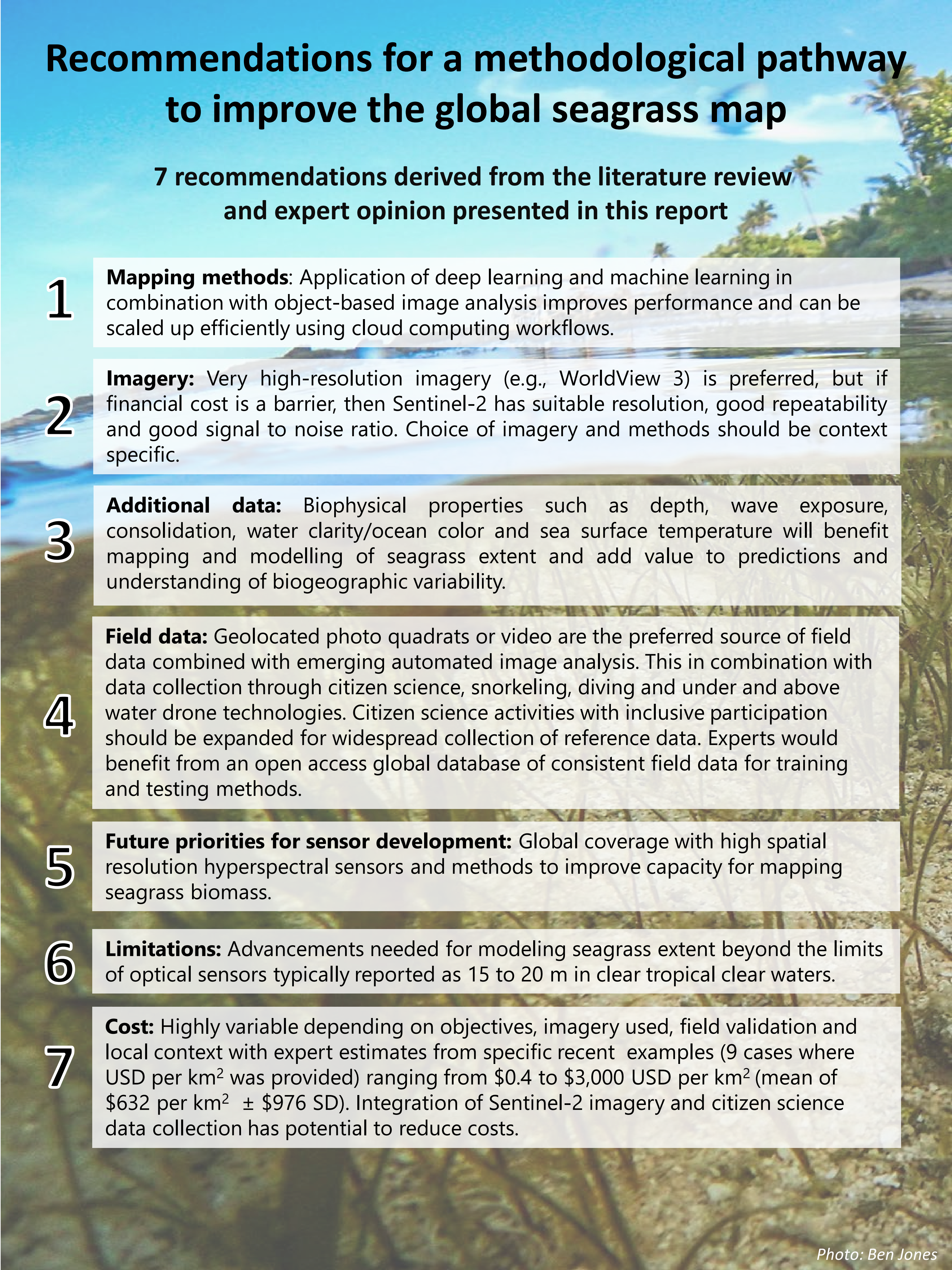
Airborne remote sensing has been used to map seagrass distributions for decades. Since the 1970s, technological advances in satellite-based sensors, data availability and machine learning algorithms have enhanced the capability to map seagrasses at high spatial and temporal resolution. Heightened societal awareness of the role of seagrasses in food security, biodiversity conservation and as ‘blue carbon’ ecosystems to help mitigate accelerated climate change has increased the global efforts to map, quantify and monitor seagrasses.

This synthesis commissioned by The Pew Charitable Trusts aims to document the global state-of-the-science in seagrass mapping through a comprehensive review of expert knowledge and recent literature to identify geographical data gaps, barriers to progress, associated mapping costs and explore potential methodological solutions to accelerate a pathway to improve the global seagrass map.

Primary Research Questions

- Who is mapping seagrasses and how?
- What and where are the data gaps?
- What are the technological solutions, costs and barriers to operationalizing mapping methods at sub-regional, bioregional and global mapping?
- Is there a single accurate, cost effective and standardized mapping method that can be applied to the equatorial region with potential for global application?


Photo: Ben Jones



Recommendations for a methodological pathway to improve the global seagrass map

7 recommendations derived from the literature review and expert opinion presented in this report

1 **Mapping methods**: Application of deep learning and machine learning in combination with object-based image analysis improves performance and can be scaled up efficiently using cloud computing workflows.

2 **Imagery:** Very high-resolution imagery (e.g., WorldView 3) is preferred, but if financial cost is a barrier, then Sentinel-2 has suitable resolution, good repeatability and good signal to noise ratio. Choice of imagery and methods should be context specific.

3 **Additional data:** Biophysical properties such as depth, wave exposure, consolidation, water clarity/ocean color and sea surface temperature will benefit mapping and modelling of seagrass extent and add value to predictions and understanding of biogeographic variability.

4 **Field data:** Geolocated photo quadrats or video are the preferred source of field data combined with emerging automated image analysis. This in combination with data collection through citizen science, snorkeling, diving and under and above water drone technologies. Citizen science activities with inclusive participation should be expanded for widespread collection of reference data. Experts would benefit from an open access global database of consistent field data for training and testing methods.

5 **Future priorities for sensor development:** Global coverage with high spatial resolution hyperspectral sensors and methods to improve capacity for mapping seagrass biomass.

6 **Limitations:** Advancements needed for modeling seagrass extent beyond the limits of optical sensors typically reported as 15 to 20 m in clear tropical clear waters.

7 **Cost:** Highly variable depending on objectives, imagery used, field validation and local context with expert estimates from specific recent examples (9 cases where USD per km^2 was provided) ranging from \$0.4 to \$3,000 USD per km^2 (mean of \$632 per km^2 ± \$976 SD). Integration of Sentinel-2 imagery and citizen science data collection has potential to reduce costs.

Photo: Ben Jones

INTRODUCTION

Project purpose

This project reports on seagrass mapping activities and methodology through a comprehensive global review of expert knowledge and the published literature in the past decade (2012-2021). The aim is to identify geographical data gaps, barriers to progress, associated mapping costs and to evaluate potential solutions for mapping seagrass at a global scale. This targeted information synthesis is intended to improve the understanding of future seagrass mapping needs and identify a rapid, standardized, and cost-effective path forward to address data gaps in equatorial waters with potential for global application.

Background

Considerable global attention is now being focused on coastal ecosystems as places where nature-based solutions can deliver multiple benefits through climate change mitigation and biodiversity conservation including securing coastal protection and crucial food resources for many people (UNEP 2020). Seagrass meadows are a globally distributed and highly productive coastal ecosystem valued for the provisioning of diverse ecosystem services and benefits including carbon storage capacity (i.e., blue carbon).

Although expanding in coverage in some areas, seagrasses globally are declining by an estimated 7% every year due to impacts from human activity and insufficient protection (UNEP 2020). Seagrass distributions exhibit complex spatial dynamics requiring up-to-date information on distribution and condition to underpin effective management decisions and reporting (Unsworth et al. 2019). Mapping the national, regional, and global distributions of seagrass meadows is essential for monitoring status and trends and for the accurate assessment of ecosystem services.

What is Blue Carbon?

Blue carbon is the carbon stored in coastal and marine ecosystems. Seagrasses cover less than 0.2% of ocean floor and sequester and store large quantities of blue carbon in both the plants and the sediment below.

Source: The Blue Carbon Initiative

Reliable maps of seagrass extent together with information on species, density and sediments enable basic blue carbon accounting and provide an opportunity for reporting Nationally Determined Contributions (NDCs) under the UN Framework Convention on Climate Change. Through Pew's Protected Coastal Wetlands and Coral Reefs Project this targeted synthesis project informs policies and actions to address UN Sustainable Development Goals SDG14, Convention on Biological Diversity's post-2020 Biodiversity Framework, UN Framework Convention on Climate Change and many national biodiversity strategies and action plans throughout the global range of seagrass species.

Identifying key knowledge gaps and potential solutions

Major geographical gaps exist in our knowledge of the global seagrass distributions with many seagrass-rich areas remaining data poor or with out-of-date information on seagrass distribution (McKenzie et al. 2020). Methodologies for mapping have been highly variable and often experimental adding uncertainty to estimates of geographical extent.

Global estimates for seagrass extent range between 177,000 to 600,000 km^2 with some models predicting two or more times the extent based on the potential habitat suitability for seagrasses with greatest discrepancy occurring in outside of the equatorial zone (Jayathilake and Costello 2018, McKenzie et al. 2020).

Accurate estimates of seagrass distributions, even in data rich areas, are challenged by data gaps and inconsistencies in methods (McKenzie et al. 2020). Current 'best-available' global maps are an amalgamation of mapping efforts and field observations (i.e., point data) across varying timescales, geographies and methods making them challenging to combine or inappropriate for quantifying geographical extent (Roelfsema and Phinn 2013).

Furthermore, new deep water seagrass meadows are increasingly being discovered. These areas cannot be mapped using optical space-borne sensors and locations are instead being revealed by satellite tracking of seagrass dependent marine herbivores such as green turtles and dugongs (Hays et al. 2018).

Technological evolution

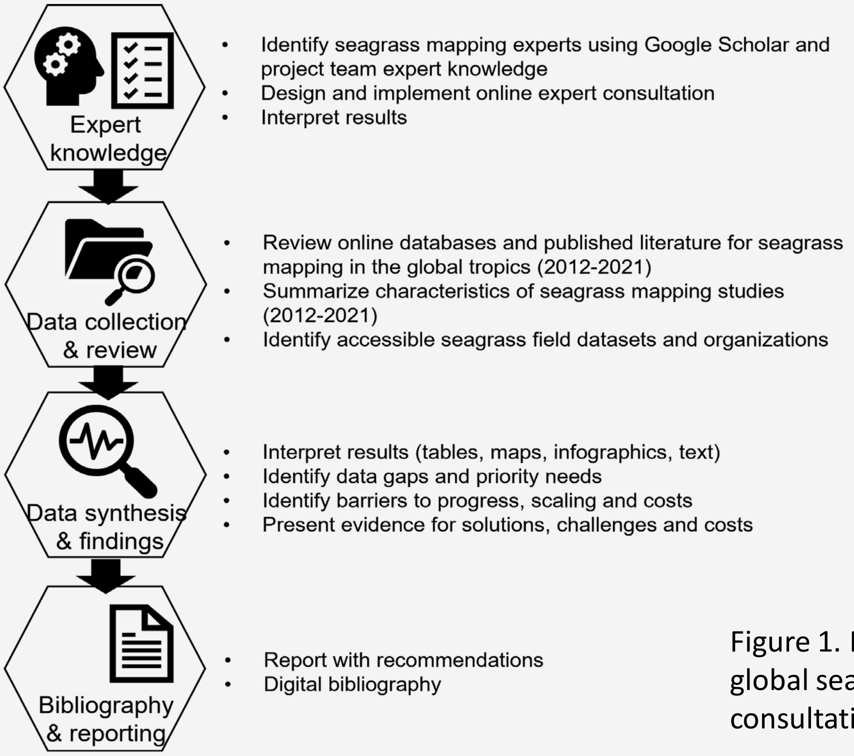
Rapid advances in remote sensing technology, image processing and increased access to imagery now offer the potential to map shallow seagrass globally with standardized high-resolution satellite-based sensors. This capability is being aided by cloud computing, data fusion and sophisticated analytical methods such as machine learning for classifying images and predicting biological distributions.

To inform future strategic decision making, this project conducts a synthesis of recent seagrass mapping studies to characterize the methods used, identify geographical patterns in mapping, reveal data gaps, and document limitations and potential solutions. Integrating evidence from published studies and expert knowledge this project identifies the latest technological advances and derives recommendations that can inform future investments to accelerate global seagrass mapping.

METHODS

Two methods were applied for information gathering: 1) A global literature review focusing on the data gaps and remote sensing methods used in the past decade, and 2) Expert consultation focusing on opinions and recommendations from lived experience and specialist technical knowledge (Figure 1).

- The literature review used a combination of Google, Google Scholar and Scopus to search for recent mapping studies that either targeted seagrass or included seagrass in mapping of shallow water seascapes. This included peer-reviewed publications and technical reports. The focus was on optical remote sensing studies rather than acoustic sensors because of the project interest in exploring the potential for scaling up and accelerating cost-effective methods. Only studies that used imagery from 2012 to 2021 were included to understand how and where progress has been made in the past decade. Metadata was reported from each study to understand what had been mapped, the data and techniques used, and the accuracy of the maps. A separate set of queries was carried out to quantify seagrass area mapped for the Allen Coral Atlas.
- The expert consultation was designed using MS Forms to be accessible on a range of devices and intended to be both comprehensive and time-efficient. The consultation was estimated to take 24 minutes to complete. Experts were identified by their relevant publication record in marine remote sensing and selected to encompass an international scope. 30 experts were invited to participate and 20 (located in 8 countries across 4 continents) completed the consultation. They worked for either universities, governments, non-governmental conservation organizations or private sector consultancies.



- Identify seagrass mapping experts using Google Scholar and project team expert knowledge
- Design and implement online expert consultation
- Interpret results

- Review online databases and published literature for seagrass mapping in the global tropics (2012-2021)
- Summarize characteristics of seagrass mapping studies (2012-2021)
- Identify accessible seagrass field datasets and organizations

- Interpret results (tables, maps, infographics, text)
- Identify data gaps and priority needs
- Identify barriers to progress, scaling and costs
- Present evidence for solutions, challenges and costs

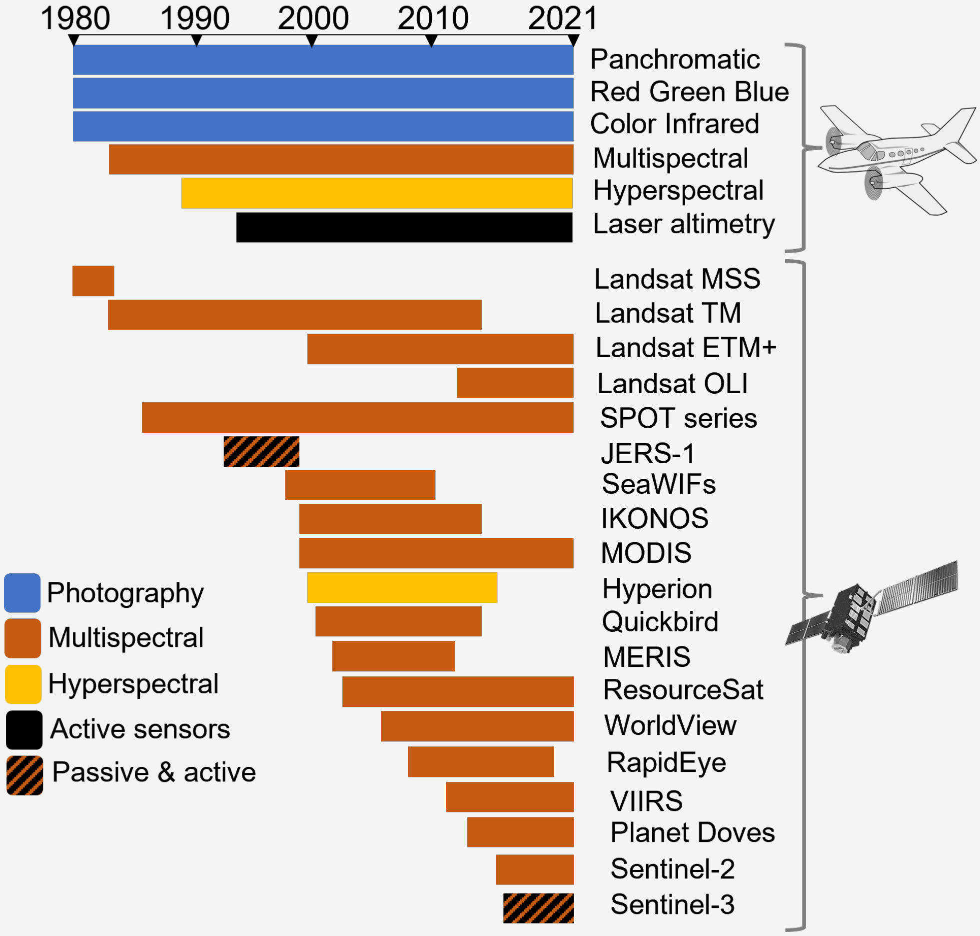
- Report with recommendations
- Digital bibliography

Figure 1. Methods applied for the global seagrass mapping expert consultation and literature review

Optical remote sensing platforms and sensors

This report focuses on map products generated from air and space-borne optical remote sensing for mapping seagrasses at a range of spatial extents and resolutions. Typically, data from passive (reflected light) and occasionally active (e.g., laser altimetry) sensors are applied to map seagrasses. Multispectral data (several discrete spectral bands) is most frequently used with moderate to very high spatial and temporal resolution. Less often, hyperspectral data (continuous spectral bands) are used which requires specialist skills for spectral discrimination. Seagrass mapping with data from multiple sensors is becoming common practice. Acoustic vessel-borne sensors (e.g., side-scan, multibeam sonar) have also been used widely and have capability for mapping seagrass beyond the optical limits of multispectral and hyperspectral sensors but currently have limitations as a rapid and cost-effective solution for scaling up globally.

The chart below shows the operational chronology for many of the platforms and sensors used to map aquatic vegetation including seagrasses over the past 30 years. Information on the spatial, temporal and spectral characteristics of many of these sensors can be found in Hossain et al. (2015).



Operational chronology (1980-2021) for a selection of passive and active optical remote sensors used in aquatic vegetation mapping. Adapted from Rowan & Kalacska 2021.

