Ocean Country Partnership Programme

Sri Lanka seagrass mapping report

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Ocean Country Partnership Programme:
The Ocean Country Partnership Programme (OCPP) is a bilateral technical assistance and capacity building programme that provides tailored support to countries to manage the marine environment more sustainably, including by strengthening marine science expertise, developing science-based policy and management tools and creating educational resources for coastal communities. The OCPP delivers work under three thematic areas: biodiversity, marine pollution, and sustainable seafood.

Summary

Seagrass habitats are ecologically and economically important coastal ecosystems that provide a wide range of benefits, including fisheries support, carbon storage, and nutrient cycling. Despite their value, seagrass habitats in Sri Lanka have previously been poorly characterised at the national scale, with existing data spatially fragmented and generated using inconsistent methodologies. This report describes work undertaken as part of the Ocean Country Partnership Programme (OCPP) to produce the first standardised, national-scale seagrass habitat map for Sri Lanka.

The map was produced using a machine learning classification applied to Sentinel-2 satellite data (European Space Agency; 10 metre pixel size), covering the full coastline of Sri Lanka down to 20 metres depth. Training data were developed through expert photointerpretation in collaboration with in-country partners at Blue Resources Trust and IUCN. The model was validated using 3,061 independent field data points collected at 16 sites across the country. The total seagrass extent predicted by the best performing model was 540 km² (probability threshold = 0.6; overall accuracy = 69.6%; user accuracy seagrass = 77.7%), with the highest concentrations of habitat predicted in the northern and northwestern regions.

The model is considered conservative in its estimations of seagrass areal extent, with higher user accuracy scores (77.7%) for the seagrass class indicating reliable predictions of seagrass presence. The data product is presented in a continuous probability format to allow flexible thresholding depending on the intended application.

This national-scale seagrass map provides an important baseline for seagrass conservation, marine planning, and research in Sri Lanka, and is intended to support ongoing efforts to monitor and manage these habitats. Capacity building delivered through OCPP has facilitated the skills and knowledge required to build upon this work in the future.

Please note, the seagrass habitat layer produced during this work is intended solely for habitat classification purposes and does not represent or imply any position regarding geopolitical boundaries or territorial disputes.

Contents

1. Introduction and background

1.1 Seagrass habitats

Seagrasses are marine flowering plants that form important habitats in coastal regions from the poles to the tropics (Green *et al.* 2003; Short *et al.* 2011). Seagrass structure and function vary substantially from large meadow-forming species that can exist for thousands of years (e.g. *Posidonia australis*; Edgeloe *et al.* 2022) to small low growing species that grow opportunistically and in ephemeral conditions (Figure 1). Across their broad distributional range, seagrass habitats underpin many key coastal ecosystem functions by influencing the physical, chemical, and biological features of their environment. In fact, seagrasses bioengineer their own environment through positive feedback mechanisms that improve conditions for further seagrass growth and habitat persistence. For example, seagrass roots and rhizomes act to stabilise loose sandy sediments and seagrass leaves slow down water currents and promote sediment accretion (Potouroglou *et al*. 2017). The combined action of these processes reduces suspended sediments and improves water clarity and quality whilst also laying down sediments required for further seagrass growth. The enhanced structural complexity introduced by seagrass plants, in otherwise bare sandy sediment, can provide food and habitat for a wide variety of marine animals including invertebrates such as crustaceans (crabs and shrimp), molluscs (gastropod snails and bivalves), echinoderms (sea stars, sea cucumbers, sea urchins) and vertebrates such as fish, sharks, skates, rays, turtles, and marine mammals (Jones *et al*. 2021; United Nations Environment Programme 2020). In the tropics, seagrasses are a key component of an interconnected seascape that can include coral reefs and mangroves.

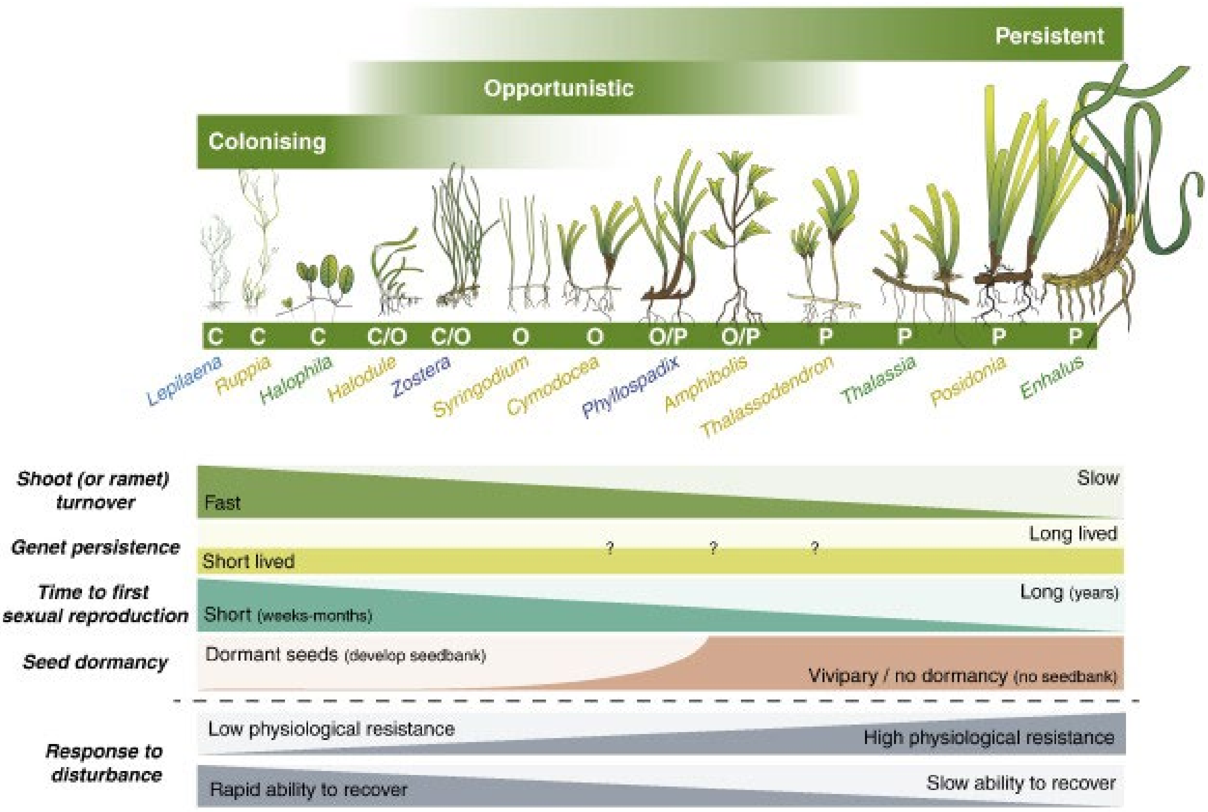

Figure 1. Broad biological characteristics of seagrass genera spanning colonising, opportunistic, and persistent life history types. Figure from Kilminster *et al.* (2022).

Due to the affinity of seagrasses to coastal areas, seagrass habitat functioning has direct implications for human health and well-being (United Nations Environment Programme 2020). Indeed, seagrass habitats contribute to achieving 16 of the 17 UN Sustainable Development Goals (SDGs) (Unsworth *et al*. 2022). Most notable are the benefits to sustainable food and, indeed, up to 20% of large-scale fisheries are supported by seagrass habitats acting as nursery grounds for juvenile fish (Unsworth *et al.* 2019). Additionally, a key research area in coastal marine science is the ability of seagrass to store carbon and thus abate the effects of anthropogenic CO_2 emissions (Macreadie *et al.* 2021). As such, conservation, protection, and restoration of seagrass habitats can provide many ecological, environmental, social, and economic benefits (United Nations Environment Programme 2020).

Despite the value of seagrass habitats, they have been historically overlooked in conservation governance and underrepresented in protected area designations. It is estimated that around 29% of seagrass habitat has been lost since the 1880s with current rates of habitat area decline estimated between 1-2% annually, with some regions experiencing declines of up to 7% per year (Waycott *et al.* 2009). The drivers of these declines are often localised and somewhat unique to each region, although, common causes of decline are related to reduced water quality, excess nutrient inputs related to land use change and coastal development, and maritime activities, such as aquaculture (shrimp farming) and boat activity (anchor damage) (Dunic *et al.* 2021).

As seagrass habitats are lost, so too are their associated benefits that support diverse and robust coastal ecosystems. For example, as seagrass cover declines, the carbon removed from the atmosphere and stored in the sediments can be remineralised and released (Aoki *et al.* 2021). Through this process, these coastal areas transition from carbon sinks to carbon sources and contribute to increasing atmospheric CO_2 levels (Arias-Ortiz *et al.* 2018). Loss of seagrass habitat is often conceptualised as a phase shift, whereby the habitat transitions from a healthy self-sustaining seagrass habitat to a barren and bare sediment state. Importantly, in this state, the conditions for suitable seagrass recovery may be lost, as sediment becomes unstable and water energy is high. Therefore, without intervention, it is unlikely that seagrasses will naturally recover once lost within a particular site.

To avoid the loss of the societal benefits provided by seagrasses, it is important that meadows are managed and monitored. To this end, seagrass habitat mapping represents a powerful tool to quantify seagrass areal extent and distribution. Initially, seagrass habitat locations can be mapped out and a monitoring plan developed to track habitat trajectories and identify localised stressors. Such maps can also be used to evidence meeting international biodiversity (e.g. Convention on Biological Diversity; Petrou *et al.* 2015) and climate change targets (e.g. Nationally Determined Contributions; Malerba *et al.* 2023).

1.2 Seagrass habitat mapping

To avoid the loss of the societal benefits provided by seagrass meadows, it is important that seagrass meadows are managed and monitored. Gathering spatial information on habitat extent and condition is a fundamental starting point to set baselines and to monitor progress in management and conservation. Put simply, to be able to protect or conserve a habitat, it is important that we know how much of that habitat there is, the spatial distribution of the habitat, and its condition. Developing spatial data on marine habitat distributions is therefore identified as a key goal across many conservation and research organisations (United Nations Environment Programme 2020)

Mapping of marine habitats can be achieved using a range of complementary techniques that are chosen based on the requirements of the project. For example, for small scale studies, swim-over surveys using handheld GPS devices can be used to record data on habitat extent and condition. At larger scales, practitioners can utilise drone data and satellite imagery to identify and map different habitat types. Over large scales (tens to thousands of kilometres), satellite data are particularly useful as they are captured over sufficiently large areas and record data on the properties of the Earth's surface. Optical data are suited to mapping benthic habitats, such as seagrasses, as they record the reflectance of light from the benthos in different spectral bands (Malerba *et al*. 2023; Petrou *et al.* 2015) – from the visible spectrum that humans can see, to the Near Infra-Red (NIR) that we cannot see. From this data, collected across a large area and in many spectral bands, training data can be extracted and used to train classification algorithms. Machine learning algorithms are commonly used in habitat classification workflows as they can handle the often-complex nature of the datasets and classification problems (Floyd *et al.* 2025). The aim of habitat classification is to assign a discrete label to each pixel in the image to produce an overall map of different habitat or land cover types. Once the map has been produced, independent field data can be used to evaluate the accuracy of the mapping outputs.

1.3 Problem statement

Previous data on seagrass habitat extent in Sri Lanka are limited and, where present, existing data are spatially fragmented and generated using different methodologies. Indeed, existing estimates of national seagrass extent are highly variable (Veettil *et al.* 2024): 23,819 ha (Gunatilleke *et al.* 2017), 37,137 ha (Udagedara & Dahanayaka 2020), and 293,400 ha (Vanderklift *et al.* 2019). As such, at the national scale, there has been a lack of information on seagrass habitat extent and location that can be used for conservation, restoration, and research. Whilst the environmental conditions make optical image-based seagrass mapping challenging in Sri Lanka (associated with high turbidity, strong seasonality, and varied sea state), a standardised national-scale seagrass habitat data product can inform marine planning and act as the basis for ongoing spatial characterisation of seagrass habitats in Sri Lanka. The development of seagrass-specific habitat maps was, therefore, identified as a research priority for OCPP through consultation with in-country partners.

2. Project Aims

This work was part of a wider two-year project to map seagrass in Sri Lanka, as well as build capacity in future seagrass habitat monitoring.

The aim of this aspect of the OCPP Sri Lanka seagrass project was to:

1. Produce a contemporary national scale seagrass habitat map for Sri Lanka.
2. Produce a comprehensive accuracy assessment of the seagrass map.

3. Methods

The workflow used to produce seagrass habitat maps at the project spatial scale reflects the current standard operating procedures developed across the international scientific community (Floyd *et al*. 2024, 2025; Lee *et al.* 2023; Lyons *et al.* 2020; Poursanidis *et al.* 2021; Traganos *et al.* 2022).

3.1 Satellite data processing

3.1.1 Background considerations and justification

3.1.1.1 Data source

Optical satellite imagery was selected as the most suitable data product due to the large spatial scale of the mapping task, strong evidence base for marine habitat mapping applications, and open-source availability of the data. Use of open-source data was prioritised to ensure that future seagrass mapping and monitoring can follow a consistent methodology, without the need to purchase costly commercial datasets.

Harmonised Level 2A Sentinel-2 satellite imagery from the European Space Agency (ESA) were used due to the favourable data specifications for seagrass mapping, including good spatial resolution, robust data quality, and open-source accessibility. For this work we utilised bands 2–4 and 8 (Table 1) (Floyd *et al*. 2024; Traganos *et al.* 2022).

