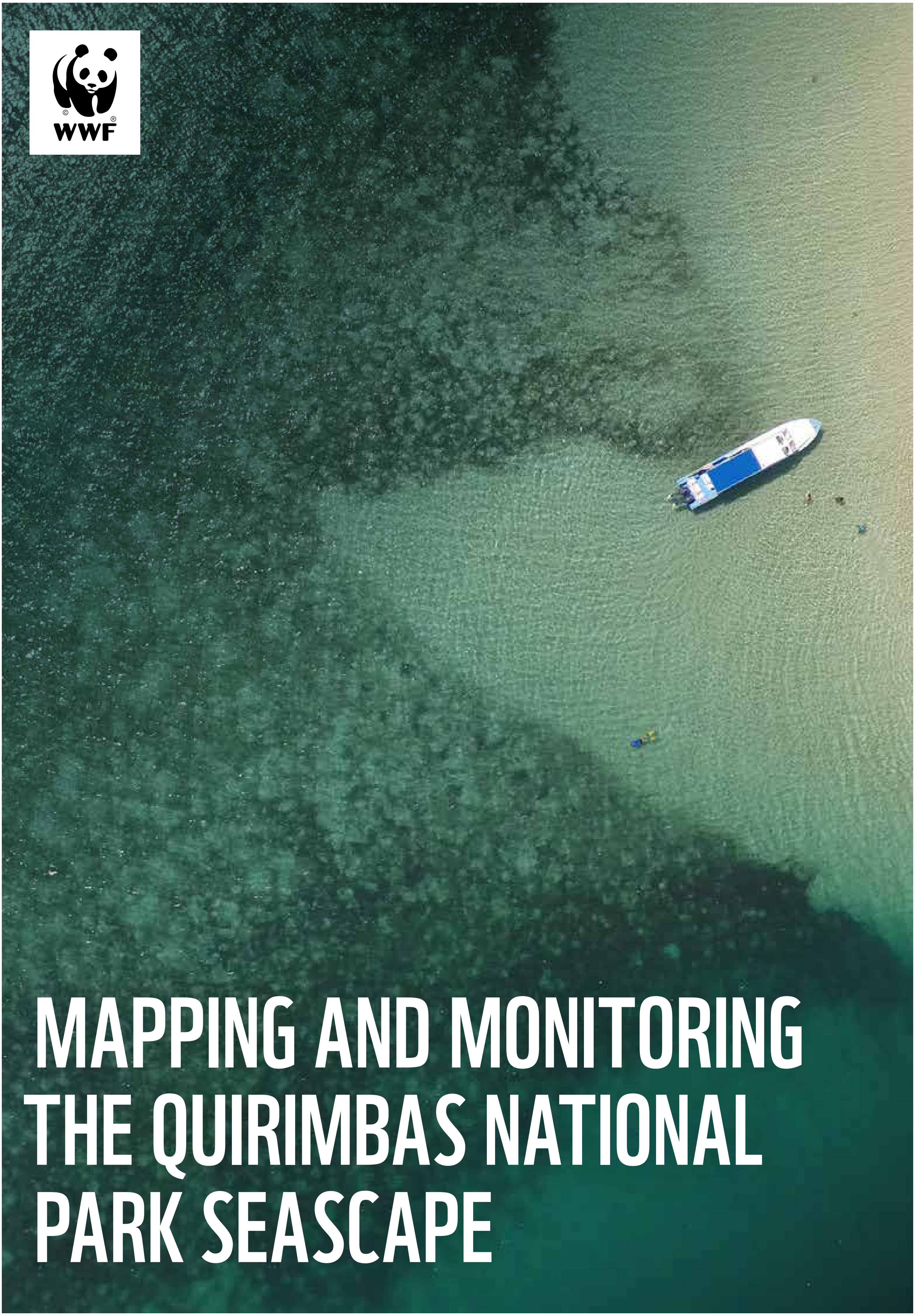

MAPPING AND MONITORING THE QUIRIMBAS NATIONAL PARK SEASCAPE

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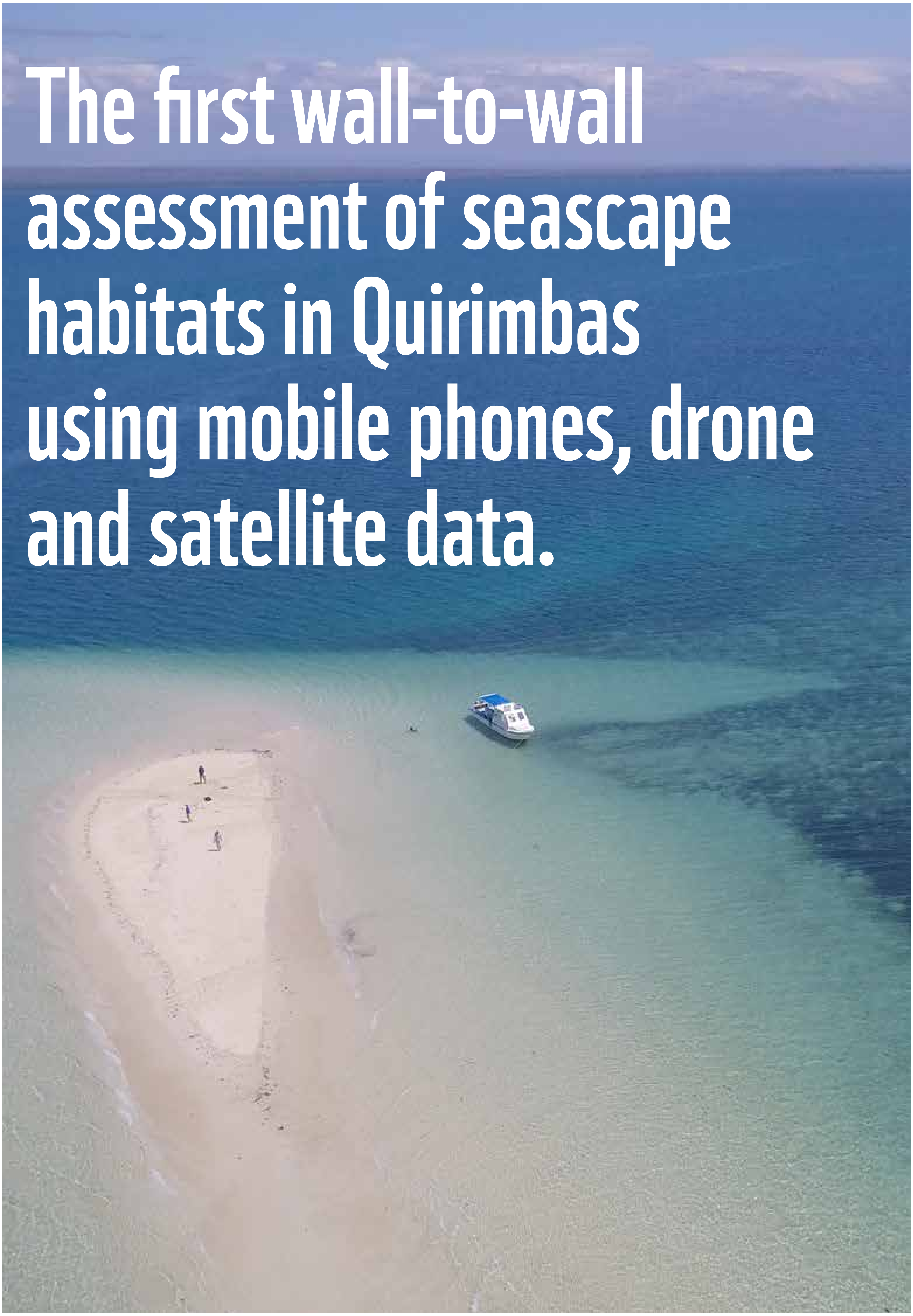
CONTENT

The first wall-to-wall assessment of seascape habitats in Quirimbas using mobile phones, drone and satellite data.

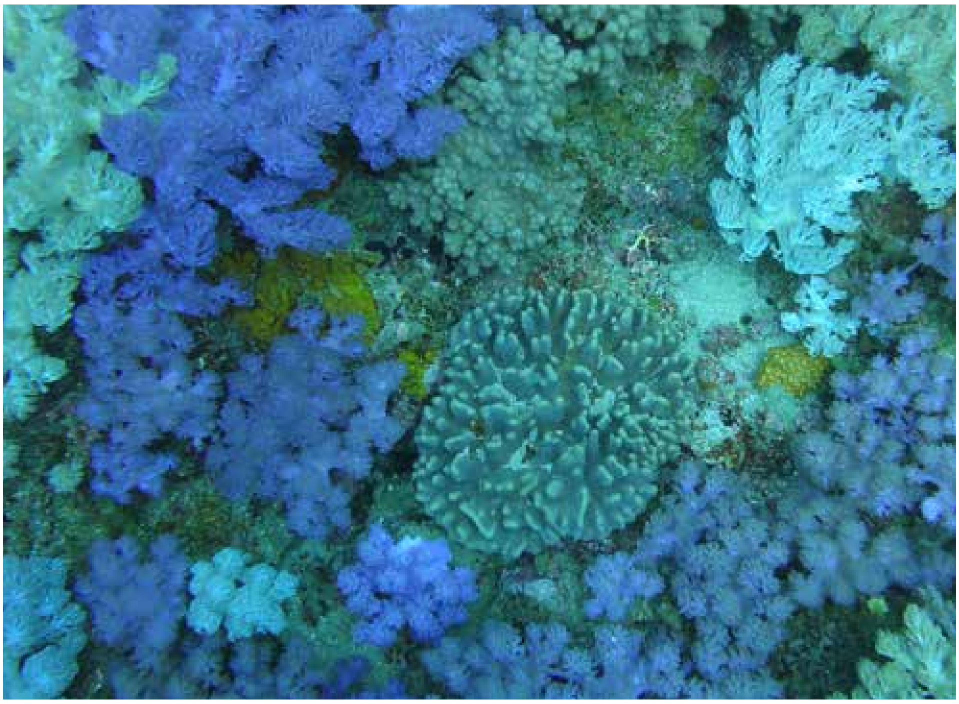


Executive Summary

The lack of detailed spatial information on coastal resources, notably shallow water coral reefs and associated benthic habitats, impedes our ability to protect and manage them in the face of global climate change and anthropogenic impacts. WWF-Germany, with support from partners from FORTH and DLR, have developed a semi-automated workflow that uses freely available Sentinel-2 data from the European Space Agency (ESA) Copernicus program to derive information on near-shore coral reef habitats in the Quirimbas National Park (QNP), a recently declared biosphere reserve. We use an end-to-end cloud-based framework within the Google Earth Engine cloud-based geospatial platform to process satellite imagery from raw pixels to cloud-free image composites, corrected for glint, surface artifacts and water column, in order to derive estimated depth and a classification of benthic habitats.

We mapped over 105,000 ha of shallow water habitat inside the protected area, with over 84% accuracy. The area is mostly comprised of seagrass habitats, followed by soft and sandy substrates, coral, and hard substrate. We employ satellite-derived bathymetry to assess the unique bathymetric position and underwater topography of these habitats. Finally, a spectral unmixing model provides further sub-pixel level information on these underwater habitats and the potential to monitor changes in habitat composition over time, due to cyclones or major events.

