Second measurement of seagrass and mangrove area cover in the five Marine and Coastal Priority Protected Areas of Phase II of the MAR Fund Project

South Water Caye Marine Reserve
Belize

Contract Services No. 002-2019 "Conservation of Marine Resources in Central America Phase II Project" (Financial Agreement 2010 66 836)

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1 Introduction

The Mesoamerican Reef Fund (MAR Fund) was created in early 2004 to support the conservation and sustainable use of natural resources in the eco-region of the Mesoamerican Reef (MAR), shared between Belize, Guatemala, Honduras and Mexico. MAR Fund is a participatory, privately managed fund with a Board of Directors comprised of international collaborators, experts, the Central American Commission on Environment and Development (CCAD), and the in-country funds from each of the Mesoamerican Reef countries – Protected Areas Conservation Trust (Belize), Fundación para la Conservación de los Recursos Naturales y Ambiente en Guatemala (FCG), Fundación Biósfera (Honduras), and Fondo Mexicano para la Conservación de la Naturaleza (Mexico). MAR Fund's mission is to drive regional funding and partnerships for the conservation, restoration, and sustainable use of the Mesoamerican Reef.

To accomplish these goals, MAR Fund operates as an ecoregional planning and coordinating body that prioritizes projects and allocates funding. MAR Fund aspires to be known and respected as a trustworthy and transparent fundraising mechanism able to sustain and finance effective transnational alliances, policies, and practices that conserve the Mesoamerican Reef and advance the health and well-being of the region's people.

Implementation of the project "Conservation of Marine Resources in Central America – Phase II" is underway. This project supports best management practices, community participation in the conservation and sustainable use of coastal and marine resources in the initial network of protected areas within the Mesoamerican Reef region. Phase I and II of this project, were both funded by the German Government through the Kreditanstalt für Wiederaufbau (KfW), for a duration of five years.

As in Phase I, the current project seeks to consolidate selected protected areas in accordance with conservation priority criteria and to ensure the sustainable use of natural resources in adjacent coastal and marine areas in the medium term, in an effort to preserve the ecological functions of the Mesoamerican Reef region. The criteria for achieving these objectives, project outcomes and the assumptions underlying the objectives and results of the project are defined within the project's Logical Framework.

The following objectives are defined for the Phase II coastal and marine protected areas (CMPAs):

1. To contribute to the conservation of the ecological functions of the Mesoamerican Reef System.
2. To consolidate selected Coastal and Marine Protected Areas (CMPA) in the project's region and to ensure the conservation and sustainable use of marine and coastal resources in the medium term.

The following project objective indicators are listed:

Indicator 1: There is no increase in the financial gap in all of the CMPAs included in the Program.

Indicator 2: Management Plans are updated and under implementation in 100% of the CMPAs included in the Program.

Indicator 3: The CMPAs included in the Program have natural resource used plans under implementation.

The coastal and marine ecosystems within the Mesoamerican Reef region are remarkable in their biological diversity and provide a variety of ecosystem services to the adjoining nations. Ecosystem services include benefits such as shelter from tropical storms, reef fisheries, sustainment of biodiversity, a prosperous tourism industry or the provision of building materials. Besides coral reefs, mangrove and seagrass habitats are an integral component of the coastal ecosystem.

Many studies and initiatives have proven the high potential of remote sensing techniques for assessing coastal habitats like seagrass coverage (Dekker et al. 2006, Mumby et al. 1997) or mangroves canopies (Kuenzer et al. 2011), health status and potential stress parameters in coastal ecosystems. Mapping those ecosystems via remote sensing using aerial and satellite sensors has been shown to be more cost-effective than fieldwork (Green et al. 2004, Mumby et al. 1999, Mumby et al 1997).

The following CMPAs are the main sites of investigation areas for Phase II of the project:

1. Manatee Sanctuary State Reserve, Mexico (277,452 ha)
2. Corozal Bay Wildlife Sanctuary, Belize (73,550 ha)
3. South Water Caye Marine Reserve, Belize (47,703 ha)
4. Río Sarstún Multiple Use Area, Guatemala (47,576 ha)
5. Turtle Harbour / Rock Harbour Special Marine Protection Area, Honduras (813 ha)

The outcome of this consultation is to provide the current status (2018) of seagrass and mangrove coverage in all five areas through a second measurement phase. This is followed by a comparison between the baseline (2015) and current measurement information.

The present report describes the procurement, pre-processing and classification of high resolution RapidEye, Sentinel-2 and Landsat 8 satellite imagery for the CMPA **South Water Caye Marine Reserve, Belize.**

RSS - Remote Sensing Solutions GmbH generated mangrove and seagrass cover maps that represent the 2018 cover status in the project area at a high spatial level of detail. These mangrove and seagrass cover maps provide information on different density classes and were compared to the mangrove and seagrass baseline maps from 2015. Through this comparison, it can be determined whether the two main objective indicators of the project were accomplished:

- Areas of mangroves in project CMPA equal to or greater than the baseline
- Areas of marine seagrass beds in project CMPA equal to or greater than the baseline

These two main objective indicators are impact indicators and are used to measure the overall positive impact through the implementation of the MAR Fund project.

2 Objectives

The objectives of the presented study are:

- Derivation of a reliable up-to-date (2018) coverage using actual RapidEye, Sentinel 2 and Landsat 8 satellite imagery
- Application of consistent modern classification methodologies
- Plausibility checks and accuracy assessment implemented by experts

The following information is provided:

- Mangrove area in the South Water Caye Marine Reserve (Belize) for the year 2018 – assessed at a reliable quality and comparable methodology
- Seagrass area in the South Water Caye Marine Reserve (Belize) for the year 2018 – assessed at a reliable quality and comparable methodology

3 Project Area

The South Water Caye Marine Reserve (Belize) is situated on the inner side of the Barrier Reef and is part of the Belize reef system (Walker 2009). In recognition of its unique ecosystem, it has been designated as one of seven components of the Belize Barrier Reef System World Heritage Site, representing the largest and potentially least impacted reef complex in the Atlantic–Caribbean area (UNESCO, 1996). The South Water Caye Marine Reserve is located 18 km east of the mainland and has a size of 47,703 ha (Figure 1), making it the second largest marine protected area in the country (Mojica, 2015). The reserve was established in 1996 in recognition of the exceptional integrity of the marine ecosystems, and its national, regional and international importance. Its level of protection is equivalent to IUCN category IV (Mojica, 2015). Three different management levels exist within the reserve: General Use Zone (81% of the area), Conservation Zone (19%), and Preservation Zone (<1%). It is host to both important mangrove systems and extensive seagrass beds, which support fisheries fundamental for artisanal fishing industries (such as the queen conch, *Strombus gigas*, and the Caribbean Spiny lobster, *Panulirus argus*). Portions of the reserve have been identified as one of the most biodiverse marine systems within the western hemisphere. Artisanal fishing remains the main economic activity for neighbouring communities, but growing tourism demand together with decline in fisheries productivity are presenting new challenges for reserve management. The majority of the cayes are now converted to tourism developments and resorts, or private residences with local or international ownership. In addition, both national and international research communities, such as the Smithsonian Institute, have continued to play an important role in promoting conservation and supporting local environmental education programs. The reserve serves as nursery and feeding areas for multiple vulnerable and endangered species, including the West Indian manatee (*Trichechus manatus*). Offering 9km of unbroken barrier reef running from Tobacco Caye in the North to South Water Caye, the marine areas of the reserve are considered to be one of the most highly developed examples of barrier reef structure. Numerous cayes have formed within the region on mangrove peat, coral outcrops or through deposition of sand. The southern section of the reserve is characterized by faro reef formations that are of particularly importance due to unique and fragile species assemblages, unparalleled in species diversity and richness within the Caribbean region. Mangrove forests within the reserve contribute continuously to soil formation, which is fundamental to the maintenance of coastal surface elevation. As such, these forests are critical for climate change mitigation and adaptation measures. Anthropogenic removal of mangroves is mainly driven by the rapidly expanding demand to build new tourism facilities on the cayes.