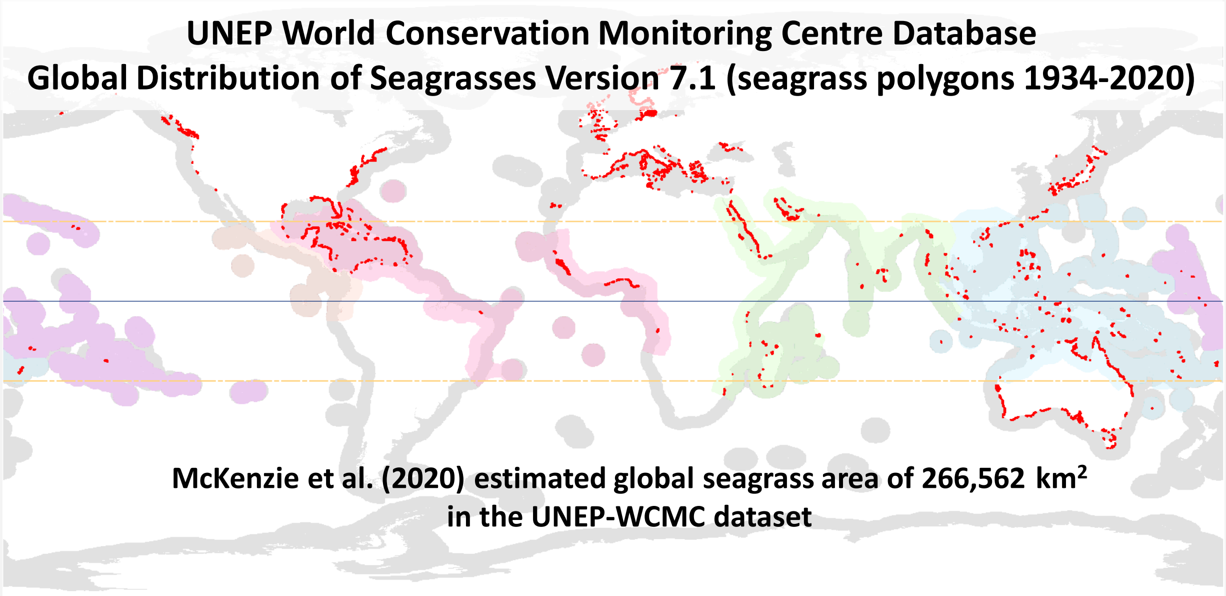

Photo: Ben Jones

Part 1: Global literature review (2012-2021)

Existing global datasets with mapped seagrass distribution

The two largest publicly available global seagrass datasets are: 1.) UNEP World Conservation Monitoring Centre Database (seagrass polygons and points); and 2.) Allen Coral Atlas.

At the time of writing these datasets have not been combined and are independently available as downloadable files with limited metadata and without comprehensive accuracy assessment data. The UNEP-WCMC datasets (UNEP-WCMC & Short 2021) are global in scope (tropical and temperate zones). The data include historical records of seagrass presence (1934 onwards) as point data and mapped and estimated geographical extents as polygons of seagrass with uncertain accuracy and resolution. Seagrass mapping methods were highly variable. McKenzie et al. 2020 scrutinized the UNEP-WCMC database and estimated seagrass area of 266,562 km^2. Other data sources for seagrass presence are the Global Biodiversity Information Facility (GBIF) and the Ocean Biogeographic Information System (OBIS).



UNEP World Conservation Monitoring Centre Database
Global Distribution of Seagrasses Version 7.1 (seagrass polygons 1934-2020)

McKenzie et al. (2020) estimated global seagrass area of 266,562 km^2 in the UNEP-WCMC dataset

Marine realms*

- 🟪 Eastern Indo-Pacific
- 🟧 Tropical Eastern Pacific
- 🟥 Tropical Atlantic
- 🟩 Western Indo-Pacific
- 🟦 Central Indo-Pacific

*Spalding et al. 2007

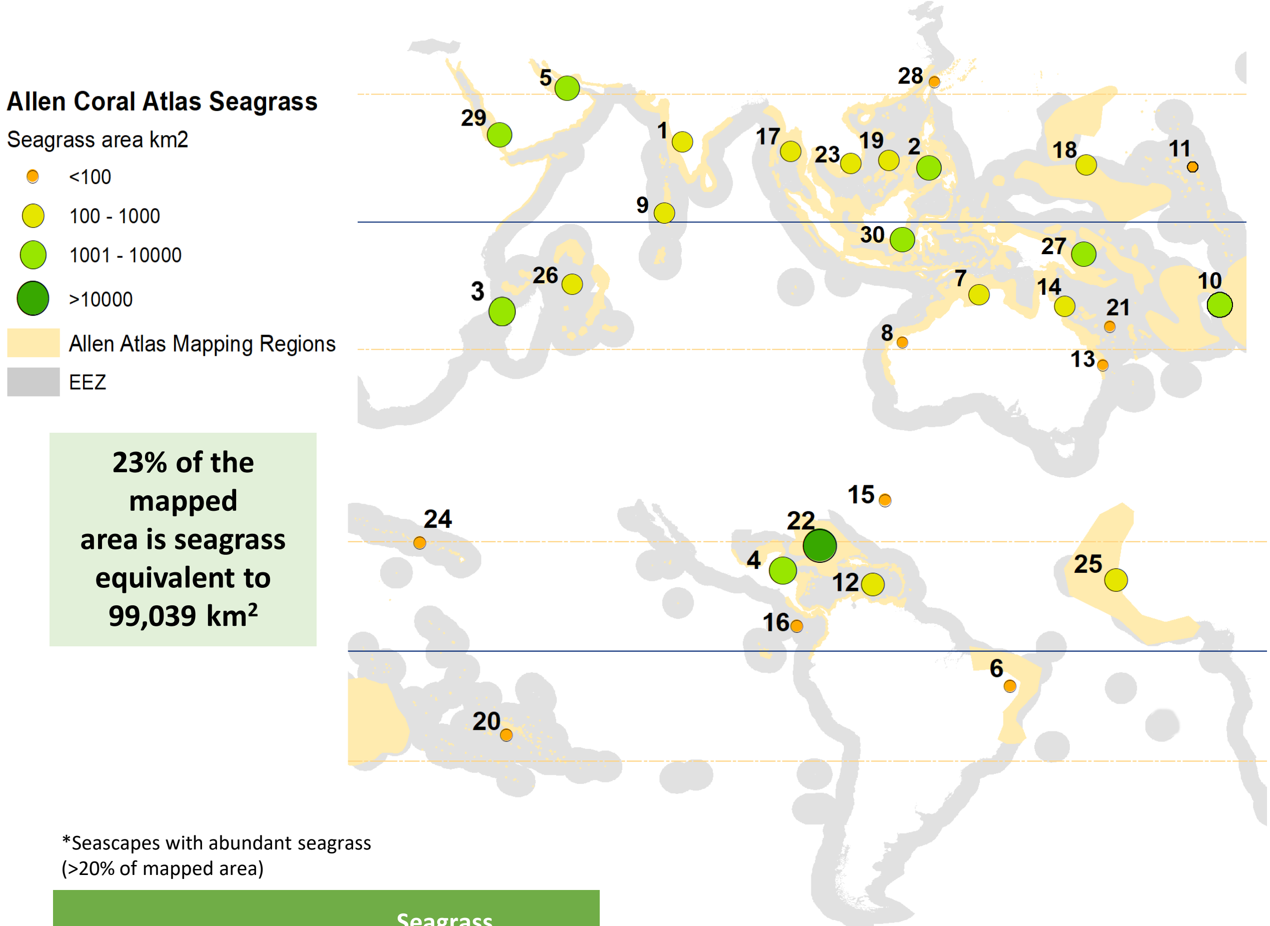
Source: UNEP-WCMC, Short FT (2021). Global distribution of seagrasses (version 7.1). Seventh update to the data layer used in Green and Short (2003). Cambridge (UK): UN Environment World Conservation Monitoring Centre. Data DOI: https://doi.org/10.34892/x6r3-d211

Note: Area of seagrass has been adjusted to be visible on the global map and is not shown to scale

In contrast, the Allen Coral Atlas and partners have mapped seagrass extent using standardized semi-automated workflows applying a single benthic classification scheme (6 classes) at a consistent 5 m resolution in locations where seagrasses are associated with tropical shallow water coral reefs - the primary target of the mapping (Lyons et al. 2020; Roelfsema et al. 2021). The geographical scope focused on equatorial waters that were not obscured by depth and turbidity. The overall map user's accuracy for Allen Coral Atlas is estimated at 78 % with seagrass user's accuracy varying between 49% and 95% (C. Roelfsema, personal communication, October 2021).

Seagrass mapped by the Allen Coral Atlas

Tropical coral reefs often co-exist with seagrasses to form interconnected habitat mosaics supporting high biodiversity and generating diverse ecosystem benefits for people. In the coastal tropics (between 30º north and south of the equator), seagrass was mapped by the Allen Coral Atlas along with coral reefs and multiple other benthic classes. The distribution and extent of mapped seagrass is available via the web-based map application called the Allen Coral Atlas.



23% of the mapped area is seagrass equivalent to 99,039 km²

*Seascapes with abundant seagrass (>20% of mapped area)

Map regions	Seagrass area (km²)	%
1 Southern Asia*	520	23
2 Phillipines	1,346	4
3 Eastern Africa & Madagascar*	5,559	20
4 Mesoamerican*	1,500	25
5 Northwestern Arabian Sea	3,236	16
6 Brazil	4	1
7 Timor & Arafura Seas	547	5
8 Western Australia	396	9
9 Central Indian Ocean	135	3
10 Southwestern Pacific	1,099	5
11 Eastern Micronesia	78	2
12 Southeastern Caribbean	715	18
13 Subtropical Eastern Australia	9	5
14 Great Barrier Reef & Torres Strait	244	1
15 Bermuda	62	12
16 Eastern Tropical Pacific	4	1
17 Andaman Sea	215	3
18 Western Micronesia	150	7
19 South China Sea	181	10
20 Central South Pacific	2	<0.1
21 Coral Sea	0	0
22 Northern Caribbean, Florida & Bahamas*	74,047	41
23 Southeastern Asia	617	11
24 Hawaiian Islands	0	0
25 Western Africa	<0.1	<0.1
26 Western Indian Ocean	451	16
27 Eastern Papua New Guinea & Solomon Islands	1,836	12
28 Northeastern Asia	96	7
29 Red Sea & Gulf of Aden	1,379	9
30 Southeast Asian Archipelago	4,613	13


Photo: Ben Jones

Understanding where and how seagrass has been mapped in the past decade

To gain a comprehensive understanding of the data available, techniques used, and the accuracy of seagrass maps, an extensive global literature search was undertaken to identify remote sensing studies that have mapped tropical seagrass extent.

Online search engines (Google and Google Scholar) and the citation database Scopus were used to identify published studies (peer-reviewed scientific and grey literature) which used satellite imagery acquired between 2012 and 2021 to map seagrass areas located within the equatorial zone.

Search terms used included '*seagrass mapping [insert country]*', *marine habitat map [insert country]*', *coral reef mapping [insert country]*', *seagrass monitoring [insert country]*'. All nations/territories with a marine coastline between the tropics of Cancer and Capricorn were included in the search terms (131 territories).

Marine realms	Number of mapping studies (2012-2021)	Studies with no seagrass extent reported	Total reported seagrass extent mapped (km^2)	Mean (±SD) seagrass area mapped (km^2)
Tropical Atlantic	62	26	90499.6	2513.9 (±10,518.0)
Western Indo-Pacific	35	19	4352.4	272.0 (±351.0)
Central Indo-Pacific	53	20	19622.8	931.2 (±3,691.3)
Eastern Indo-Pacific	1	1	0.0	n/a
Tropical Eastern Pacific	0	0	0.0	n/a
Totals	151	66	114,474.80	

Global literature review: Remote mapping of tropical seagrass extent

2012-2021

- 151 published remote sensing studies mapped seagrass using remote sensing imagery between 2012 and 2021
- These 151 studies were applied within the sovereign waters of 54 nations
- Seagrass mapping in Indonesia yielded the largest number (18) of published studies of any nation followed by Mozambique (7), Australia (6) and Vietnam (5)
- 91 territories/EEZs (60 sovereign nations) in the tropics were found to have no published seagrass mapping using imagery between 2012 and 2021
- The combined mapping efforts of these 151 studies resulted in a total mapped area of 114,474.8 km^2 globally (mean of 2,715.8 (±SD 9,908.0 km^2) between 2012 and 2021
- 44% (66 of 151) of studies did not report the area extent of seagrass mapped
- An additional 99,039.0 km^2 of seagrass has been mapped by the Allen Coral Atlas making a total of 213,101.0 km^2 of seagrass mapped in global equatorial waters between 2012 and 2021
- 50.7% of studies used satellite imagery obtained between 2017 and 2020

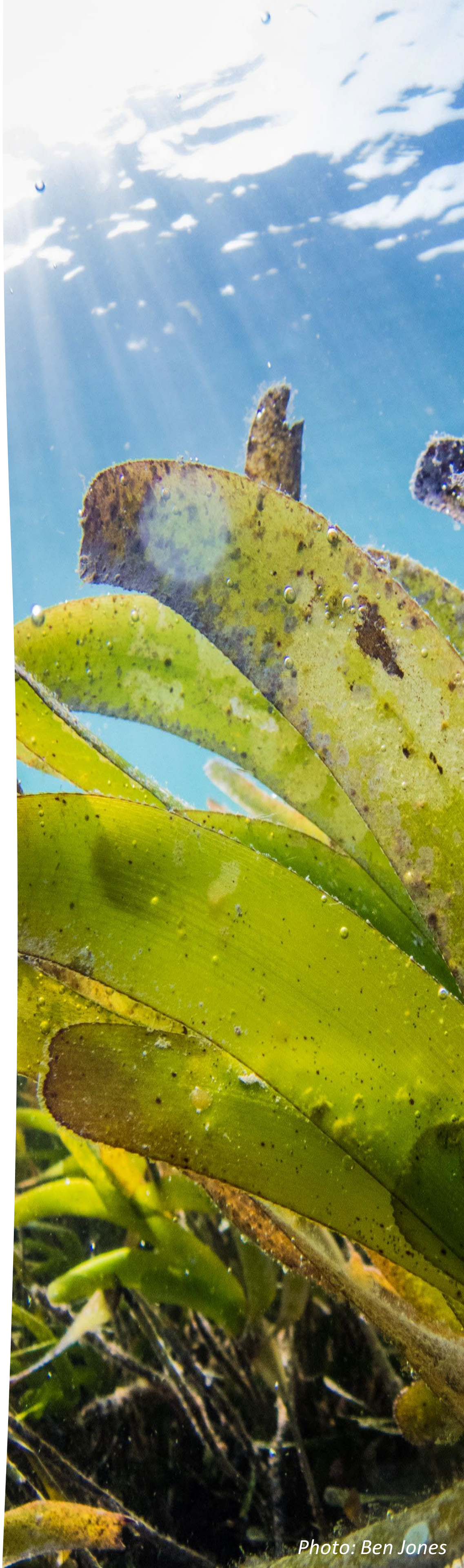
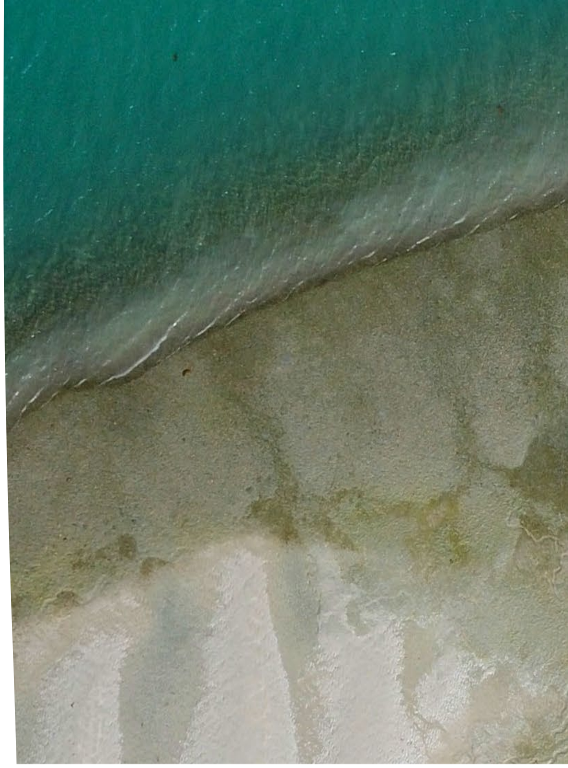
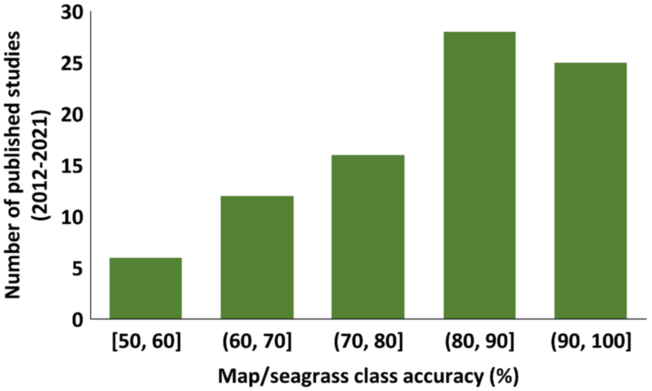


Photo: Ben Jones

Global literature review: Further synthesis of mapping methods including map accuracy and validation

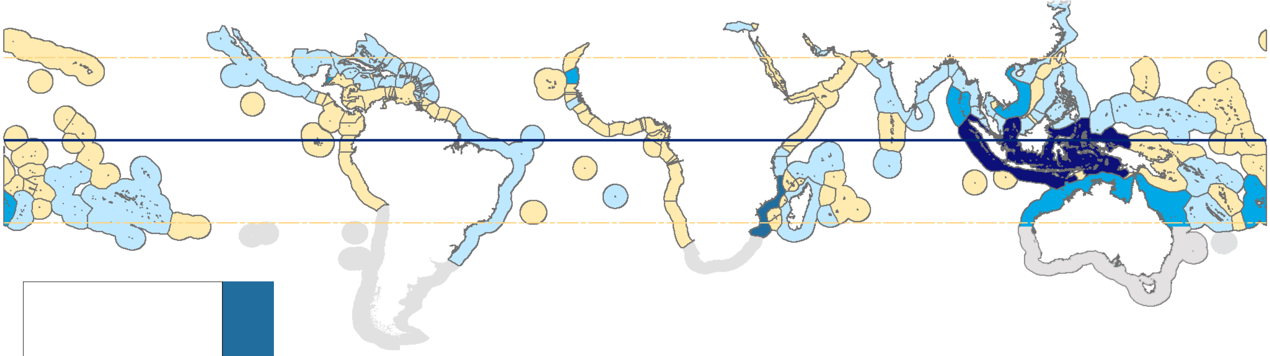


- Mean seagrass extent mapped (1,909.6 km^2) with very high resolution (≤ 5 m) imagery was greater than extent mapped (712.4 km^2) with high to moderate (>5 to 30 m) resolution imagery
- 19% (28 of 151) of studies measured change in seagrass spatial extent
- Maximum map accuracy ranged from 50% to 100% with a mean of 82% ±13% SD



- Most studies mapped multiple shallow water benthic classes including seagrass, coral reefs, sand, mud, algae, etc.
- 42.3% of studies did not report map accuracy
- A total of 235,954 field samples (photos, video transects, cores, dives) were reported across all studies combined.
  Mean = 3,104.7 ±SD 16,866.8
- The highest number of field samples reported in a single study was 128,619 in China and 74,000 in Qatar
- 45.7% of studies did not report sample size for field data, although some did make reference to having used ground truth data

Geographical distribution of published seagrass mapping activity (imagery from 2012-2021) based on a global literature review



Map shows 156* marine EEZs (109 sovereign nations) across the global tropics
*EEZs with overlapping claims counted as one.

ough many EEZs had no recent published record of seagrass mapping (2012-2021) some EEZs had been mapped recently by the Allen Coral Atlas team or had older historical records in the UNEP-WCMC dataset (see table below).