Table 1. Sentinel 2 band specifications.

Band name	Wavelength (nm)	Resolution (m)	Band ID
Aerosols	443.9 S2A / 442.3 S2B	60	B1
Blue	496.6 S2A / 492.1 S2B	10	B2
Green	560 S2A / 559nm S2B	10	B3
Red	664.5 S2A / 665 S2B	10	B4
Red Edge 1	703.9 S2A / 703.8 S2B	20	B5
Red Edge 2	740.2 S2A / 739.1 S2B	20	B6
Red Edge 3	782.5 S2A / 779.7 S2B	20	B7
NIR	835.1 S2A / 833 S2B	10	B8
Red Edge 4	864.8 S2A / 864 2B	20	B8A
Water vapour	945 S2A / 943.2 S2B	60	B9
Cirrus	1373.5 S2A / 1376.9 S2B	60	B10

Band name	Wavelength (nm)	Resolution (m)	Band ID
Short Wave Infrared 1	1613.7 S2A / 1610.4 S2B	20	B11
Short Wave Infrared 2	2202.4 S2A / 2185.7 S2B	20	B12

3.1.1.2 Image acquisition period

Sentinel-2 imagery is collected in tiles (images of 100 by 100 km) at a cadence of 5-days, therefore, there is a large volume of data potentially available for habitat mapping. As these tiles are collected systematically throughout any given period, they capture a range of atmospheric and sea state conditions and often contain substantial sources of noise, such as clouds, cloud shadows, and water column turbidity. To reduce noise, image compositing is a commonly used data processing technique that can create a standardised pseudo-image over large spatial extents (Poursanidis *et al*. 2021; Traganos *et al.* 2022). Put simply, composites are created by combining all of the satellite imagery collected within a particular time window using an average (e.g. mean, median, medoid) or percentile (e.g. 20th, 50th, 75th). The result is to produce a highly robust data product upon which the classification can be performed.

Choosing the appropriate time window to collect satellite imagery from was a key consideration for this project (Floyd *et al.* 2025). The compositing approach was used to utilise the full catalogue of suitable satellite images. In many regions globally, coastal conditions are turbid and highly variable over time and, as such, it is common for workflows to utilise multi-year composites to reduce the overall noise in imagery (Blume *et al.* 2023; Floyd *et al*. 2024; Traganos *et al.* 2022). For example, separate studies to map seagrass across the full extent of the Mediterranean Sea and Bahama banks utilised Sentinel-2 data collected over 5 years (Blume *et al.* 2023; Traganos *et al.* 2022). Composites of the 20th percentile reflectance values are particularly suitable as they can remove high reflectance anomalies from cloud cover (opaque and cirrus), sun glint, and wave whitecaps whilst also avoiding pixels with low reflectance anomalies such as cloud shadows (Traganos *et al.* 2022).

For seagrass habitat mapping, the decision on when to retrieve the imagery is not just related to appropriate atmospheric and sea conditions, but also on the seasonal variability of seagrass habitat cover (Floyd *et al.* 2025). From previous work, and through consultation with in-country experts at Blue Resources Trust and IUCN, it is apparent that seagrass habitat cover can vary substantially in association with seasonal monsoon patterns that can drive localised pulses of freshwater and turbidity. This is likely most prevalent in enclosed lagoons and bays; indeed, a similar process has been reported at enclosed sites in southeast India (Green *et al.* 2003). Additionally, the effect of the monsoons is spatially heterogeneous and therefore fluctuations in seagrass extent are likely asynchronous across the country.

In the planning phase of this project, we tested the effects of multiple periods of image acquisition and consulted international experts who had previously worked with Sentinel-2 data in the coastal zone of Sri Lanka (personal communications Dr Mitchell Lyons). These initial tests showed that when restricting image retrieval to months with lower rainfall (and therefore lower turbidity) the limited number of images resulted in an increase in atmospheric artefacts in the imagery, such as unmasked clouds and cloud shadows. Collecting more imagery over the full year reduced the prevalence of this noise. As such, due to the high degree of variability both in atmospheric conditions, ocean conditions, and seagrass habitat cover, a multi-year composite approach where images from all months are included, was most suitable for this project. We acknowledge that a pseudo-image produced using multiple years' worth of data is likely to be temporally mismatched with validation data that is collected over a limited time window (2024–2025). Due to the reasons described above, retrieval of satellite data that covered the dates of validation data collection did not produce a composite image of sufficient quality. This is a consideration, and in many cases a trade-off, for all satellite-based mapping work.

3.1.1.3 Turbidity

Water column turbidity is a major source of noise in satellite imagery of coastal areas. Turbidity and turbidity plumes are a common feature of coastal waters in Sri Lanka and therefore were a key consideration for this project. The compositing methods described above can mitigate the effects of turbidity by utilising many satellite observations over time. Despite this, turbidity noise remains in areas that are almost permanently turbid, such as lagoons, some bays, and areas subject to riverine influence. Habitat mapping that uses optical imagery is not suitable in permanently or near-permanently turbid zones and these areas are often masked out (removed) during coastal remote sensing workflows (Pertiwi *et al.* 2021).

Referring to the findings and recommendations of Pertiwi *et al.* (2021), we trained a Random Forest classifier to identify turbid regions from the feature space layers. This model was trained using manual photointerpretation to generate turbid training points and non-turbid training points on the same composite image used to produce the seagrass map. The resulting turbidity data layer was used to provide useful contextual information to the seagrass data layer only. This model is based purely on the spectral properties of turbid water to guide a Random Forest model of turbidity probability and is not an attempt to retrieve any parameters from the water column.

3.1.1.4 Area of interest

The area of interest is the geographic location of the study, which included the continental shelf waters of Sri Lanka down to 20 metres depth (as defined by the General Bathymetric Chart of the Oceans (GEBCO) gridded layer; Mayer *et al.* 2018). To increase the availability of training sites, particularly in the northwest region of Sri Lanka, we included some regions from the southeast coast of India (Mandapam to Valinokkam, and northward to Manamelkudi) and also some sites with well-studied and extensive seagrass meadows from the Maldives (e.g. Laamu Atoll and Huvadhoo Atoll). These areas were used for training and are not included in the resulting map for Sri Lanka.

Please note, the seagrass habitat layer produced during this work is intended solely for habitat classification purposes and does not represent or imply any position regarding geopolitical boundaries or territorial disputes.

3.1.2 Data filtering

The satellite data filtering process was undertaken as follows:

1. Date filter and area of interest: Sentinel-2 imagery was accessed through Google Earth Engine from the European Space Agency archive. The time window used was 01.01.2020 to 01.05.2025. To define an appropriate area of interest, a polygon was manually delineated that included the entire continental shelf around Sri Lanka, including coastal marine and brackish waterbodies. This area was further refined by removing areas with water depths > 20 metres as below this depth, even in clear waters, retrieving benthic signals using optical data is inaccurate.

2. Cloudy image removal: The filtered image collection was then further refined by removing images with high cloud cover. This is particularly important because downstream cloud masking is imperfect, and therefore cloudy images can introduce substantial noise even after cloud masking. The Sentinel-2 image metadata 'CLOUDY_PIXEL_PERCENTAGE' was used to remove images with cloud cover > 15% (Floyd *et al.* 2024). Following this step, there were 3,579 suitable Sentinel-2 images retained.

3. Cloud masking: To remove pixels that were occluded by clouds and associated shadows, we used the Google Cloud Score+ dataset. This dataset acts as a quality assessment reference layer and represents the probability that a given pixel is clear. For more information on this dataset, please refer to Pasquarella *et al.* (2023). This dataset was used to set a threshold of 0.83 for the cloud score cumulative distribution function 'cs_cdf', which is the threshold value recommended by the data providers. Put simply, this method allows for the removal of clouds from satellite images.

4. Band selection and image compositing: For marine habitat mapping the visible portion of the electromagnetic spectrum is most useful. Near infrared (NIR) is strongly absorbed by water but can still be used in intertidal or very shallow areas. As such, we retained the visible (RED, GREEN, BLUE) and the NIR bands. We then calculated 3 image composites across different percentile thresholds (20, 30, and 40) and a Normalised Difference Vegetation Index (NDVI) following Lyons (2025).

5. Land masking: Areas of land are not of interest to this work; therefore, a land mask was developed by applying a threshold to a Modified Normalised Difference Water Index (MNDWI). The MNDWI was used to identify the presence of water in each pixel. A threshold value of 0.1 was established based on previous work (Floyd *et al.* 2024, 2025) and fine tuning guided by visual inspection of results.

The pre-processing produced a satellite data product that included a feature space with 10 bands: RED (20th percentile), GREEN (20th percentile), BLUE (20th percentile), RED (30th percentile), GREEN (30th percentile), BLUE (30th percentile), RED (40th percentile), GREEN (40th percentile), BLUE (40th percentile), and NDVI.

3.2 Training data

Following satellite data preparation, a machine learning-based habitat classification workflow was developed. A fundamental aspect of any machine learning classification workflow is the collection of high-quality representative training data. The main requirements of a satellite-based habitat mapping training dataset are as follows:

- Representative: For any given class, the training sites chosen should be representative of a clearly defined benthic cover type. The decision to include or exclude habitat classes is taken early in the habitat classification workflow and is based on the requirements of the project. In this case, we chose to create a binary classification of seagrass and non-seagrass areas as seagrasses are the focus of this work.

- Incorporate normal within class variability: To build a comprehensive seagrass and non-seagrass training dataset, points were sampled across a range of habitat and environmental conditions across Sri Lanka. The spatial distribution of data points was somewhat concentrated in the north and northwest regions as knowledge of seagrass habitats is strongest in these regions.

Seagrass habitat data are scarce across much of Sri Lanka, and whilst data were collected as part of this OCPP project by collaborators at Blue Resources Trust, these data were retained exclusively for model validation to ensure an independent and robust accuracy assessment. Over large spatial scales, such as in this work, it is common for mapping workflows to use training data manually labelled by experts through photointerpretation (Roelfsema *et al.* 2021). This method seeks to capture expert knowledge to produce high volumes of robust training data whilst limiting the effort required to collect data in the field.

We sampled training sites from known areas of consistent seagrass habitat both in Sri Lanka and neighbouring regions. Training sites for seagrass were identified through a combination of existing habitat knowledge, consultation with in-country experts at Blue Resources Trust and IUCN, and detailed examination of the satellite imagery. This collaborative approach aimed to identify and delineate different habitat areas based on the collective expertise of contributors (Figure 2).

To increase the volume of training data, sites from the southeast coast of India (Mandapam to Valinokkam, and northward to Manamelkudi) and well-studied seagrass meadows from the Maldives (e.g. Laamu Atoll and Huvadhoo Atoll) were included. Although the geomorphological conditions of the Maldives are distinct from Sri Lanka, the seagrass areas are well documented and represent dense seagrass presence of similar species (East *et al.* 2023; Floyd *et al.* 2024).

Non-seagrass training sites were sampled to represent the full range of alternative benthic habitat types present in Sri Lankan coastal waters, including sand, macroalgae, rock, and coral reef.

3.2.1 Spatial modelling strategy

During the development of the model training data, it was apparent that the environmental conditions and seagrass habitat characteristics across Sri Lanka were distinct in the north and northwest region versus the east, west, and southern regions of the country. The main differences were that seagrass habitats in the north and northwest were more extensive with denser cover, additionally, these regions tended to be more sheltered with generally calmer waters.

When the model was trained over the whole extent of the Sri Lankan coastline, the initial results showed an underestimation of seagrass cover in the north and northwest, whilst simultaneously overestimating seagrass cover in the remaining regions. To improve the model performance at the national scale, we chose to spatially segment the modelling so that the north and northwest were trained and classified separately from remaining coastal regions. To achieve the spatially segmented classifications, an initial national training dataset was developed, which was then tailored specifically for two segmented regions. For the northwest section of the map, we used 53,541 non-seagrass and 80,559 seagrass training points. For the remaining east, south, and west seagrass map we used 44,162 non-seagrass and 63,495 seagrass training points.