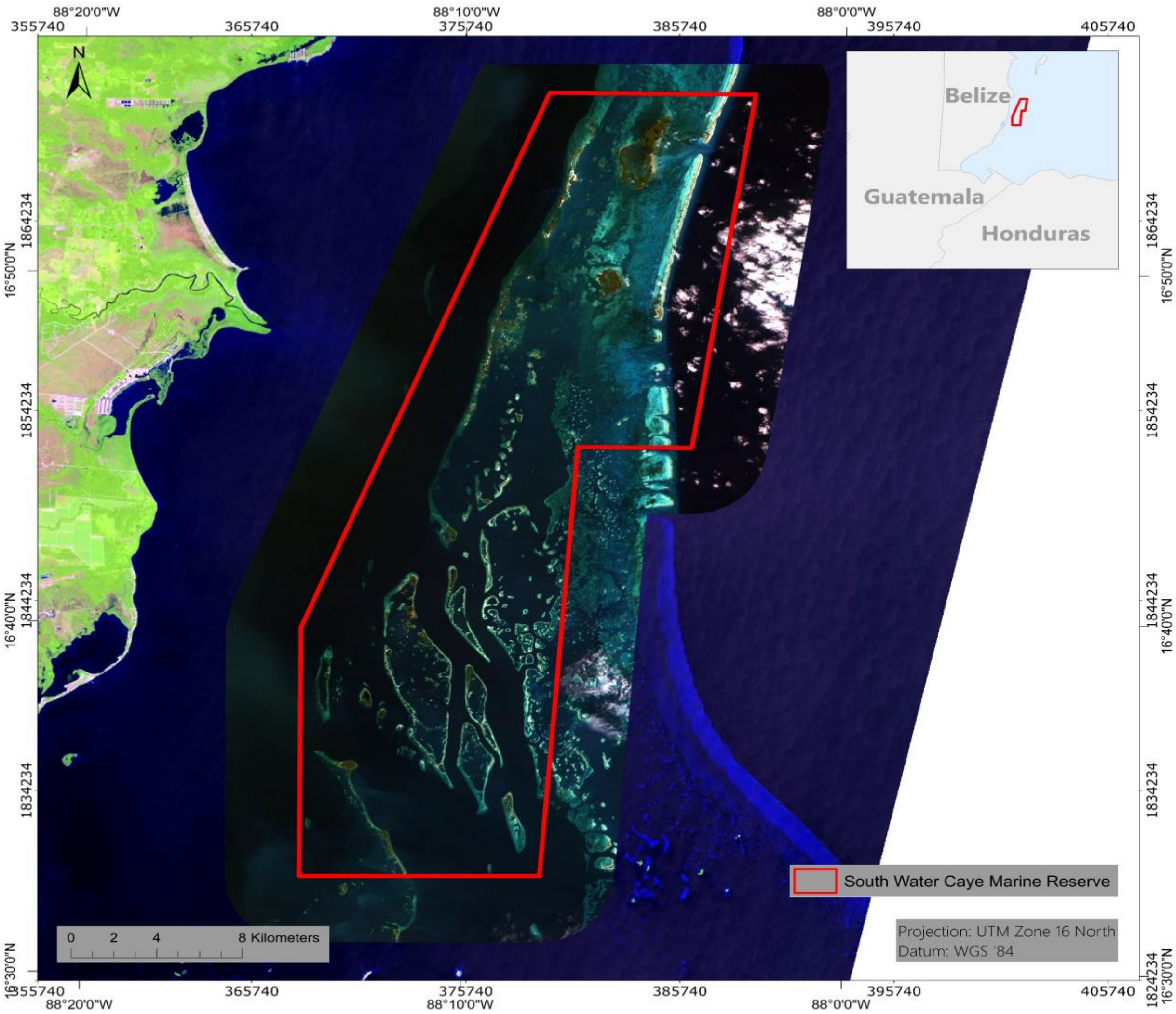


Figure 1: Overview of the South Water Caye Marine Reserve. True-color RapidEye imagery (2018-01-08). The border of South Water Caye Marine Reserve is displayed in red.

Of the coastal marine ecosystems, mangroves and seagrass meadows are considered to be among the most productive (McField and Kramer 2007; Wabnitz 2007). The main threats to the mangroves and seagrass in this area are due to: land-use change, changes in urban infrastructure, hydrological changes, anthropogenic contamination, and changing meteorological conditions (Sosa-Escalante 2013). New research on the role of vegetated coastal ecosystems has highlighted their potential as highly efficient C sinks, and led to the scientific recognition of the term "Blue Carbon" (Nellemann, 2009). Blue Carbon refers to the carbon captured by the world's coastal ocean ecosystems, mostly mangroves, salt marshes, seagrasses and potentially macroalgae. The role of Blue Carbon in climate change mitigation and adaptation has now reached international prominence (Macreadie et al., 2019).

Baseline studies of mangrove and seagrass distribution are important as damages to these ecosystems have direct and indirect negative effects on different environmental services such as: breeding areas for fish populations, reproduction, refuge, nesting, growth of different species, source of organic matter, beach stability, and sediment dynamics including capture, stabilization and formation. Seagrass meadows and mangrove forests capture and store carbon, thus protecting and restoring these coastal habitats is a good way to reduce/mitigate climate change.

Further knowledge of existence, quantity, quality, and distribution of mangroves and seagrass is indispensable to suggest adequate laws, develop strategic plans and cost / benefit assessments. Restoration measures benefit not only the environment, but also can also be designed to contribute positively the financial well-being of the local communities.

4 Data and Methods

4.1 Remote Sensing Data

Under the given framework conditions, three sources of remote sensing data were used:

RapidEye constellation

The generation of high-resolution land cover/vegetation type maps that also take different vegetation density classes into account require specific data characteristics and image analysis techniques. RSS therefore used data of the advanced satellite system constellation RapidEye, which provides high-resolution imagery within very short revisit times. The RapidEye satellite system, launched in August 2008, is a constellation of five identical satellites and thus has the unique ability to acquire high-resolution image data with 5 spectral bands on an almost daily basis (Table 1). The satellite constellation was developed by RapidEye AG and was financed with help from DLR and the state of Brandenburg. The company today belongs to Planet Labs Germany in Berlin, an offshoot of the US company Planet Labs Inc. The satellites record data with a spatial resolution of 6.5 m, which is resampled to 5 m during preprocessing by the data provider. Being able to collect more than 4 million km^2 of data per day as a constellation, each satellite can acquire imagery in 77 km-wide swaths extending at least 1,500 km in length. RapidEye has imaged more than 2 billion km^2 of Earth since February 2009.

Table 1: Characteristics of the RapidEye satellite constellation (Source: Planet Labs).

Mission Characteristics	Information	
Number of satellites	5	
Spacecraft lifetime	Over 7 years	
Orbit altitude	630 km in sun-synchronous orbit	
Equator crossing time	11:00 am local time (approximately)	
Sensor type	Multi-spectral push broom imager	
Spectral bands	Capable of capturing all of the following spectral bands:	
	Band Name	Spectral Range (nm)
	Blue	440-510
	Green	520-590
	Red	630-685
	Red edge	690-730
	NIR	760-850
Ground sampling distance (nadir)	6.5 m	
Pixel size (orthorectified)	5 m	
Swath width	77 km	
On board data storage	Up to 1,500 km of image data per orbit	
Revisit time	Daily (off-nadir) / 5.5 days (at nadir)	
Image capture capacity	5 million km^2/day	
Camera dynamic range	12 bit	

The high temporal repetition rate of RapidEye is of vital importance in regions with frequent cloud cover and short dry seasons, since it increases the probability of area coverage with acceptable cloud cover and thus makes detailed monitoring possible. RapidEye data is particularly suitable to precisely assess forest cover and forest status since their spectral, spatial, and temporal characteristics allow for a repetitive monitoring of tropical forests at high spatial detail (Figure 2).