Addressing data gaps where no published studies were found between 2012-2021

North Brazil Shelf Tropical Atlantic

French Guiana ○
Guyana ○
Suriname ○

Central Indo-Pacific

Brunei ○ 🔵
Cambodia ○ 🔵
Christmas Island 🟢 🔵
East Timor 🟢 🔵
Guam 🟢 🔵
Matthew and Hunter Islands ○
Niue ○
Northern Mariana Islands ○ 🔵
Oecusse ○ 🔵
Papua New Guinea 🟢 🔵
Taiwan 🟢 🔵
Vanuatu 🟢 🔵

Western Indian Ocean

Pakistan ○ 🔵
Bassas da India ○ 🔵
Comores 🟢 🔵
Europa Island ○ 🔵
Ile Tromelin ○
Juan de Nova Island ○ 🔵
Maldives 🟢 🔵
Mayotte 🟢 🔵
Republic of Mauritius 🟢 🔵

Other Tropical Atlantic

Cape Verde ○
Gambia ○
Ascension ○
Trindade ○

Eastern Indo-Pacific

American Samoa 🟢 🔵
Easter Island ○
Gilbert Islands 🟢 🔵
Hawaii 🟢
Howland and Baker islands ○
Jarvis Island ○
Johnston Atoll ○
Line Group ○ 🔵
Marshall Islands 🟢 🔵
Nauru ○
Palmyra Atoll ○ 🔵
Phoenix Group ○ 🔵
Pitcairn ○
Samoa 🟢 🔵
Tokelau ○ 🔵
Tuvalu ○ 🔵
Wake Island ○ 🔵
Wallis and Futuna ○ 🔵

Red Sea & Gulf of Aden Western Indo-Pacific

Eritrea 🟢 🔵
Israel 🟢 🔵
Jordan 🟢 🔵
Saudi Arabia 🟢 🔵
Sudan 🟢 🔵
Yemen 🟢 🔵

Gulf of Guinea Tropical Atlantic

Angola 🟢
Benin 🟢
Cameroon ○
Democratic Rep. Congo ○
Equatorial Guinea ○
Gabon ○
Ghana 🟢
Guinea ○
Ivory Coast ○
Liberia ○
Nigeria 🟢
Republic of the Congo ○
São Tomé and Principe ○
Sierra Leone 🟢
Togo 🟢

Tropical Eastern Pacific

Clipperton Island ○
Cocos Islands 🟢
Costa Rica ○
Ecuador ○
El Salvador ○
Galápagos Islands ○

Arabian Sea Western Indo-Pacific

Federal Rep. Somalia ○ 🔵
Iraq 🟢
Kuwait 🟢 🔵
Oman ○

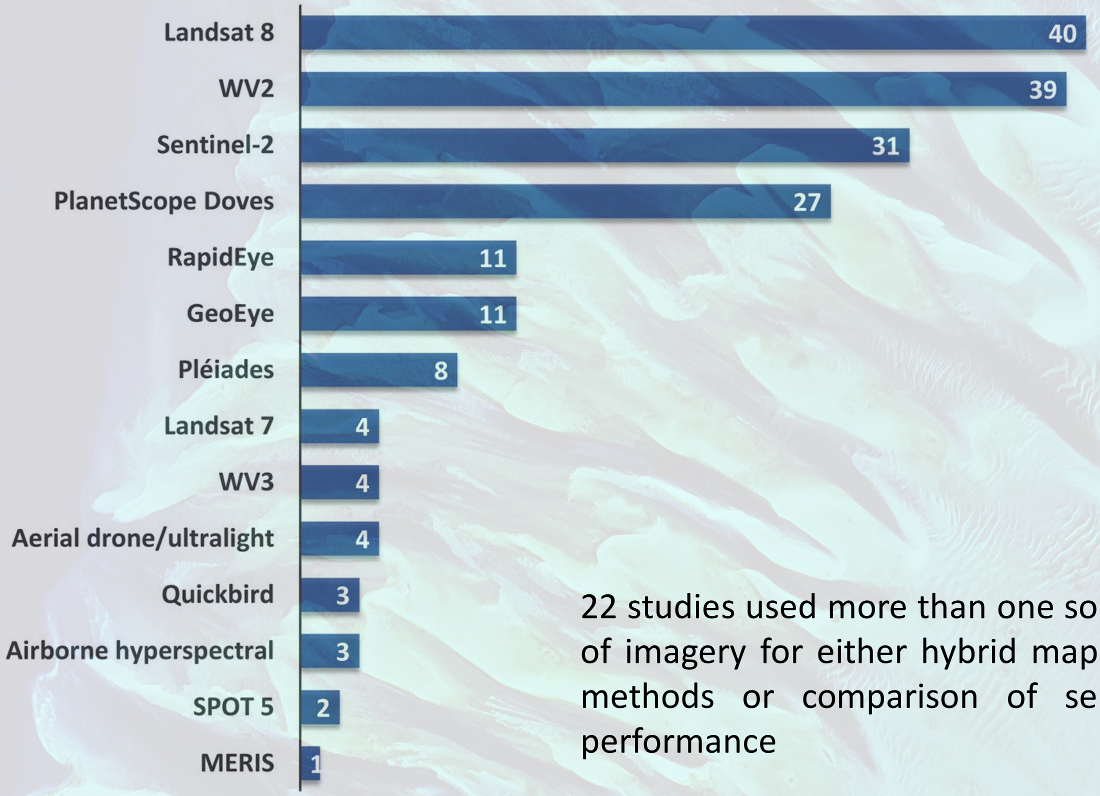
Caribbean Tropical Northwest Atlantic

Aruba 🟢 🔵
Bajo Nuevo Bank ○
Collectivity of Saint Martin 🟢 🔵
Curaçao ○ 🔵
Navassa Island ○
Nicaragua 🟢 🔵
Panama 🟢 🔵
Quitasueño Bank ○
Saba 🟢 🔵
Saint-Barthélemy 🟢 🔵
Serrana Bank ○
Serranilla Bank ○ 🔵
Sint-Eustatius 🟢 🔵
Sint-Maarten 🟢 🔵
Trinidad and Tobago 🟢 🔵
Venezuela 🟢 🔵

🟢	UNEP-WCMC Seagrass polygon
○	No UNEP-WCMC Seagrass polygon
🔵	Allen Coral Atlas Seagrass polygon

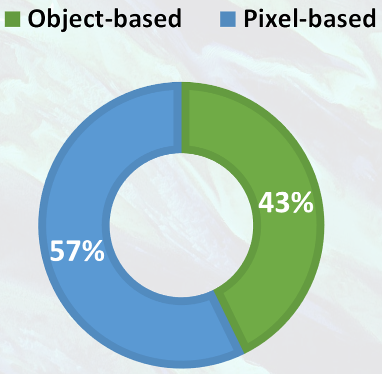
Mapping methods synthesis
Summary results from publications (2012-2021)

Choice of imagery applied



22 studies used more than one source of imagery for either hybrid mapping methods or comparison of sensor performance

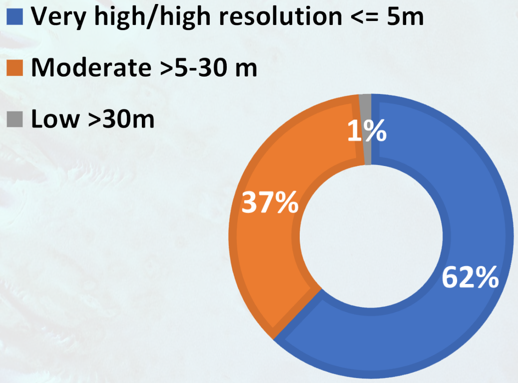
Image classification method



Object-based
Mean map accuracy
= **82.9**% SD± 12.7

Pixel-based
Mean map accuracy
= **78.9**% SD± 17.2

Image spatial resolution



Moderate res.
Mean map accuracy
= **79.0**% SD± 13.6

Very high/high res.
Mean map accuracy
= **82.4**% SD± 17.1

Image: Great Bahama Bank, Landsat 8 OLI Feb 8, 2020

Overview and recommendations for comprehensive reporting

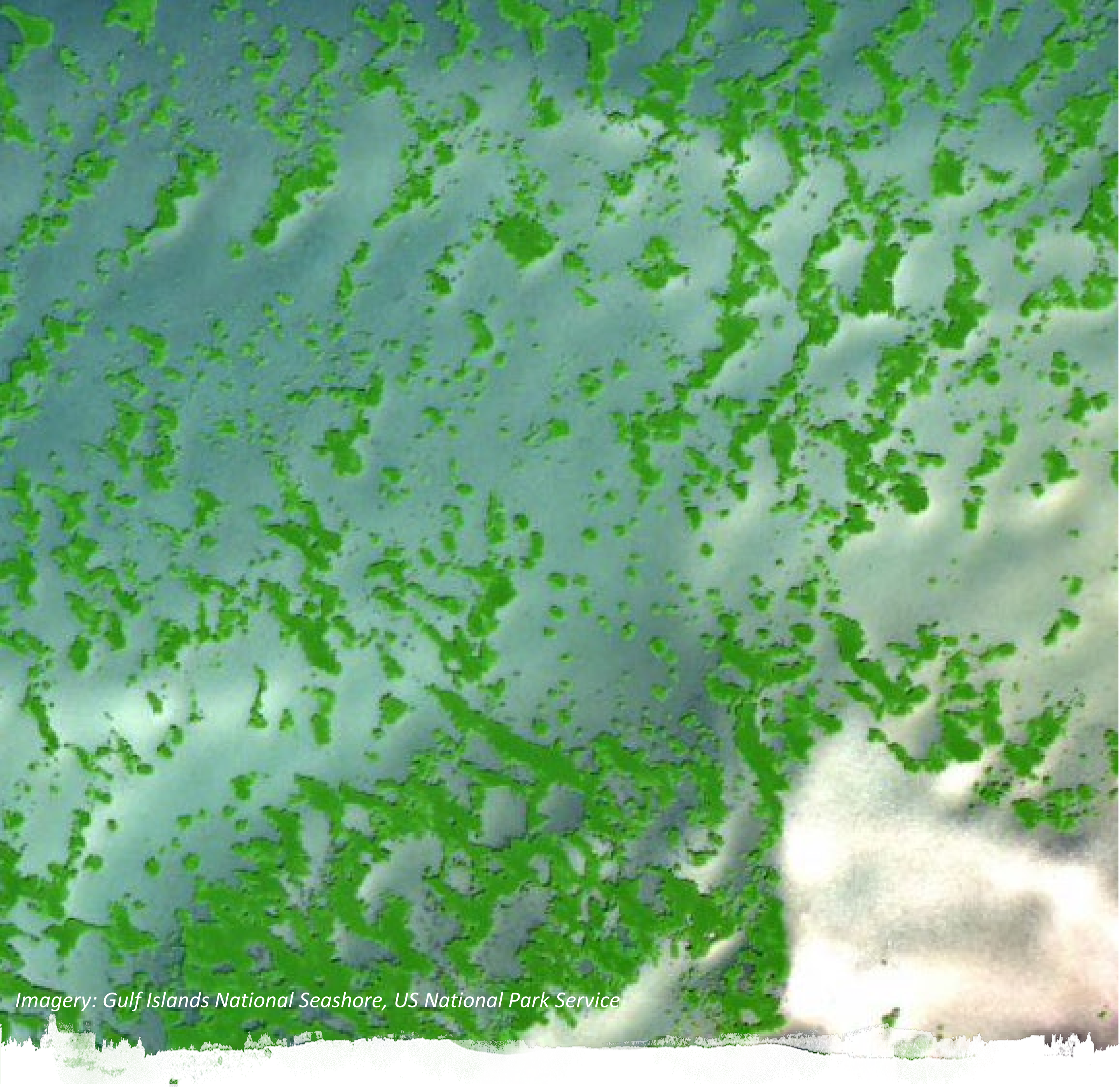
This global synthesis of reported seagrass map data in published remote sensing studies revealed important gaps in data availability. 151 publications globally were identified as having mapped seagrass extent (using imagery between 2012 and 2021), with over half of sovereign nations not having any published seagrass reporting available.

Additionally, this synthesis of seagrass mapping activity provides a unique breakdown of the various mapping approaches used and identifies inconsistencies in information reported. Below outlines standard information that should be included in marine mapping projects, but which is too often left out (Roelfsema and Phinn 2013, Morales-Barquero 2019).

- Field data used for training classifiers and map validation. Specifically, sample size and method/design used.
- Sampling design and spatial distribution of sampling points.
- Area mapped for each benthic class.
- Accuracy assessment (i.e., error matrix showing sample size) for each benthic class.
- Limits to sensor performance (depth, turbidity).
- Image resolution and minimum mapping unit if different from pixel resolution of source imagery.

This global literature review highlights the need for greater detail and consistency in reporting of methods and uncertainty when mapping seagrass extent.

Photo: Ben Jones



Imagery: Gulf Islands National Seashore, US National Park Service

Part 2: Expert Consultation

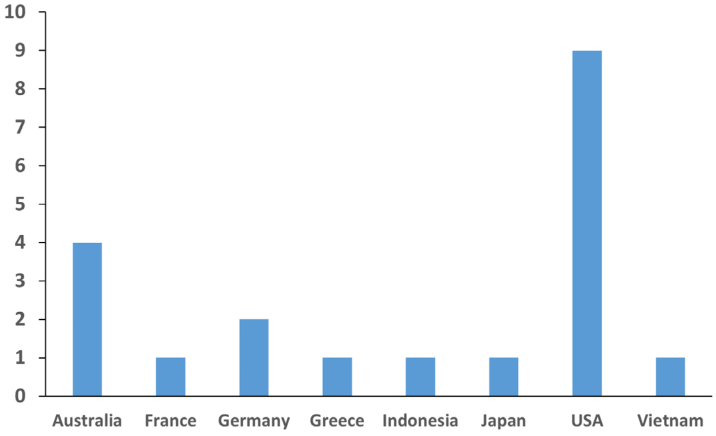
Expert consultation: Defining a way forward for global seagrass mapping

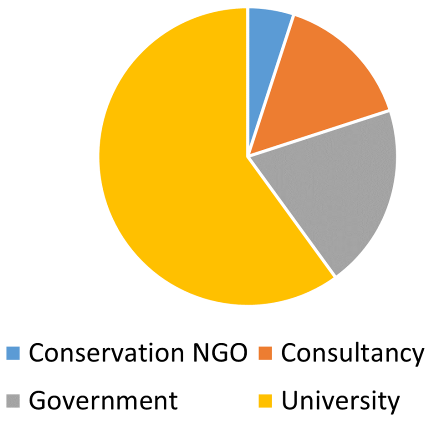
The objective of this expert consultation was to harness the knowledge and advice of the global experts in seagrass mapping to:

1) better understand the barriers, limitations and solutions associated with mapping seagrass extent; and
2) define a way forward for a cost-effective and standardized remote sensing framework to accelerate blue carbon accounting.

In this consultation we focused on the equatorial region (i.e., between the Tropics of Cancer and Capricorn 23 degrees north and south of the Equator) with potential for global applications of seagrass mapping.

30 remote sensing experts were invited to participate and 20 completed the consultation. The results presented here are a synthesis from 20 experts.





Nine of the respondents were already involved in a project to map global seagrass extent and all 20 were interested in collaborating in future global seagrass mapping.

The 20 experts had a self reported total of 125 years of experience with marine remote sensing ranging from 3 to 40 years and averaging 20.8 years.

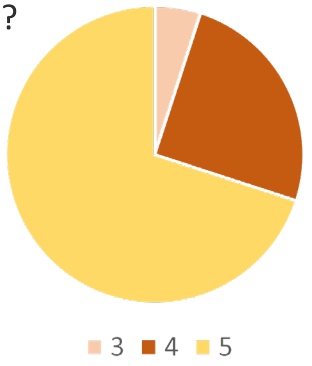
Expertise in mapping seagrasses had been gained from all bioregions except the sub-arctic with 10 experts having experience in Central America and the Caribbean; 9 in Australia and New Zealand, 7 in the Pacific Islands and 7 in India and Southeast Asia, 7 in Eurasia, 5 in Africa, 5 in South America, and 2 in China and Japan.

Respondents were asked a series of questions

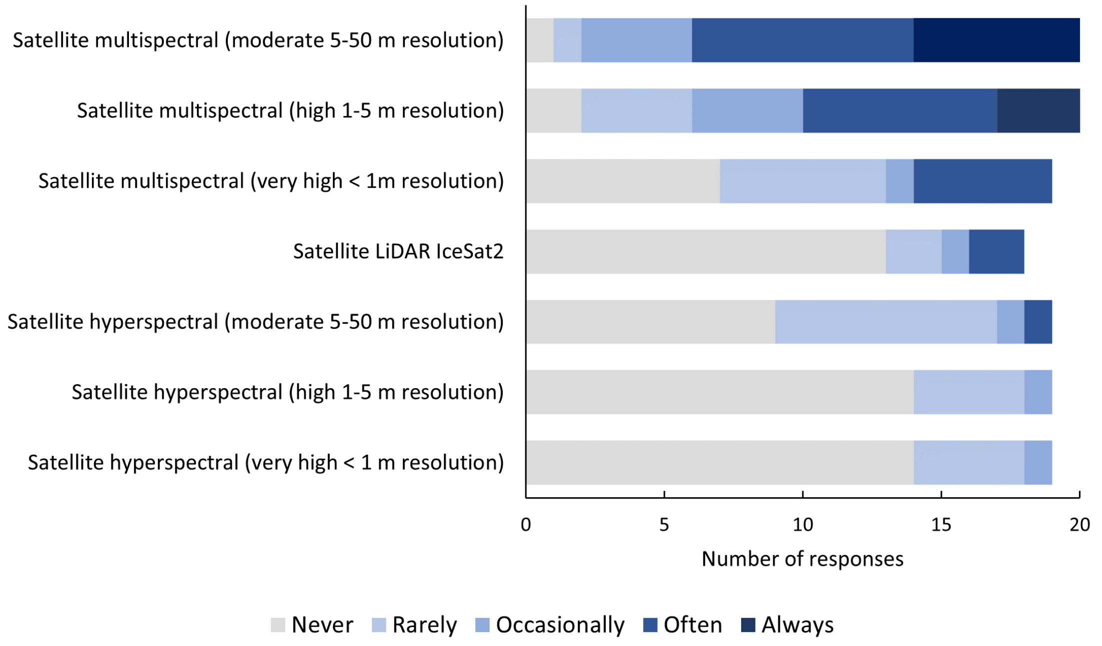
- When asked "**how important is it that global seagrass extent is mapped with a standardized methodology** when being used for accounting and reporting of ecosystem services such as blue carbon?