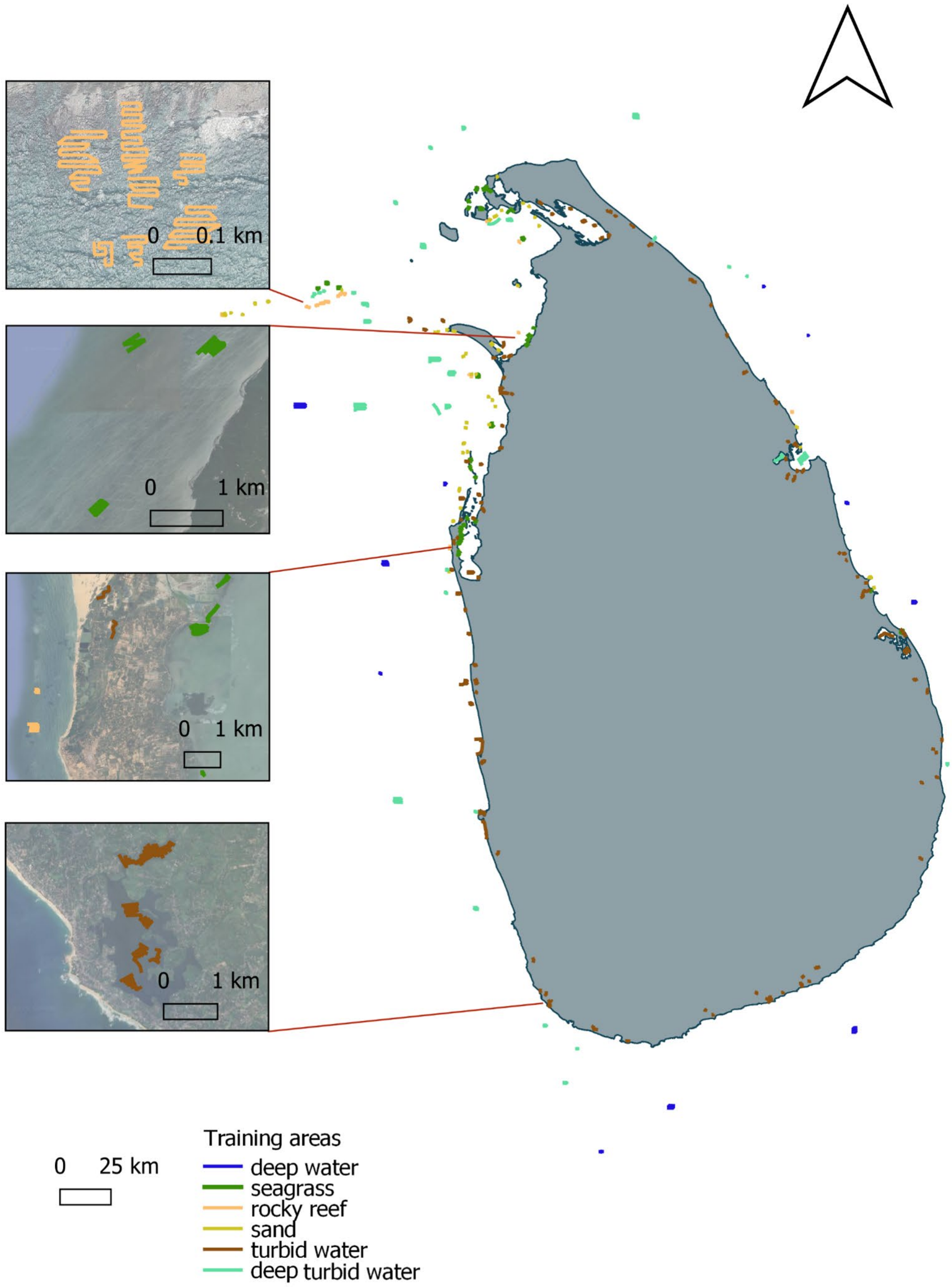

Figure 2. Training data locations used for seagrass habitat classification in Sri Lanka.

3.3 Classification model

3.3.1 Machine learning approach

Machine learning algorithms are a flexible and powerful tool for habitat classification as they can handle large volumes of complex data and identify non-linear relationships between satellite data and habitat types. The aim of any satellite-based classification method is to produce a generalisable differentiation between habitat types based on spectral differences in the imagery. Areas with very clear spectral differences, for example very dark areas of rock versus very bright areas of sand, can be classified with a high degree of accuracy. Conversely, areas with more subtle spectral differences, for example seagrass meadows and macroalgae beds, are more challenging to successfully separate and classify and are therefore a source of classification error.

For this work, a Random Forest classification framework was applied as the suitability of this method has been demonstrated for seagrass mapping in other regions globally (Blume *et al.* 2023; Floyd *et al.* 2024; Pertiwi *et al.* 2021; Traganos *et al.* 2022). Random Forest is an ensemble learning method that combines multiple decision trees to produce robust predictions. Random Forest is particularly well-suited to this application as it is robust to overfitting and is therefore likely to produce a generalisable classification across Sri Lanka. Additionally, Random Forest can handle the high-dimensional feature space generated from the satellite image composites and can identify complex spectral patterns that distinguish seagrass from other benthic habitat types.

3.3.2 Model implementation

The Random Forest classification was conducted in Google Earth Engine using 200 trees. Each 'tree' in the Random Forest is a separate decision tree that is trained on a different random subset of the training data and feature space. In this way, each individual tree produces an independent prediction of the habitat class for any given pixel. The model was configured to output probability estimates rather than categorical classifications. This means that for each pixel, the Random Forest produced a probability estimate of seagrass presence, calculated as the proportion of the 200 independent decision trees that assigned a seagrass label to that pixel. Following model implementation, the results were checked visually by experts and amended where appropriate.

3.3.3 Model outputs and interpretation

The probabilistic approach used here aims to provide more detail on the confidence of the model predictions. A pixel with a probability value of 0.9 indicates that 90% of the decision trees classified that pixel as seagrass, suggesting high model confidence, whereas a pixel with a probability value of 0.55 indicates lower model confidence with 55% of trees predicting seagrass presence. It is important to note that these probability values represent the proportion of decision trees in agreement rather than true statistical probabilities, though they serve as useful indicators of model confidence.

3.4 Validation data

Model validation is an important component of any habitat mapping workflow as it provides an assessment of model performance and accuracy. For this work, validation data were collected separately from training data to ensure an independent evaluation of the classification model's ability to generalise across unseen locations.

Validation data for this project were collected by collaborators at Blue Resources Trust during 2024–2025 through dedicated field surveys across coastal waters of Sri Lanka. Field surveys were designed to capture the full range of seagrass and non-seagrass habitat conditions and environmental gradients present across the study area. In total, 16 validation sites were chosen (Table 2; Figure 3).

Table 2. Validation site locations and metadata.

Site name	Location	Seagrass points	Non-seagrass points	Notes	Source
Addukaparu	East Coast	83	318	Exposed coastal backreef site	Blue Resources Trust field surveys 2024–2025
Ahangama	South Coast	3	66	Rocky exposed	Blue Resources Trust field surveys 2024–2025
Batticaloa	East Coast	21	45	Lagoon site, high turbidity	Blue Resources Trust field surveys 2024–2025 and S. Udagedara personal data
Dondra	South Coast	3	94	Rocky exposed	Blue Resources Trust field surveys 2024–2025
Hiriketiya	South Coast	1	120	Rocky exposed	Blue Resources Trust field surveys 2024–2025
Jaffna	North Coast	21	0	Multiple sites over islands in Jaffna	S. Udagedara personal data
Kalkudah	East Coast	14	114	Exposed coastal backreef on headland	Blue Resources Trust field surveys 2024–2025 and S. Udagedara personal data
Kayankerny	East Coast	47	56	Coastal adjacent to reef system	Blue Resources Trust field surveys 2024–2025 and S. Udagedara personal data
Kokkilai	East Coast	481	388	Large lagoon, sampled along shoreline, high turbidity	Blue Resources Trust field surveys 2024–2025
Mannar	Northwest Coast	44	0	Shallow low energy mudflats intertidal and subtidal	S. Udagedara personal data

Site name	Location	Seagrass points	Non-seagrass points	Notes	Source
Mihiripenn	South Coast	13	77	Rocky exposed	Blue Resources Trust field surveys 2024–2025
Poonryn	North Coast	190	174	Lagoon, high turbidity	Blue Resources Trust field surveys 2024–2025
Puttalam	West Coast	64	0	Large semi-enclosed lagoon	S. Udagedara personal data
Rekawa	South	4	400	Lagoon, high turbidity	Blue Resources Trust field surveys 2024–2025
Vaalaicheai	East Coast	39	123	Estuarine, moderate turbidity	Blue Resources Trust field surveys 2024–2025 and S. Udagedara personal data
Weligama	South Coast	2	41	Open bay area, moderately exposed	Blue Resources Trust field surveys 2024–2025

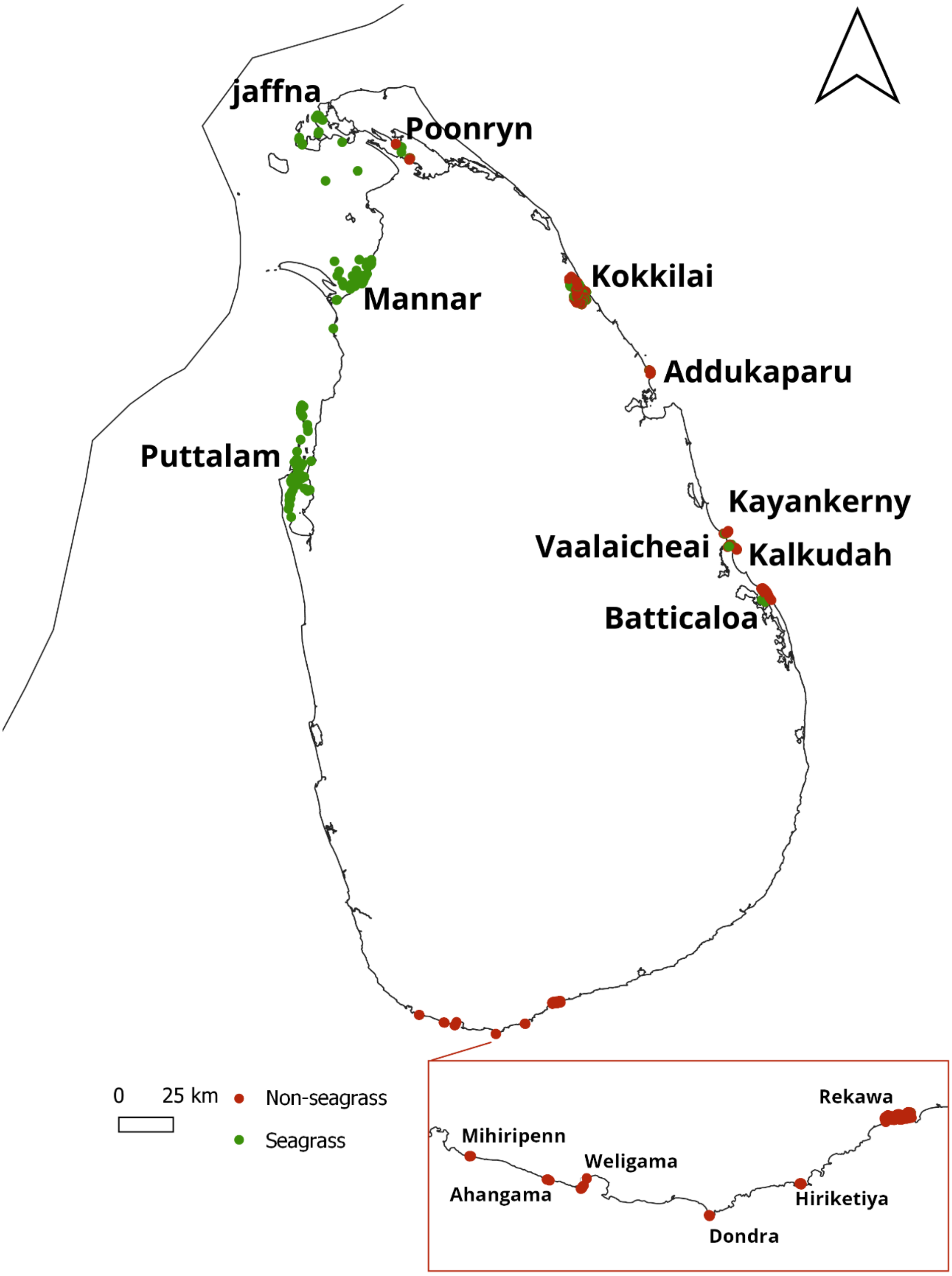

Figure 3. Seagrass model validation points across Sri Lanka.

For the Blue Resources Trust field data, at each validation site, benthic cover type, seagrass species composition, and other relevant environmental variables were recorded. GPS coordinates were recorded for each validation point using a handheld device.

3.5 Accuracy assessment

The validation dataset was used to calculate overall accuracy, producer's accuracy, and user's accuracy. Overall accuracy represents the proportion of validation points that were correctly classified. Producer's accuracy indicates the probability that a given habitat type on the ground is correctly classified in the map, whilst user's accuracy represents the probability that a pixel classified as a given habitat type represents that habitat on the ground. The probabilistic nature of the random forest output allows for flexible threshold selection when converting probability estimates to binary classifications. For validation purposes, a range of thresholds were applied, and a separate accuracy assessment applied to each threshold.

3.5.1 Accuracy assessment uncertainty

It is acknowledged that several factors could affect the balance of the accuracy assessment and may lead to overly conservative accuracy scores, the main factor being the temporal mismatch between the dates of image acquisition (01.01.2020 to 01.05.2025) and the dates of the validation data collection (2024–2025). One of the challenges for large scale habitat mapping is to produce a high-quality image over the full area of interest by combining many images taken at different time and in different conditions (cloud cover, cloud shadow, image brightness, etc). This task is particularly important over waterbodies where turbidity and sun glint on the water surface add further noise. Compositing is a useful method to produce a clear and standardised image over large spatial scales. However, to produce a clear image in noisy conditions requires many more images and therefore a longer period of data collection time. This trade-off is a key consideration of any optical based habitat mapping workflow.

In this project, we prioritised producing a high quality and clear composite basemap for the basis of the seagrass classification over matching the satellite image acquisition to the validation data collection. Due to high image noise in Sri Lankan coastal areas, we used an image acquisition period of 64 months (5 years and 4 months from 01.01.2020 to 01.05.2025). Importantly, for the accuracy assessment, the data were collected between 2024 and 2025. As a result, there exists a temporal mismatch between the image composite and the validation data that could not be avoided. This error comes from the variation in seagrass extent and location between the two differing time periods. It is difficult to quantify the effect size of the temporal mismatch as the degree of seagrass habitat area change over space and time is poorly understood. There is, however, a clear indication through our conversations with local experts that seagrass habitats are ephemeral in Sri Lanka in response to both seasonal and interannual environmental changes. This appears to be particularly true along the southern and eastern coastlines where seagrass cover is also generally lower. As a result, it is probable that the accuracy assessment is skewed lower and therefore the true accuracy of the map is likely to be higher than the figure reported from the accuracy assessment.