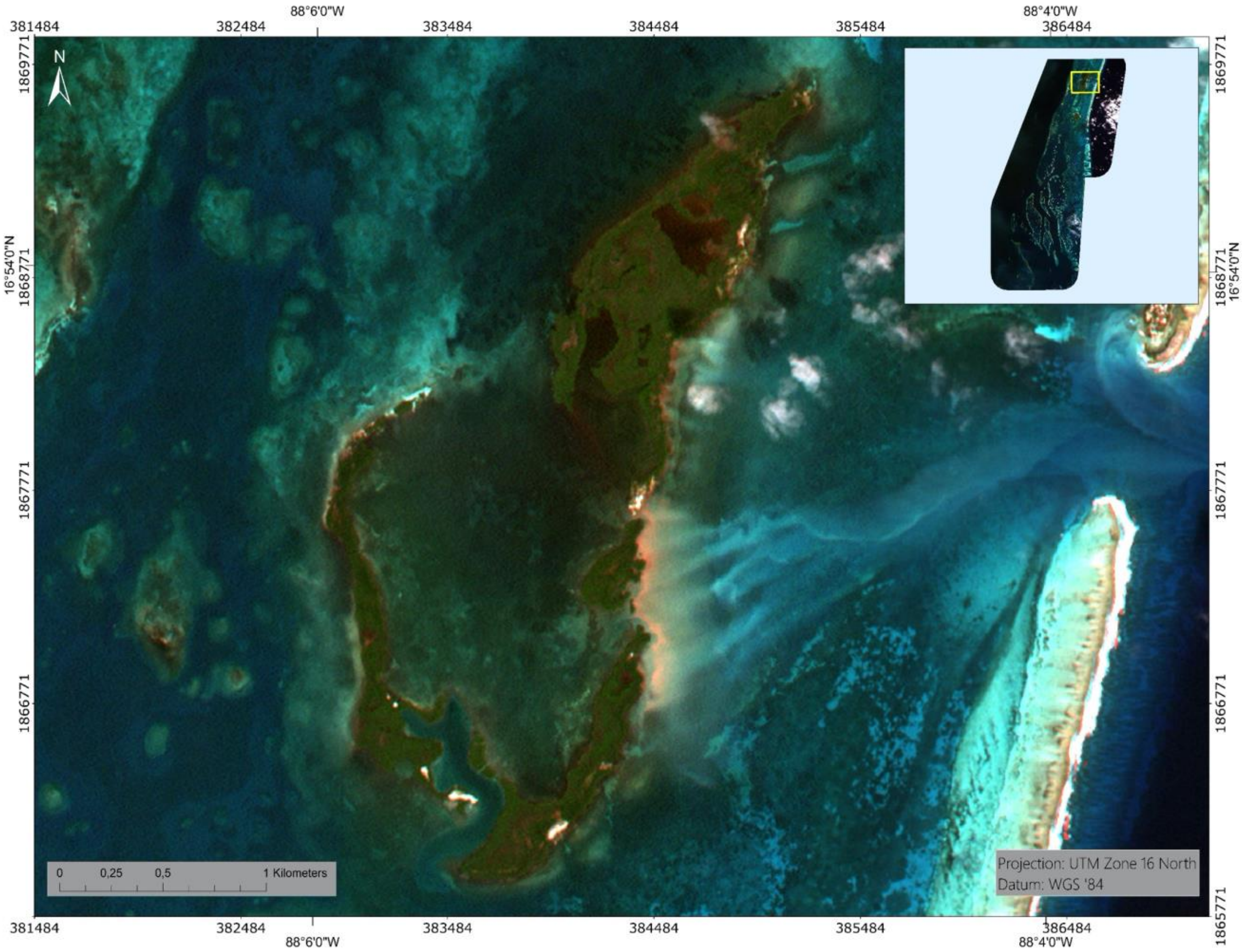


Figure 2: Subset of a RapidEye image (true color) showing the spatial detail in land cover. The yellow rectangle in the upper right image shows the location of the subset within the South Water Caye Marine Reserve.

In the present study, Level 3A RapidEye imagery was used. Radiometric, sensor and geometric correction is applied to the data (

Table 2). More detailed information on the data product is given in the Satellite Imagery Product Specification from Planet Labs available at:

https://assets.planet.com/docs/combined-imagery-product-spec-april-2019.pdf (April 2019)

Table 2: Level 3A RapidEye product specifications.

Product Attribute	Description
Product Components and Format	RapidEye Ortho image product consists of the following components: Image File – GeoTIFF file that contains image data and geolocation information Metadata File – XML format metadata file Browse Image File – GeoTIFF format Unusable Data Mask (UDM) file – GeoTIFF format
Product Orientation	Map North up
Product Framing	Image Tile (image tiles are based on a worldwide, 24km by 24km grid system). To each 24km by 24km grid square, a 500m overlap is added to produce a 25km by 25km image tile. Image tiles are black-filled 1km beyond the order polygon used during order placement. Tiles only partially covered an image take will be also black-filled in areas containing no valid image data.
Pixel Spacing	5m
Bit Depth	16-bit unsigned integers.
Product Size	Tile size is 25km (5000lines) by 25km (500 columns). 250 Mbytes per tile for 5 bands at 5m pixel spacing.
Geometric Corrections	Sensor-related effects are corrected using sensor telemetry and sensor model, bands are co-registered, and spacecraft-related effects are corrected using attitude telemetry and best available ephemeris data. Orthorectified using GCPs and fine DEMs (30m to 90m posting).
Horizontal Datum	WGS84
Map Projection	Universal Transverse Mercator (UTM)
Resampling Kernel	Cubic Convolution (default), MTF, or Nearest Neighbor

Level 3A RapidEye data from imagery 2018-01-08 was used for the mangrove and seagrass classification in South Water Caye Marine Reserve. Figure 3 displays this almost cloud free imagery.

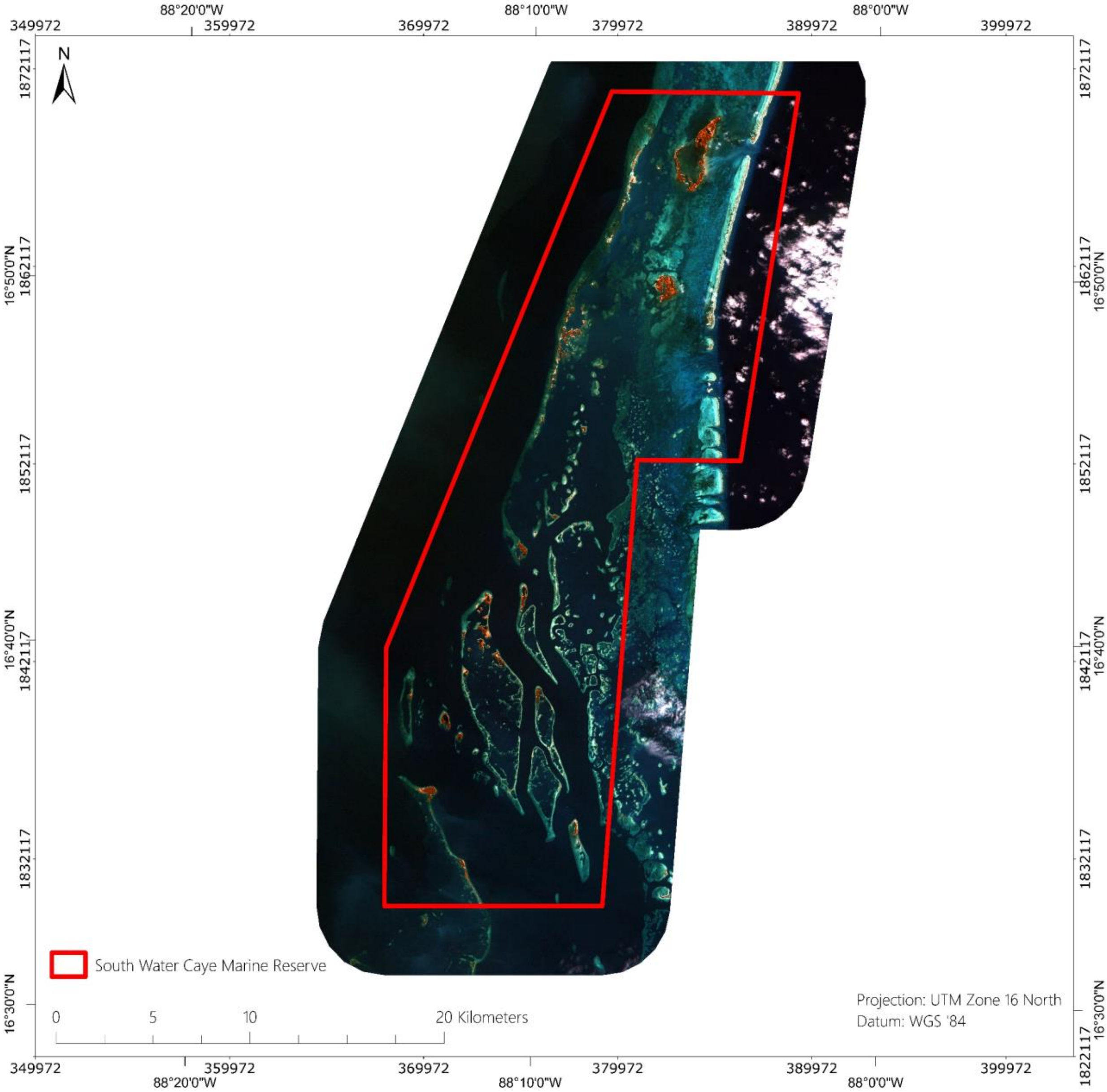


Figure 3: True-color RapidEye imagery (2018-01-08) used for mangrove and seagrass mapping.