	1	2	3	4	5	
Not important	○	○	○	○	○	Very important

All experts said that a standard methodology was important to very important.

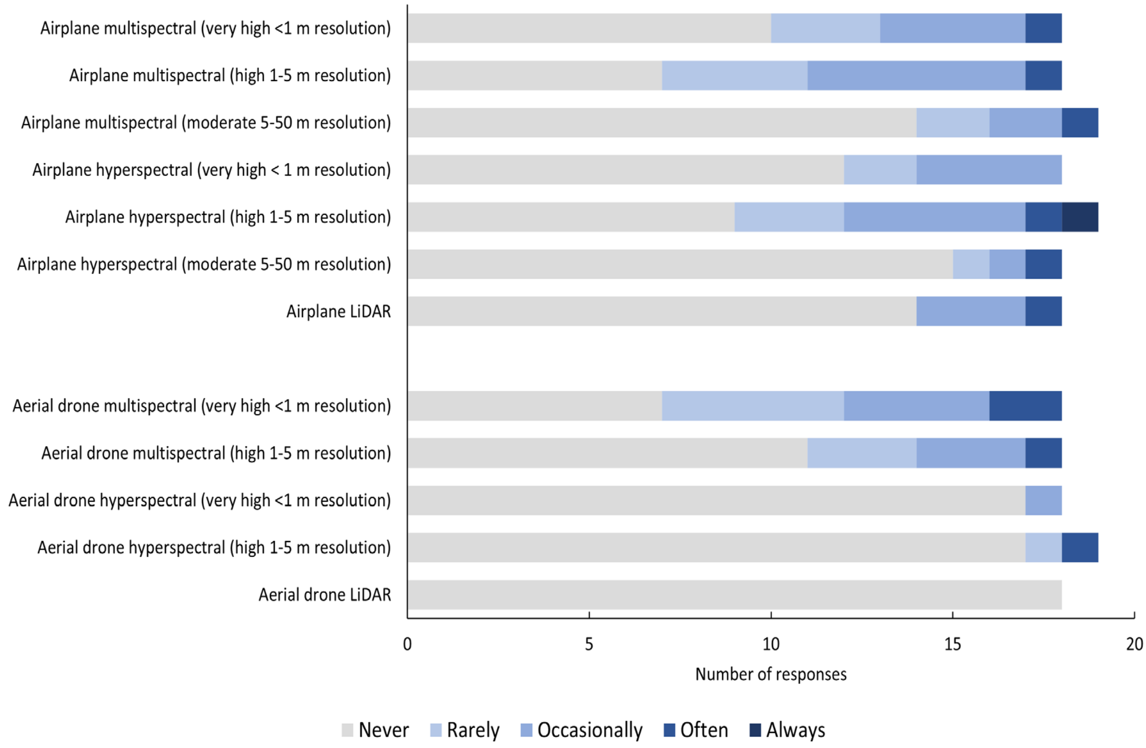


- Which **satellite remote sensing technique(s)** do you use to map seagrass extent?



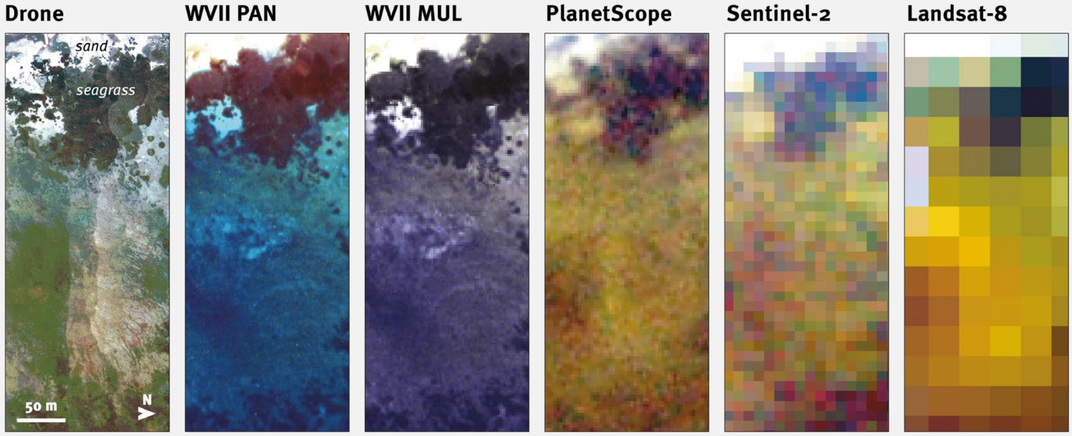
Experts more often used multispectral satellites imagery than hyperspectral. Moderate and high resolution (<5-50 m) imagery was used most often to map seagrass.

Which **airborne remote sensing technique(s)** do you use to map seagrass extent?



High (1-5 m) and very high-resolution (<1 m) multispectral aerial imagery was used to map seagrass extent more than moderate resolution (>5 m) imagery. Few experts used LiDAR or drone-based hyperspectral sensors.

Example images from Lesbos, Greece. 39°09'30.6"N 26°32'01.8"E

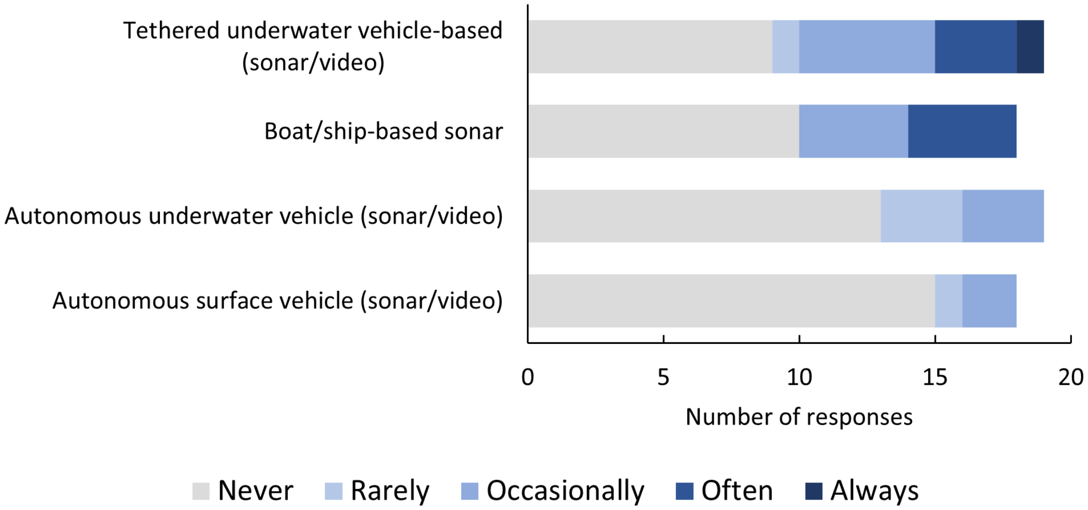


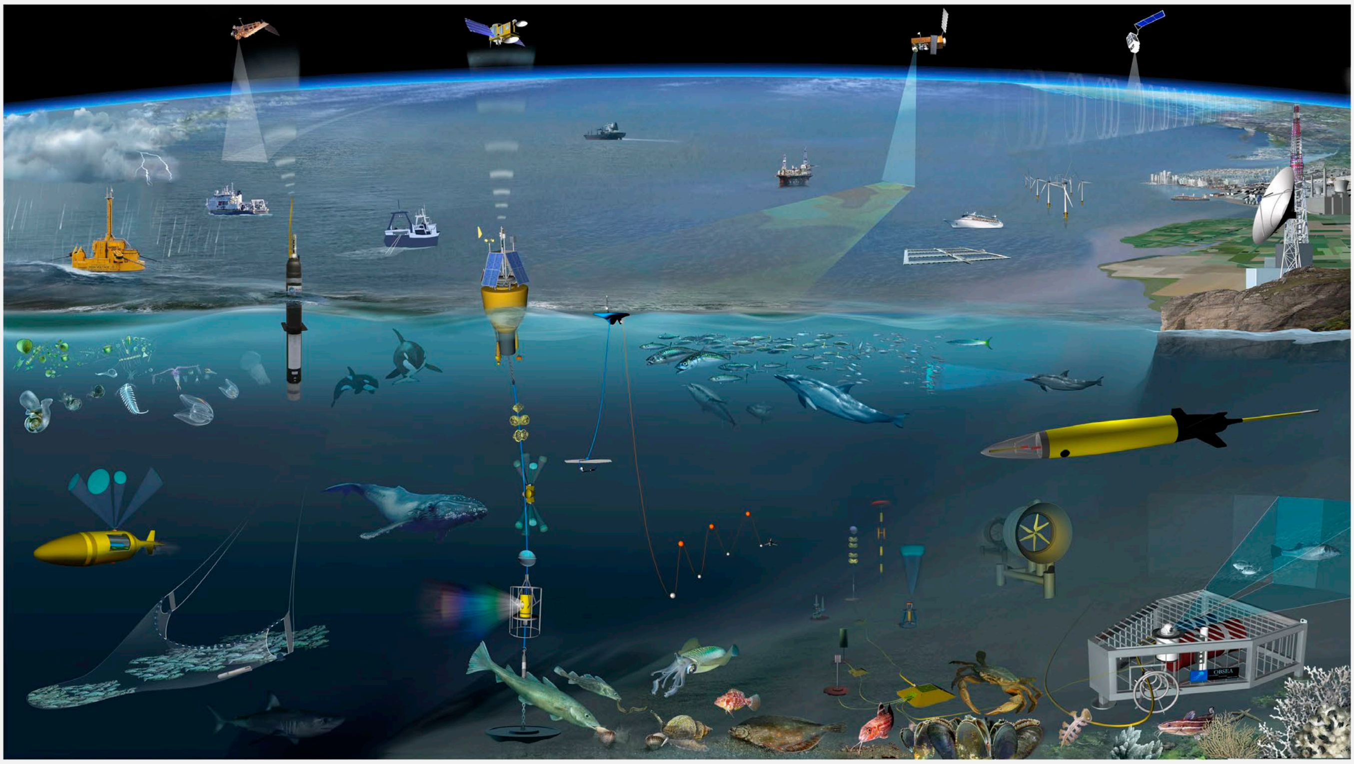
Drone	**WVII PAN**	**WVII MUL**	**PlanetScope**	**Sentinel-2**	**Landsat-8**
resolution: 4 cm	*resolution: 50 cm*	*resolution: 2 m*	*resolution: 3 m*	*resolution: 10 m*	*resolution: 30 m*
⊕ Very high spatial resolution, Low cost of acquisition, High flexibility of deployment	⊕ Very high spatial resolution, High spectral information, Direct and flexible sensor tasking	⊕ Very high spatial resolution, High spectral information, Direct and flexible sensor tasking	⊕ High spatial resolution, High temporal resolution, Free under a scientific license	⊕ High spatio-temporal resolution, Open, free and public datasets, Archive between 2015-2029	⊕ Large area coverage, Free datasets, Historical archive back to 1972
⊖ Small ground area coverage, Limited optical bands, Required laborious image pre-processing	⊖ Commercial imagery, Very high cost of imagery	⊖ Commercial imagery, Very high cost of imagery	⊖ Radiometric differences betweem, Low spectral information	⊖ Multiple spatial bands, Spectral technological-related artifacts over seagrass areas	⊖ Low spatial resolution, Low temporal resolution

Sources: Topouzelis, K. University of Aegean (2018); Digital Globe (2018); PlanetScope (2018); Copernicus Sentinel data (2018); Lansdat-8 (2018) U.S. Geological Survey.

Graphic: Out of the Blue. 2020. GRID-Arendal.
https://www.grida.no/resources/13591

Which **water-based remote sensing technique(s)** do you use to map seagrass extent?

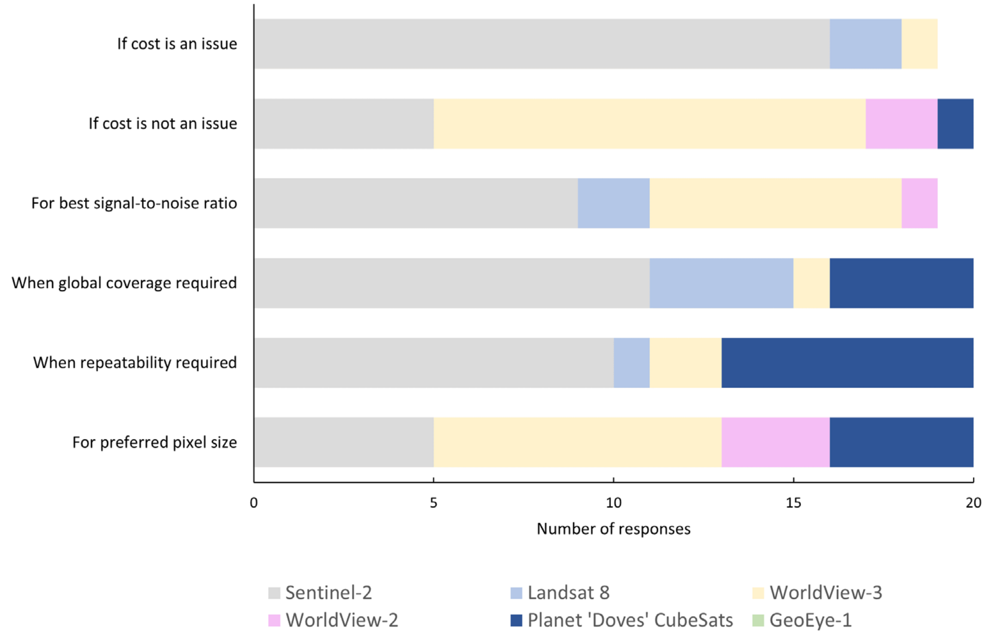




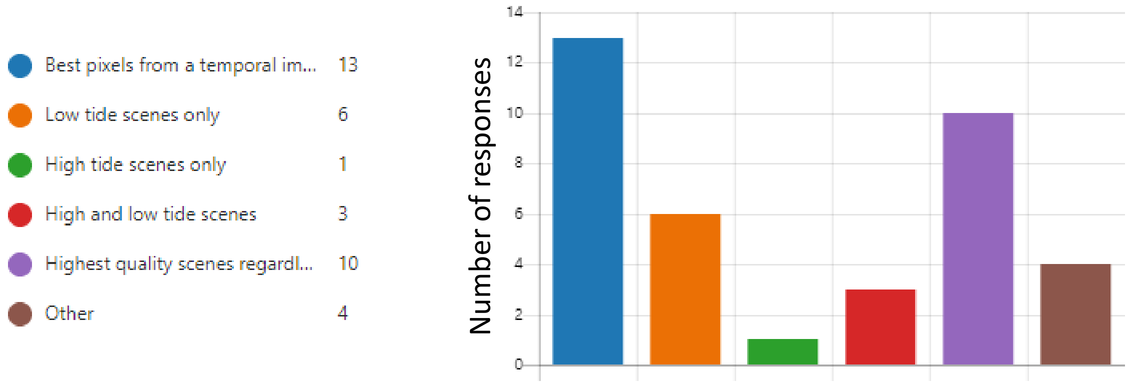
Depiction of autonomous and remote sensing platforms in global ocean observing systems.

Source: Whitt et al. 2020.

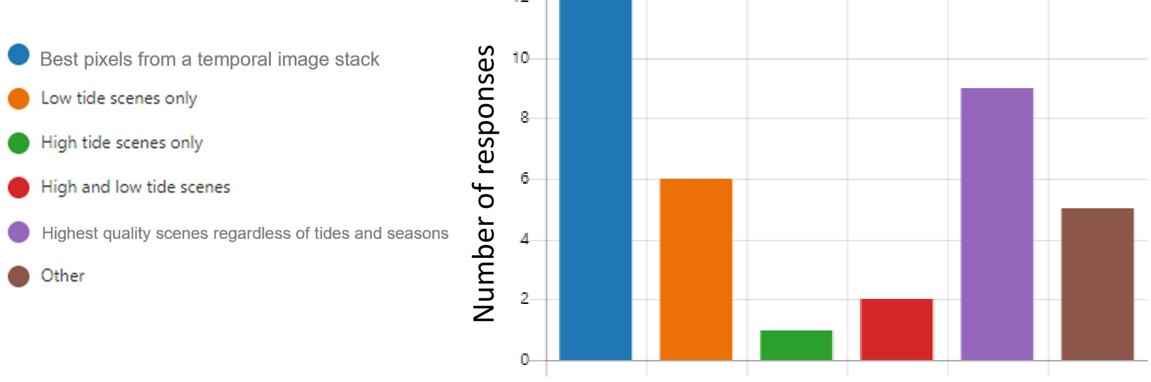
- Where seagrass is visible from space, could you please select **your preferred source of imagery** for global mapping of seagrass extent with each of the following considerations.



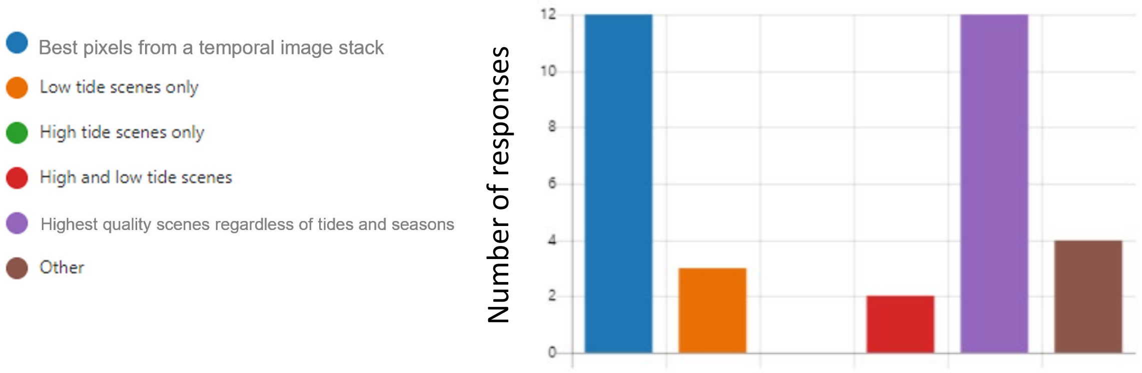
- Please select what type(s) of image mosaic you would use for global mapping of seagrass extent when representing the **season with the largest extent**?