This effort provides the first, consistent and repeatable coastal information system for an east African tropical marine protected area, which hosts shallow-water ecosystems of great significance to both local communities and building global resilience towards climate change.



Introduction

Northern Mozambique has been identified as one of 50 global sites comprising an optimal portfolio for strategic coral reef conservation.

For more information visit 50reefs.org

With a shoreline of over 2,700 km, Mozambique hosts a unique number of coastal habitats, including some of the most climate-resilient coral reefs in the world, representing some of the best global opportunities for conservation (Beyer et al., 2018). These globally significant marine and coastal habitats provide essential ecosystem services such as carbon sequestration and climate mitigation, while providing essential nurseries for aquatic species to support food and livelihoods of local communities (Mcleod et al., 2011; Nordlund et al., 2018; Sitoe et al., 2010). The western Indian Ocean, in particular, features a very high biodiversity: more than 1,500 fish species, 200 coral species, 14 mangroves, 12 seagrass species, 1000 marine algae species, hundreds of sponge species, and 300 crab species (Richmond, 2000). The region also hosts unique megafauna, including whales, sharks, rays, and endangered marine turtles and dugongs (UNEP, 2004).

The dependence on natural resources in Mozambique is high, with as much as 80% of employment relying on natural resources, such as agriculture, fisheries and mining (Macamo, 2019). The fishing industry has a significant contribution to the national GDP, while artisanal fisheries comprise 90% of production and the main source of employment and food sources in coastal communities – where most of the Mozambique's population reside (Macamo, 2019). Meanwhile, Mozambique is a rapidly growing tourism destination, relying on these intact ecosystems and the wealth of biodiversity. Despite the value of these coastal ecosystems, for over a century, increased pressure on marine resources has resulted in significant ecological changes in many parts of the East African coastline. Overfishing has resulted in the decline of great whale populations, valuable fisheries, as well as the degradation of important seagrass beds and coral reef habitats (Sjöstedt and Sundström, 2013). Many species are heavily over-fished, with destructive methods such as gill nets and dynamite usage (Obura et al., 2005), and under-reported catches putting the industry at risk of overexploitation (Jacquet et al., 2010).

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Demand for building materials such as mangrove poles and corals for lime, along with increasing agricultural land, have further contributed to habitat destruction (Kideghesho, 2009). All these activities disturb the ecological balance, reduce the capacity to secure livelihoods and affect food security for local populations, where severely damaged coral reefs and seagrass beds can no longer support nurseries for future generations of marine life.

Management approaches to mitigate the pressures in the marine regime have been developed and applied worldwide, including via Marine Protected Areas (MPAs) and Marine Managed Areas (MMAs) which can be managed to offer a range of ecological, social, cultural and economic benefits (Claudet, 2011). The location, design, characteristics, and on-going management of these areas, however, ultimately determine the extent to which the benefits can be achieved in practice. In Mozambique, several MPAs and MMAs have been designated, including the Quirimbas National Park (QNP), a recently designated international biosphere reserve (UNESCO, 2018) protecting some of the most resilient reef systems in the region (Hill et al., 2010).

Although QNP was established in 2002, little readily accessible, accurate spatial information exists to contribute to the comprehensive baseline for the coastal marine seascape ecosystems, to enable informed management practices, detailed zoning and distribution of human activities, such as fishing limitations, no take zones, or adaptive management responses to address changes in ecosystems. The types of management practices which benefit from accurate spatial data include: the location and designation of temporary closures and sanctuary zones for management of fish resources, regulating uses in designated tourist areas, and continued monitoring over time to ensure resilient and functioning reef systems. This monitoring ensures that the goals of the protected area are being achieved, namely, that local livelihoods are sustainably using the protected area resources.

The limited available data that exist (RCRMD, 2015) are either out of date, of insufficient resolution, do not have any comprehensive metadata to assess their status, they lack statistical accuracy assessments; or are not derived from automated methods, making them difficult to reproduce over time. Other data sets, like the recently released Allen Coral Atlas (B. Lyons et al., 2020), are global products derived from commercial imagery, which have limited local validation and accuracy assessments, and, despite a much improved spatial resolution, come with the potential trade-off of a lower temporal resolution, and updates which cannot be programmed or requested.

The main objective is to provide baseline mapping for management, sustainable development, climate change mitigation and adaptation.

Here, we present the first comprehensive, cloud-based semi-automated approach that uses Copernicus Sentinel-2 data to map the entire coastal area of Quirimbas National Park, whose reefs possess world-reknowned refugia and environmental variability enabling resilience and potential adaptation of rapid climate change (McClanahan and Muthiga, 2017). Our main aim is to provide consistent baseline mapping of the underwater structure and habitats of the coral reefs, seagrasses and neighboring underwater shallow-water seascape which can be repeated over time for monitoring and scaled and expanded to other regions. This information can assist comprehensive conservation activities, management decisions, sustainable development planning for more effective climate change mitigation, resilience and adaptation in the broader region of East Africa providing a crucial starting point for continued operational monitoring.

Many small-scale coral reef habitat mapping studies have relied on high-resolution commercial data, while larger scales and longer term monitoring are more appropriate for medium resolution (30 m) from Landsat which, up until 2016, were the dominant free data source (Hedley et al., 2016). The open availability of the Landsat archive since 2008 (Wulder et al., 2012), has provided millions of scenes covering almost all areas of the world, allowing huge progress for seascape mapping, monitoring and change detection. This data helps assess the impacts of natural hazards and climate change, including the increase in frequency and severity of cyclones and associated surges, and coral bleaching due to sea surface temperature increases (Dat Pham et al., 2019; Green et al., 1998; Hedley et al., 2016; Liu et al., 2014). Despite being launched as a terrestrial mission in 2015, the Copernicus Sentinel-2 has notably increased resolution and data availability for a significant number of coral reefs since its launch (Hedley et al., 2018). A significant benefit is the minimum mapping unit (MMU), whereas for Landsat is 900 m^2 as a result of the 30 m square pixel, while for Sentinel-2 is 100 m^2 due to the 10-m resolution (Tobler, 1988). The higher temporal resolution also increases the chances for suitable cloud-free data and stable sea states. As such, the five-day time interval and the smaller pixel size allow more effective multi-temporal image composition (Traganos et al., 2018a, 2018b, 2017) rendering better detection of homogeneous seascape elements, such as hard bottom substrates for coral reefs, seagrass meadows and algae/turfs, which is beneficial as the coastal seascape is rarely a homogeneous system, in the tropics, or elsewhere.

This data can also be used to evaluate relative bathymetry and underwater structure which also informs marine spatial planning, such as zoning and managing uses of resources (Douvere, 2008). These elements greatly enhance coastal seascape mapping and monitoring, when accompanied by high quality *in situ* data that match the temporal window of the image composite and the trajectories of habitats of interest.

To map this seascape via these abundant data streams, we exploit a cloud-based algorithmical framework—within the geospatial platform of Google Earth Engine (Gorelick et al., 2017), which features the entire open-access satellite image archive of Sentinel-2. The power of cloud computing enables multi-temporal analytics and machine-learning algorithms, calibrated by field data collected by local conservation scientists, who observed the occurrence and depth of coral reefs, seagrass meadows and the sandy/soft bottoms. We use a geoprocessing framework designed for submerged vegetation monitoring in temperate waters (Traganos et al., 2018; Traganos and Reinartz, 2017) and apply them to multiple benthic habitat types in the tropical seascape. This provides the first automated, consistent and expandable assessment for tropical coastal resources in QNP, creating a pre-cyclone baseline and valuable opportunities for repeatable and automated monitoring; which all comes at a crucial time of political instability and insecurty in the area resulting in limited accessibility, and lack of monitoring resources due to the COVID-19 pandemic.

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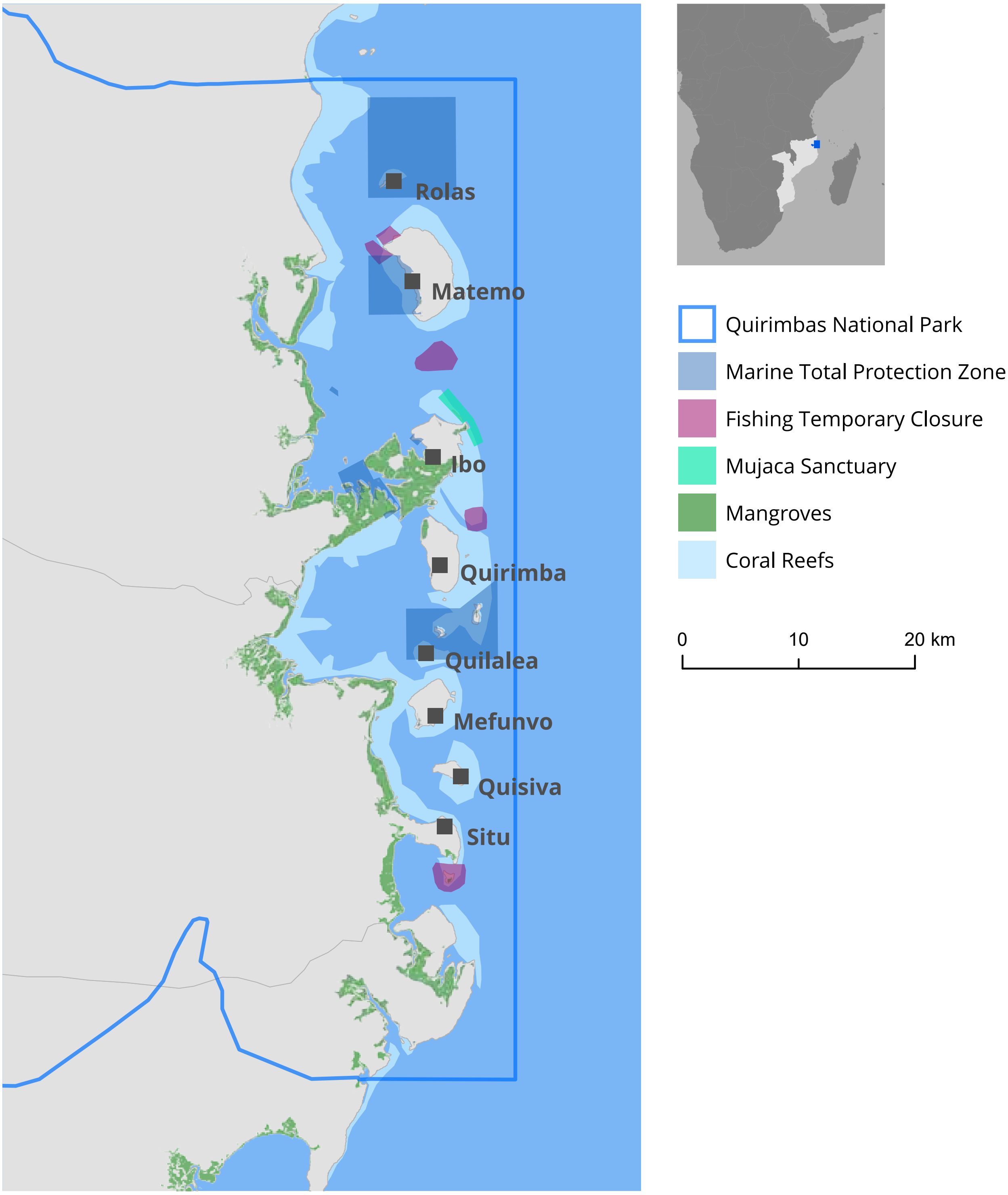

Figure 1. Quirimbas National Park is located in seven districts in Cabo Delgado Province, and is the northernmost marine protected area in Northern Mozambique. Coral reef extent from WCMC; Mangrove data derived from Sentinel-2 by WWF-Germany.