Landsat 8

Landsat surveys the Earth's surface along the satellite's ground track in a 185-kilometer-swath as the satellite moves in a descending orbit over the sunlit side of the planet. Landsat 8 orbits the earth at 705 km altitude, crossing every point on the Earth once every 16 days. The OLI sensor onboard Landsat 8 collects data in nine shortwave bands – eight spectral bands at 30 m spatial resolution and one panchromatic band at 15 m. Refined heritage bands and the addition of a new coastal/aerosol band create data products with improved radiometric performance. OLI data products have a 16-bit range. Table 3 gives an overview of the Landsat 8 data specifications. More detailed information on Landsat 8 data is given at: https://www.usgs.gov/land-resources/nli/landsat/landsat-8. Landsat 8 data is free of charge and available from the U.S. Geological Survey (USGS) agency via their ftp server: http://earthexplorer.usgs.gov/.

Table 3: Landsat 8 product specifications.

Product Attribute	Description
Processing	Level 1 T- Terrain Corrected
Pixel Size	OLI multispectral bands 1-7, 9: 30m OLI panchromatic band 8: 15m TIRS bands 10-11: collected at 100m but resampled to 30m to match OLI multispectral bands
Data Characteristics	• GeoTIFF data format • Cubic Convolution (CC) resampling • North Up (MAP) orientation • Universal Transverse Mercator (UTM) map projection (Polar Stereographic projection for scenes with a center latitude greater than or equal to -63.0 degrees) • World Geodetic System (WGS) 84 datum • 12m circular error, 90% confidence global accuracy for OLI • 41m circular error, 90% confidence global accuracy for TIRS • 16-bit pixel values

Landsat data has proven to be very appropriate for detecting forest ecosystems like mangroves (Chen et al. 2013, Kuenzer et al. 2011) (Figure 4).

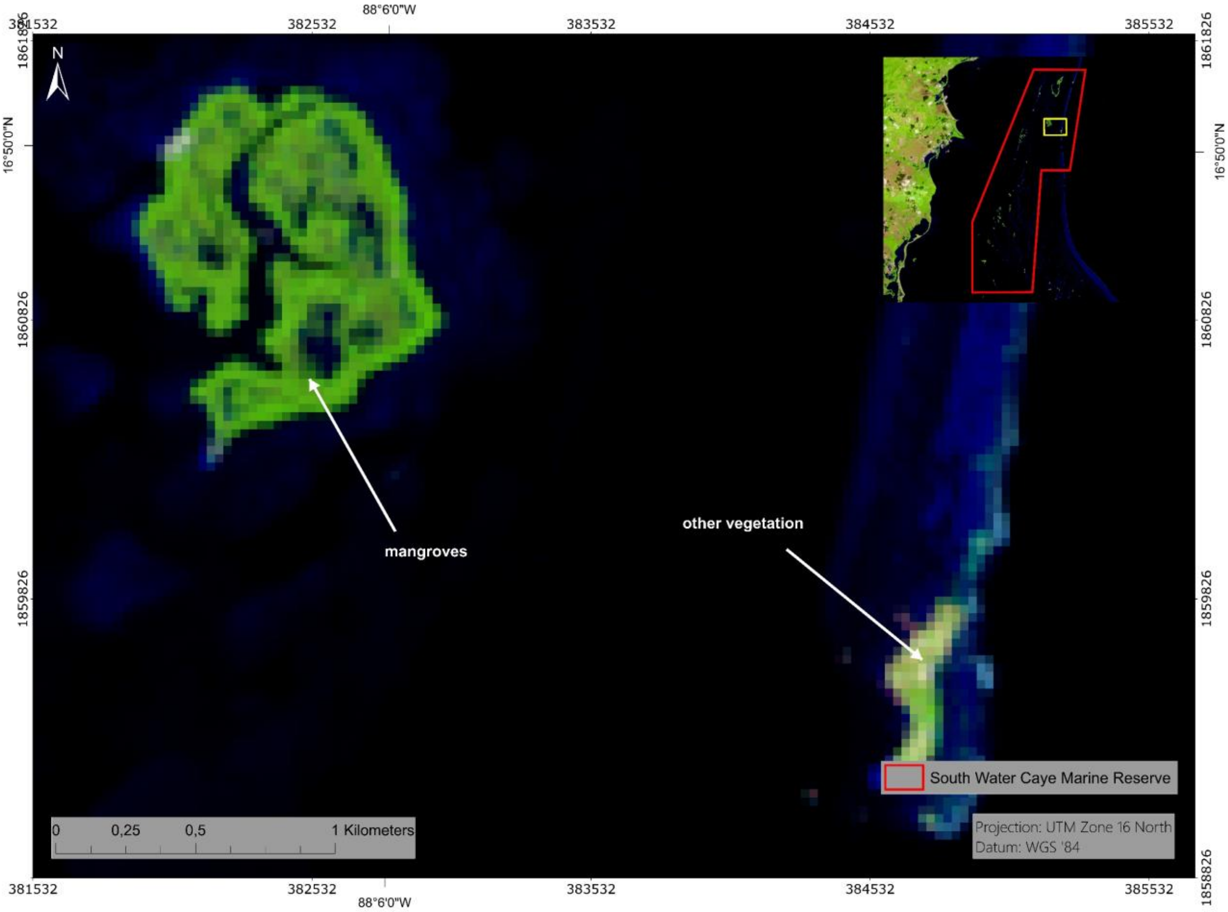


Figure 4: Subset of a Landsat 8 imagery (bands: short wavelength infrared (band 7), near infrared (band 5), and red (band 4)) showing that mangroves can be differentiated from other vegetation types. The yellow rectangle in the upper right image shows the location of the subset within the South Water Caye Marine Reserve.

The Landsat 8 archive was checked and the most appropriate image (2019-01-28) was downloaded. Figure 5 shows the acquired Landsat 8 data for the South Water Caye Marine Reserve.