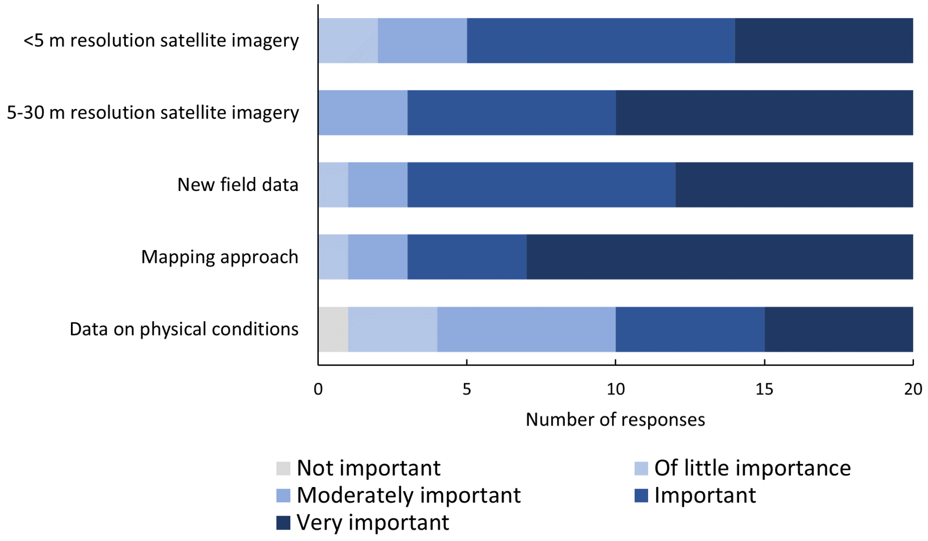
- Please select what type(s) of image mosaic you would use for global mapping of seagrass extent when representing the **seagrass extent over 1 year**?



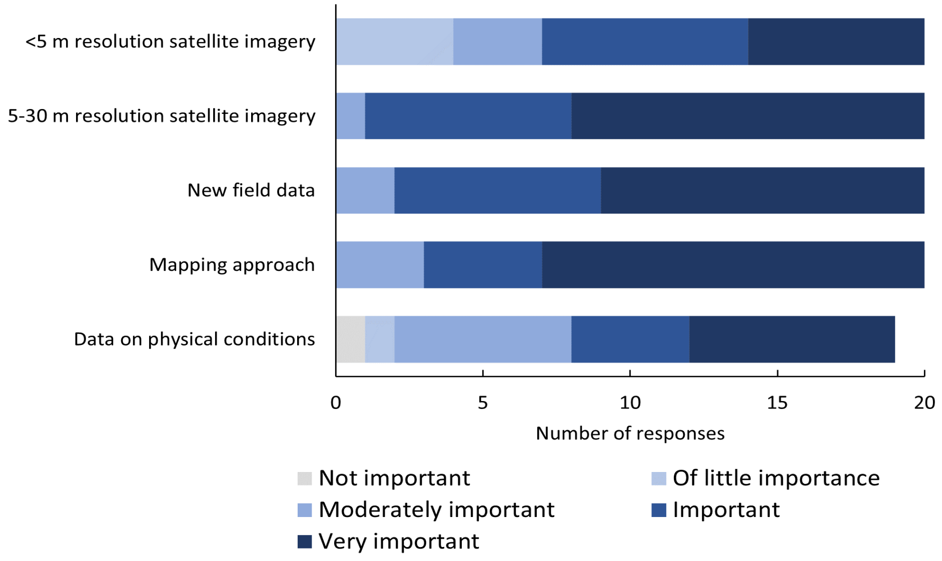
Please select what type(s) of image mosaic you would use for global mapping of seagrass extent for **the best representation** of the seagrass extent?



For **global mapping of seagrass % cover**, please rank the importance of the following requirements.



For **global mapping of seagrass biomass**, please rank the importance of the following requirements.



Based on your knowledge and experience can you **recommend a currently available mapping methodology with potential for global mapping of seagrass** extent for blue carbon accounting? If available, please **cite a publication** to support your recommendation. *NB: Each shaded box represents an individual expert's comments.*

Expert's written comments

I highly recommend the use of radar and optical satellite imagery (S-1 and S-2) combined with advanced ensemble-based decision tree learning and metaheuristic optimization techniques to detect and map seagrass extent for blue carbon accounting.

Ha et al. 2021a, Ha et al. 2021b

Allen Coral Atlas approach works well for seagrass extent. Lyons et al. (2020)

Global Seagrass Watch from DLR (German Aerospace Center) is probably the most advanced, but once again, I would tailor approaches based on local conditions, water quality, species, etc.

In the presence of adequate field data of high quality and a global collaboration of several partners, it is feasible to go for a global map. Here is an example that has been scaled to the East Africa coastline Poursanidis et al. 2021.

The use of Google Earth Engine would play a major role for mapping seagrass at global scale. This would allow people to maintain efforts around the world, specially in developing countries. One example of a methodology using Sentinel-2 and Google Earth Engine is: Traganos et al. (2018).

Methods for water column correction
Sagawa et al. (2010).
Method for bathymetry estimation used as water column correction
Sagawa et al. (2019)

Ideally a mix of OBIA and physics-based inversion methods should be used possibly combined with AI/ML).

From my perspective, a combination of our Global Seagrass Watch project framework, mainly the pre-processing and creation of high-quality optically shallow Sentinel-2 mosaics, and the classification system of the Allen Coral Atlas should be the most practical and relevant way forward to achieve global scale mapping of seagrasses. Essentially, our pre-processing framework will allow more high-quality repeatable mosaics of Sentinel-2 which will be fed into the high-quality classification framework of the Allen Coral Atlas and will allow global scale mapping of seagrasses akin to the recently achieved global mapping of coral reefs by the latter project.
Traganos et al. (2018).

(continued from previous question)

Using remote sensing data and biophysical properties, combined with machine learning and object based clean up.

Full radiometric correction Sentinel 2 imagery with machine learning for classification (A comparative assessment of ensemble-based machine learning and maximum likelihood methods for mapping seagrass using Sentinel-2 imagery in Tauranga Harbor, New Zealand)

I do not have a single methodology that I can recommend. Rather, I believe the best approach will utilize a combination of existing methods (both multispectral and hyperspectral) as well as development of new methods using modern advances in image analysis and machine learning.

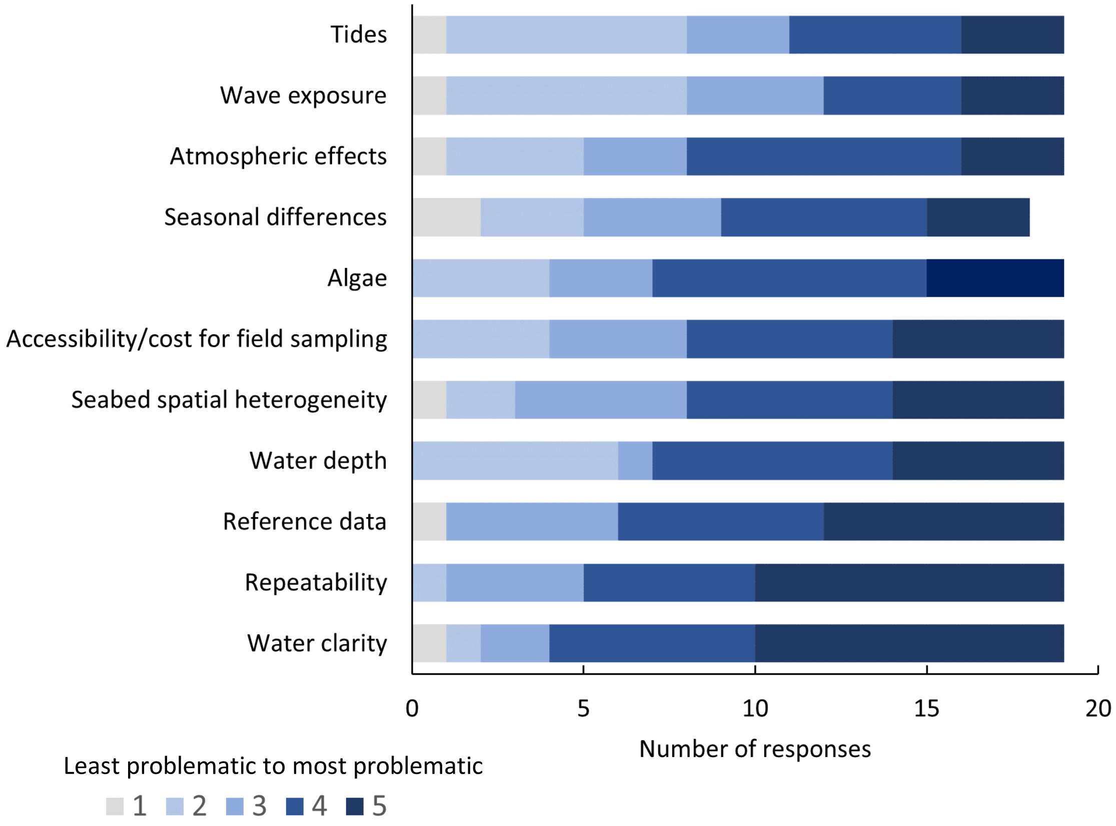
No single mapping approach is appropriate - as approach will vary from field-based to near-field/EOS remote sensing - depending on the habitat, species, water depth, etc. So, an individual mapping event could include multiple approaches. See also McKenzie et al. (2000).

I would recommend an artificial intelligence (AI)-based approach deployed in the cloud. For any AI based approach, quantifying the uncertainty associated with the output seagrass maps will be critical--both for understanding the uncertainty in their distribution and how this uncertainty impacts estimates for seagrass carbon sequestration.

To date, my team's work has implemented ensemble machine learning (ML) techniques to predict seagrass distributions (see Kendall et al 2017, Costa et al. 2018, Costa 2019). This approach has not yet been deployed in the cloud (Azure), but we have deployed similar R-based code in virtual environments for species distribution modeling. We have also recently purchased micro-underwater autonomous vehicles (uUUV) for ground truthing and are evaluating AI COTS solutions to annotate habitats (including seagrass) in underwater imagery from these and other platforms (Costa 2021).

Machine learning classification or regression algorithm. We're currently working on it and use a single-date training data to map seagrass multi temporally. We yield a consistent monthly pattern on seagrass distribution over 2 years time. It is planned to be submitted to the journal by the end of this year.

How important are the known barriers and limitations, technological or otherwise, to address when applying **your recommended approach to mapping seagrass extent** in the tropics?



Expert's written comments

Repeatability and reference data are one of the most important driving factors for mapping seagrass extent. Also, atmospheric correction techniques using Polymers or Acolite algorithms are recommended for the coastal environment.

The biggest challenges are usually acquiring high quality imagery with minimal clouds and acquiring sufficient in situ data on seagrass to train visual observers and/or models.

Additional consideration is needed for the temporal period being considered. Environmental factors become more challenging with shorter periods as the availability of high-quality data becomes more limited. For longer periods, greater amounts of data can be integrated for the best possible mapping; however, one must be cautious not to overlook how seasonal and long-term changes can influence results.

At **what level of turbidity does your recommended approach become inadequate for mapping seagrass extent** due to high uncertainty/errors?

Expert’s written comments

If there are seagrasses at 50 cm depth and visibility (in Secchi Disk terms) is 1 m you can still map seagrasses; if the seagrasses are down to 30 m depth and Secchi Disk depth is 20 m you cannot map the seagrasses. As visibility is down to deeper depths there will be a spectral narrowing of measurable upwelling radiance at the surface beginning to limit the spectral discrimination.

1 m secchi, however if seagrass 0.5 m deep it still will work.

<0.5m visibility

Chla> 5 mg/m3; Turbidity >~2.5 NTU

Need more research to determine this.

My recommended approach works even in extreme turbidity levels due to the incorporation of a turbidity mapping and masking component in our Global Seagrass Watch system. This component allows high-quality and accuracy in mapping of moderate to extreme levels of yearlong turbidity and their subsequent masking out of the downstream analysis (Pertiwi et al. 2021). This allows the creation of the best optically shallow mosaics, free of turbidity and optically deep waters.

Turbidity can be a temporal condition due to water runoff. However, the temporality of Earth Observation data can allow the user to identify areas where sediments are always present and thus, the seagrass growth might be limited or even seagrass does not exist. This can be coupled with local ecological knowledge, avoiding parachute science and active involvement of local scientists and citizens.

Turbidity or attenuation coefficients can be included in the modeling framework to explore this question, and other environmental information (e.g., depth, acoustic backscatter etc.) relevant to seagrass distributions could be included to enhance predictions in turbid locations.

A way to deal with this is using Sentinel-2, because there is more chance to obtain an image when turbidity is low in the area of interest. So, the area need to be very turbid throughout the year to be inadequate for mapping.

It depends on seagrass extent related with depth. Secchi depth should be deeper than seagrass extent depth.

This is of course a depth dependent relationship, where lower amounts of turbidity are needed to obscure results at deeper depths.

Any level of turbidity can affect the outcome. Turbid areas - river plumes - should be avoided or treated separately. Consider sampling during the dry season.

● In clear and calm water, at **what water depth (meters) does your recommended approach become inadequate** for mapping seagrass extent due to high uncertainty/errors?

Expert's written comments

Less than several meters are ideal for recommended approaches.

For seagrass extent up to half the secchi depth roughly but depends on how dense the seagrass is for species and % cover is different.

EOS limited to waters shallower than 6-10m. Field-based approach with modelling required for deeper waters (>10m).

Deeper than 10 m.

30 m.

Deeper than 15 m in the tropics, deeper than 30-35 m in temperate waters like the Mediterranean, and deeper than 5 m in the most optically challenging waters of North Europe, Scandinavia, etc.

Depending on the bioregion, beyond 20 meters is challenging.

3 – 5 m.

Around 30 m if the transparency of water is very high.

10 meters.

Below 15 m approximately.

25 m.

Approximately 20 m.

Similar to coral reefs, this limit is around 20m (and up to 30m in exceptional situations).

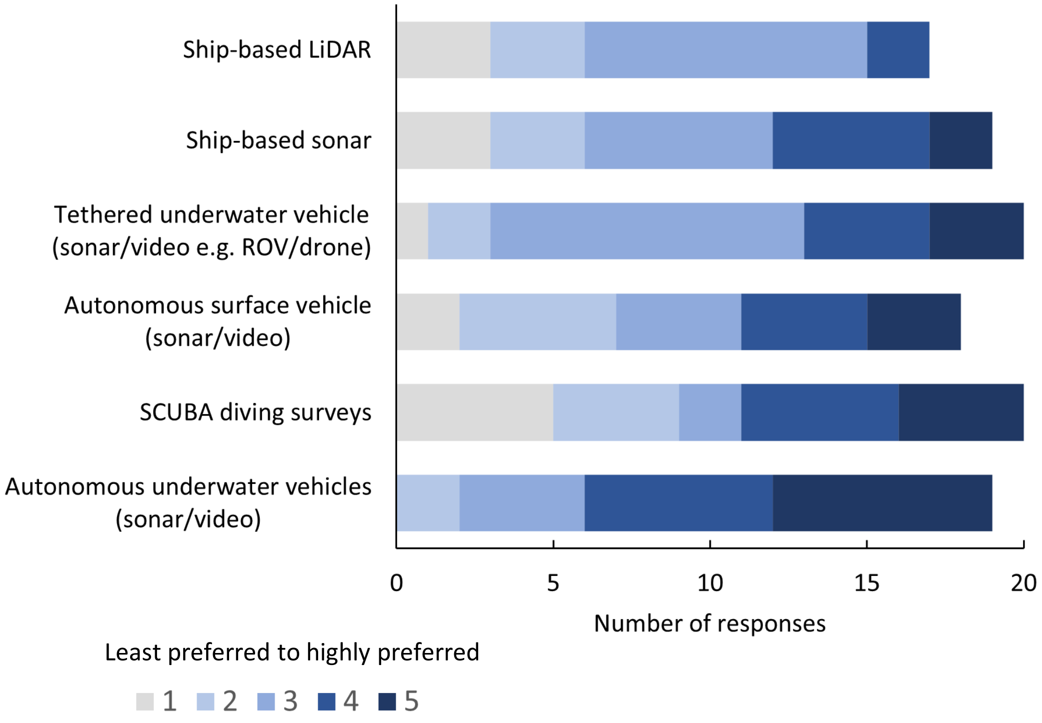
15 feet.

In the western Pacific, this approach is being used to classify habitats to 45 m depths using satellite imagery.

Beyond 20 m.

We were able to map coral cover and depth to about 30 m in very clear coral waters. As visibility is down to deeper depths there will be a spectral narrowing of measurable upwelling radiance at the surface beginning to limit the spectral discrimination. So uncertainty increases with depth (also in clear waters). If the question is absence /presence only in a e.g. sand environment this is easier than discriminating seagrass species in a substratum + benthic micro-algae environment etc.

For deeper and turbid waters where seagrass is often not visible or cannot be adequately classified with optical satellite data, **what alternative in-situ cost-effective technique(s) do you recommend** to map seagrass extent?



Expert's written comments

The preferred method is a drop camera to get as many non-spatially autocorrelated sites as possible. Ideally, the drop camera would have a DSLR camera, USBL/LBL, lasers and strobes. The resulting photographs can be processed in structure from motion software to develop high resolution (mm) photomosaics and 3D models that are georeferenced. The presence/abundance of seagrass can be annotated from the photomosaics.

What is the **optimal minimum mapping unit** for mapping seagrass extent for blue carbon accounting?

Expert's written comments

5 - 10 m

10 m^2

0.25 - 0.5 ha

100 m^2 the spatial resolution of Sentinel-2 will allow high-accuracy mapping of the extent of seagrasses, and thus accurate stratification of the densest seagrass beds that will contain the highest stocks of carbon in their soils. This mapping unit is a trade off between accurately detecting high density seagrasses (*Thalassia* and *Posidonia* species) and "losing" some of the medium to low density ones but gaining a good confidence in blue carbon accounting for seagrasses.

The scale is the factor that will define the optimum MMU. Talking about a global product, a 10 m MMU with accurate blue carbon information could be achieved under the available technological tools and methods.

Depends on the complexity of the seagrass meadows and the mixing with other benthic covers such as macroalgae.

10 m x 10 m.

~10-15 m.