Study Area

Following the independence of Mozambique in 1975, more than 5 marine conservation areas have been established by the government. Among them, the Quirimbas National Park (QNP), in the Province of Cabo Delgado (**Figure 1**), Northern Mozambique, was created with an intrinsic goal to value and protect the biodiversity of Cabo Delgado (MITUR, 2003). In 2018 it was declared a UNESCO international Biosphere Reserve due to its unique terrestrial and marine fauna (UNESCO, 2018). An important aspect of this conservation area is that it follows the "bottom-up" approach: it was designed at the request of communities who, at the time, suffered from human-wildlife conflicts, competition for depleting natural resources, poverty and declining ecosystem services upon which they were, and are, dependent. The QNP is a protected area with a significant local population of 166,000 people living within its boundaries, 40% of whom are living in the transition and buffer zone (Mucova et al., 2018).

The QNP comprises seven partially-integrated districts, namely Macomia, Metuge, Ancuabe, Montepuez and Meluco, and two integrally associated districts, Ibo and Quissanga. Being the third largest conservation protected area in Mozambique, with a significant ecological and economic value, it faces several challenges like deforestation, poaching, illegal mining, hunting, over-fishing and over-exploitation of basic goods for survival. All these combined pressures negatively impact biodiversity and resource conservation, and the livelihoods of the vulnerable local communities. This region is therefore an important conservation area for collaborative research.

Field Data

To achieve the mapping objectives, we collected data from snorkel swims, boat, and drone surveys in expeditions led by WWF-Mozambique, including the seascape mapping survey in September, 2018, and the octopus closure survey conducted in April 2019 (Muaves, 2019). In both surveys, depth information was recorded using a Fishfinders Lucky hand-held portable depth finder, to support the derivation of satellite-derived bathymetry (SDB) from the Earth Observation (EO) data. Three major habitat types to map included hard substrate, veg-

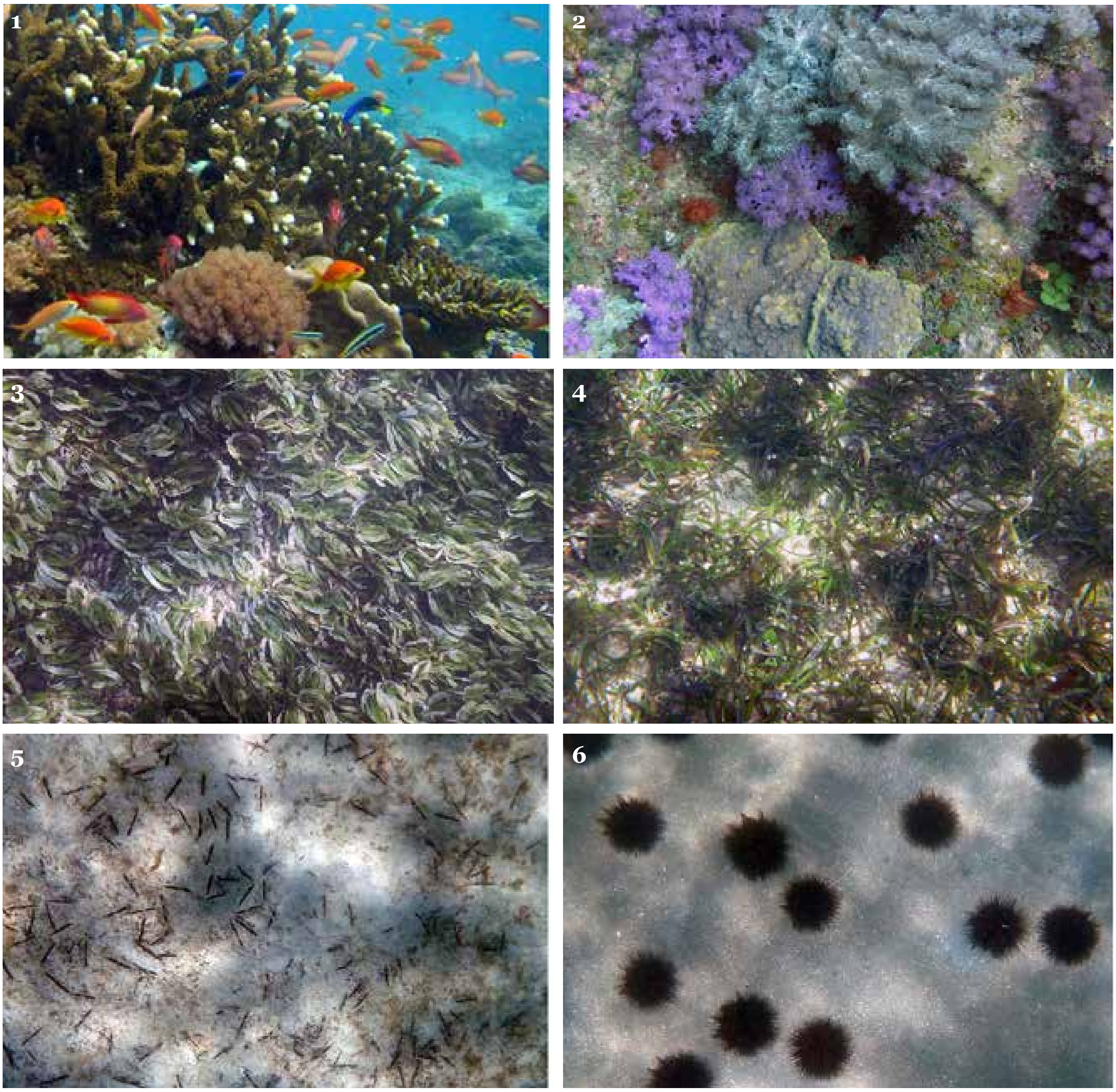

Figure 2. Representative images of the classification scheme. coral and hardbottom (1,2); submerged vegetation (3,4) and soft substrate (5,6).

etation and soft substrate (examples shown in **Figure 2**). We also documented the persence of multiple habitats within an approximate 10 m by 10 m area, assessed either by snorkel, or from the boat using a glass bottom bucket and waterproof camera (GoPro inside a waterproof case) mounted on a 50 cm stick. Habitat classes were identified a priori and according to three major class types. Coral and hardbottom habitats (hard substrate) include any coral or rock dominated surface, alive or dead; Seagrass and submerged vegetation (vegetation) comprise all surfaces with at least 30% seagrass cover and underwater flowering plants (Klemas, 2016). Soft and sandy substrates (soft substrate) include all sandy and fine rubble surfaces and may include turf macroalgae. These classes were determined by the characteristics of the seascape, the degree of feasibility and efficiency of field data collection, as well as our main aim of the outputs: to provide baseline mapping for the management of protected areas. Due to the nature of the different field surveys, and the characteristics of typical octopus closures areas (tidal flats), these exposed reef areas, which trap sediment and sand and are increasingly silted and highly reflective like sand, are considered to be soft substrate. Optically deep areas fall into the deep-water class.

To support QNP conservation management efforts, we opted to use these four major discernible, and ecosystem important, classes for our approach, defined primarily by their substrate, which is an important determinant of the ecology of the reef ecosystem, as these habitats associate with certain functional groups of species or life cycles (Osuka et al., 2018); while the changes between these classes can be an indicator of degradation (Bellwood et al., 2004). A simple classification scheme was selected to provide unambiguous classes whose presence can be easily identified *in-situ*, while maximizing potential accuracy from a medium resolution sensor (Hochberg and Atkinson, 2003).

Over 1200 training points were collected from boat, snorkel, drone and satellite imagery

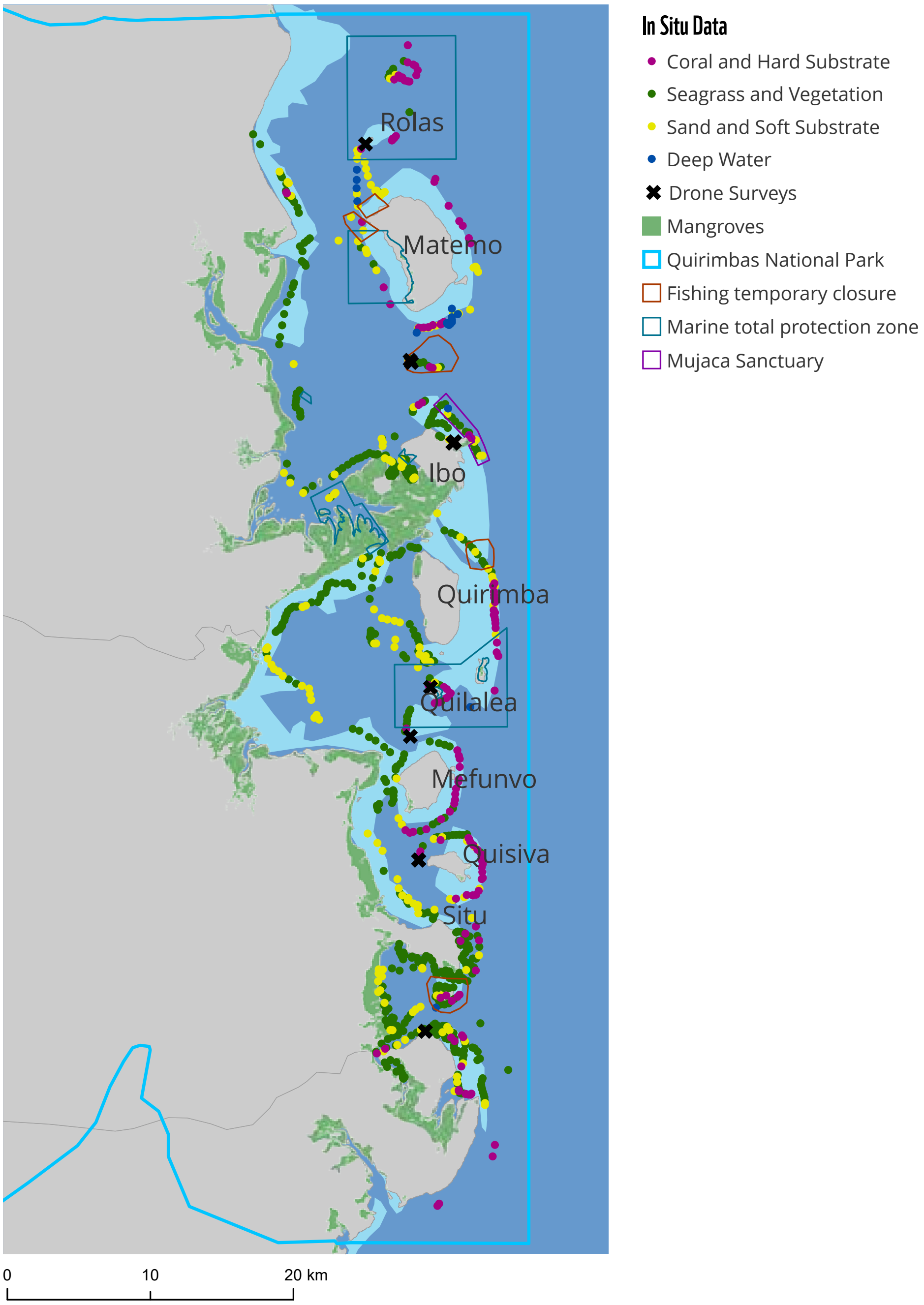

Figure 3. In-situ data used to train analysis of Earth Observation data, which included boat and drone surveys.