3.5.2 Validation data processing

The accuracy assessment uses the validation points collected in the field to assess the performance of the model predictions at the pixel level. As such, each point on the ground corresponds to an individual pixel in the satellite image and the spacing of GPS points should reflect the pixel size of the satellite data product (Sentinel-2 pixel size = 10 metres). The data collected for validation were screened to ensure that GPS points were sufficiently spaced in relation to the Sentinel-2 pixel grids. Where points were clustered within the same pixel, a filter was used to amend the number of points within the pixel so that only one point was present within each pixel (see Figure 4). The initial validation dataset contained 3,529, which was reduced to 3,061 following this filtering process.

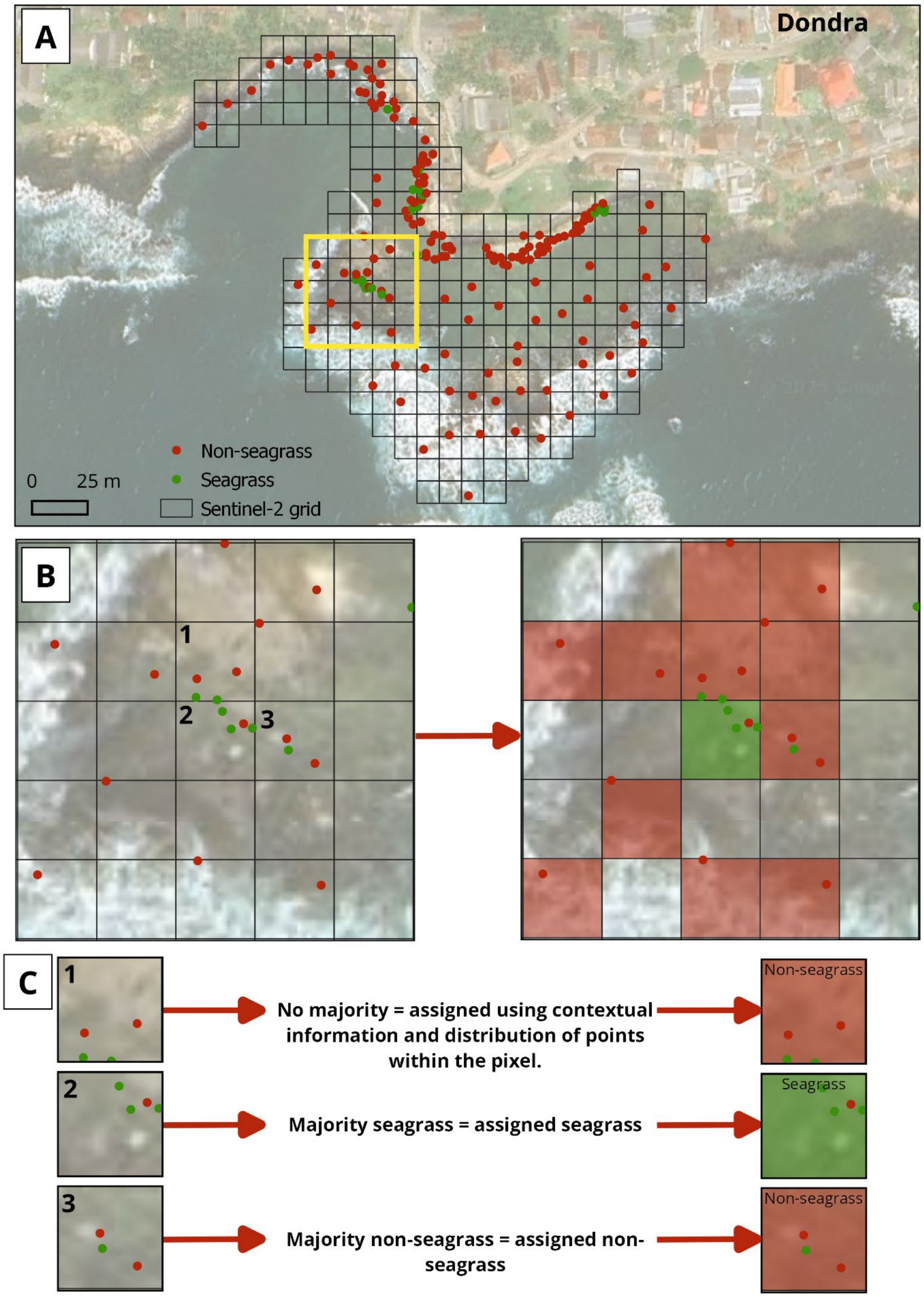

Figure 4. Method for processing spatial clustered validation pixels to match the dimensions of the Sentinel-2 data grid.

4. Results and discussion

This OCPP work package has produced the first standardised seagrass habitat map for the entire coastline of Sri Lanka. The data product has built upon previous datasets and mapping efforts by expanding spatial coverage, aligning data standardisation with other national and regional seagrass maps, and quantifying model confidence through a full accuracy assessment with field data collected in collaboration with Blue Resources Trust. The data produced here can inform a wide range of conservation, restoration, management, and scientific research activities. These data are presented in a continuous probability format (between 0 and 1), with the assigned probability reflecting the proportion of random forest decision trees that predicted seagrass in each pixel. This format aims to provide greater insight and flexibility for data users as varying levels of model confidence may be required depending on the application. For example, thresholding of the probability layer can be used to convert the probability layer into a binary classification allowing map users to choose the degree of confidence required for their work.

It is envisaged that this work can be the basis of ongoing efforts to further improve the characterisation of seagrass habitats in Sri Lanka using complementary methods, including targeted drone, field, and acoustic surveys where appropriate.

4.1 Seagrass habitat distribution

The seagrass model produced from this work estimates a total seagrass habitat area of 540 km^2 (probability threshold set to 0.6) around the coastline of Sri Lanka down to 20 metres depth. The distribution of seagrass habitat around the coast of Sri Lanka as predicted by this model is congruent with available existing data sources (Figure 5). For example, the model predicts a substantial proportion of seagrass habitat in the northern and northwestern regions of Sri Lanka from the southern end of the Puttalam lagoon to the northern tip of the Jaffna peninsula. Across the eastern and southern regions, where there is a lack of previous mapping data for comparison, much of the seagrass habitat is found in sheltered lagoon and estuarine areas with substantial seagrass habitat predicted in the bays south of Trincomalee, Kokkilai lagoon, and lagoon areas between Batticaloa and Kattankudy.

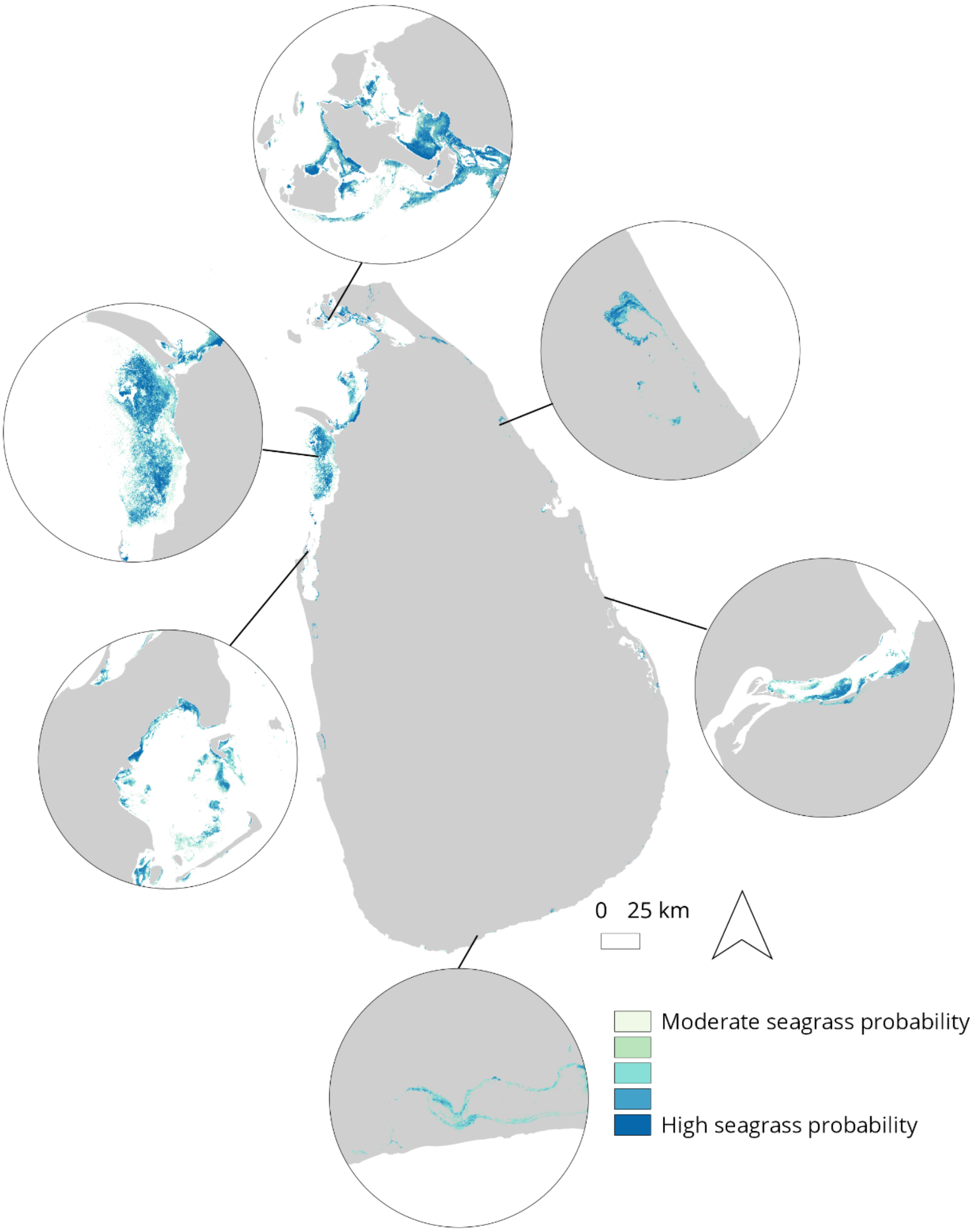

Figure 5. Random Forest seagrass probability model for the entire coast of Sri Lanka.

Where existing datasets are available, particularly mapping data, qualitative comparisons show a good degree of similarity with the model produced as part of OCPP – these results are particularly encouraging, despite differences in methodology and period. For example, the seagrass habitat model produced from high resolution satellite imagery (0.5 m pixel size) by Dahanayaka and Pahalawattarachichi (2017) cover Mannar in the south up to Palavi in the northern province (Appendix figure 1). This model reports a very high overall accuracy of 94% (Dahanayaka & Pahalawattarachchi 2017). Qualitative comparison of these two datasets shows a reasonable level of similarity when representing the broad patterns of seagrass distribution in the region.

Additionally, maps are available from the Ocean Resources Conservation Association (2016), produced from existing data and community information (Appendix figure 2). These maps cover from Dutch Bay in the west to Mannar. Again, these maps show broadly similar patterns in seagrass distribution compared to the model predictions produced as part of OCPP, particularly to the north of Dutch Bay.

At a finer scale, existing data from the IUCN report authored by Weerakoon *et al.* (2020) provide valuable comparisons for islands in the north. To the best of our knowledge, there are no accuracy metrics available for these maps. The results of these comparisons are presented in Figures 3-12 in the appendix and indicate a range of contrasting and similar predictions from the OCPP model compared to the IUCN mapping undertaken in 2020.

Finally, as part of the Allen Coral Atlas project (Lyons *et al.* 2020), the benthic habitats of Sri Lanka were previously mapped including seagrass. This model is produced with global coverage of tropical and subtropical regions using Planet data at 5 m pixel size. Qualitative comparison of the Allen Atlas data to the maps produced by OCPP here show an improved degree of detail for seagrass (Figure 6).