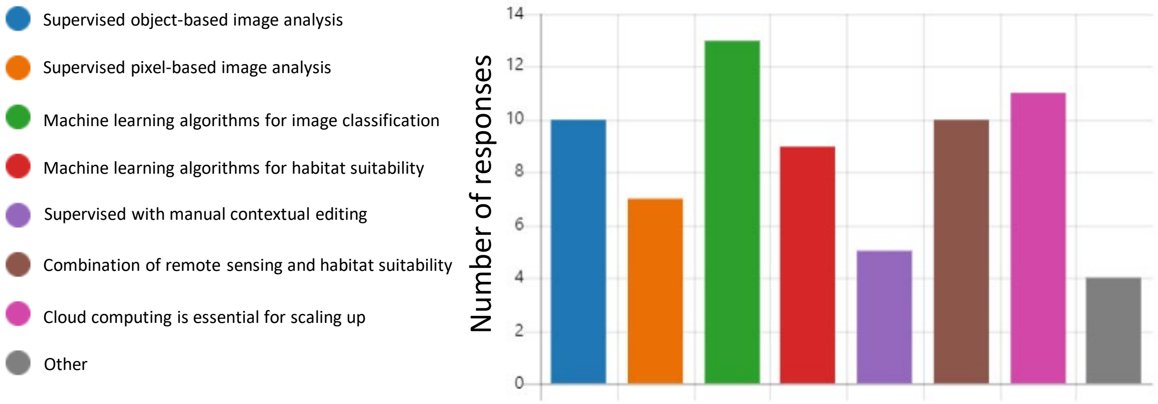
100 m^2

4-10 m.

Cover per m^2 with total area aggregated to km^2 for a region or nation.

The native resolution of the source imagery (e.g., 15 m for Landsat 8, <1 m for Worldview 3).

To accelerate the scaling-up of seagrass mapping for blue carbon accounting, which of the following analytical techniques, or combinations of techniques, would you recommend?



What are the **next steps required to advance your recommended approach** to mapping seagrass extent globally?

Expert's written comments

An HPC or cloud-based such as GGE using S-1 and S-2 for mapping seagrass extent globally.

Merge physics-based inversion methods with OBIA and ML/AI methods.

Getting funding to select the right imagery.

Establishment of globally standardized methods for each seagrass habitat type.

I think methods need to be applied within specific contexts rather than globally. There is no single approach.

Improvement of the pre-processing component for the optically shallow Sentinel-2 mosaics (i.e., normalization of the Sentinel-2 mosaics using Sentinel-3 stable image mosaics, currently under development, to reduce the striping of the Sentinel-2 data which causes spectral dissimilarities within the mosaics) and combination of the Global Seagrass Watch and Allen Coral Atlas framework across all ranges of turbidity intensities at national scales with high densities of reference data.

(continued) What are the **next steps required to advance your recommended approach** to mapping seagrass extent globally?

Expert's written comments

High quality field data that match up with the scale of the satellite mission. Cloud computing resources that will allow the scalability at the level of continent and beyond.

Develop an automatic mapping approach to map seagrass extent by considering different water quality and image quality.

Share field survey data through international network.

A globally distributed, consistent field calibration dataset that includes seagrass at differing % cover per pixel and/or biomass per unit area, combined with areas of non-seagrass cover, especially dark algal covers. Take our already well calibrated global Planet Dove datasets, integrate where needed with Sentinel-2 data as backfill, homogenize spectrally, control for bathymetry and tide (we have both), and train OBJ-ML codes. Verification and iteration for best possible uniformity globally.

Training more people for reproducing the seagrass mapping in the cloud computing resources.

Use the same approach as Allen Coral Atlas

Accuracy assessment

This should be a large team effort in which information is shared openly (within and with external community), with possible tests of different approaches, mosaics of regional mapping efforts in standard format, etc

I suggest compiling a set of example training, testing and validation data (including data from different remote sensing platforms) for a collection of representative seagrass areas, and then opening up this data for scientists to develop and apply their best efforts at seagrass mapping.

Collect/model global bathymetry data. Collect seagrass distribution data globally (representing areas)

● If possible, please provide an **approximate cost estimate** ($USD) per unit area for mapping seagrass **using your recommended standardized method**(s).

Expert's written comments

Not possible.

Not possible, as many configurations occur.

$100,000-500,000 USD per national scale depending on the spatial size of the given national seagrasses and national scale.

1$/10000 km^2

It depends on a few things: (1) on the imagery being acquired. Ship-based acoustic mapping is much more expensive than satellite imagery mapping. (2) whether the field data is already collected and annotated. If not, this can be an enormous cost. (3) If the field data exists for training, the cost to apply machine learning is low and mainly computing time (which is not costly if done on local machines). If the machine learning approach is deployed in the cloud, CPU/GPU hours are typically <$1.

$25 per km^2.

Difficult to say - Based on imagery and field work effort.

No idea and this would vary based on region, method.

Per unit area is tough. We are scoping seagrass and mangroves for a global extension of the Allen Coral Atlas in the $1.2M USD direct cost range for analysis/compute/R&D. We already bought/own 2019-2021 global coverage for the tropics and sub-tropics. Need to do another ~$1M USD purchase for remaining regions of the world.
Net: $2.2M USD for best possible products.

If possible, please **provide an approximate cost estimate for a recent seagrass mapping project** in clear water providing the location, size of area mapped and depth limit.

Expert’s written comments

We attempted to map seagrass extent in New Zealand using free-of-charge Sentinel and Landsat datasets, the cost involved was only field surveying for collecting ground-truth datasets (labour cost, equipment: GPSs, water-proof cameras) estimated at $50,000 USD.

$130,000 USD for 1500 km^2 area up to 5 m deep.

In clear water, costs have ranged from $500 to $3000 USD per km^2 mapped. Sizes have ranged from 20 to 700 km^2 . Depths have ranged from 0 to 50 meters.

Not possible as often related/combined with other activities.

Seychelles, 1,350,000 km^2, 0-15 m, $500,000 USD.

Mapping seagrass meadows in South Crete, in 2021, using VHR commercial EO data and updated field work campaign, for an area of 25 km^2, €15,000 euros.

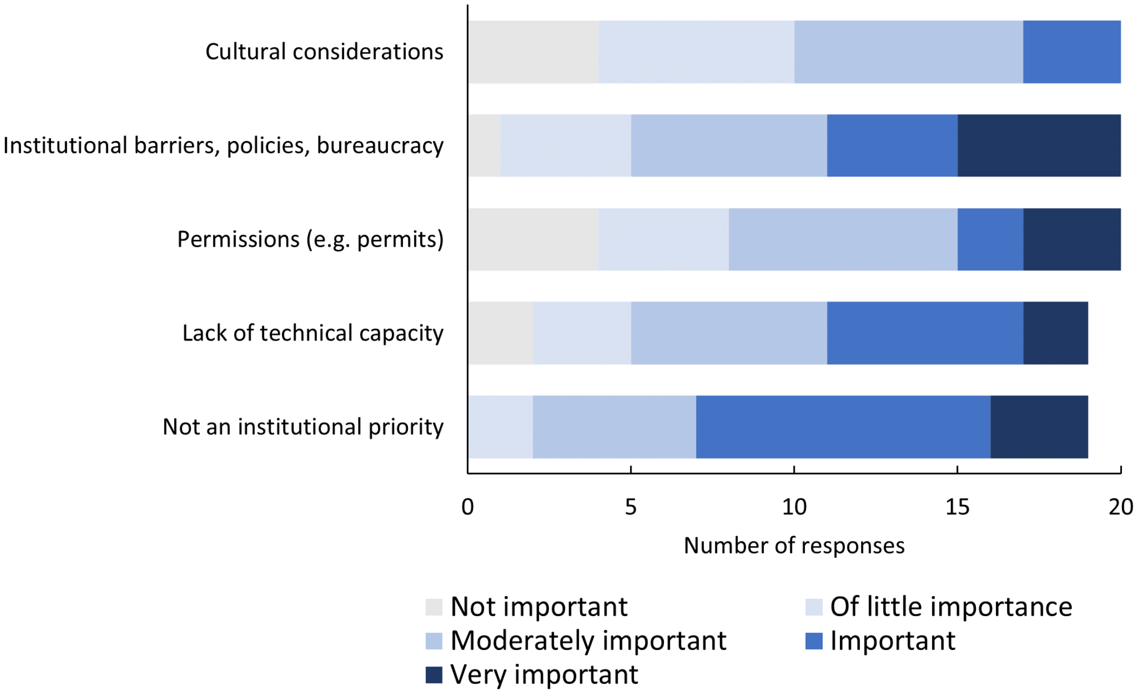
$5 USD per km^2

$100 USD per km^2

$10 USD per ha (0.01 km^2)

Tampa Bay, 1 person, 2 years, 2 m, ~38,000 acres (~153.8 km^2) $150,000 USD

How important are the following **logistical barriers** to national and regional mapping of seagrasses in the part(s) of the world where you work?

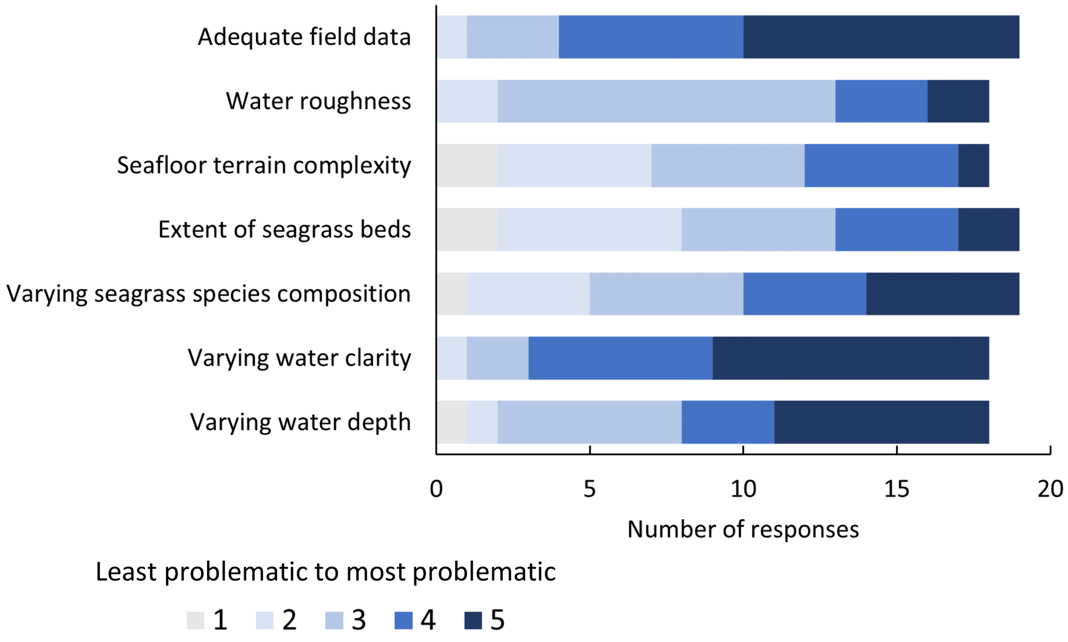


Lack of trained people.

Some countries are not easy to get permissions to conduct a survey.

Cultural considerations: as far as I know the Australian indigenous community is usually in favour of mapping e.g. seagrasses provided they are consulted from a very early stage and are involved in decision making. They also appreciate being able to identify sacred sites and to manage that sensitivity.

Please rank the potential barriers for efficient scaling up of the current seagrass mapping activities in the region(s) you work.



Expert’s written comments

Australia has water clarity varying from muddy tropical water with 20 cm visibility to coral reef waters (e.g., Lihou Reef) with more than 40 m visibility and southern bight waters of 30 m visibility. Some coasts have massive surf others are calm, some intertidal areas stretch for 10's km's seawards etc. New South Wales has over 120 intermittently closed and open saltwater lagoons-each one different from the other. There is no "one size fits all" solution or approach.

Time and extent of areas to be covered by ground-truthing.

While water depth and clarity will remain a challenge, the other barriers will become more significant as mapping is expanded to other regions with higher environmental variability and less available field data.

Time and cost constraints.

Large variation in spectral characteristics of the substrate can be highly problematic. For example, seagrass growing over black sand or muddy estuaries versus those growing over white sand.

Please **list any emerging technologies and approaches that you think will offer viable solutions** to current challenges in mapping seagrasses for blue carbon accounting (e.g., AI, new sensors?)

Expert's written comments

Advanced machine learning and meta-heuristics optimisation techniques and transfer learning in Deep Learning. New Sensors will be available such as ALOS-3 (JAXA) very high spatial resolution 3 with 6 multispectral bands.

Our new hyperspectral satellite that my team is launching in 2023. This will greatly increase accuracy of seagrass determination and biomass. Moving from OBJ-ML to CNN-ML. Already working well from airborne program. Need to scale it up for space-spectral application at larger geographic scales (extents).

Autonomous Underwater Vehicles offer significant promise for remote and/or turbid waters. Space borne hyperspectral sensors will enable much more discrimination. Data blending and data-data fusion could be very useful. There is lot to be done still in the area of using physics-based forward and inverse models to train AI/ML methods.

ICESat-2 data integration within the cloud computing platform of GEE for accurate calibrated SDB mapping, integration of ENMAP hyperspectral data within the cloud of GEE, normalization and design of accurate, fit-for-purpose reference data for calibrating and validating relevant global optically shallow water mosaics

To automate the field mapping/validation efforts as much as possible using a combination of high-frequency multi-beam from autonomous surface vehicles, Lagrangian floats with optical cameras, and other robotic technologies with machine learning and AI for data processing.

Machine learning, high temporal resolution remote sensing data, citizen science to assist collecting field data

Machine learning and deep learning for image classification and modeling; new atmospheric correction algorithms; UAVs mapping technology

Hyperspectral sensors mounted on drones or AUV.

Machine learning and citizen science

Scaling up from field to satellite with drones

Hyperspectral, cloud computing, machine learning

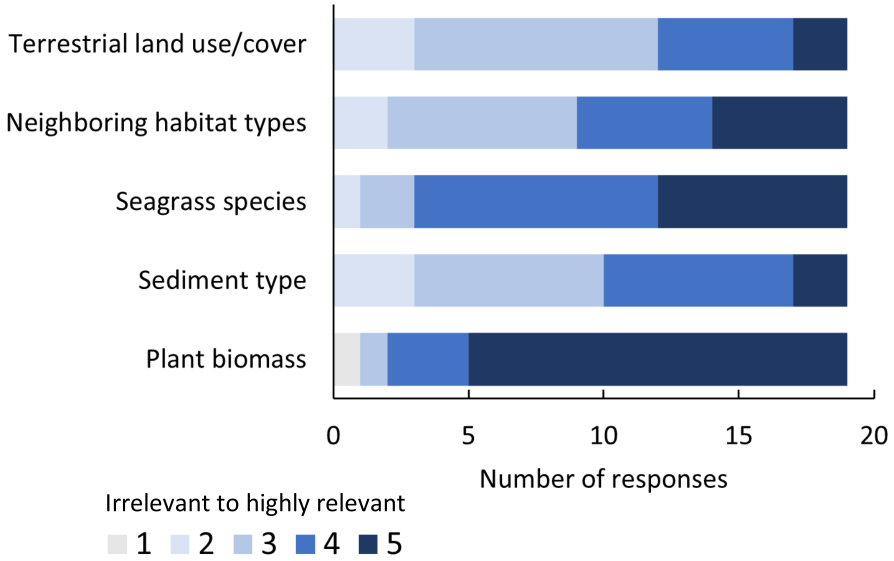
(Continued) Please **list any emerging technologies and approaches that you think will offer viable solutions** to current challenges in mapping seagrasses for blue carbon accounting (e.g., AI, new sensors?)

Expert's written comments

The inclusion of space-based altimetry data like IceSat2, can be an important ally in the seascape mapping via satellite bathymetry. Therefore, the analytical workflow can include seabed information and advanced water column corrections in a cloud-based approach.

One of the biggest challenges to global seagrass mapping is collecting field data efficiently and cost effectively. In recent years, the costs of uncrewed systems (UUVs, AUVs, UASs) have come down dramatically, and will be key to collecting georeferenced underwater photographs for ground truthing seagrass habitats and for establishing baselines to track changes over time. As mentioned above, AI will also be critical for both annotating/extracting seagrass information from uncrewed systems imagery, and for developing predictive models globally. Predictive models should be deployed in the cloud will provide flexibility to scale the characterization process up or down as appropriate.

In addition to the spatial extent of seagrass beds, how important do you consider the following variables as a **next step in refining the accounting of seagrass blue carbon storage?**



Expert's written comments

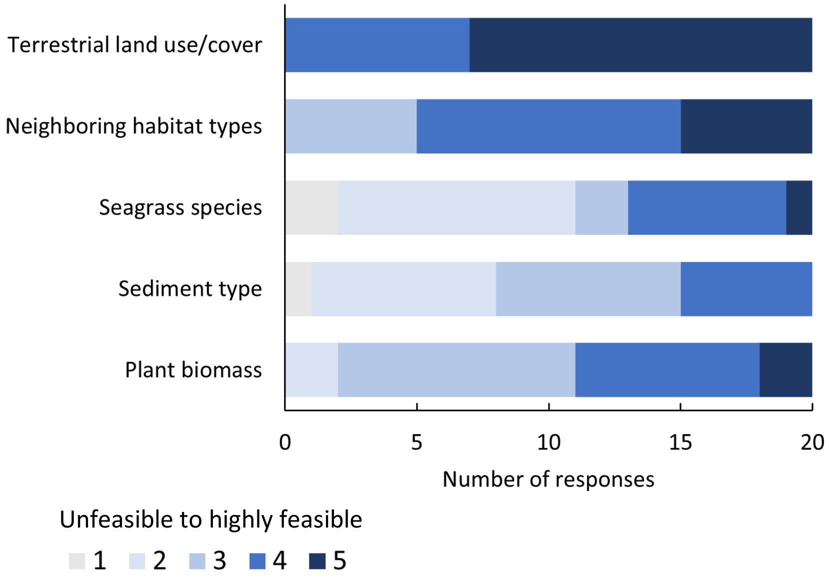
As seagrass mapping shifts from mapping to monitoring, associated variables such as neighboring habitat type and terrestrial land use/cover will become more significant as a means to assess change and the reasons for that change.