All information was collected in the field using a customized Survey 123 for ArcGIS application, which automatically included geo-location from the Android phone or tablet in addition to position information collected using a Garmin 64s GPS. Drone surveys were conducted at six locations using a 3DR Solo drone mounted with a GoPro 4 camera with a custom-fitted straight 4mm lens to avoid fish-eye effect. Surveys were flown with 80% side overlap and 60% forward. Images were geo-located to the drone GPS position obtained from flight logs using GeoSetter 3.4.16 (images are shown here: https://space-science.wwf.de/QNP_drone_survey).

Data to train the machine learning algorithm were distributed over the three habitat types, plus optically deep water (where insufficient light is reflected from the seabed and subsequently measured from the satellite) via the digitization of features detected in Google Earth and Google Earth Engine, using information from the *in-situ* data (shown in **Figure 3**), as well as older commercial high resolution imagery from QuickBird and IKONOS, acquired in 2004, to enhance the distribution of points in all bottom classes (**Table 1**).

Table 1. QNP in-situ data: field survey data from 2018, 2019, and the desktop-added points (image interpretation in conjunction with drone and underwater photos).

	2018		2019		Desktop points	
Class	**Number**	**%**	**Number**	**%**	**Number**	**%**
Soft substrate	182	21	446	67	426	33
Seagrass	518	60	69	10	490	38
Coral	145	17	140	21	320	25
Deep water	18	2	10	2	44	3
Total points	**863**		**665**		**1280**	

Image Processing

The entire processing chain is performed in the cloud

The satellite image processing was performed in the Google Earth Engine (GEE) cloud environment for the analysis of Earth Observation data (Gorelick et al., 2017), using the workflow of Traganos et al. (2018a, b) which was adapted to the QNP tropical landscape. Sentinel-2 L1C data were filtered by acquisition dates that coincided with the field surveys and prior to the 2019 cyclone season with adequate cloud-free coverage. We selected all data collected during the dry season months (May to December) for 2017 and 2018 with an overall cloud cover of less than 5%, resulting in a collection of 212 available images to create a best pixel composite. The cloud-free image composite was created by masking clouds using the Sentinel-2 QA60 bitmask, and then taking the median values of the first quintile (20%) of best quality pixels. Next, we performed sun glint removal applying the method of Hedley et al., (2005), and automatic water masking using the Otsu method (Donchyts et al., 2016; Otsu, 1979). We also derived a post-cyclone composite in the same manner using imagery acquired between May 2019 and February 2020.

The pre-cyclone raw multi-temporal image mosaics, as well as the de-glinted and water column corrected outputs, are shown in **Figure 4**. Surface artifacts and waves are removed in the deglinted image, while the water column corrected image shows coral reefs and seagrass habitats with similar reflectance independent of their depth.

Next we derived a relative bathymetry and depth-invariant index following the log-linear transformed linear model (Lyzenga, 1981, 1978) resulting in a relative estimation of depth (m) and three-band reflectance image derived from ratios which are independent of water column (Traganos et al., 2018a). This satellite-derived relative depth (SDB) shown in **Figure 5** was estimated up to 15 m for optically clear waters (Figure 5), with (MAE) of 1.21 m, RMSE of 1.61 m and an R^2 of 0.62.

The derived bathymetry shows the entire shallow reef shelf throughout the protected area and around the atolls. The lagoon bathymetry was also retrieved, showing underwater channels, features and underwater topography in far greater detail than best available information in nautical maps or charts which are out of date and limited in resolution in shallow waters.

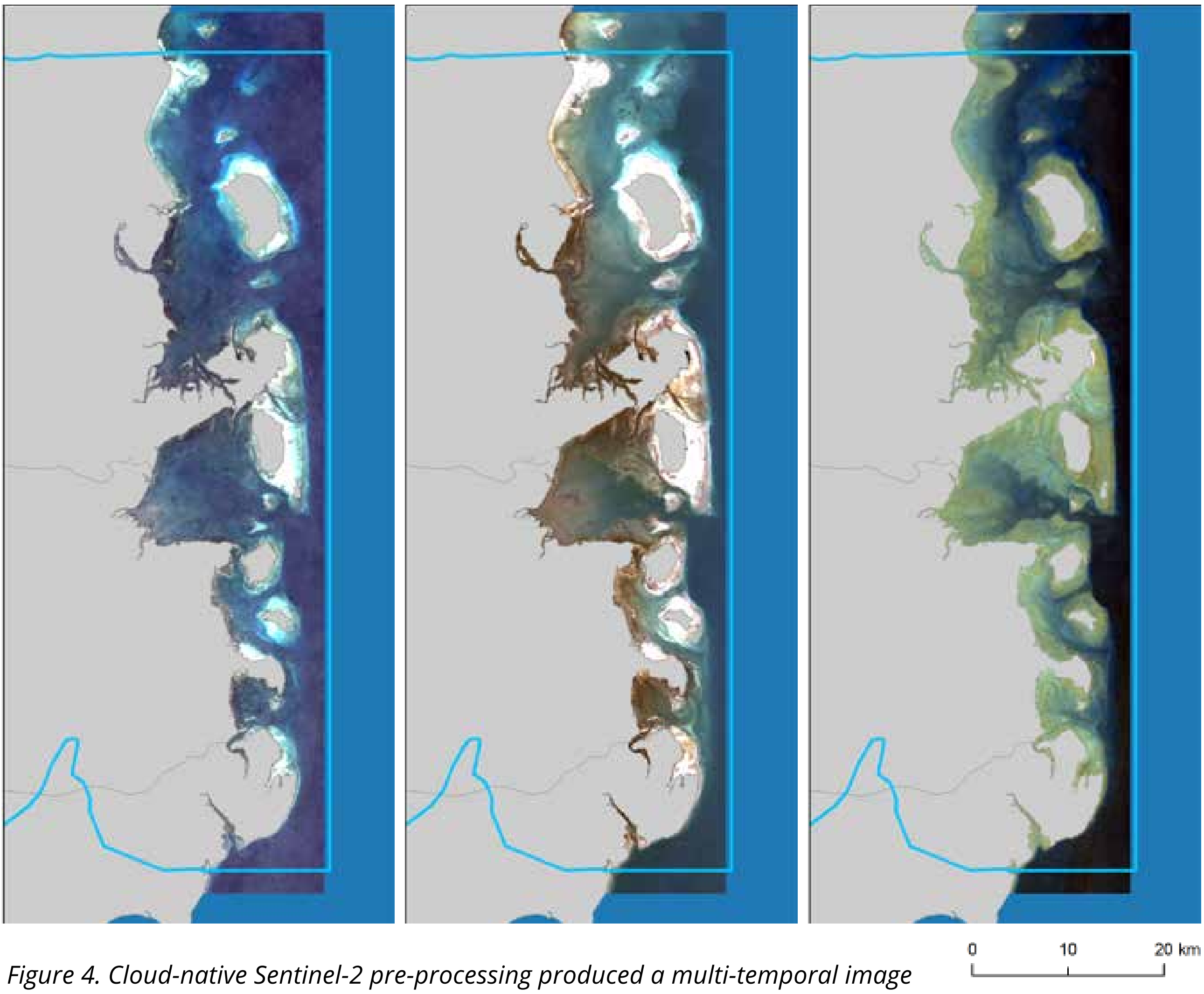

Figure 4. Cloud-native Sentinel-2 pre-processing produced a multi-temporal image composite (left), which was corrected for sunglint (middle); and water column (right).

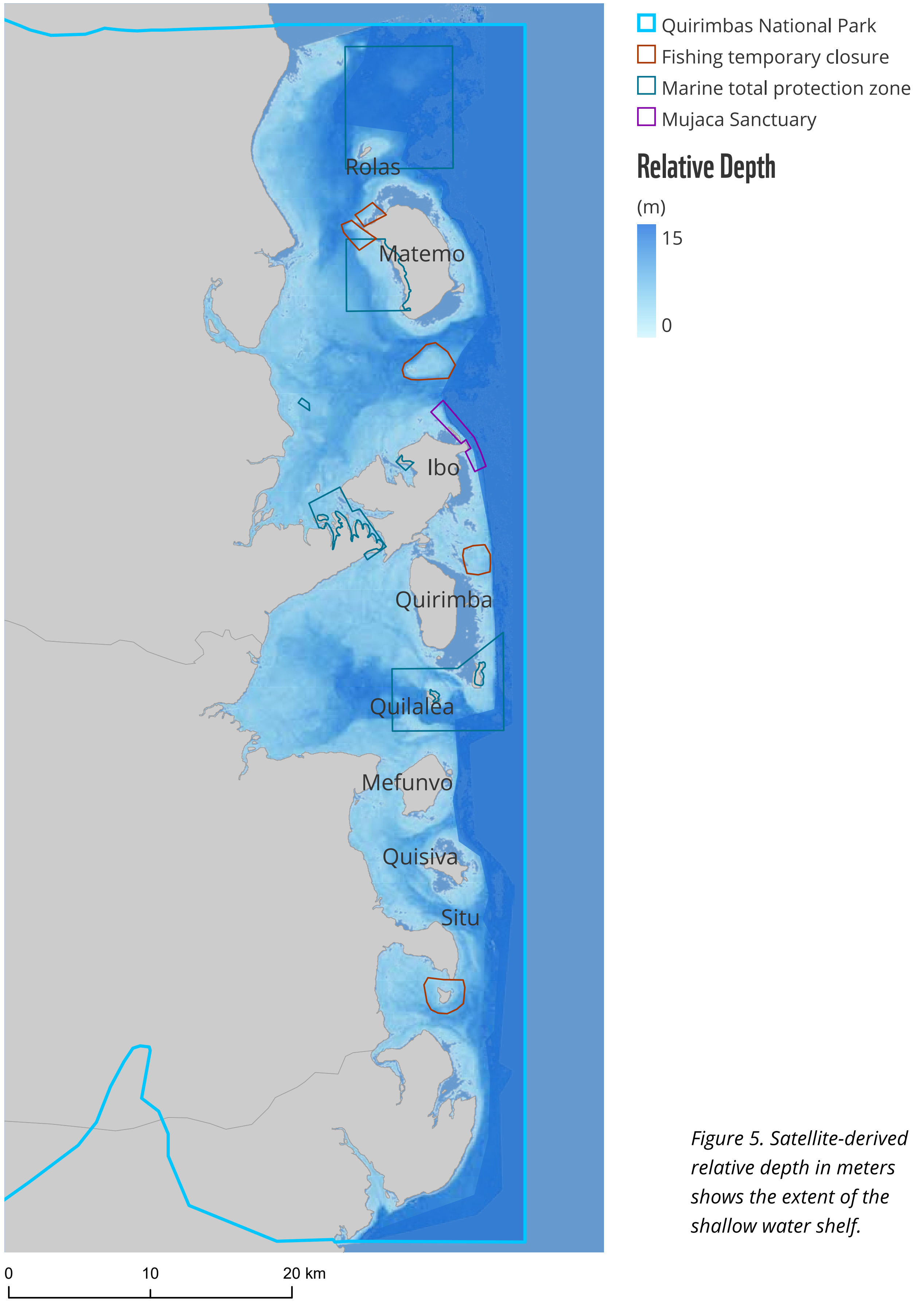

Figure 5. Satellite-derived relative depth in meters shows the extent of the shallow water shelf.