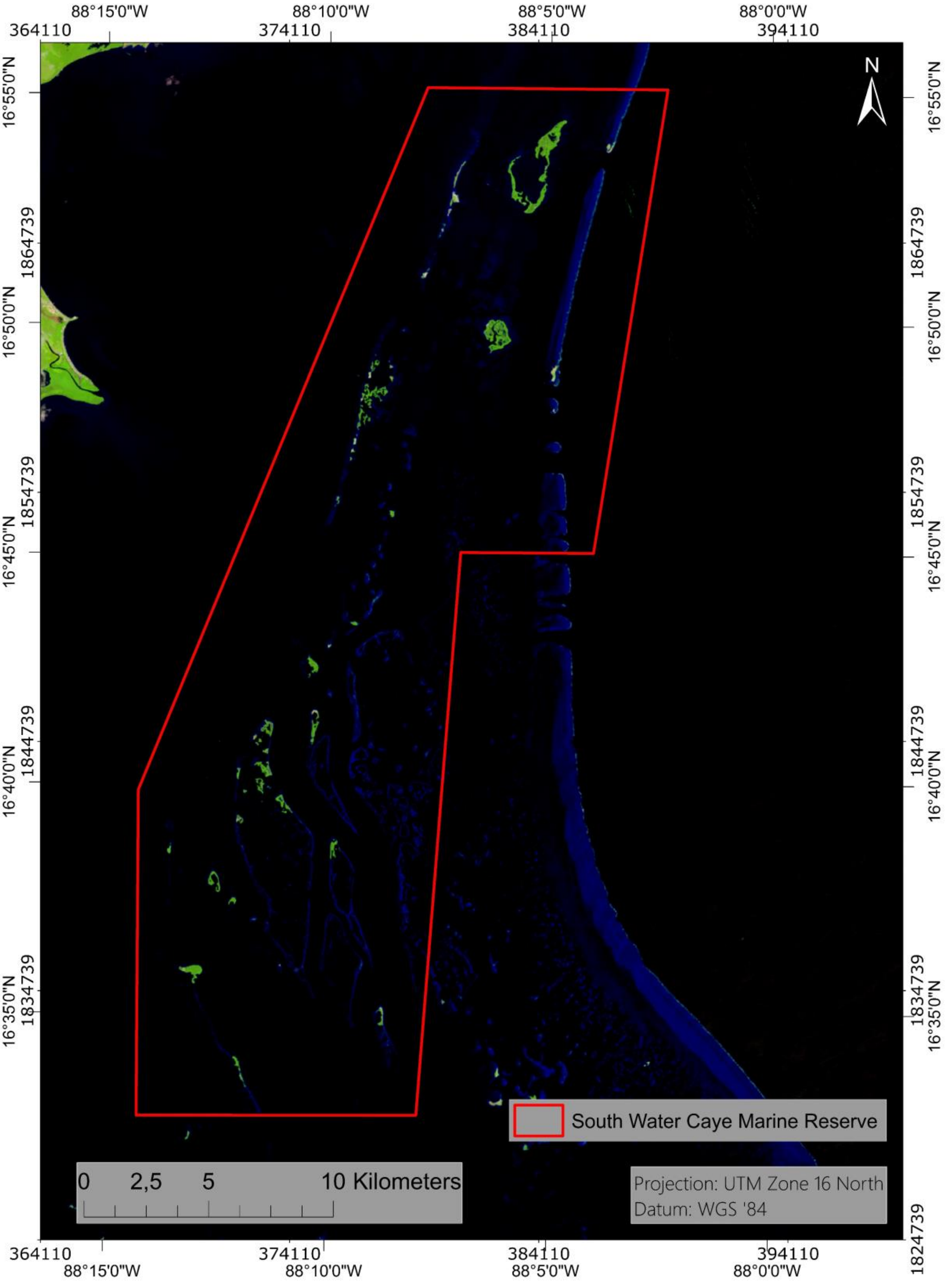


Figure 5: Landsat 8 scene (2019-01-28; bands: short wavelength infrared (band 7), near infrared (band 5), and red (band 4) used for the mangrove and seagrass mapping.

Sentinel-2 constellation

The Sentinel-2 mission is based on a constellation of two satellites, both orbiting Earth at an altitude of 786 km but 180° apart. This configuration optimizes coverage and global revisit times. Sentinel-2A was launched on 23 June 2015 and Sentinel-2B was launched in March 2017. The instrument on-board the Sentinel-2 platforms is a multispectral imager (MSI) covering 13 spectral bands (443 nm – 2,190 nm) with a swath width of 290 km and a spatial resolution of 10 m (4 visible and near infrared bands), 20 m (6 red edge/short wavelength infrared bands) and 60 m (3 atmospheric bands). Table 4 gives an overview of the Sentinel-2 data specifications. More detailed information on Sentinel-2 data is provided at:
http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2.

Sentinel-2 is free of charge and available via the ESA Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home, assessed July 2019).

Table 4: Sentinel-2 product specifications.

Sentinel-2A bands	Central wavelength (µm)	Spatial resolution (m)
Band 1 – Coastal aerosol	0.443	60
Band 2 – Blue	0.490	10
Band 3 – Green	0.560	10
Band 4 – Red	0.665	10
Band 5 – Vegetation red edge	0.705	20
Band 6 – Vegetation red edge	0.740	20
Band 7 – Vegetation red edge	0.783	20
Band 8 – NIR	0.842	10
Band 8A – Vegetation red edge	0.865	20
Band 9 – Water vapor	0.945	60
Band 10 – SWIR – cirrus	1.375	60
Band 11 – SWIR	1.610	20
Band 12 – SWIR	2.190	20

Especially due to the red-edge and short wavelength infrared bands, Sentinel-2 data has proven to be very appropriate for investigating forest ecosystems (see https://sentinel.esa.int/web/sentinel/thematic-content/-/article/sentinels-accelerate-monitoring-of-forest-change, November 2019), such as mangroves (Figure 6).

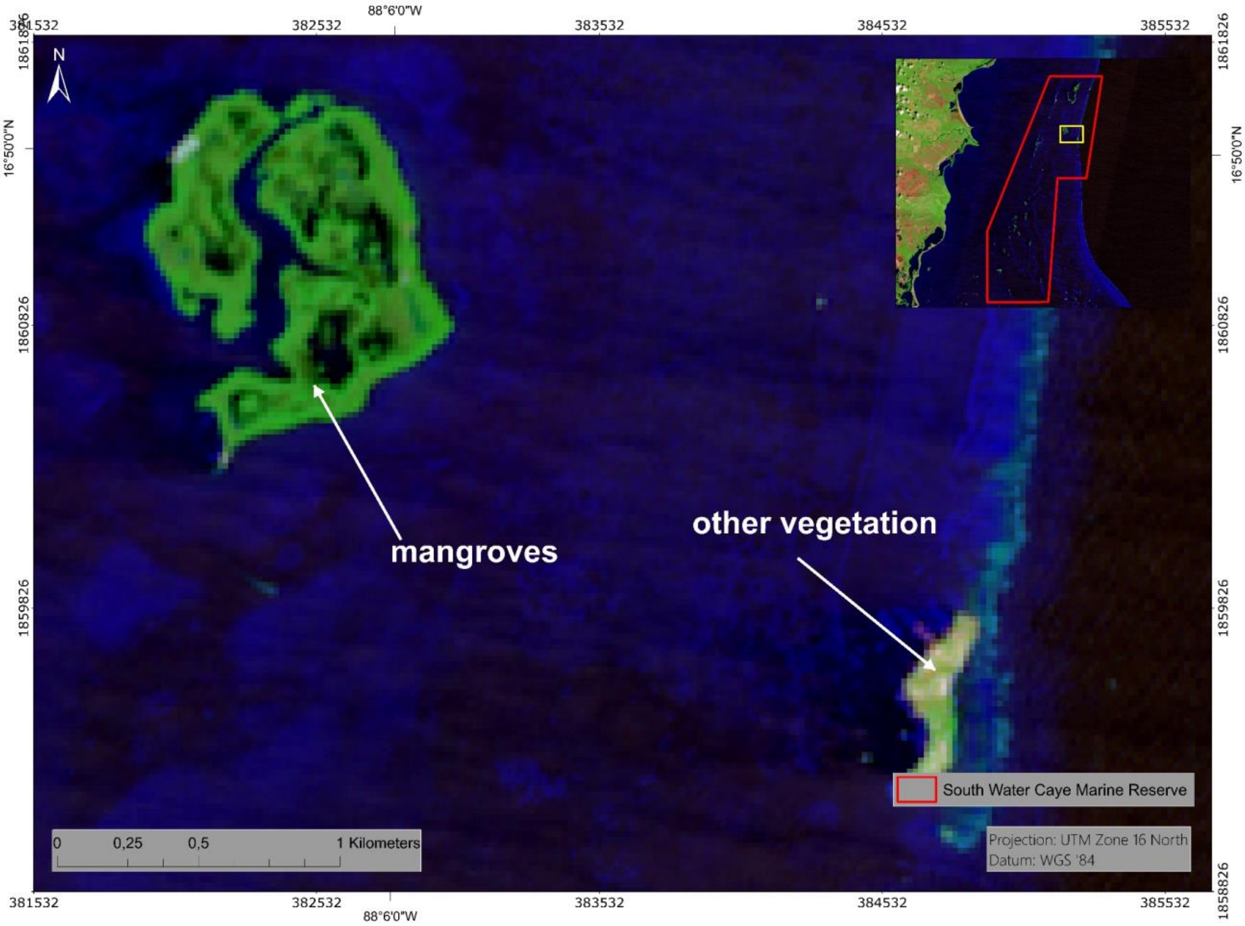


Figure 6: Subset of a Sentinel-2 imagery (2019-03-12; bands: short wavelength infrared (band 11), near infrared (band 8), and red (band 4) showing that mangroves can be differentiated from other vegetation types. The yellow rectangle in the upper right image shows the location of the subset within the South Water Caye Marine Reserve.

The Sentinel-2 archive was checked and the most appropriate imagery (2019-03-13) downloaded. Figure 7 shows the acquired Sentinel-2 data for the South Water Caye test site.