Within seagrass bed structural heterogeneity

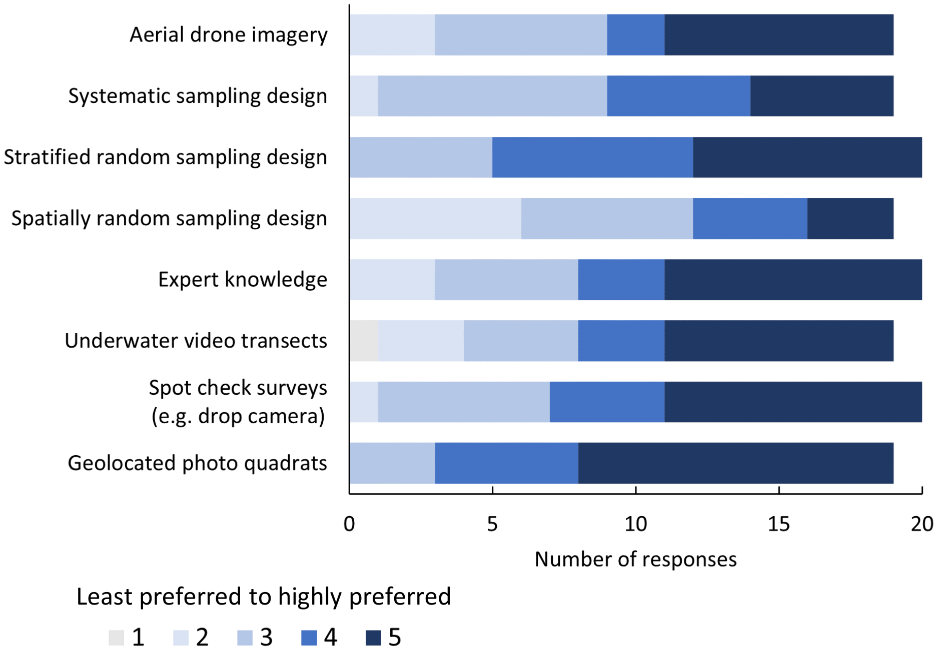
Field research is required to determine below root biomass and sediments

Density, homogeneity, distance to shoreline, eutrophication, turbidity, species composition, water depth, sediment type and size, light attenuation and intensity, hydrodynamics, mud content are some of the most important variables that can and should be characterized with remote sensing that relate to higher carbon sequestration rates and stocks.

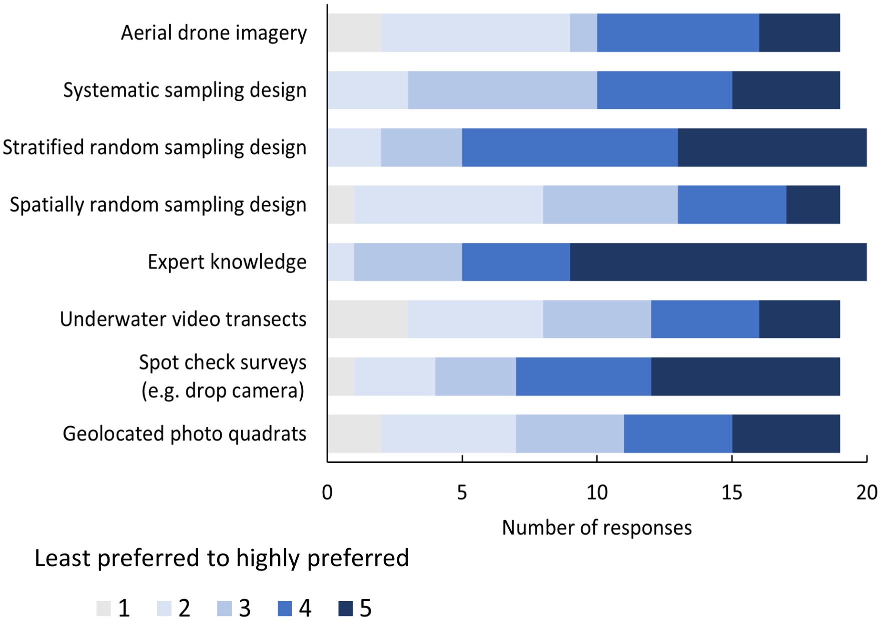
How reliably **can these variables be mapped with current remote sensing approaches?**



Please can you **rank your preference** for different types of data/methods required for training and validation when mapping global seagrass extent **where cost is not an issue**.



Please can you **rank your preference** for different types of data/methods required for training and validation when mapping global seagrass extent **where cost is an important issue.**



Expert’s written comments

As cost concerns increase, greater emphasis should be placed on maximizing both efficiency and spatial coverage for field data collection.

Active sampling techniques combined with semi-supervised learning may help in sampling and collecting training and validating data

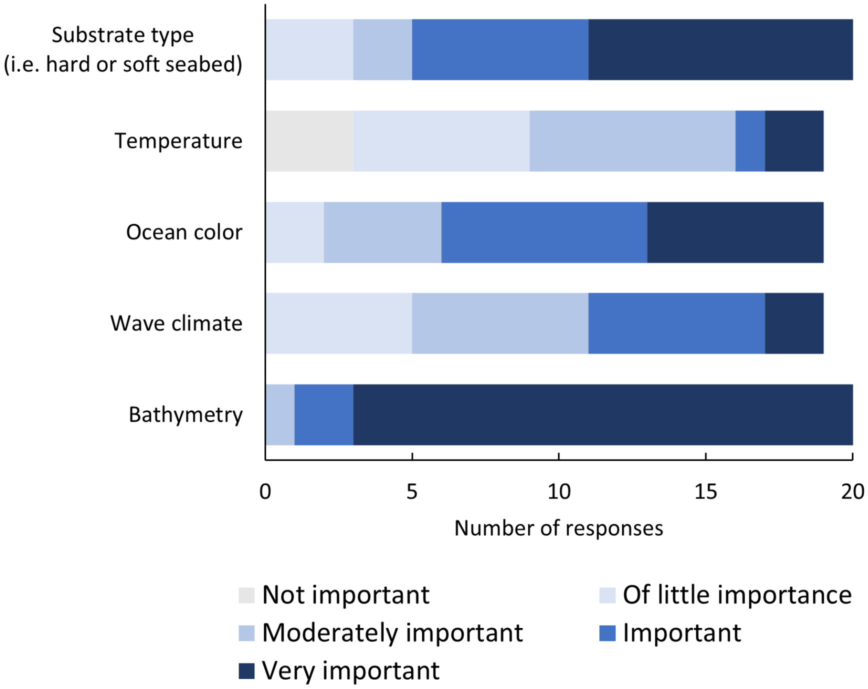
If video transects come from AUV, rather than divers, it can be a useful 'costly' approach.

Cost should not really be an issue if you focus on smaller/relevant scales which are those for decision making, carbon assessment projects, etc.

Answering these questions is so dependent on circumstances and local access and infrastructure etc. It also presumes lots of validation is needed. when using physics-based inversion methods once a representative spectral library is available (such as a national one in Australia I compiled recently with Digital Earth Australia) much less validation is needed.

The systematic sample design should be used to collect the model training data and should ensure the range of seagrass habitat types and environmental variables have been sampled. The random stratified sampling design should be used to collect the model validation data and should be randomized based on seagrass habitat type and model uncertainty.

Please rank the following **environmental variables** in order of the value that they add to mapping global seagrass extent.



Expert's written comments

Ocean colour is such a generic term. e.g., when mapping seagrasses on the Queensland coast seasonal weather patterns are key due to resuspension of TSS. When rivers flow after massive rainfall CDOM and TSS and as the river plume progresses mainly CDOM can obscure the seagrasses etc.

More data is always better. Leveraging data that directly complements image classification is particularly useful.

Density, homogeneity, distance to shoreline, eutrophication, turbidity, species composition, water depth, sediment type and size, light attenuation and intensity, hydrodynamics, mud content are some of the most important variables that can and should be characterized with remote sensing that relate to higher carbon sequestration rates and stocks.

Synthesis of evidence for a methodological pathway to improve the global seagrass map

This synthesis section integrates key findings from Part 1 and Part 2 to address: What is needed, What are the challenges and limitations, and What are the current solutions and future priorities in global seagrass mapping.

Geographical gaps in seagrass mapping. The comprehensive global literature review revealed some geographical variability in recent documented seagrass mapping (2012-2021) and inconsistences in the information recorded. The highest number of published seagrass mapping studies were recorded for Indonesia, Mozambique and Australia. The marine biogeographic realms with most published studies were the Tropical Atlantic (mostly Caribbean Sea) and the Central Indo-Pacific. In contrast, only one published study was found for the Eastern-Indo Pacific and none for the Tropical Eastern Pacific. Thirty-one of the forty locations without any reported seagrass mapping in the present literature review have, however, received recent seagrass mapping effort through the Allen Coral Atlas project. The Gulf of Guinea region of the Tropical Atlantic is the exception with few of the areas with recorded historical presence of seagrass being mapped. Recent habitat suitability models of seagrass distribution in South China indicate that remote mapping has likely underestimated the full extent of seagrass in the region (Hu et al. 2021).

Little is known about the global spatial extent of seagrasses distributed in turbid waters and waters deeper than 15 m. An additional focused review of published records, datasets and local knowledge will be required to better understand the distribution of deeper water seagrass. Recent progress in environmental data availability suggest that investment in predictive mapping of seagrass distributions for optically deep and turbid waters would be a cost-effective solution to address data gaps in areas where water conditions form barriers to optical remote sensing.

Mapping methods. A wide range of imagery and analytical methods have been applied with high resolution (≤ 5 m) satellite-based multispectral data being most frequently applied using pixel-based and object-based classification, or both. Although reporting of map accuracy was inconsistent, what had been reported suggested that higher mean map accuracy was achieved with object-based analyses and generally with high (≤ 5 m) resolution imagery compared to moderate (5-30 m) resolution. Experts preferred WorldView-3 (≤ 2 m pixels) when cost was not an issue and Sentinel-2 (10 m pixels) when cost was an issue. A 10 m pixel size was identified as optimal for mapping seagrass extent for blue carbon accounting.

It was noted that deep learning and machine learning classifiers increasingly played a role in data analyses. Additional research is required to determine the uptake and comparative effectiveness of machine learning classifiers for seagrass mapping and the performance of pixel and object-based approaches. This global synthesis of reported seagrass mapping highlighted considerable variability in methodology, however, there was a clear consensus among experts that a standardized, and repeatable, methodological approach was essential to achieve a global map for seagrass extent.

Highly variable environmental conditions and biological characteristics is a challenge for global seagrass mapping with experts exclaiming that multiple data types and processing methods are sometimes required, and that the choice of imagery and methods should be context dependent (e.g., local conditions, objectives). A new low Earth orbit hyperspectral satellite with 500 bands launching in 2023 is expected to increase the accuracy of seagrass and biomass discrimination. Experts have cited several recommended mapping methods.

Barriers. Over 60% of experts agree that water clarity and adequate field data were the most important logistical barriers to scaling up remote sensing of seagrass meadows. Turbidity mapping and masking together with reliable bathymetry can help to refine analyses and help predict areas where conditions may be unsuitable for seagrasses. The timeseries selected is important to consider seasonality, pulse events and tidal influence. The most important logistical barriers to national and regional scale mapping were for locations were mapping seagrass was not an institutional priority and where insufficient technical capacity was available. Most experts considered that cultural considerations were not an important barrier to seagrass mapping in the countries where they worked.

Field data. In addition to a high preference for expert knowledge, field data is highly valued as training and validating data by experts. Surveys with geolocated photos using drop cameras, photo quadrats or underwater video and a stratified random sampling design for model training data and a systematic sampling design for model validation data was considered important. Autonomous marine vehicles and drones with multiple sensors (sonar, optical cameras) are rapidly emerging as viable solutions to enable scaling up from field to satellite data. Citizen science has great potential to accelerate and broaden the extent of field data collection.

Additional data. Bathymetric data was considered very important by most experts followed by substrate type and wave climate. ICESat-2 laser altimetry together with passive optical satellite-derived bathymetry can enhance mapping. Most experts considered plant biomass, seagrass species and sediment type as highly relevant for blue carbon accounting, but also revealed that with current data and methods satellite imagery cannot be used to reliably discriminate species and sediment types. Spatial and temporal heterogeneity influence seagrass contributions to carbon sequestration and storage. For example, even the same species can be highly variable depending on the environment in which they grow. For mapping seagrass biomass, new field data acquisition and data on physical conditions was considered important by experts in addition to image resolution.

Cost. Several experts found cost estimation impossible due too many context-dependent variables. Where costs were estimated they were highly variable depending on objectives, imagery used, field validation and local context with expert estimates from specific recent examples (9 cases where USD per km^2 was provided) ranging from \$0.4 to \$3,000 USD per km^2 (mean of \$632 per km^2 ± \$976 SD). Integration of Sentinel-2 imagery and citizen science data collection has the potential to reduce costs.

Suggested next steps to improve existing methods.

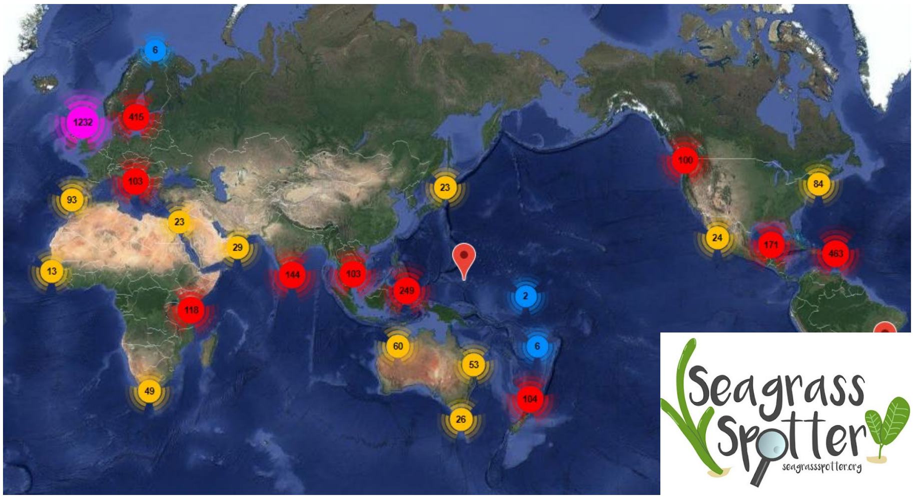
- Merge physics-based approaches with object-based and machine learning methods.
- Combine Seagrass-Watch and Allen Coral Atlas methods into a single framework for global shallow water benthic mapping.
- Improve the pre-processing of imagery.
- Advance the application of hyperspectral data from air and space-borne sensors
- Establish standardized methods for different contexts (e.g., seagrass types, local field logistics, environmental conditions).
- Improve comprehensive reporting of area mapped by benthic class, accuracy assessment, field collection methods, data and methodological limitations.
- Improve the quality and open access sharing of global field survey data.
- Expand citizen science programs globally to increase field data collection.
- Create a high-resolution global bathymetry for shallow coastal waters.
- Conduct synthesis research and habitat suitability modeling to better understand deeper water seagrass distribution.
- Improve mapping of variables that can better account for carbon sequestration and storage (i.e., biomass, species, sediments, proxies for below-ground biomass).

Photo: David Troeger

Complimentary approaches for mapping and validating seagrass presence and spatial extent

Crowdsourced geo-tagged data and participatory citizen science

More inclusive public participation in seagrass mapping can advance the cost-effective mapping and validation of global seagrass distributions. Participatory mapping, citizen science and synthesis of information from geo-tagged images on social media provide opportunities to address data gaps and increase public awareness of seagrasses (Jones et al. 2018). Smartphone applications such as Project Seagrass' Seagrass Spotter (see below) and data mining of geo-tagged content on photo- and video-sharing platforms provides a rapid tool for locating seagrass beds including those that may exist in waters deeper than can be detected by optical satellite remote sensing (McKenzie et al. 2016).



PROJECT SEAGRASS

>3,600 geo-tagged seagrass sightings globally with (36% in equatorial waters)

Use of artificial intelligence including machine learning

70% of experts consulted in this project had indicated that machine learning for image classification was required to accelerate the scaling-up of seagrass mapping. Review of the literature also demonstrated that deep learning and machine learning algorithms are increasingly used to boost performance in image classification and object recognition (Pérez-Carabaza et al. 2021, Li et al. 2020). AI algorithms have also been applied in predictive mapping of seagrass habitat suitability (Folmer et al. 2016, Jayathilake & Costello 2018). Recognizing a knowledge gap for seagrass distribution in the South China Sea, Hu et al. (2021) used machine learning to map approximately 3,536 to 4,852 km^2 of suitable habitat for seagrasses. With sufficient and reliable environmental predictors, spatial predictive mapping with deep learning or machine learning offers great potential to complement remote sensing approaches to accelerate global mapping of seagrass including ocean spaces beyond the limits of optical satellite or aerial remote sensing.

Cloud computing and workflows

55% of experts indicated that to accelerate the scaling-up of seagrass mapping would require analytical workflows through cloud computing infrastructure (e.g., Google Earth Engine). Locating image processing to cloud-based computing enables flexible, rapid, scalable and cost-efficient analyses of large data volume workflows that include deep learning and machine learning algorithms (Traganos et al. 2018, Lyons et al. 2020). Workflow management software (Sun et al. 2020) can now fully automate the complex steps applied to multi-dimensional data from access to files, managing scripts and code, pre-processing data, training and testing models, through to image post-processing.

Mapping deep water seagrass

Most of what we know about seagrass distribution and ecology comes from shallow (<15 m depth) seagrass beds in optically clear waters. Seagrasses, however, also exist in deeper (15 – >70 m) and turbid waters in some regions (Esteban et al. 2018).

Where turbidity is transient then multi-temporal data may be a feasible solution (Pertiwi et al. 2021). Although technological innovation in optical image processing has extended the depth limits for satellite remote sensing there remains a challenge with mapping seagrass in very deep and continuously turbid water. In these places, alternative and less cost-effective in-situ mapping would be required including ship-based acoustic sensors or autonomous underwater vehicles. The movement patterns of satellite tracked air-breathing herbivores (i.e., green sea turtles, dugongs) that forage on seagrass beds have been used to reveal seagrass beds in deep water (Hays et al. 2018).

Autonomous and remotely piloted platforms

Scaling up mapping of seagrass extent and other benthic habitats can be costly when in-water validation data is required. A wide range of surface and subsurface platforms are being applied to map and ground truth seafloor structure in a wide range of water conditions. Some of these marine platforms carry sonar and optical devices with potential to survey seagrasses in deeper and turbid waters that challenge aerial and space-borne sensors.

Aerial drone imagery can also provide cost-effective mapping and validation as an alternative to in situ surveys when processed through automated or semi-automated workflows (Bennett et al. 2020). Mapping and monitoring of shallow coastal seascapes using inexpensive commercial aerial drones equipped with multispectral cameras and less frequently with hyperspectral or LiDAR is increasing.

Spectral libraries and hyperspectral data

Spectral characteristics of seagrasses under different environmental conditions and with differing biological composition are held in field-based surface reflectance signatures, or spectra, and could provide another alternative for cost-effective seagrass mapping. Using reference data from spectral libraries to classify benthic classes could enable rapid image correcting and classification and reduce the cost of collections of new field calibration data. In Australia, the Digital Earth Australia's Aquatic Substratum Spectral Library Project has compiled and catalogued a large database of more than 2500 spectra and metadata (1994 to 2016) and transformed it into a publicly available and searchable database called AUS-SPECCHIO (Dekker 2021). Another 1100 aquatic spectra are catalogued by the Wollongong Spectral Library (Fyfe 2003). These spectra can enable the retrospective processing and validation of satellite data (such as the Landsat and Sentinel-2 archives) to map optically shallow aquatic ecosystems. Dekker (2021) estimates that each spectrum has a value of approximately 2,000 AUD when accounting for total cost savings on field missions. The spectral library includes spectra for seagrasses by species and seagrasses with and without epiphytes. The approach is based on understanding both the spectral properties of the water column above the area mapped and the seagrass, hence spectra can be highly variable in time and space. Application is reliant on hyperspectral imagery and could therefore be limiting factor for scaling up to a global framework. Data fusion approaches together with object-based analysis and the potential for future development of high-resolution hyperspectral sensors, however, could be beneficial for genus level classification, biomass estimation, and condition assessments (Hedley et al. 2021).