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Satellite derived relative depth provides information on underwater topography

The bottom surface slope, and bathymetric structure, notably rugosity, are critical drivers for fish communities and biodiversity (Dustan et al., 2013; Wedding et al., 2019). We derived bathymetric slope in degrees, rugosity and bathymetric position index (BPI) using the NOAA Benthic Terrain Modeler extension for ArcGIS (Walbridge et al., 2018) shown in **Figure 6**. The broad-scale bathymetric position was calculated using an inner radius of 25 and an outer radius of 50 pixels. We use these outputs to evaluate relative depth and position of the benthic habitat classification and to provide auxiliary data products for underwater topography of the reef environment. These show the areas of relatively homogenous flat surfaces in the lagoons, compared to those with more complex topography. The BPI discerns shallow reef flats from slopes and deeper flat zones typical for the lagoon areas around the islands and along the mainland shore. These data directly enhance the benthic habitat mapping classification as habitats and substrates tend to occur in unique underwater zones, and knowing relative depth helps account for effects of a varying water column (Eugenio et al., 2015).

The bathymetry-related information also contribute to the baseline requirements for designating potential fishing areas, temporal closures and use zones, but also can be utilized to evaluate major changes in depths due to cyclones or storm events which might cause extensive sedimentation or changes in the seafloor.

To maximize the data available for classification of benthic habitats we derived two additional bands which are the first and second principle components layers derived from the sun-glint corrected image. A 3x3 boxcar convolution filter is applied to the image stack before classification to remove any artifacts or anomalies by a low-pass smoothing. The data layer used for the habitat classification model include the coastal aerosol, blue, green and red (bands 1, 2, 3 and 4 of S2 L1C), as well as the two depth invariant bands, the relative bathymetry and two principle components layers.

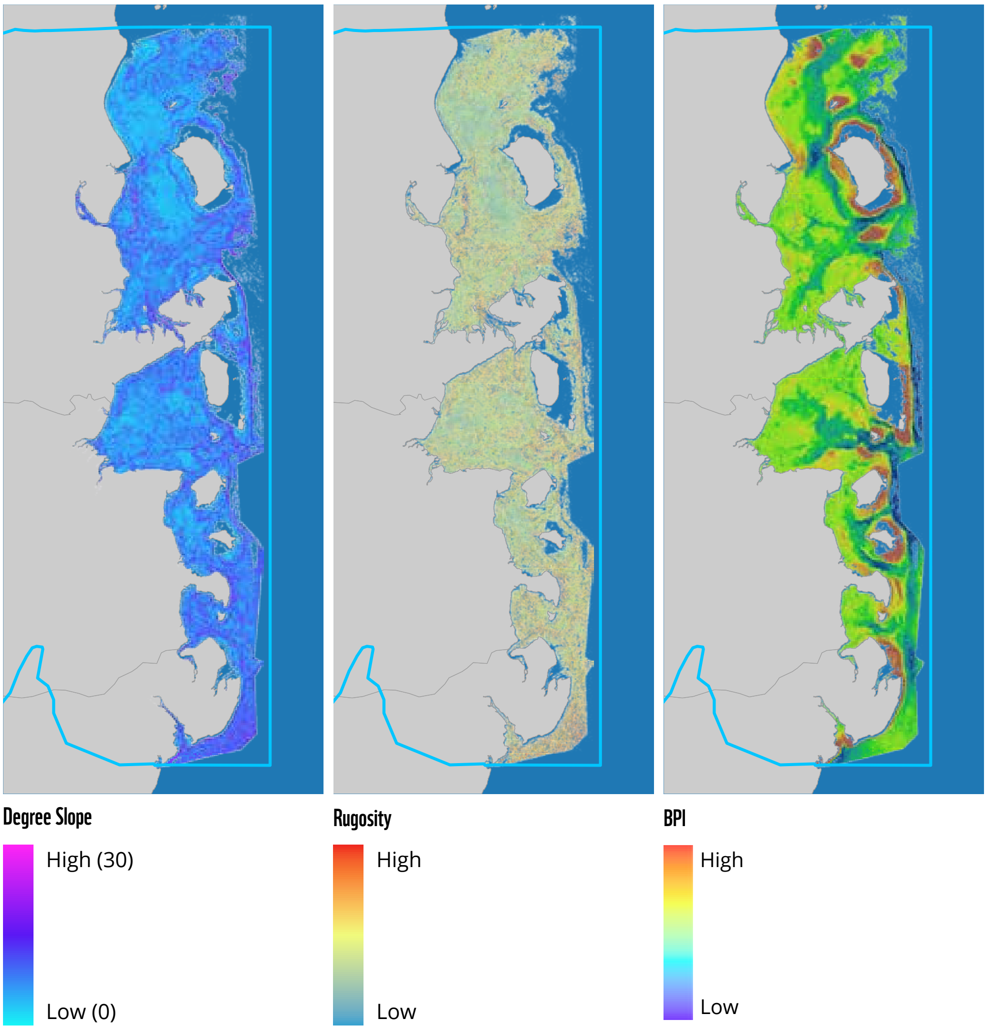
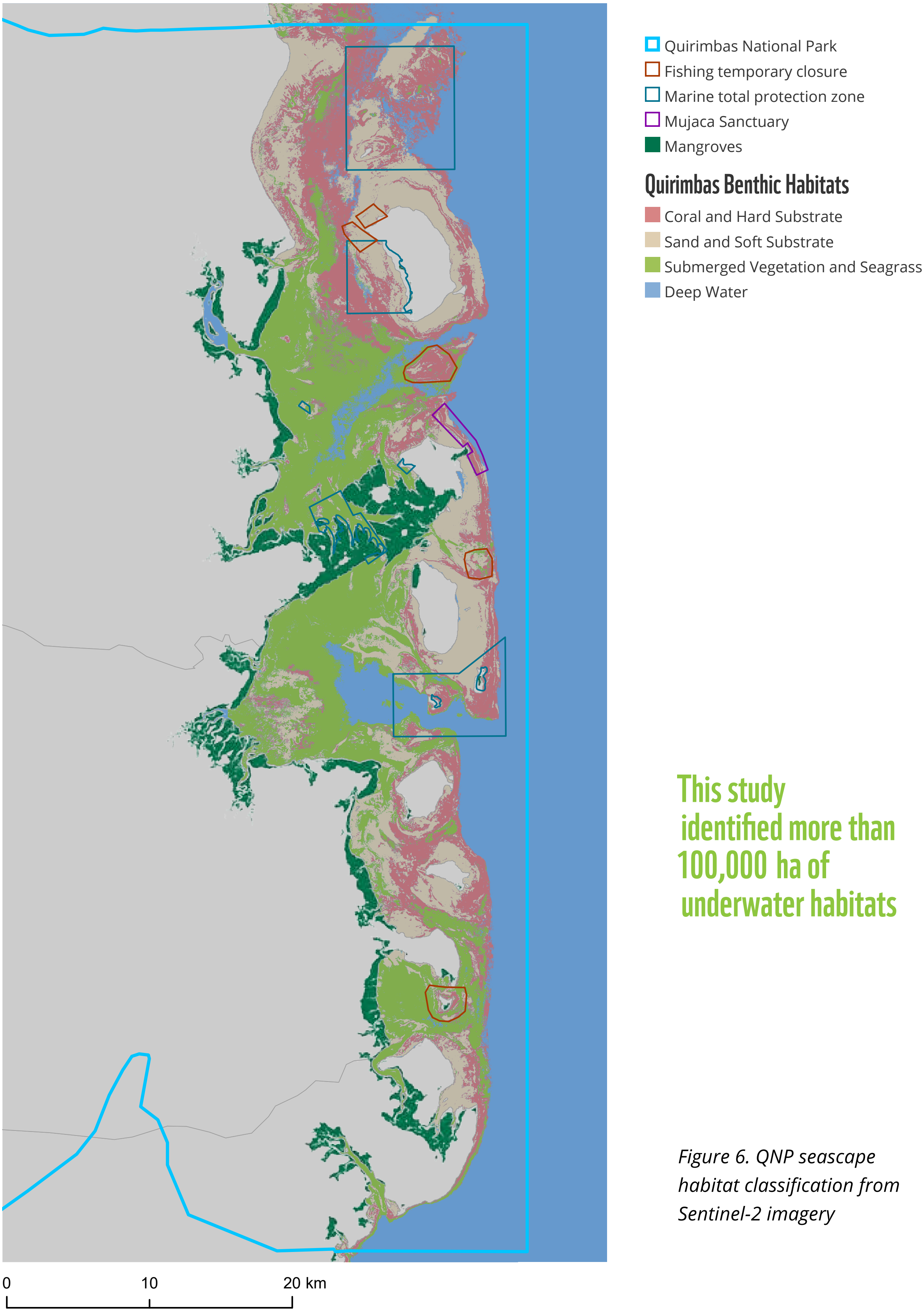


Figure 6. Satellite-derived benthic slope, rugosity and broad scale bathymetric position index (BPI)

Benthic Habitat Mapping

To create the map of benthic habitat types, we applied a Random Forests (RF) machine learning classification method (Breiman, 2001), to the satellite data stack (which included the relative bathymetry layer).

The resulting classified habitat maps have four broad classes: coral, seagrass, soft substrate, and deep water (**Figure 6**). The training data were split into 70% for training and 30% for validation to assess training and classification accuracy. We evaluate the classification results (the coastal habitat maps) by calculating overall (OA), producer (PA) and user accuracy (UA) of each class and estimate habitat area based on weight-adjusted accuracies within a 95% confidence interval according to Olofsson et al., (2013).



This study identified more than 100,000 ha of underwater habitats

Figure 6. QNP seascape habitat classification from Sentinel-2 imagery

The map has an overall accuracy of 84.6% (**Table 2**). Coral is the least accurate class, being most often confused with soft substrate and to a lesser extent vegetation. Soft substrate had the highest producer accuracy, while vegetation has the highest user accuracy. Based on the accuracy assessment of the Random Forest classifier, except from the class of the optically deep waters, all other three classes are neither overestimated, nor underestimated, following their balanced producer and user accuracies.

The extent of each habitat type with error-adjusted estimates are summarized in **Table 3**, with seagrass the most dominant habitat, followed by soft substrate. Our habitat classification and bathymetric terrain maps indicate a diverse distribution of habitats distributed throughout the seascape, with extensive seagrass beds located at river mouths and bordering mangroves in relatively flat, shallow near-shore lagoons. Sand and soft substrates dominate the shallower zones near the atolls, with reef lining the outward edges of the atolls, extending to the lagoon areas in the northern and southern parts of the protected area.