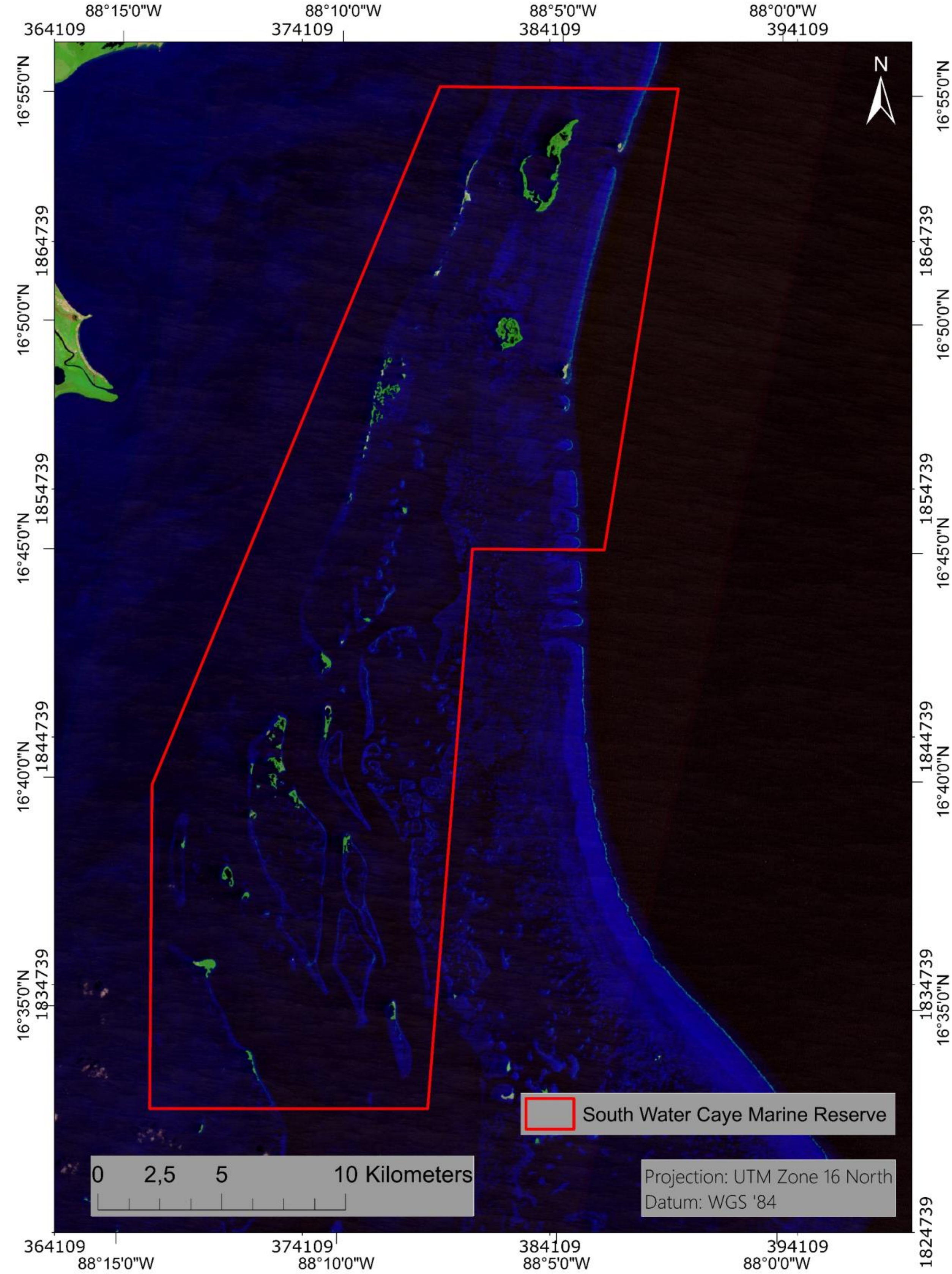


Figure 7: Sentinel-2 imagery (2019-03-13; bands: short wavelength infrared (band 11), near infrared (band 8), and red (band 4)) used for the mangrove and seagrass mapping.

4.2 Data Preprocessing

An essential preprocessing step was the removal of atmospheric effects that influence the signal, induced by water vapor and aerosols in the atmosphere as well as varying sun illumination angles in different seasons. This preprocessing step results in the calibration of the data and allows an estimation of the surface reflectance without atmospheric distortion effects. The calibration method facilitates an improved scene-to-scene radiometric measurements comparability, which is a necessary precondition for the subsequent semi-automatic object-based rule-set classification method.

Atmospheric correction of Sentinel-2 data

Sentinel-2 data was corrected with Sen2Cor, a processor published by ESA (https://step.esa.int/main/third-party-plugins-2/sen2cor/). Sen2Cor is a processor for Sentinel-2 Level 2A product generation and formatting; it performs the atmospheric-, terrain and cirrus correction of Top-Of- Atmosphere Level 1C input data. Sen2Cor creates Bottom-Of-Atmosphere, optionally terrain- and cirrus corrected reflectance images; additional, Aerosol Optical Thickness-, Water Vapor-, Scene Classification Maps and Quality Indicators for cloud and snow probabilities. Its output product format is equivalent to the Level 1C User Product: JPEG 2000 images, three different resolutions, 60, 20 and 10 m.

Atmospheric correction of Landsat 8

Landsat 8 data were corrected using ARCSI (https://www.arcsi.remotesensing.info/, July 2019). ARCSI is a software that provides a command line tool for the generation of Analysis Ready Data optical data including atmospheric correction, cloud masking, topographic correction etc. of Earth Observation optical imagery (Blue-SWIR).

Landsat 8 product specifications state that the OLI has a geolocation uncertainty of less than 12 m circular error. Visual analysis showed that the Sentinel-2 and Landsat 8 data had an excellent geometrical fit with the RapidEye data so no geometrical co-registration was necessary.

Atmospheric correction of RapidEye

RapidEye imagery was corrected with ATCOR-2 (Richter and Schläpfer 2011; http://www.rese.ch/products/atcor/atcor3/atcor2_method.html). The following parameters were used in ATCOR-2:

- Atm. Correction: pre-defined sensors, flat terrain
- Acquisition date of the satellite data
- Selection of sensor (RapidEye) and corresponding calibration file
- Atmospheric file: tropical maritime
- Satellite and sun geometry from the metadata of the satellite data
- Ground elevation: 0 km

4.3 Mangrove and Seagrass Maps

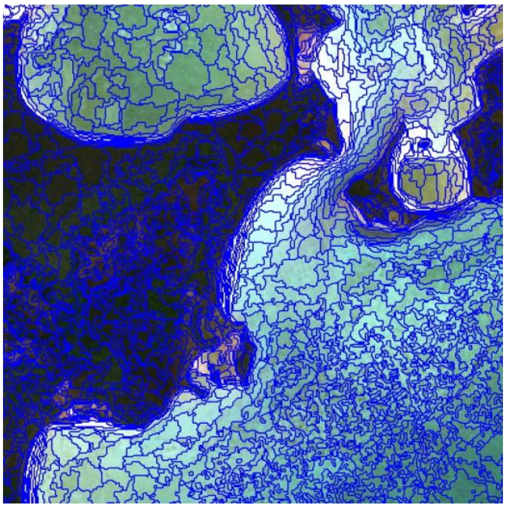
The basic classification method was an object-based image analysis approach using eCognition software (Trimble Geospatial, Munich, Germany). This methodology classifies spatially adjacent and spectrally similar groups of pixels, so called image objects, rather than individual pixels of the image. Traditional pixel-based classification uses multi-spectral classification techniques that assign a pixel to a class by considering the spectral similarities with the class or with other classes. The resulting thematic classifications are often incomplete and non-homogeneous. The received signal frequency does not clearly indicate the membership to a land cover class, e.g. due to atmospheric scattering, mixed pixels, or the heterogeneity of natural land cover. Improvements in the spatial resolution of remote sensing systems employed results in increased complexity of the data. The representation of real-world objects in the feature space is characterized by high variance of pixel values, hence statistical classification routines based on the spectral dimensions are limited and a greater emphasis must be placed on exploiting spatial and contextual attributes (Guindon 1997, Guindon 2000, Matsuyama 1987). To enhance classification, the use of spatial information inherent in such data was proposed and studied by many researchers (Atkinson and Lewis 2000). A lot of approaches make use of the spatial dependence of adjacent pixels. Approved routines are the inclusion of texture information, the analysis of the (semi-)variogram, or region growing algorithms that evaluate the spectral resemblance of proximate pixels (Hay et al. 1996, Kartikeyan et al. 1998, Woodcock et al. 1988). In this context, the use of object-oriented classification methods on remote sensing data has gained immense popularity, and the idea behind it was subject to numerous investigations since the 1970’s (Haralick and Joo 1986, Kartikeyan et al. 1995, Kettig and Landgrebe 1976)

In the object-oriented approach in a first step a segmentation of the imagery generates image objects, combining neighboring pixel clusters to an image object. Here the spectral reflectance, as well as texture information and shape indicators are analyzed for generating the objects. The attributes of the image objects like spectral reflectance, texture or NDVI are stored in a so-called object database (Benz 2004, Mott 2005). Classification itself corresponds in fact to a complex database query by formulating rule bases on how the object attributes should be evaluated. Additionally, expert knowledge can be implemented in the classification process.