Integration of bathymetric data

Integration of reliable bathymetric data is beneficial for any mapping and monitoring of submerged habitats. In addition to depth, bathymetric data in the form of digital terrain models provides information on terrain morphology (slope, topographic complexity) that can be identify the relative suitability of terrain for seagrasses and to improve wave climate models. Bathymetry has been applied to inform object-based classification of coral reef ecosystems (Lyons et al. 2020, Kennedy et al. 2021). Spatial information on depth, slope and waves can be combined to refine the targeting of mapping efforts. The process of deriving depth from satellite imagery involves correcting the imagery to bottom reflectance products which could improve the mapping (Poursanidis et al. 2019). Experimental space-based laser altimetry (ICESat-2) has been used to train satellite-derived bathymetry from Sentinel-2 with potential for scaling up the global mapping of nearshore tropical habitat mapping that exist in optically shallow water (Thomas et al. 2021). Finer scale mapping of shallow (<16 m) seagrass extent and canopy height has been achieved with topo-bathymetry (green and infrared lasers) derived from airborne LiDAR using a machine learning classifier applied to the full waveform (Letard et al. 2021).

Cited Literature

Bennett, M.K., Younes, N. and Joyce, K., 2020. Automating drone image processing to map coral reef substrates using Google Earth Engine. *Drones*, *4*(3), p.50.

Costa, B. 2019. Multispectral acoustic backscatter: How useful is it for marine habitat mapping and management?. *Journal of Coastal Research*, 35(5), 1062-1079.

Costa, B., M. Kendall, and S. McKagan. 2018. Managers, modelers, and measuring the impact of species distribution model uncertainty on marine zoning decisions. *PLoS ONE*, 13(10):e0204569.

Costa, B. 2021. Enhancing Habitat Mapping Accuracy and Efficiency Using Artificial Intelligence: https://coastalscience.noaa.gov/project/enhancing-habitat-mapping-accuracy-and-efficiency-using-artificial-intelligence/

Dekker, A.G. 2021. Aquatic Spectral Library Phase 2. A report to Geoscience Australia by SatDek Pty Ltd, Sutton, NSW, Australia; 10 p.

Esteban, N., Unsworth, R.K.F., Gourlay, J.B.Q. and Hays, G.C., 2018. The discovery of deep-water seagrass meadows in a pristine Indian Ocean wilderness revealed by tracking green turtles. *Marine Pollution Bulletin*, *134*, 99-105.

Folmer, E.O., van Beusekom, J.E., Dolch, T., Gräwe, U., van Katwijk, M.M., Kolbe, K. and Philippart, C.J., 2016. Consensus forecasting of intertidal seagrass habitat in the Wadden Sea. *Journal of Applied Ecology*, *53*(6), 1800-1813.

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

Ha, N.T., Manley-Harris, M., Pham, T.D. and Hawes, I., 2020. A comparative assessment of ensemble-based machine learning and maximum likelihood methods for mapping seagrass using sentinel-2 imagery in Tauranga Harbor, New Zealand. *Remote Sensing*, 12(3), p.355

Ha, N.T., Manley-Harris, M., Pham, T.D. and Hawes, I., 2021a. The use of radar and optical satellite imagery combined with advanced machine learning and metaheuristic optimization techniques to detect and quantify above ground biomass of intertidal seagrass in a New Zealand estuary. *International Journal of Remote Sensing*, *42*(12), pp.4712-4738.

Ha, N.T., Manley-Harris, M., Pham, T.D. and Hawes, I., 2021b. Detecting Multi-Decadal Changes in Seagrass Cover in Tauranga Harbour, New Zealand, Using Landsat Imagery and Boosting Ensemble Classification Techniques. *ISPRS International Journal of Geo-Information*, *10*(6), p.371.

Hays, G.C., Alcoverro, T., Christianen, M.J., Duarte, C.M., Hamann, M., Macreadie, P.I., Marsh, H.D., Rasheed, M.A., Thums, M., Unsworth, R.K.F., York, P.H. and Esteban N. 2018. New tools to identify the location of seagrass meadows: marine grazers as habitat indicators. *Frontiers in Marine Science* 5:9.

Hossain, M.S., Bujang, J.S., Zakaria, M.H. and Hashim, M., 2015. The application of remote sensing to seagrass ecosystems: an overview and future research prospects. *International Journal of Remote Sensing*, *36*(1), 61-114.

Hu, W., Zhang, D., Chen, B., Liu, X., Ye, X., Jiang, Q., Zheng, X., Du, J. and Chen, S., 2021. Mapping the seagrass conservation and restoration priorities: Coupling habitat suitability and anthropogenic pressures. *Ecological Indicators*, *129*, p.107960.

Jayathilake D.R.M., Costello M.J. 2018. A modelled global distribution of the seagrass biome. *Biological Conservation* 226:120-126.

Jones, B.L., Unsworth, R.K.F., McKenzie, L.J., Yoshida, R.L., Cullen-Unsworth, L.C. 2018. Crowdsourcing conservation: The role of citizen science in securing a future for seagrass. *Marine Pollution Bulletin* 134:210-215.

Kendall, M., B. Costa, S. McKagan, and L. Johnston. 2017. Benthic habitat maps of Saipan Lagoon, Commonwealth of the Northern Mariana Islands (NCEI Accession 0162517). NOAA National Centers for Environmental Information. Dataset. doi:10.7289/V5NV9GB9

Kennedy, E.V., Roelfsema, C.M., Lyons, M.B., Kovacs, E.M., Borrego-Acevedo, R., Roe, M., Phinn, S.R., Larsen, K., Murray, N.J., Yuwono, D. and Wolff, J., and Tudman, P. 2021. Reef Cover, a coral reef classification for global habitat mapping from remote sensing. *Scientific Data*, *8*(1), 1-20.

Li, J., Knapp, D.E., Fabina, N.S., Kennedy, E.V., Larsen, K., Lyons, M.B., Murray, N.J., Phinn, S.R., Roelfsema, C.M. and Asner, G.P., 2020. A global coral reef probability map generated using convolutional neural networks. *Coral Reefs*, *39*(6), 1805-1815.

Letard, M., Collin, A., Lague, D., Corpetti, T., Pastol, Y., Ekelund, A., Pergent, G. and Costa, S., 2021. Towards 3D mapping of seagrass meadows with topo-bathymetric Lidar full waveform processing. p8069-8072. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*. IEEE.

Lyons, M.B, M. Roelfsema, C., V. Kennedy, E., M. Kovacs, E., Borrego-Acevedo, R., Markey, K., Roe, M., M. Yuwono, D., L. Harris, D., R. Phinn, S. and Asner, G.P., 2020. Mapping the world's coral reefs using a global multiscale earth observation framework. *Remote Sensing in Ecology and Conservation*, *6*(4), 557-568.

McKenzie, L.J., Yaakub, S.M., Tan, R., Seymour, J. and Yoshida, R.L., 2016. Seagrass habitats of Singapore: environmental drivers and key processes. *Raffles Bulletin of Zoology 34: 60-77*.

McKenzie, L.J., Nordlund, L.M., Jones, B.L., Cullen-Unsworth, L.C., Roelfsema, C., Unsworth, R.K.F., 2020. The global distribution of seagrass meadows. *Environmental Research Letters* 15(7):074041.

Morales-Barquero, L., Lyons, M.B., Phinn, S.R. and Roelfsema, C.M., 2019. Trends in remote sensing accuracy assessment approaches in the context of natural resources. *Remote sensing*, *11*(19), p.2305.

Pérez-Carabaza, S., Boydell, O. and O'Connell, J., 2021. Habitat classification using convolutional neural networks and multitemporal multispectral aerial imagery. *Journal of Applied Remote Sensing*, *15*(4), p.042406.

Pertiwi, A.P., Lee, C.B. and Traganos, D., 2021. Cloud-native coastal turbid zone detection using multi-temporal Sentinel-2 data on Google Earth Engine. *Frontiers in Marine Science*, 8.

Poursanidis, D., Traganos, D., Chrysoulakis, N. and Reinartz, P., 2019. Cubesats allow high spatiotemporal estimates of satellite-derived bathymetry. *Remote Sensing*, *11*(11), p.1299.

Poursanidis, D., Traganos, D., Teixeira, L., Shapiro, A. and Muaves, L., 2021. Cloud-native seascape mapping of Mozambique's Quirimbas National Park with Sentinel-2. *Remote Sensing in Ecology and Conservation*, *7*(2), 275-291.

Roelfsema, C.M. and Phinn, S.R. 2013. Validation. p375-401. In (Goodman J., Purkis S., Phinn S. eds.) Coral Reef Remote Sensing. Springer.

Roelfsema, C.M., Lyons, M., Murray, N., Kovacs, E.M., Kennedy, E., Markey, K., Borrego-Acevedo, R., Alvarez, A.O., Say, C., Tudman, P., Roe, M., Wolff J., Traganos D., Asner, G.P., Bambic, B., Free, B., Fox, H.E., Lieb, Z., and Phinn, S.R. 2021. Workflow for the generation of expert-derived training and validation data: A view to global scale habitat mapping. *Frontiers in Marine Science*, *8*, p.643381.

Sagawa, T., Boisnier, E., Komatsu, T., Mustapha, K., Hattour, A., Kosaka, N. and Miyazaki, S., 2010. Using bottom surface reflectance to map coastal marine areas: a new application method for Lyzenga's model. *International Journal of Remote Sensing*, 31, 3051-3064.

Sagawa, T., Yamashita, Y., Okumura, T. and Yamanokuchi, T. 2019. Satellite derived bathymetry using machine learning and multi-temporal satellite images, *Remote Sensing*, 11, 1155, 1-19.

Spalding, M.D., Fox, H.E., Allen, G.R., Davidson, N., Ferdaña, Z.A., Finlayson, M., Halpern, B.S., Jorge, M.A., Lombana, A., Lourie, S.A., Martin, K.D., McManus, E., Molnar, J., Recchia, C.A. and Robertson J., 2007. Marine ecoregions of the world: a bioregionalization of coastal and shelf areas. *BioScience*, *57*(7), 573-583.

Sun, Z., Di, L., Burgess, A., Tullis, J.A. and Magill, A.B., 2020. Geoweaver: Advanced cyberinfrastructure for managing hybrid geoscientific AI workflows. *ISPRS International Journal of Geo-Information*, *9*(2), p.119.

Thomas, N., Pertiwi, A.P., Traganos, D., Lagomasino, D., Poursanidis, D., Moreno, S. and Fatoyinbo, L., 2021. Space-borne cloud-native satellite-derived bathymetry (SDB) models using ICESat-2 and Sentinel-2. *Geophysical Research Letters*, *48*(6), p.e2020GL092170.

Traganos, D., Aggarwal, B., Poursanidis, D., Topouzelis, K., Chrysoulakis, N. and Reinartz, P., 2018. Towards global-scale seagrass mapping and monitoring using Sentinel-2 on Google Earth Engine: The case study of the Aegean and Ionian Seas. *Remote Sensing* 10:1–14.

United Nations Environment Programme. 2020. Out of the blue: The value of seagrasses to the environment and to people. UNEP, Nairobi.

UNEP-WCMC, Short FT (2021). Global distribution of seagrasses (version 7.1). Seventh update to the data layer used in Green and Short (2003). Cambridge (UK): UN Environment World Conservation Monitoring Centre.
Data DOI: https://doi.org/10.34892/x6r3-d211

Unsworth, R.K., McKenzie L.J., Collier C.J., Cullen-Unsworth L.C., Duarte C.M., Eklöf J.S., Jarvis J.C., Jones B.L., Nordlund L.M. (2019) Global challenges for seagrass conservation. *Ambio* 48(8): 801-815.

Whitt, C., Pearlman, J., Polagye, B., Caimi, F., Muller-Karger, F., Copping, A., Spence, H., Madhusudhana, S., Kirkwood, W., Grosjean, L., Fiaz, B.M., Singh, S., Manalang, D., Sen Gupta, A., Maguer, A., Buck, J.J.H., Marouchos, A., Atmanand, A., Venkatesan, R., Narayanaswamy, V., Testor, P., Douglas, E., de Halleux, S. and Khalsa, S.J. 2020. Future vision for autonomous ocean observations. *Frontiers in Marine Science*, *7*, p.697.

Appendices

Photo: Ben Jones

A1: Case study of field data utility: Indonesian Archipelago

A2: Table 1 seagrass-focused organizations
Table 2 key global seagrass datasets

A1: Case study of field data utility: Indonesian Archipelago

A key aspect to habitat mapping highlighted by the expert consultation is the importance of having adequate field data that is of a high quality for map calibration and validation. However, obtaining sufficient georeferenced ground truthing data has also been considered by experts in the field as one of the challenges when undertaking mapping efforts, especially at large scales.

Here we undertook an in-depth literature review within the Indonesian Archipelago to identify non-mapping studies that have collected georeferenced benthic field data, which has the potential to assist with future seagrass mapping efforts for the region.

- 14 non-mapping studies with georeferenced seagrass data were identified within the Indonesian Archipelago
- These 14 studies are in addition to the key global datasets (outlined in the Tables 1 & 2) which were also identified as having potential seagrass data
- These datasets consisted of various formats of data including photos, quadrats and point-based benthic information, collected using multiple methods.
- These data were collected between 2005 and 2019, with six datasets from 2008.

This case study for the Indonesian Archipelago identified 14 potential studies spanning across the Indonesian Archipelago. However, these studies were not designed specifically for map validation and do not provide consistent methods. The data format, method of collection and geospatial accuracy varies between the datasets. This dataset literature review also highlights that the year of acquisition of the data could influence the reliability of these datasets if used to map seagrass in the future. The data do indicate locations of seagrass beds that can inform future mapping. This case study therefore highlights potential limitations that could be encountered if mapping efforts were to utilise previously collected georeferenced data for map calibration and validation.

Photo: Ben Jones

A2: Table 1: Key seagrass-focused organizations

Organisation	Geographical scope	Main activities	Primary products
Seagrass-Watch	Global	Mapping and monitoring	Data and reporting
Project Seagrass	Global	Monitoring, research and restoration	Data and reporting
Ocean Health Index	Global	Status and trends for ecosystem services	Data and reporting
UNEP World Conservation Monitoring Centre	Global	Global distribution of seagrasses	Maps
Allen Coral Atlas & Blue Carbon Mapper	Global	Mapping coral reef ecosystems	Maps
Coordinated Global Research Assessment of Seagrass System (C-GRASS)	Global	Research and synthesis	Status and trends
International Seagrass Experts Network	Global	Research and knowledge sharing	Reporting
European Marine Observation & Data Network	Europe	Spatial data including seagrass species distributions	Maps
Global Wetlands Project	Global	Reporting	Global status & trends
US National Oceanic & Atmospheric Administration	US waters	Seafloor mapping & field surveys in US waters	Seafloor maps & field data
Khaled bin Sultan Living Oceans Foundation	Global	Seafloor mapping & field surveys in global tropics	Seafloor maps & field data
Seagrass integrated mapping & monitoring (SIMM) program	Florida, USA	Monitoring	Seafloor maps & field data
SeagrassNet	Global	Monitoring	Data portal in progress
Western Indian Ocean Seagrass Network	Western Indian Ocean	Platform for knowledge sharing and collaboration	Reporting
ResilienSEA	Western Africa	Monitoring and mapping	Data and Maps
Great Barrier Reef Marine Monitoring Program	Australia	Field monitoring	Data & reports
GRID-Arendal	Global	Seagrass & blue carbon information	Reports
Maldives Seagrass Monitoring Network	Maldives	Monitoring	Data & reports
International Blue Carbon Initiative	Global	Reporting and implementation	Coordination & Reports
Coastal Carbon Research Coordination Network	Global	Research	Coordination & Data
Blue Carbon Partnership	Global	Networks	Coordination & Reports

Table 1 (continued): Key seagrass-focused organizations

Organisation	Geographical scope	Main activities	Primary products
World Seagrass Association	Global	Training and comms.	Research network
Indo-Pacific Seagrass Network (IPSN)	Indo-Pacific	Data collection, training, and reporting	Data sets and reporting
MarineGEO & Tennenbaum Marine Observatories Network	Global	Ocean science research network	Data collection and reporting
The Atlantic and Gulf Rapid Reef Assessment (AGRRA)	Caribbean & Gulf of Mexico	Monitoring, training and reporting	Data sets and training tools
Caribbean Coastal Marine Productivity (CARICOMP)	Caribbean Sea	Monitoring, research and synthesis	Data, reports on status and trends
Brazilian Long Term Ecological Research (BR-LTER)	Brazil	Data collection, research and knowledge sharing	Monitoring data and maps
ReBentos (Brazilian Benthic Monitoring Network)	Brazil	Research and monitoring	Coordination, data synthesis, protocols
International Blue Carbon Initiative	Global	Conservation and restoration actions	Research, assessments and field projects

Table 2: Key global seagrass datasets

Organisation	Geographical scope	Data type	Data size	Source
UNEP World Conservation Monitoring Centre	Global 1934-2020 Latest version online: 7.1 (March 2021)	Points and polygons (presence & species richness)	853 MB (293,147 polygons); 21 MB (17,667 points)	https://data.unep-wcmc.org/datasets/7
Seagrass Watch	Global long-term monitoring since 1999	Photo quadrats at geolocated sites	192,827 quadrats 415 sites in 21 countries	https://www.seagrasswatch.org/
Allen Coral Atlas	Global distribution of tropical coral reefs	Spatial distributions & summary statistics	99,039 km² across 30 predefined regions. Can also be downloaded in user-defined areas of interest	https://allencoralatlas.org/atlas/
Reef Check Worldwide	Global Since 1997	Point data and transects. Mostly reef focused but some seagrass.	Reef tracker portal under construction	https://www.reefcheck.org/global-reef-tracker/
Reef Life Surveys	Global 2008-2020	Georeferenced photo-quadrats but not analyzed for seagrass	3537 sites in 53 countries	Edgar, G.J et al. (2020). Establishing the ecological basis for conservation of shallow marine life using Reef Life Survey. Biological Conservation 252, 108855.
Global Biodiversity Information Facility	Global	Occurrence datasets (from years 1792 to 2016)	>80,000 georeferenced records	Reported by Jayathilake & Costello 2018
Ocean Biodiversity Information System	Global	Occurrence datasets	3,806	Reported by Jayathilake & Costello 2018
Project Seagrass	Global	Occurrence datasets	3718 points from 99 countries	http://www.SeagrassSpotter.org

Note: Some overlap in records occurs between these datasets.

Photo: Ben Jones

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