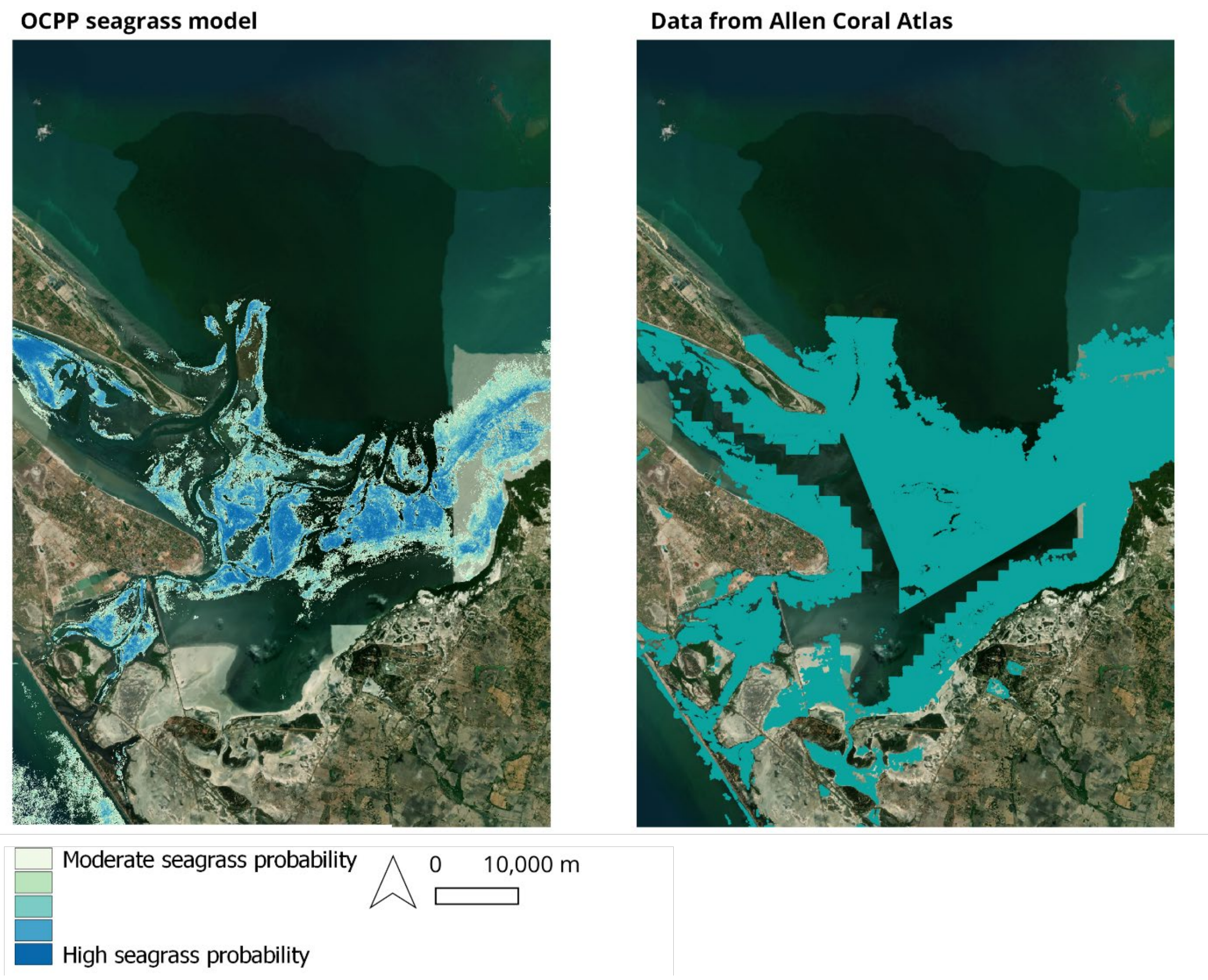

Figure 6. Comparison of seagrass habitat maps produced for Sri Lanka showing intertidal areas near Mannar island.

4.2 Seagrass mapping accuracy

The seagrass habitat maps produced here are in a continuous data format with each pixel representing a proportion (between 0 and 1) of the 200 random forest decision trees used to models seagrass presence. In contrast, the accuracy assessment data are in a binary format of seagrass presence or absence. As such, for the accuracy assessment, the results will vary depending on where the threshold is set to consider a pixel seagrass or non-seagrass. The highest overall model accuracy is produced at a seagrass probability threshold of 0.6 with an overall accuracy of 69.6% (Table 3). The response in overall accuracy values to thresholding is shown in Figure 7 and Table 3.

Table 3. Accuracy assessment for seagrass habitat model produced for Sri Lanka using Random Forest classifier.

Probability threshold	Overall accuracy	Kappa	Producer accuracy non-seagrass	Producer accuracy seagrass	User accuracy non-seagrass	User accuracy seagrass
0.1	0.637	0.188	0.760	0.421	0.697	0.501
0.2	0.659	0.202	0.834	0.353	0.693	0.548
0.3	0.668	0.207	0.867	0.320	0.690	0.580
0.4	0.675	0.207	0.895	0.288	0.688	0.612
0.5	0.691	0.229	0.937	0.261	0.689	0.703
0.6	0.696	0.227	0.962	0.231	0.686	0.777
0.7	0.680	0.168	0.972	0.168	0.671	0.775
0.8	0.655	0.080	0.983	0.082	0.652	0.730
0.9	0.644	0.035	0.992	0.036	0.643	0.725

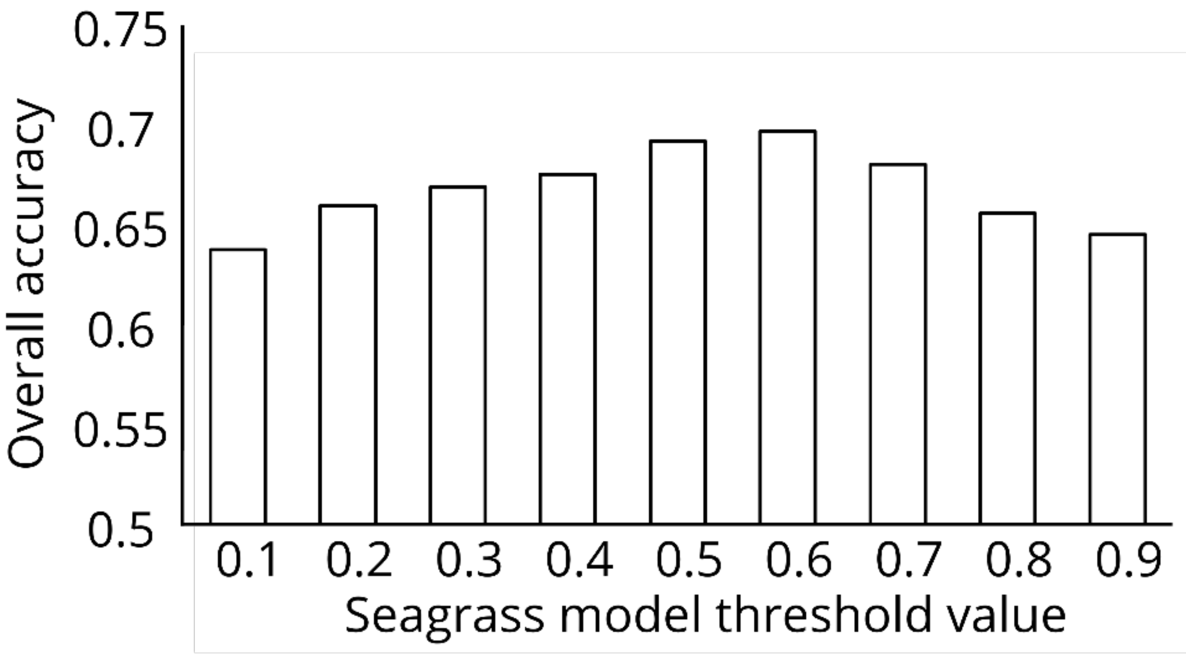

Figure 7. Seagrass model Overall Accuracy scores of a range of random forest confidence threshold values.

The model produced here should be considered a conservative estimate of seagrass presence, which is evidenced in the consistently higher user accuracy scores for the seagrass class compared to the producer accuracy scores. This pattern of higher user accuracy scores is common in seagrass habitat models (Floyd *et al.* 2025). When the model predicts seagrass presence, the degree of confidence in this prediction is relatively high which points to good reliability. For example, at the seagrass probability threshold of 0.6, the user accuracy for seagrass is 77.7%, which means that where the map shows seagrass presence in a location, the probability that seagrass is actually found on the ground in that particular location is 77.7%. It is our view, when considering the application of these data including conservation and marine spatial planning, that a conservative model with stronger reliability is more appropriate than a model that is less conservative and therefore more likely to overestimate seagrass area.

As the model produced here is conservative, it is likely that in some areas, seagrass habitats are not represented. Further research to build on and add to this seagrass model in the future can continue to develop our understanding of seagrass distribution around Sri Lanka. The seagrass mapping training workshop delivered as part of OCPP has built capacity for such mapping work across the country. In regions with particularly high turbidity, it may be appropriate to use complementary methods, such as drone surveys, in field monitoring, and acoustic monitoring.

The overall mapping accuracy from this study is comparative to results reported in other locations globally using the same methods. For example, overall accuracy here is 69.6% compared to accuracies of 82.04% Maldives (Floyd *et al.* 2024), 71% Bahamas banks (Blume *et al.* 2023), 64% and 79% in the western and eastern Mediterranean basin respectively (Traganos *et al.* 2022), and 69.7 to 75.7% in the Seychelles (Lee *et al.* 2023).

The accuracy assessment for this study utilises 3,061 field data points over a 30,933 km^2 area of interest. This results in a validation density of one point per 10.1 km^2, representing a rigorous sampling effort. For context, our density exceeds that of similar mapping work in the Maldives (1 per 22.4 km^2; n = 1,019; Floyd *et al.* 2024), the Mediterranean (1 per 22.9 km^2; n = 2,480; Traganos *et al.* 2022), and the Bahamas (1 per 102.8 km^2; n = 1,100; Blume *et al.* 2023). The size of the validation dataset used here ensures a robust accuracy assessment across the entire study area.

5. Conclusions

This work, as part of OCPP, has produced the first standardised, national-scale seagrass habitat map for Sri Lanka, estimating a total seagrass extent of 540 km^2 around the coastline down to 20 metres depth. The map was produced using a Random Forest classification framework applied to Sentinel-2 image composites and validated using 3,061 independent field points across 16 sites spanning the full range of coastal environments in Sri Lanka.

The overall mapping accuracy of 69.6% is comparable to seagrass mapping studies conducted elsewhere using equivalent methods. The model predictions are considered conservative, with consistently higher user accuracy scores for the seagrass class (77.7%) indicating that pixels predicted as seagrass in the map are likely to represent true seagrass presence on the ground. For conservation and marine spatial planning applications, this reliability is particularly appropriate. It is also likely that the temporal mismatch between the image composite acquisition period (2020–2025) and the validation data (2024–2025) has introduced a degree of bias into the accuracy assessment, meaning the true map accuracy is likely higher than the reported figure.

The data product is presented in a continuous probability format to maximise flexibility for those wishing to use the maps, allowing variable confidence thresholds to be applied depending on the intended application. This map provides an important dataset for seagrass conservation, marine planning and research in Sri Lanka. Future work to build upon this map has been facilitated through capacity building delivered as part of OCPP and should focus on improving coverage in persistently turbid zones through complementary drone, field survey, and acoustic methods, and on developing targeted monitoring programmes to track habitat change over time.

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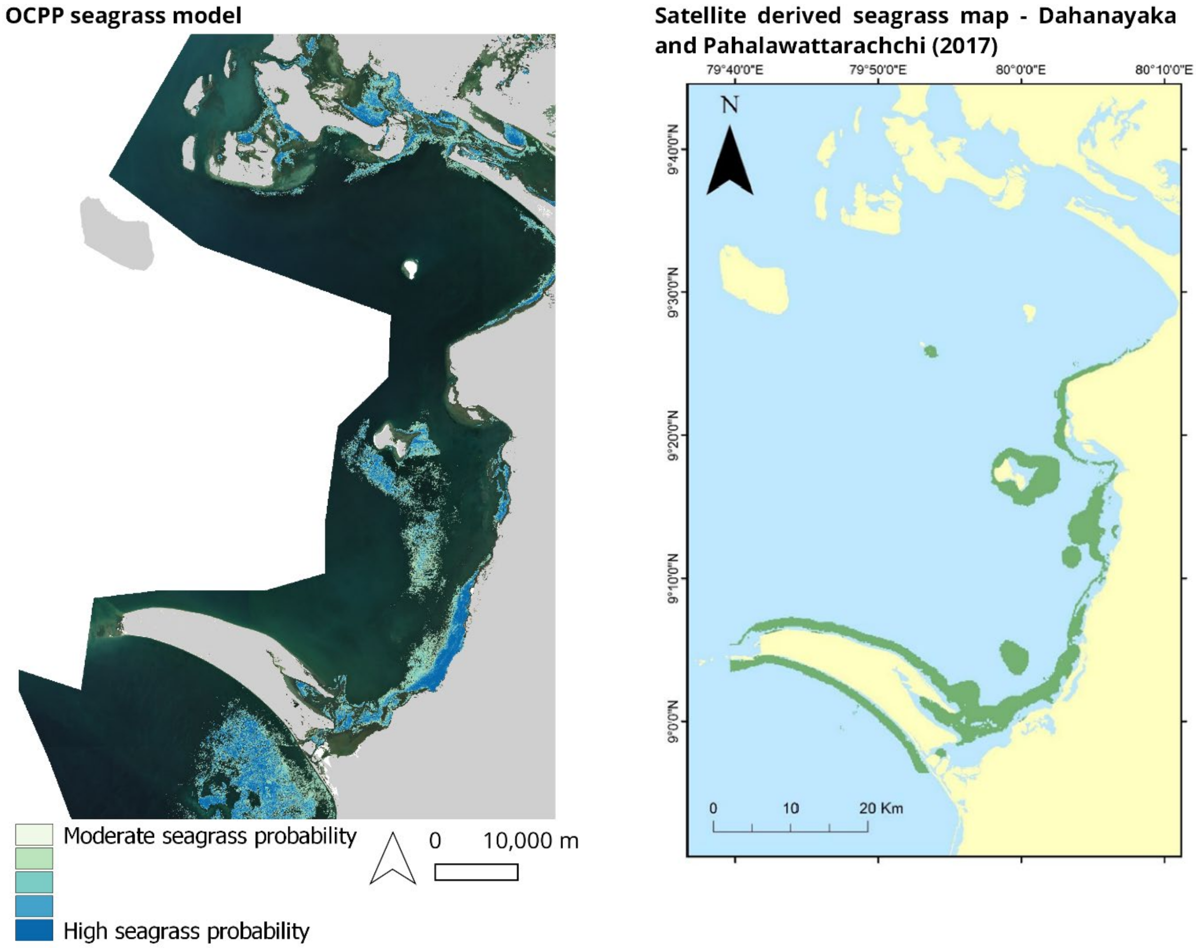
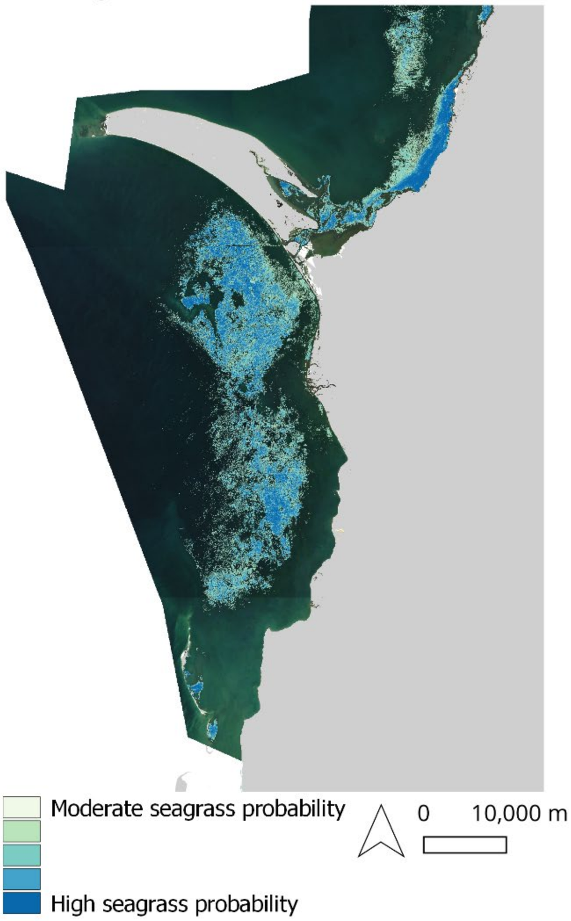
Appendix