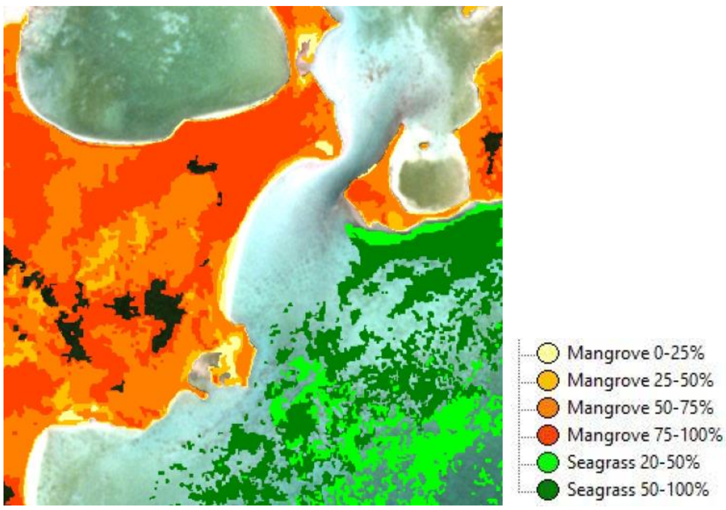
This approach consists of three basic procedures (depicted in Figure 8):

- **Design of a class hierarchy:** Definition of classes and inheritance rules between parent and child classes
- **Image segmentation:** The input image raster dataset is segmented into homogeneous image objects according to their spectral and textural characteristics
- **Classification:** The image objects are assigned to the predefined classes according to decision rules which can be based on spectral, spatial, geometric, thematic or topologic criteria

(a) RapidEye satellite image



(b) Image segmentation



(c) Classification based on image object attributes

Figure 8: Example of the basic procedures of an object object-based image analysis. The input satellite imagery (a) is first segmented into homogeneous image objects (b) and then assigned to predefined classes using decision rules (c).

A total of seven ecological classes were defined for this project:

4 mangrove density classes:

1. 0-25%
2. 25-50%
3. 50-75%
4. 75-100%

3 aquatic classes:

1. Water, including 0-20% seagrass coverage
2. 20-50% seagrass coverage
3. 50-100% seagrass coverage

In keeping with the results from the 2015 baseline of South Water Caye Marine Reserve, the originally proposed classification scheme stratifying 25% levels of coverage was not possible to implement while keeping with reliable scientific standards. Due to turbidity of the ocean, especially in shallow waters, very low seagrass coverages may not be reliably detected. Turbidity, caused by high concentrations of suspended matter in shallow waters, makes a reliable detection of isolated seagrass patches difficult. Total suspended matter can include a wide variety of material, such as slit, decaying plant and animal matter, industrial waste as well as sewage (Figure 9).

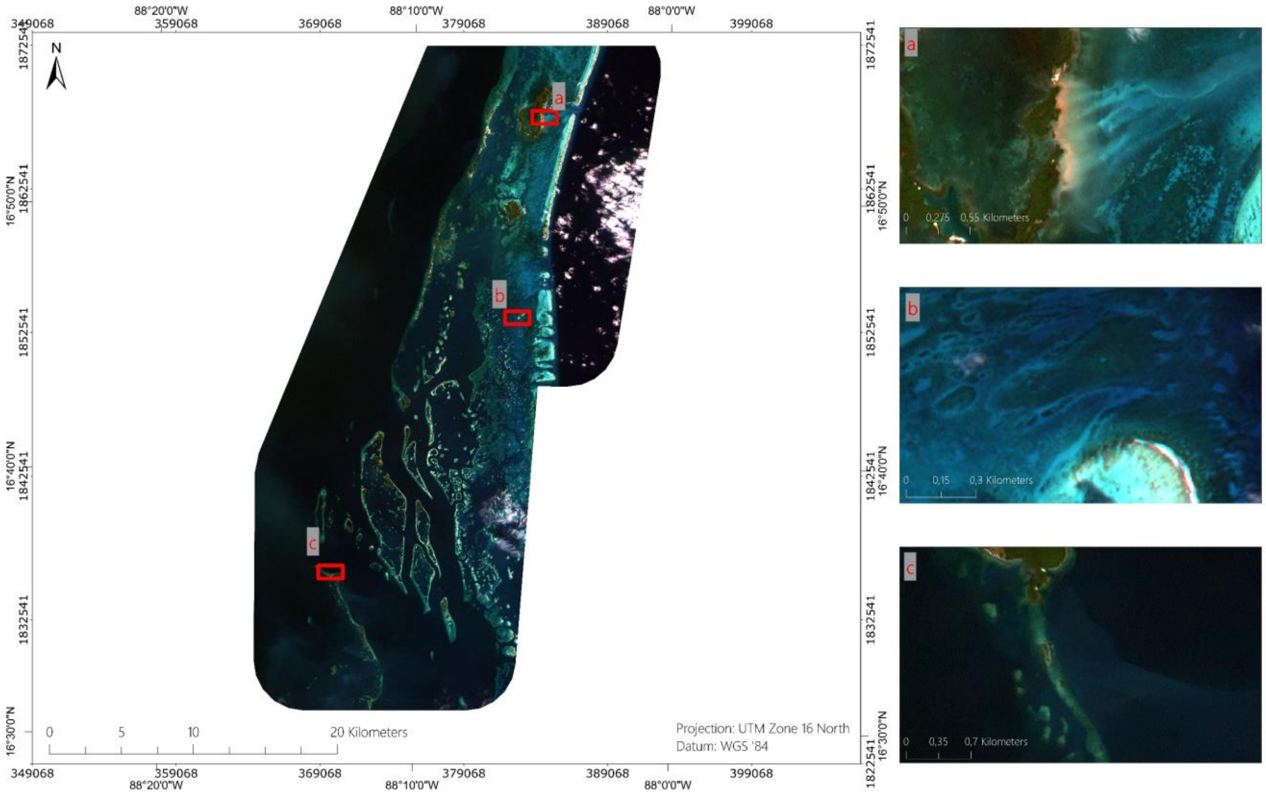


Figure 9: Examples for strong turbid sea within the project area. Here it was not possible to detect 4 density classes for seagrass. True-color RapidEye imagery (2018-01-08).

The classification scheme concerning aquatic habitats was adjusted to the same three classes used in the 2015 baseline study: Water including 0-20% seagrass coverage, 20-50% and 50-100% seagrass coverage.