Table 2. Accuracy assessment of the benthic habitat classification derived from Sentinel-2 imagery

		In-Situ data					Producer Accuracy (%)
		Soft Substrate	Submerged Aquatic Vegetation	Coral and Hard-bottom	Deep Water	Total Points	
Map Data	Soft Substrate	98	6	9	1	114	**86**
	Submerged aquatic vegetation	9	127	14	2	152	**83.5**
	Cora and hardbottom	9	13	62	0	84	**73.8**
	Deep Water	0	1	0	9	10	**90**
	Total points	116	147	85	12	360	
User Accuracy (%)		**84.5**	**86.4**	**72.9**	**75**	**overall:**	**84.6%**

Table 3. Error-adjusted area calculations and percent composition of benthic habitats in the marine area in QNP

Class	Area (ha)	Area (%)
Soft substrate	24,720 ± 1,183	23.4
Seagrass	29,073 ± 1,278	27.5
Coral/Hard Bottom	19,413 ± 1,319	18.3
Deep Water	32,610 ± 346	30.8
Mangrove	12,696	-

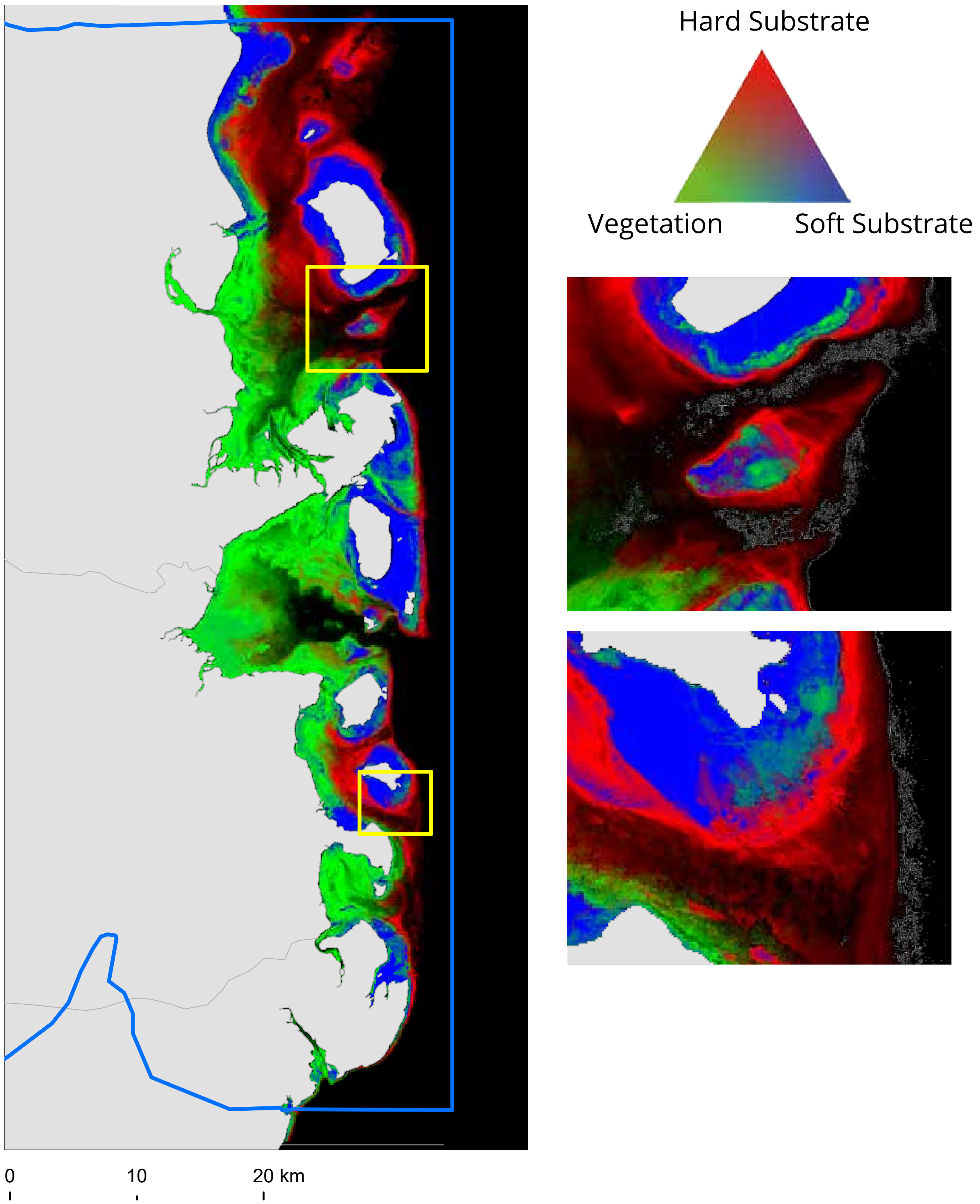


Figure 7. Spectral umixing of deglinted image using pure endmembers to detect pixel level mixing of the 3 major habitats in red, green and blue image channels. An absence of all three habitat types is shown dark, indicating optically deep areas.

The mapped habitats have unique depth ranges and topographic position (**Table 4**) where sand is generally on shallower, flatter, smoother underwater surfaces in comparison to the other habitats.

Table 4. The benthic habitats assessed according to bathymetric indicators

Class	Mean depth (m)	Mean Slope (degrees)	Mean bathymetric position	Mean Rugosity index (unitless)
Soft substrate	4.18	0.93	-17.52	1775
Seagrass	5.2	1.22	6.31	2293
Coral/Hard Bottom	6.99	1.08	-10.76	2010
Deep water	12.85	1.32	26.52	74179

The accuracy values are within the generally accepted range for management activities, although more classes, such as a macroalgae class, could potentially support a greater number of applications, such as the detection of bleaching, or dead coral, or use macroalgae cover as an indicator of reef health (Roff and Mumby, 2012). Most classifications define homogenous classes, however we found that this is often not the case *in situ*, and within the 10-m Sentinel-2 pixel size, there is in fact a high likelihood of finding mixed coral and rubble, vegetation and sandy seabeds. Our discrete classification results owe to the fact that we could produce a clear satellite image composite with minimal water quality and natural artifacts, and a reference dataset with an adequate horizontal and vertical distribution of benthic habitat classes.

Therefore, we derived a mixed habitat assessment using the same training data. We apply a spectral unmixing algorithm (Adams et al., 1986) to the deglinted Sentinel-2 image using a random sample (70%) of the “pure” endmembers identified visually in the imagery at various depths. We then interpret a continous measure of percentage contribution of the four habitat classes, essentially providing sub-pixel estimates of habitats (**Figure 7**). The data are comprised of three unique continuous estimates representing a proportion of habitat from 0 to 1, where the sum of all habitats is 1. The zoomed-in areas show the presence of mixed habitats. We note sand mixed with seagrass on the outward edges of the atolls, and some areas of seagrass and corals in the southern half of the protected area.

The spectral unmixing approach was enabled by clear water image composition, although it is more often used with hyperspectral imagery (Hedley et al., 2004) and might benefit from additional non-linear techniques to address different water depths (Hedley and Mumby, 2003). There is a great value in fuzzy classifications however: to accompany thematic maps, to provide additional detail for mixed and hetergeneous environments and identify areas which potentially support unique fish assemblages and require additional assessments - this is even more important at spatial resolutions which are larger than the fine scale habitats of interest for mapping and management.

Change Detection

We can monitor over time to identify areas vulnerable to climate change or extreme events

Shallow-water coral reef systems are inherently dynamic, and it is crucial to be able to monitor their changes over time. Seascapes in Quirimbas have been exposed to several extreme cyclones, notably cyclone Kenneth in April 2019, which made landfall in Pemba and had devastating consequences on the fragile ecosystem. Although we received reports of mass changes in coral cover (see **Figure 10**, page 31), unfortunately we have no field data due to limited access to the area. Therefore, we use the datasets and algorithms we have developed for spectral unmixing, to attempt to assess changes in habitats from before and after the cyclone in consistent pre- and post- cyclone data. This analysis should help identify potential sensitive areas, and targets for futher field data collection. As these cannot be currently verified, we use them as guides for future efforts.

After having determined the fractional cover of sand, seagrass and coral in a pre-cyclone satellite image composite, we do the same to the composite developed from imagery after the cyclone and perform a subtraction to identify areas of increase and decrease in each of the components. This identifies which pixels have different proportions of coral, sand and seagrass in the pre and post image, and how they changed. We identify major decreases in coral fractions in Matemo, which are accompanied by increases in soft substrate, which could be indicative of sedimentation and correspond to local reports of large-scale coral cover loss. We can see an increase in sand and corresponding decrease in coral signal in the northern total protection zone, which could be indicative of sedimentation, or die-off. There is a large area of increased seagrass with reduced which could be a result of denser seagrass or macro-algae cover. Overall, a few areas of marked reduction in seagrass between Situ and Mefunvo (**Figure 8**).

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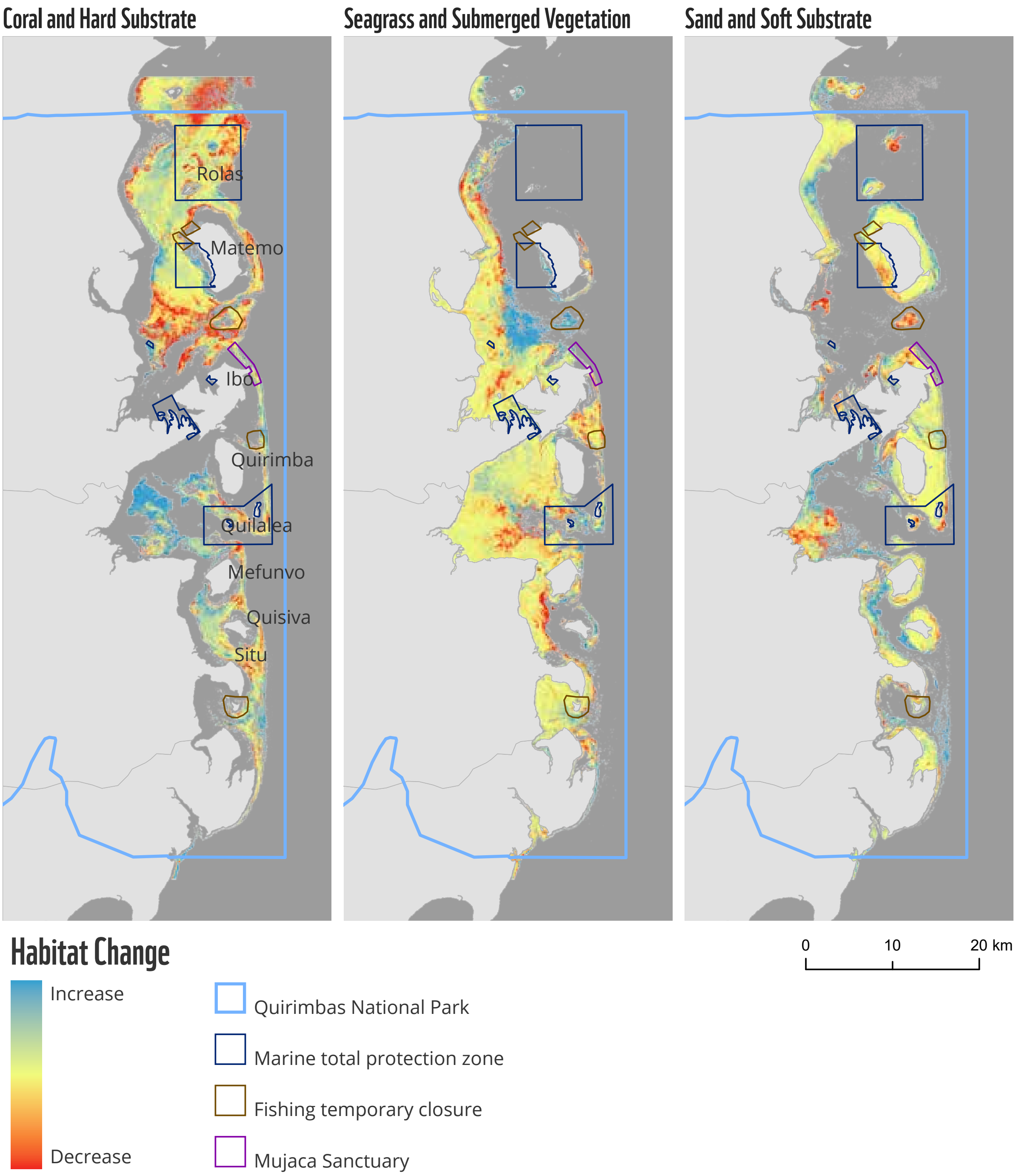