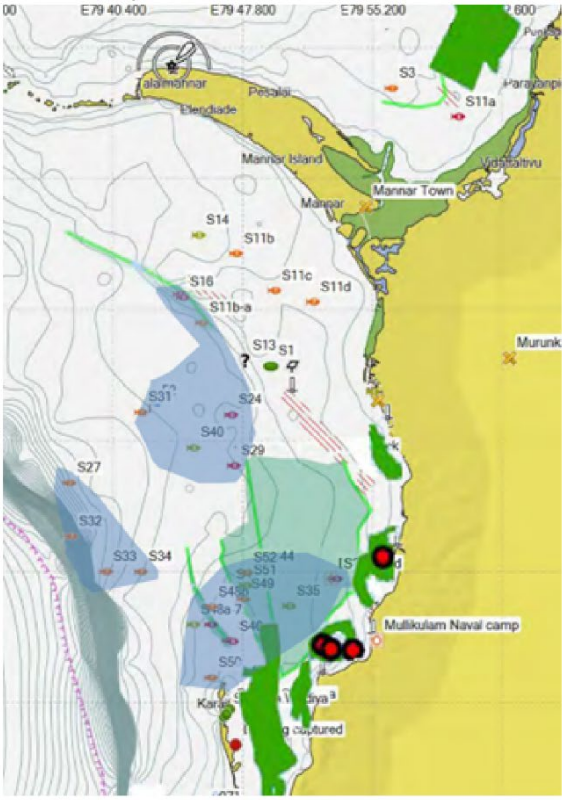


Appendix figure 1. Comparison of seagrass habitat maps produced for Sri Lanka showing northwest region.

OCPP seagrass model

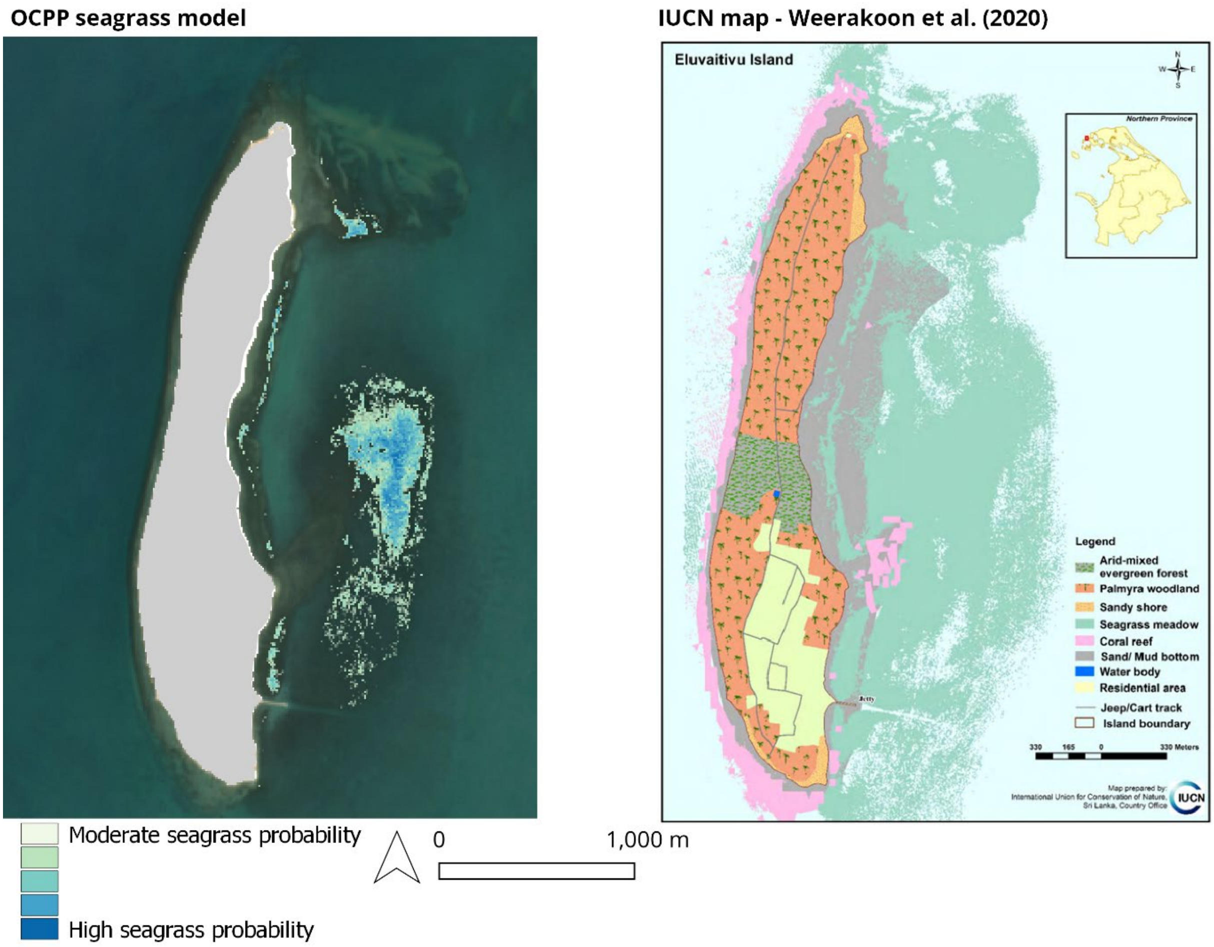


Data from Ocean Resources Conservation Association, 2016



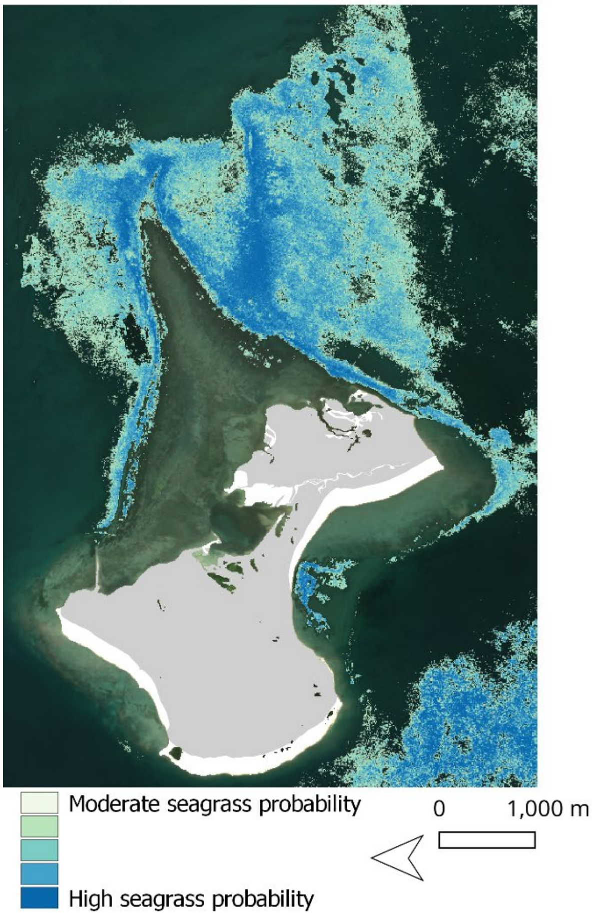
This map is produced from existing data and community information. Light green and dark green areas indicate seagrass habitat. Navy indicate areas with high Dugong activity.

Appendix figure 2. Comparison of seagrass habitat maps produced for Sri Lanka showing northwest region.

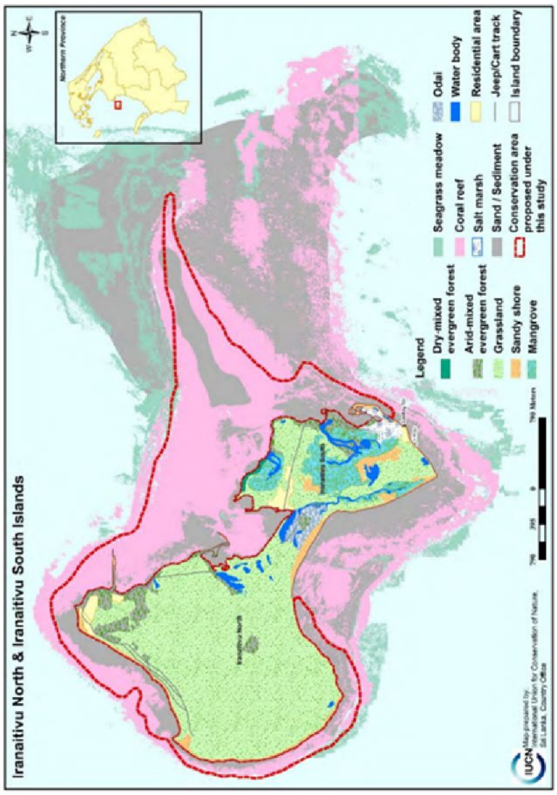


Appendix figure 3. Comparison of seagrass habitat maps produced for Sri Lanka showing Eluvaitivu island.