Figure 8. The percent change in the pre- and post- cyclone habitat fractions

The Land-Sea Interface

We use these data to evaluate the entire seascape: including land and sea

The seascape ecosystem is comprised of both land and sea; coastal terrestrial areas and benthic habitats are intrinsically linked. Previous studies have evaluated the complementary, and positive, influences of these environments at the land sea interface (Guannel et al, 2016) and the importance of their connectivity (Mumby, 2006). When these ecosystems are present together, the seascape benefits from greater productivity and resilence.

We use the data derived from this analysis to present the first ever combined assessment of mangroves, seagrass, sand and coral in QNP. We use the mangrove map developed by WWF-Germany for 1995-2018 (Shapiro, 2018). We aggregate the seascape into 100 hectare hexagons to create a general lattice for assessment of patterns and support for management interventions. For each hexagon we evaluate the presence of mangroves and a net gain or loss greater than 10%, and the same trends are evaluated in the benthic zone, using the percent increase or decrease of the unmixed fraction for each benthic habitat. This allows us to evaluate changes in all habitat types over time and view their change together (**Figure 9**).

Overall, mangroves are mostly increasing in the protected area, most prominently in the southern portion of the park, in an area with a small fringing reef, experiencing little change. The central region of QNP south of Ibo is experiencing mangrove gain and increase in coral dominated habitats, and a decrease in seagrass. Meanwhile in areas southwest of Matemo we observe a decrease in coral dominated habitats, and an increase in seagrass. Sedimentation (an increase in sand with a decrease in seagrass) is observed on the mainland across from Quilalea.

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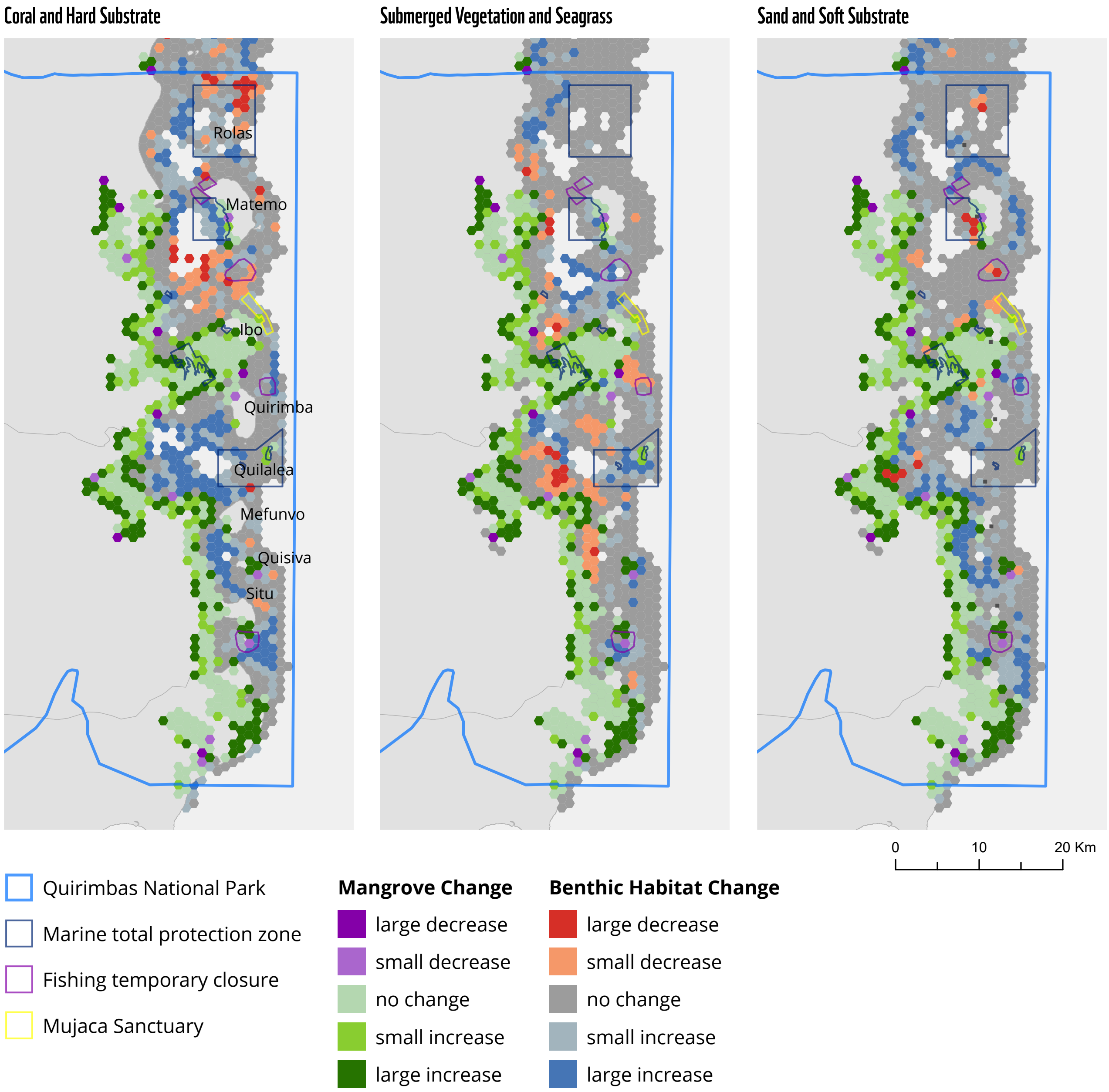
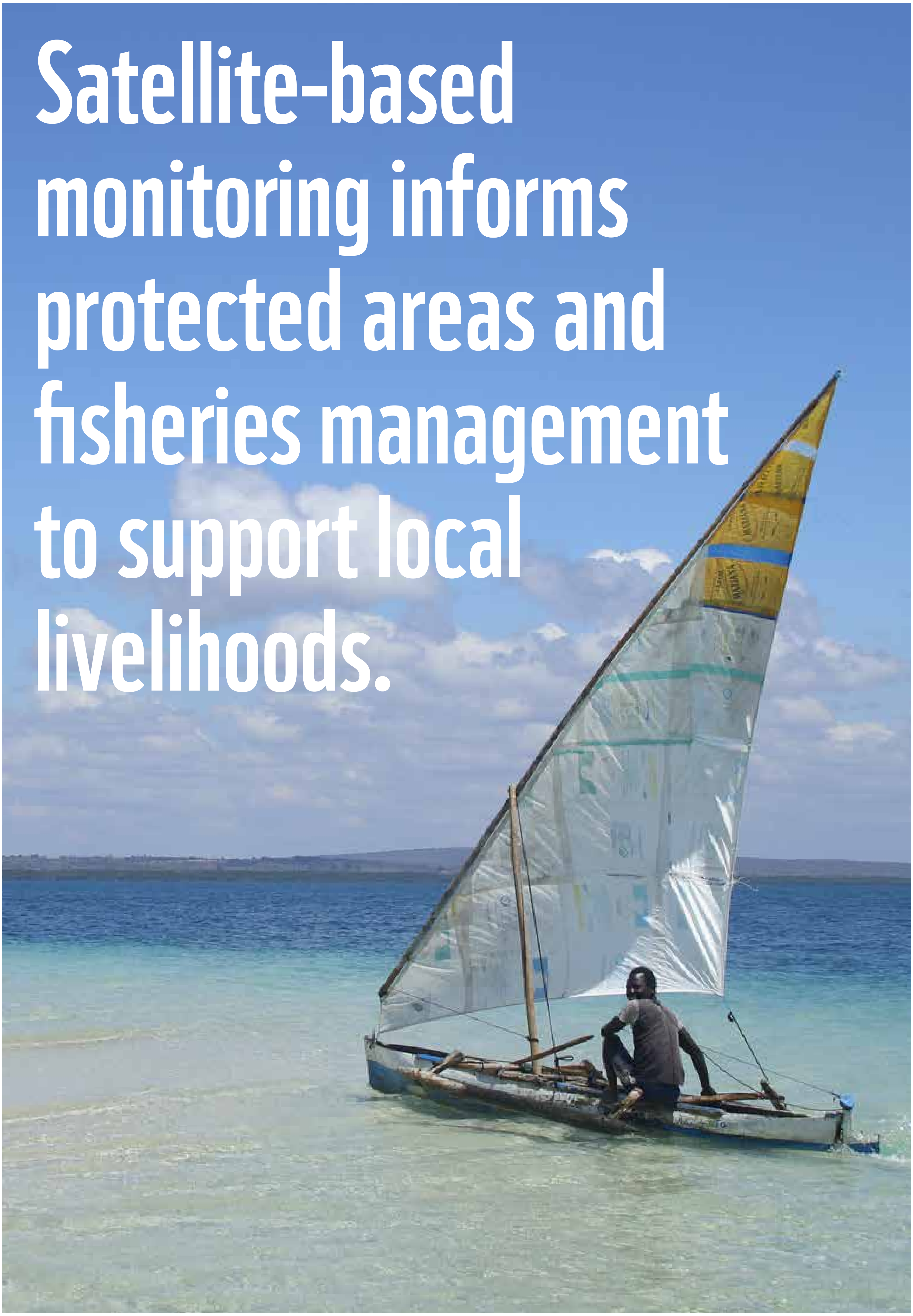


Figure 9. Change detection at the land-sea interface showing trends in mangroves, sand and soft substrates, coral and hardbottom, and submerged vegetation and seagrasses.

These data products provide the first available baseline insight into the dynamics and resilience of the seascape in QNP and indicate the ability of EO products to provide up-to-date and informative products for MPA management. With the increasing availability of satellite data over time, we can only expect these types of monitoring efforts to expand and improve.

Satellite-based monitoring informs protected areas and fisheries management to support local livelihoods.



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Summary

Well-informed and effective conservation management in the coastal zone requires an up-to-date state of knowledge and comprehensive data concerning the resources to be managed. In particular, the coastal marine seascape, its distribution of major habitats and underwater morphology are all absolute prerequisites to conservation activities for these assemblages, their context and distribution, not only presence or absence (Purkis et al., 2019).

> **Our results are the first validated baseline benthic habitat map of the Quirimbas coastal seascape**

Accurate and reliable spatial data are required for active and efficient management of marine protected areas, and more recently applied to restoration activities. The baseline requirements to manage coastal ecosystems include the typology and structure of the seascape environment, dynamics through time, its state of health and/or conservation, and a suitable monitoring system to support adaptive management or interventions as needed. In the Quirimbas National Park there has been relatively little spatial data available for marine resource management, although it is a highly valuable and resilient reef system of global importance (Beyer et al., 2018) fundamental to shaping policies and decision-making, notably related to fisheries management and zoning. These types of information are now more critical than ever, particularly in countries facing significant challenges to sustainable management of coastal resources in the face of climate change and instabilities (Diop et al., 2012) and the long term human impacts that have drastically altered coral reef systems and associated biodiversity already (Mcclenachan et al., 2017). Our benthic habitat mapping approach assesses over 100,000 ha of underwater shallow habitats classified into soft and hard substrates, vegetation with over 84% accuracy. The outputs are needed for efficient and effective fisheries management and support of local livelihoods and programs such as temporal closures, which are important management tools for coral reef ecosystems (Friedlander, 2015).

An effective baseline study should underly any establishment of MPAs and include the mapping and quantification of the spatio-temporal distribution of the habitats to be conserved, using replicable methods for status monitoring. As such, remote sensing plays an increasingly important role in the monitoring and management of coastal seascapes, including the mapping and monitoring of coral reefs, seagrass meadows and other shallow aquatic environments (Foo and Asner, 2019). Ongoing advances in the development of satellite imagery, cloud computing, machine learning and associated technologies are continuing to improve our ability to accurately derive information on the seascape composition (habitats and species), water properties (nutrients and sedimentation) and water depth which are important for assessing the ecosystem health of a shallow-water MPA. However, given the physical complexity and inherent variability of the aquatic environment, most of the remote sensing models used to address these challenges require localized input parameters to be effective and are thereby limited in geographic scope.

Although there have been considerable efforts to assess biodiversity in East Africa (Richmond, 2000) QNP has lacked detailed coastal seascape maps since its establishment in 2002. Currently available data are not able to meet the requirements of protected area managers. Our results provide the first holistic view of underwater resources that protected area managers are tasked to conserve for the future. Knowing where habitats exist, their relative depth, structure and pattern are the first step in assessing coral reef resilience, exposure to extreme events, accessibility by humans and potential management or restoration strategies to avoid ecosystem collapse (Bland et al., 2017).

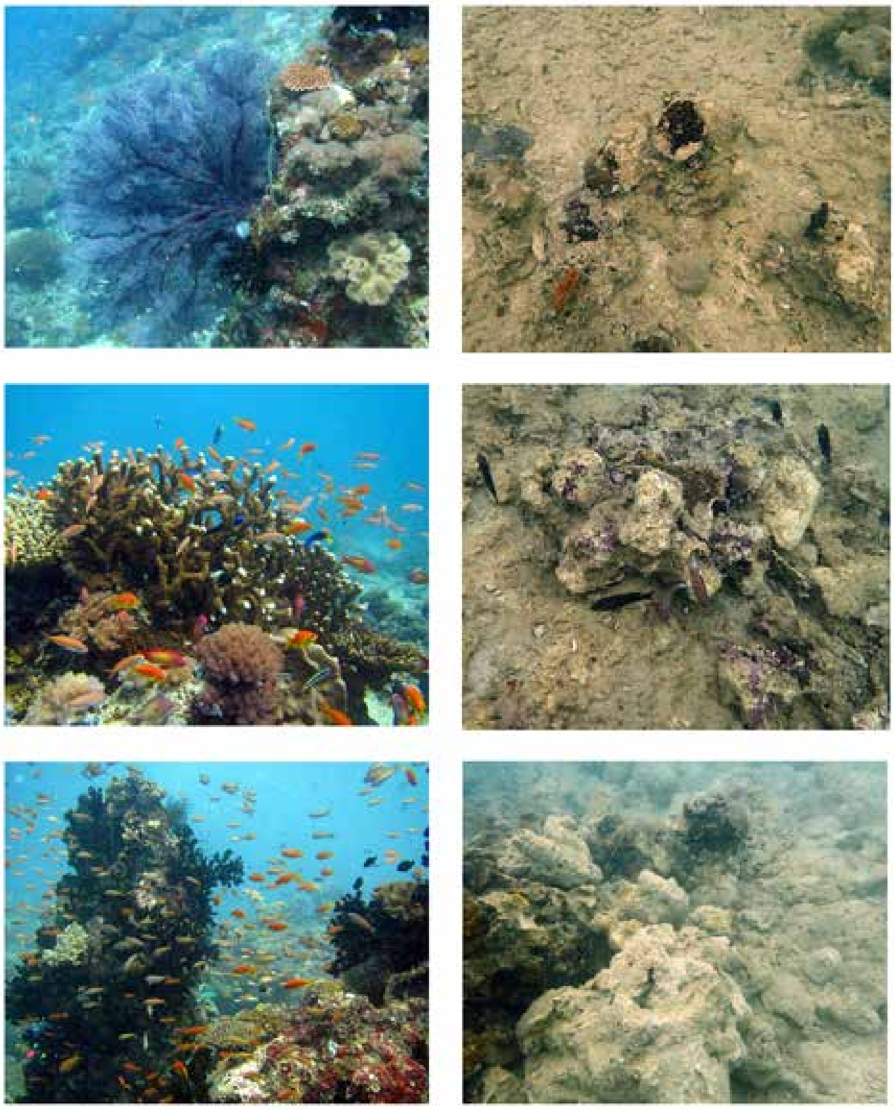
The method lays the groundwork for future monitoring of cyclones, climate change and human impacts

Given the increasing availability of the Copernicus Sentinel-2 constellation, we see a great potential in consistent, long term monitoring. The benefits of frequent observations allow the creation of optimum surface and water-column corrected reflectance image composites suitable for optically shallow coastal aquatic remote sensing for desired time frames, removing obstacles such as clouds, cloud shadows, turbid waters, sunglint. The use of machine learning algorithms and cloud processing allow for a nearly automated workflow, which improves with calibration via reference data. The automated aspect of the process means that repeated assessments may be performed over different temporal scales providing results as consistently as possible with minimal user interference.

While the classification workflow shown here can be used for the baseline mapping, we have also presented a potential approach to detect sub-pixel changes and trends using spectral unmixing, and potentially to assess disturbances from cyclone Kenneth, which delivered a direct hit to Quirimbas in April of 2019 and reportedly caused extensive damage to coral reefs (**Figure 10**). Our baseline dataset was developed for a crucial time period before a significant cyclone season in 2019, further compounded by recent political instability and the global COVID-19 pandemic, which has eliminated most of the protected area enforcement capabilities. Preliminary reports have indicated major damage from the cyclones as shown, and simultaneously little capacity on the ground for collection of additional data in 2020. Given the highly automated nature of our cloud-native geoprocessing framework and the stability and consistency of the Sentinel-2 sensors, we have several options to assess changes, either by evaluating major changes in benthic habitats, either via the random forest supervised, or by changes in the sub-pixel proportions of the spectral unmixed product.

Cloud-based infrastructures and frameworks for regional or continental scale mapping have demonstrated powerful and long-term impacts and originated in the terrestrial realm (Hansen et al., 2013) but recent efforts have been targeting the coastal zone (B. Lyons et al., 2020; Murray et al., 2012). Disk space and bandwidth are no longer barriers in the quest for large scale mapping efforts, allowing scientists to tailor better methods and apply computation-heavy algorithms such as machine learning. The designed and adapted cloud-native workflow can be rapidly updated by changing the temporal window to update the coastal seascape maps of habitat and bathymetry, ideally calibrated and validated with updated and suitable field data. The use of a cloud computing infrastructure like the Google Earth Engine and making the developed code available to local scientists, and outputs visible and accessible via GLOBIL (globil.panda.org), is an important step towards the simplification of the use of such tools for the management of an MPA, the creation of baseline maps for conservation prioritization and zonation of the desired area, and the detection of changes after natural hazards. With this effort we aim to implement new baselines for higher temporal resolution monitoring in the long term.

Figure 10. Images taken before and after cyclone Kenneth ©Situ Island Lodge



The significant advances of cloud computing, public satellite data archives, and automated artificial intelligence frameworks have given birth to several efforts to map and monitor the entire coastal seascape ecosystem. These include the Allen Coral Atlas project, the German Aerospace Center, funded Global Seagrass Watch project, and Global Mangrove Watch (Bunting et al., 2018). Leveraging cloud-native geoprocessing frameworks for regional, continental and even global-scale coastal habitat mapping, they are demonstrating their value and impact towards effective and accurate seascape inventories, which will highlight priority areas of resilience or sensitivity for protection, restoration, and conservation, enhancing the capacity of countries to measure and monitor their natural resources.

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This seascape mapping is the first in East Africa to address the entire coastal ecosystem and its essential components, including corals, seagrasses and coastal mangroves. When present together, these elements have been shown to provide better coastal protection and resilience to the impacts of climate change (Guannel et al., 2016). A national mangrove assessment, also using Sentinel-2 (Shapiro, 2018), has shown that overall, mangroves are increasing in the Quirimbas region, which lends additional support to this relatively intact and important natural resource, which provides significant ecosystem service benefits in the face of climate change, and warrants long term protection (Beyer et al., 2018).

The East African seascape can benefit from coordinated attempts at a national dataset to support sustainable development and international financing mechanisms in support of conservation, protection, climate change adaptation and Nationally Determined Contributions (NDCs); which are at the heart of the Paris Agreement and long-term climate goals. As "blue carbon" from seagrasses is increasingly recognized for potential carbon stock and sequestration (Fourqurean et al., 2012; United Nations Environment Programme, 2020) countries can adapt strategies to reduce national emissions through coastal management and restoration. The International Coral Reef Initiative (ICRI) recently endorced the inclusion of coral reefs and related ecosystems within the CBD post-2020 Global Biodiversity Framework, of which a number of indicators for priority development will be derived from remote sensing, including Copernicus data and cloud-computing (ICRI, 2020).

Regarding the near future of our efforts, we are currently scaling up our geoprocessing framework to the regional extent of four East African countries (Mozambique, Tanzania, Kenya, Madagascar) to holistically map their coastal seascape. Such scalability can empower the measurement and accountability of blue carbon inventories which will, in turn, support conservation and national climate change policy agendas for the four concerned countries; and could potentially serve as good practices to more countries, which feature these blue carbon habitats, for data-driven and effective ecosystem-based adaptation to climate change, both nationally and globally.

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Why we are here
To stop the degradation of the planet's natural environment and to build a future in which humans live in harmony with nature.

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