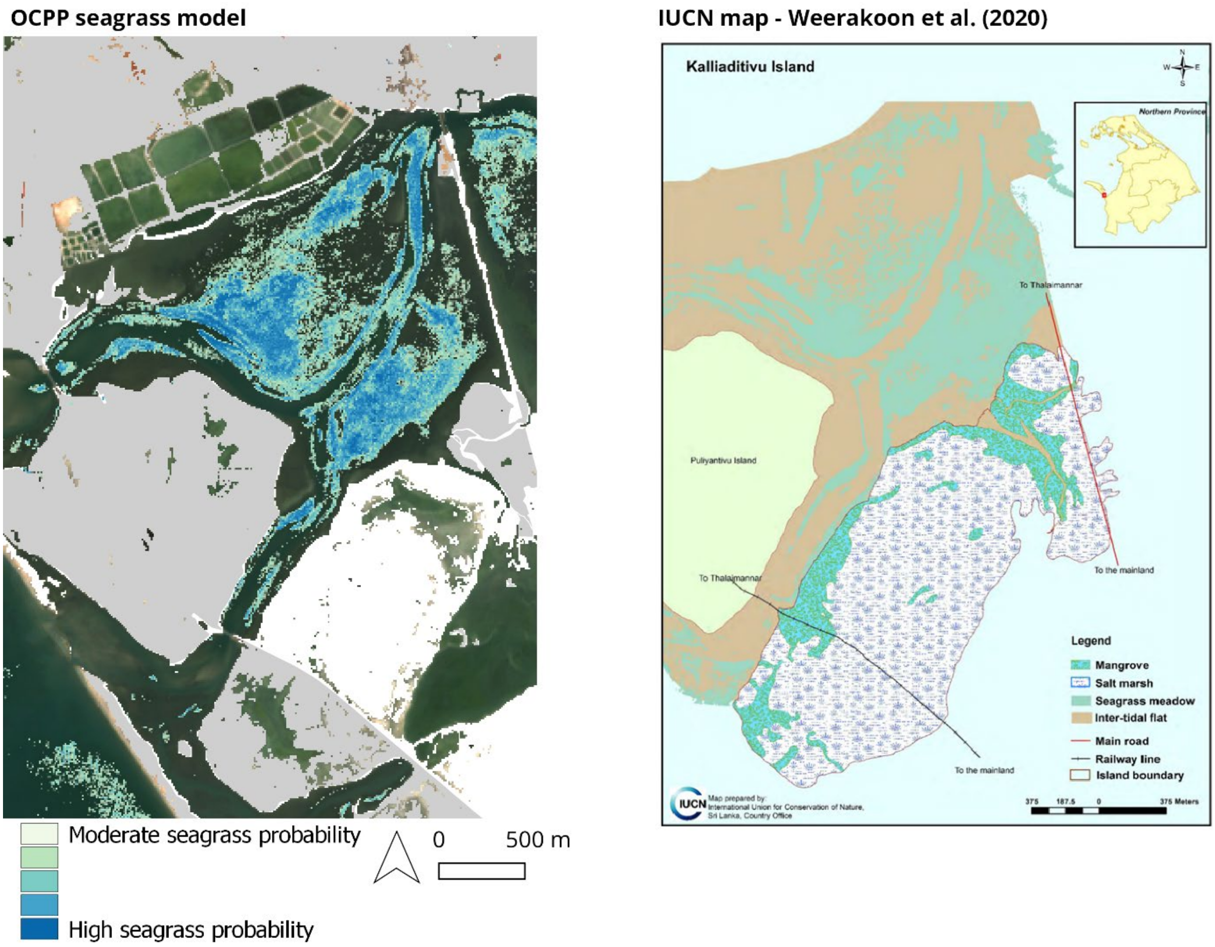
OCPP seagrass model



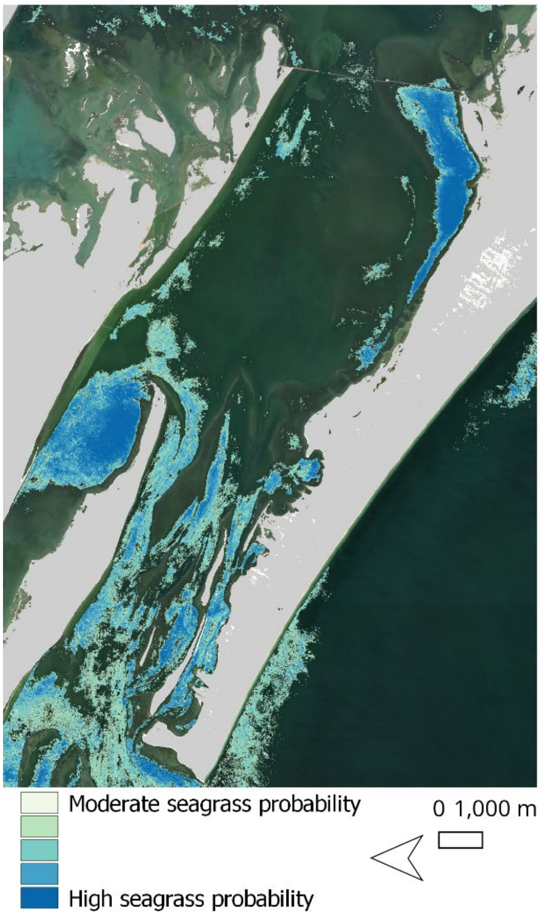
IUCN map - Weerakoon et al. (2020)

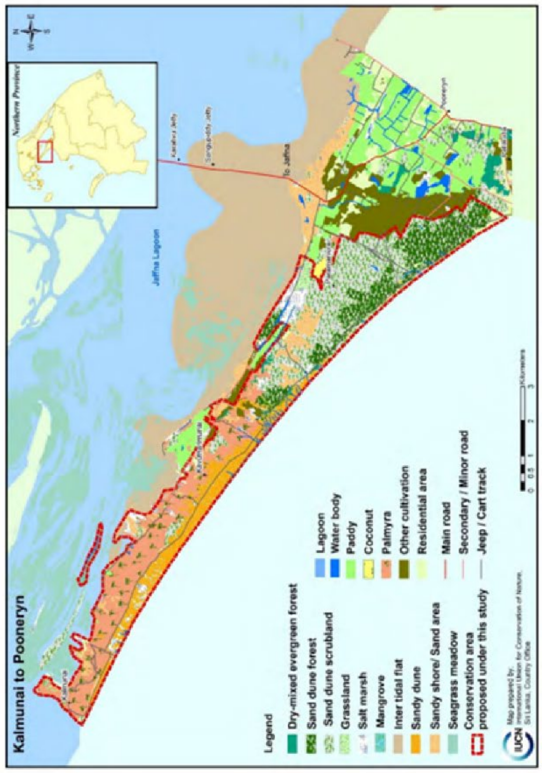


Appendix figure 4. Comparison of seagrass habitat maps produced for Sri Lanka showing Iranaitivu north and south islands.

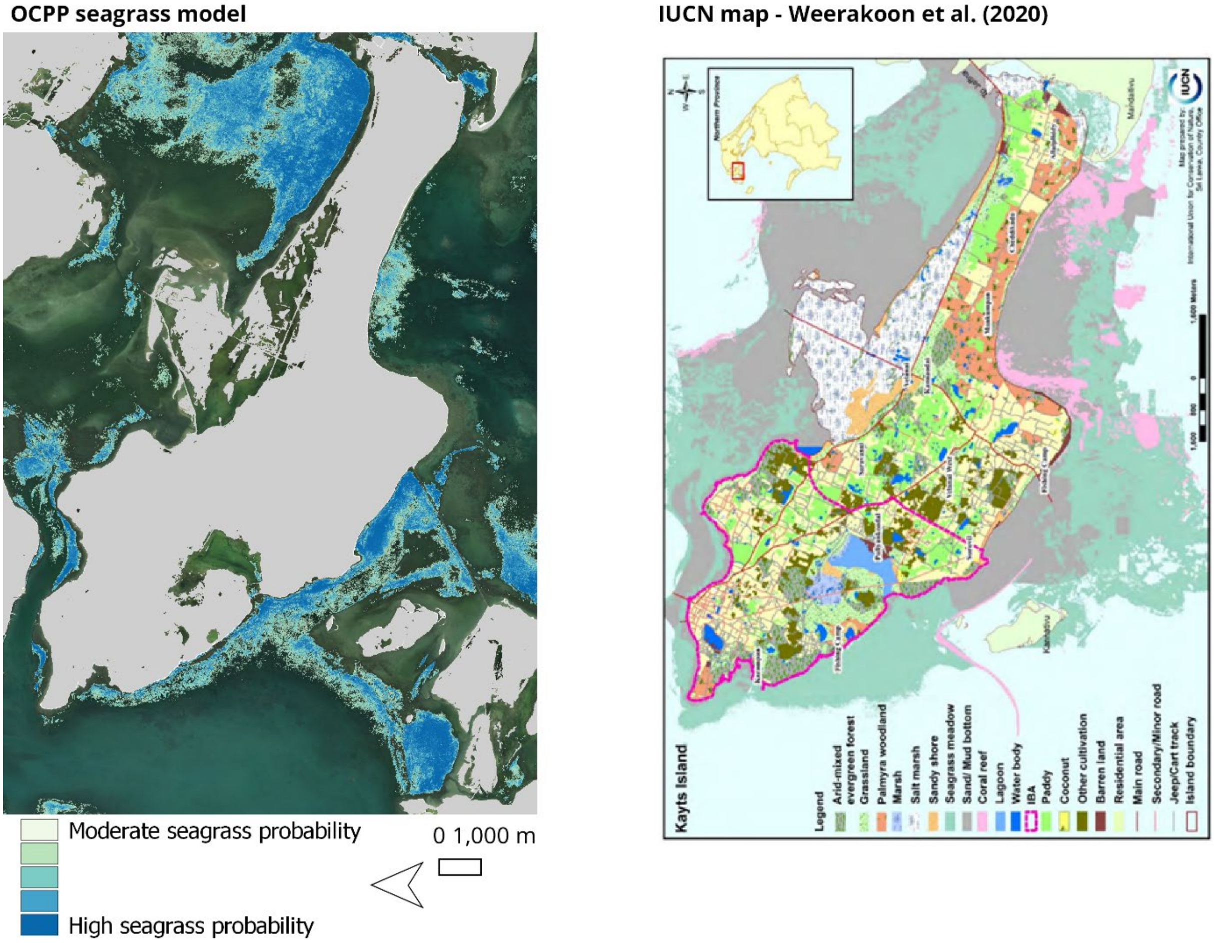


Appendix figure 5. Comparison of seagrass habitat maps produced for Sri Lanka showing Kalliaditivu island.

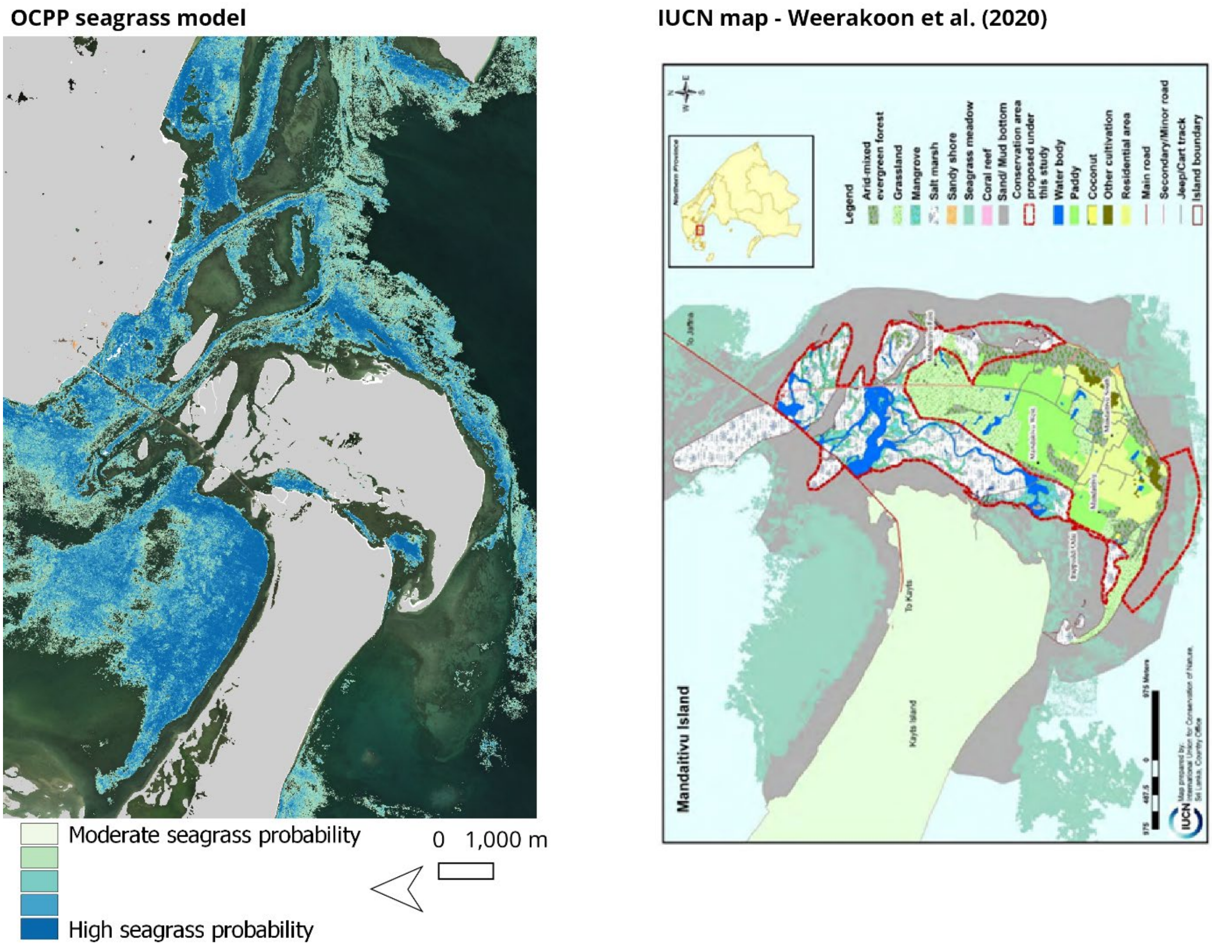




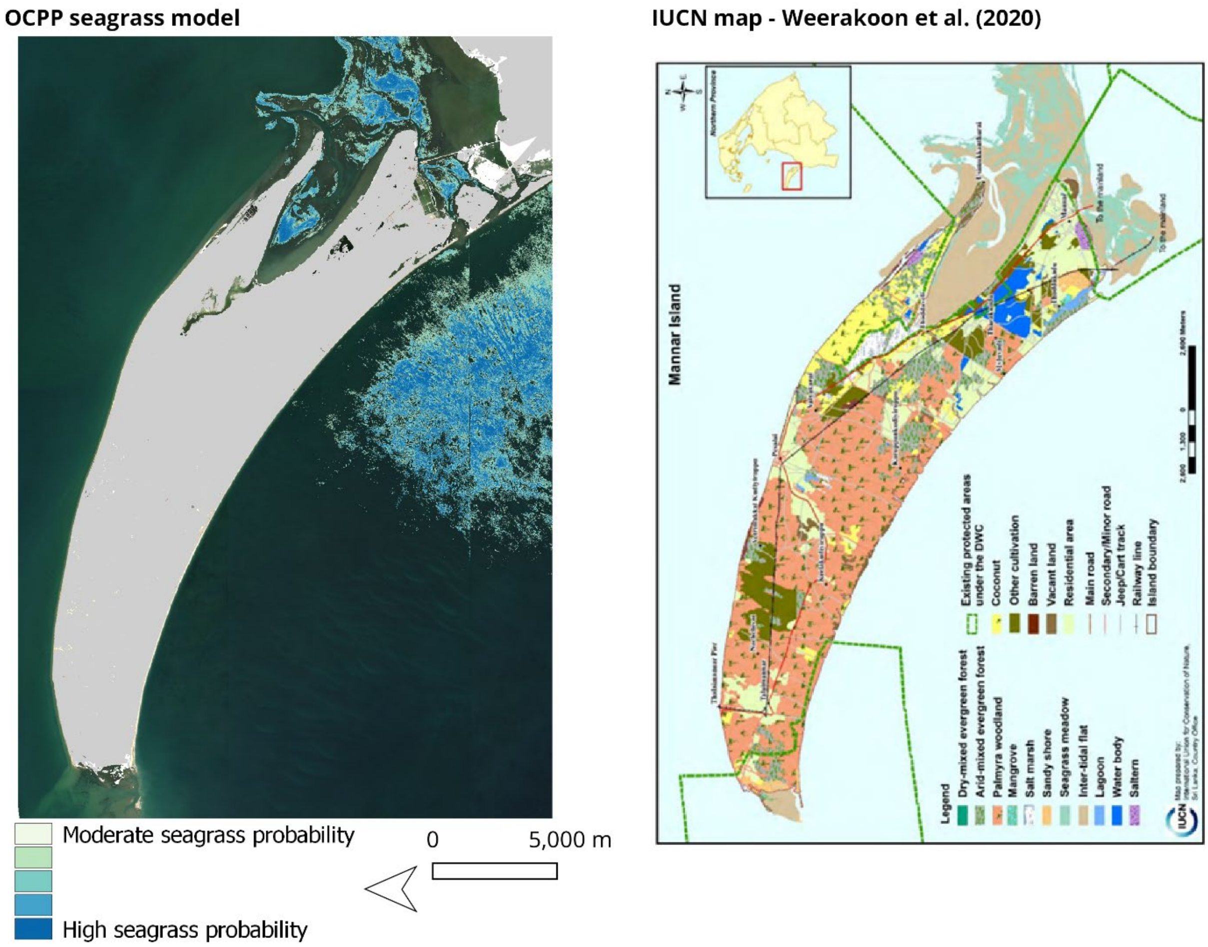
Appendix figure 6. Comparison of seagrass habitat maps produced for Sri Lanka showing Kalmunai to Pooneryn.



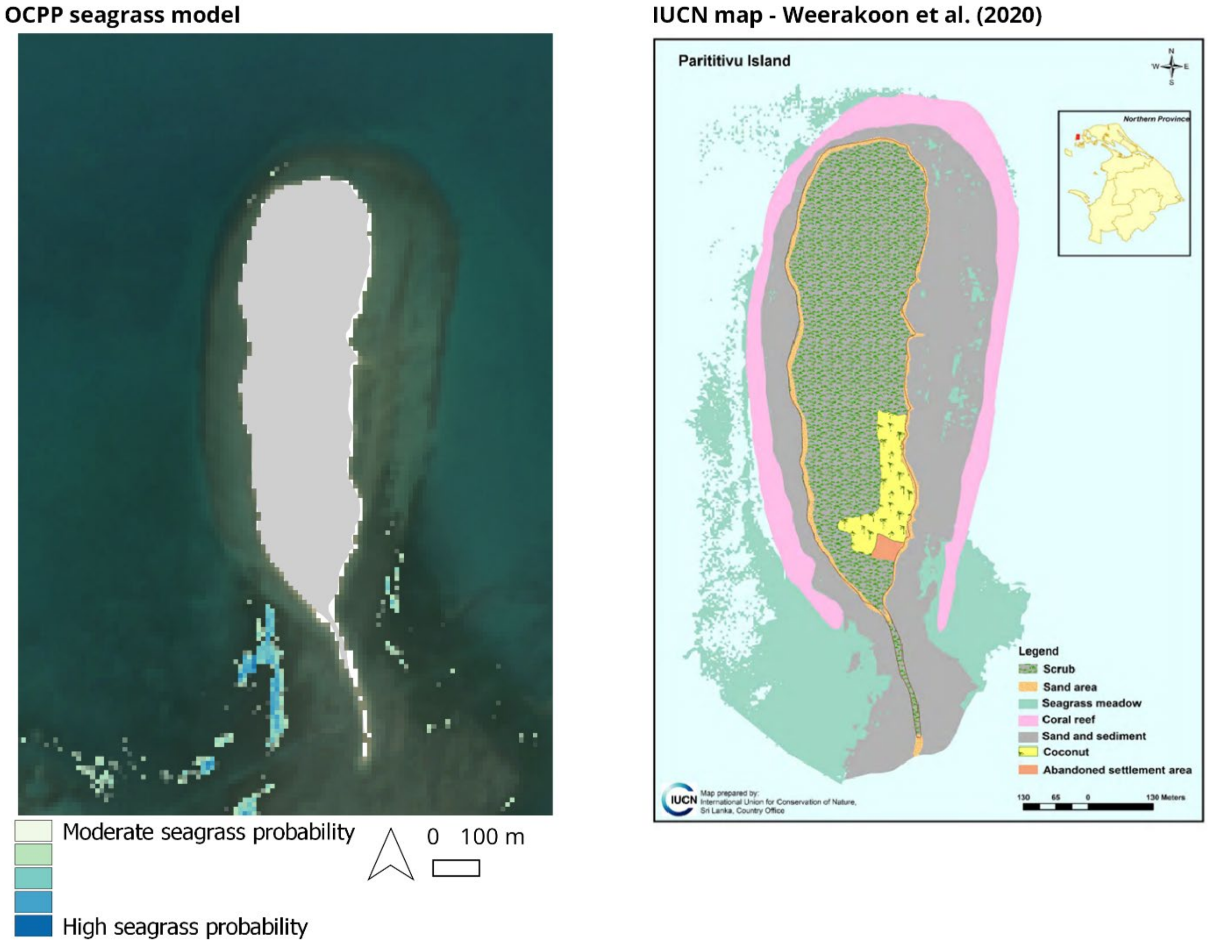
Appendix figure 7. Comparison of seagrass habitat maps produced for Sri Lanka showing Kayts island.



Appendix figure 8. Comparison of seagrass habitat maps produced for Sri Lanka showing Mandaitivu island.

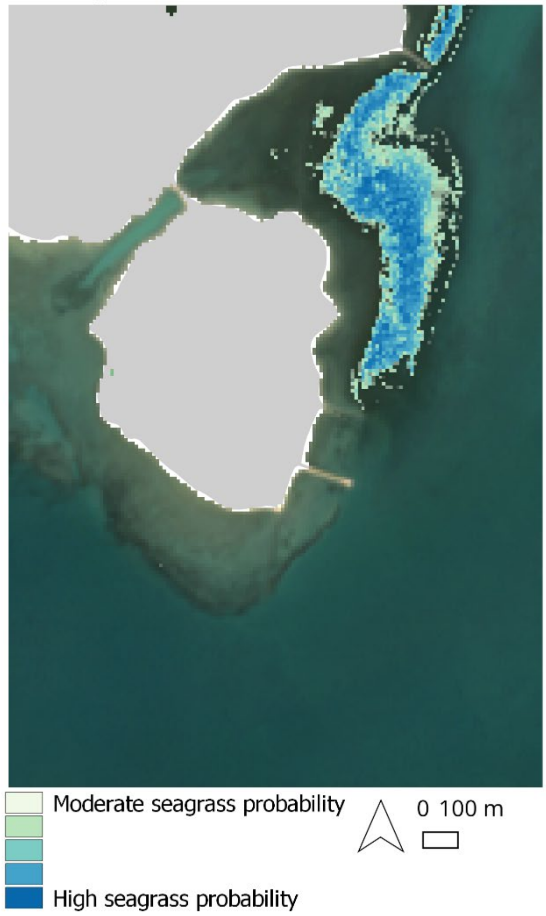


Appendix figure 9. Comparison of seagrass habitat maps produced for Sri Lanka showing Mannar island.

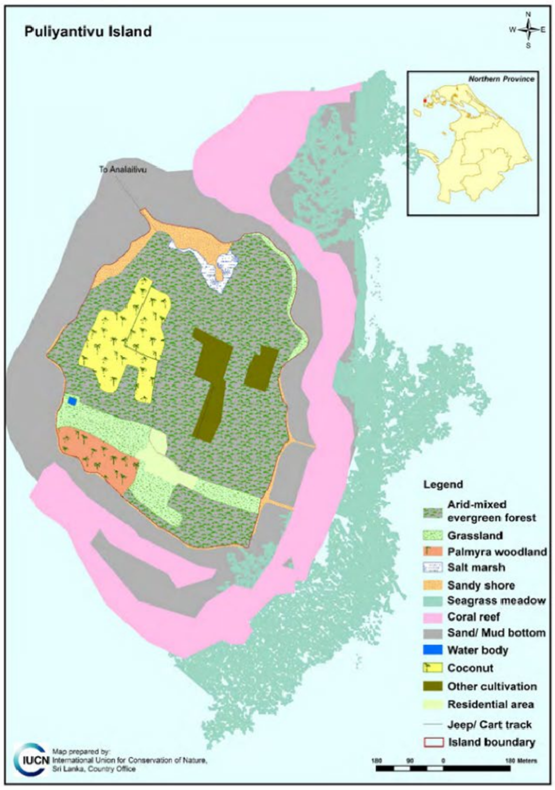


Appendix figure 10. Comparison of seagrass habitat maps produced for Sri Lanka showing Parititivu island.

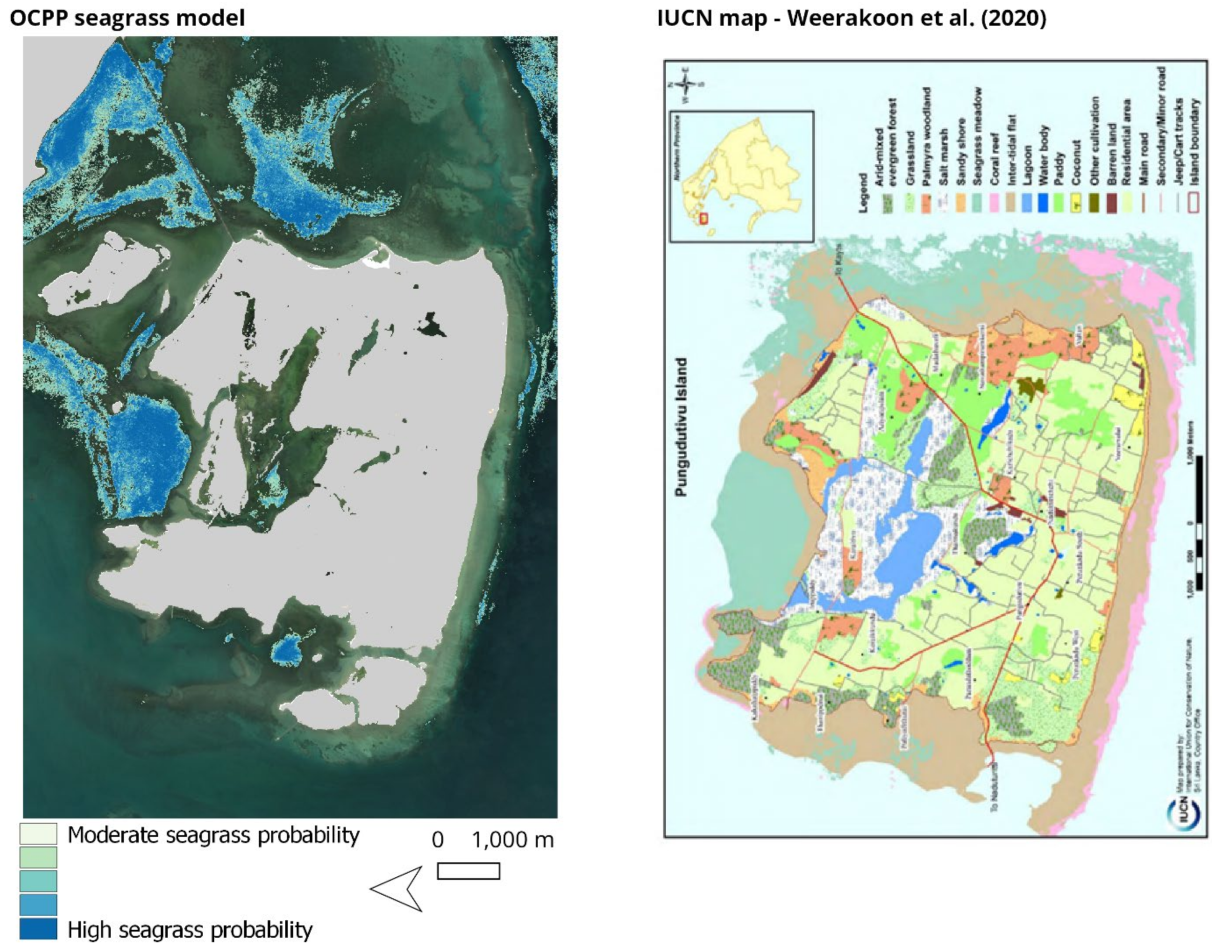
OCPP seagrass model



IUCN map - Weerakoon et al. (2020)



Appendix figure 11. Comparison of seagrass habitat maps produced for Sri Lanka showing Puliyantivu island.



Appendix figure 12. Comparison of seagrass habitat maps produced for Sri Lanka showing Pungudutivu island.