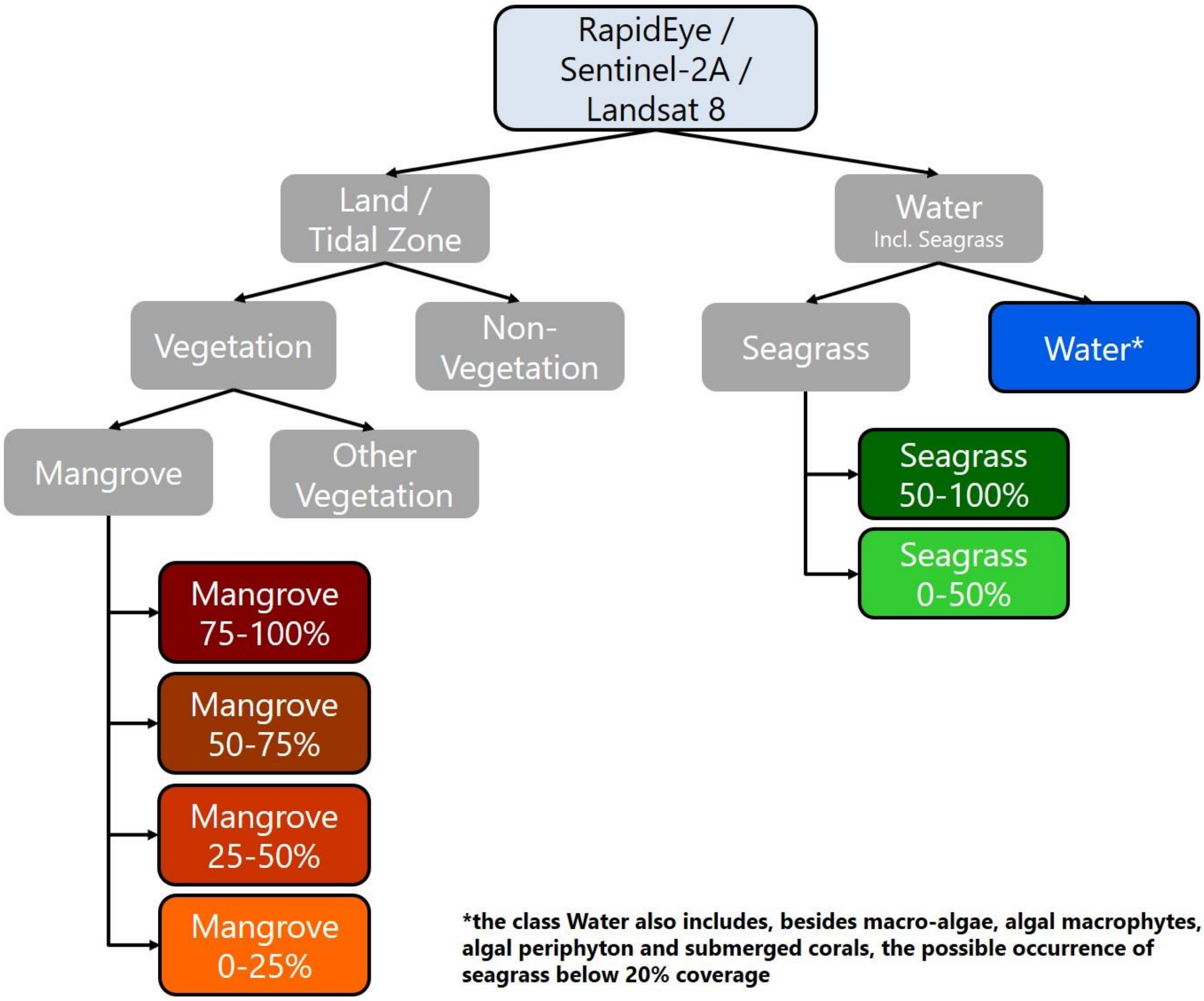


Figure 10: Classification scheme of the mangrove and seagrass cover classification of the South Water Caye Marine Reserve. Grey boxes without frame represent parent classes, framed boxes represent the final classes with the associated color from the land cover maps (Figures 10-11 and 14-15). It is important to notice that the class Water also includes, besides macro-algae, algal macrophytes, algal periphyton and submerged coral, the possible occurrence of seagrass below 20% coverage.

The RapidEye image mosaic was segmented into objects of adjacent, spectrally similar pixels by the multi-resolution segmentation algorithm implemented in eCognition, and subsequently classified according to the classification scheme shown in Figure 10. The classification rule-set works in a hierarchical manner from coarse to fine thematic details. On the first hierarchy level, discrimination between Land / Tidal Zone areas and Water areas (incl. seagrass) was conducted based on spectral thresholds. On the next level of the hierarchy, all Land / Tidal Zone objects were discriminated into Vegetation and Non-Vegetation objects according to their spectral properties. Water was discriminated into Seagrass and Water. On the third hierarchy level the vegetated objects were distinguished into Mangrove and Other Vegetation according to their spectral properties.

The analyses showed that the spatial and spectral resolution of the RapidEye satellite data does not allow for seagrass to be detected unambiguously below 20% coverage. As a result, the class water includes macroalgae, algal macrophytes, algal periphyton and submerged corals, as well as the possible occurrence of seagrass below 20% coverage. Mangroves were further distinguished into 4 density classes (75-100%, 50-75%, 25-50%, and 20-25%) and seagrass into two density classes (50-

100% and 20-50%) based on spectral and texture properties, as well as visual interpretation of the imagery. After the object-oriented classification, an intensive visual revision by a trained expert was conducted. The results are georeferenced shp-files ready to be used in a geographic information system, like ArcGIS. XML-Metadata was generated for all deliverables. Annex I gives an overview of the segmentation parameters and spectral bands used in the baseline classification. Further the statistical parameters of the feature objects for the different classes are shown.

4.4 Change Detection

In order to assess the changes in South Water Caye of the recent years we compare the up-to-date mangrove and seagrass maps from 2018 with the ones derived for the year 2015 baseline (Ballhorn et al. 2016); a post-classification change detection was conducted. In ArcGIS, the resulting mangrove and seagrass maps of the two classifications (2015 and 2018) were intersected in order to derive areas of change.
Figure 11 schematically displays the workflow of this post-classification change detection process. Our approach is a quantitative and qualitative comparison of two classifications (baseline, 2015 and final measurement, 2018).

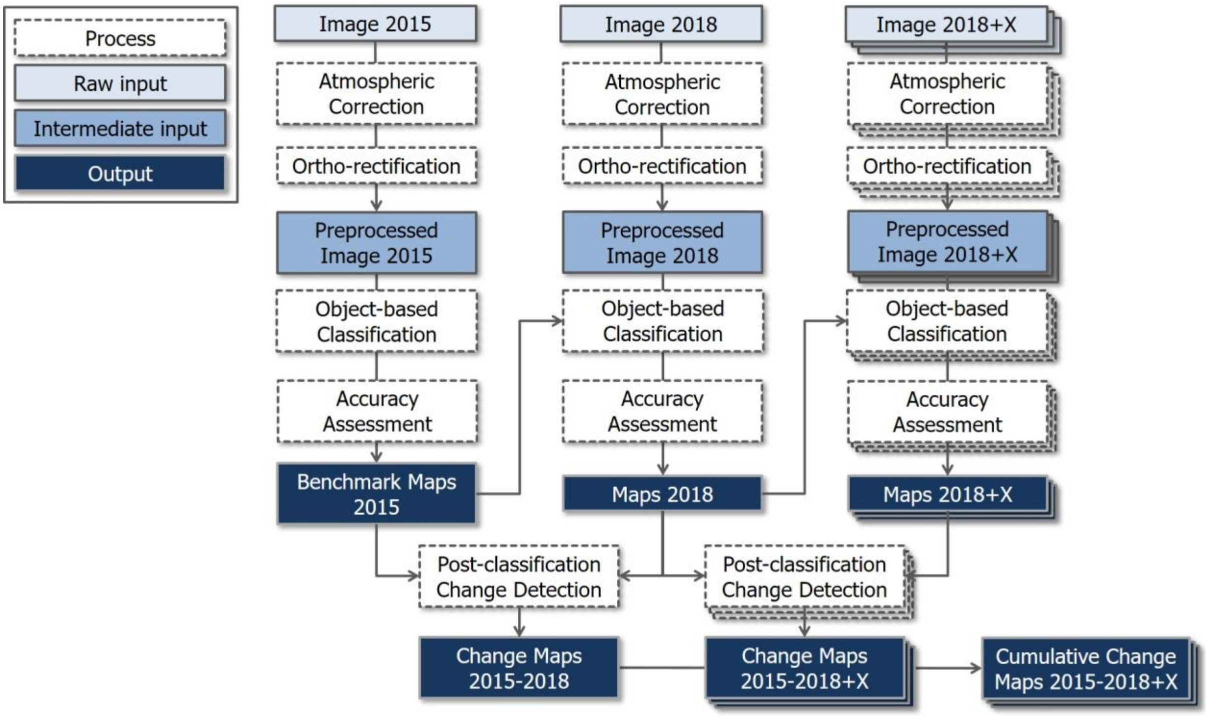


Figure 11: Schematic representation of the post-classification change detection process in order to analyze changes in mangrove and seagrass cover between the two classifications. Here, 2015 indicates the baseline, and 2018 denotes the final measurement.

Monitoring techniques based on multispectral satellite-acquired data have demonstrated potential as a means to detect, identify, and map changes in forest cover (Coppin 2004) and seagrass (Misvari and Hashim 2016).

5 Results

Figure 14 and Figure 15 show the results for the final measurement of mangrove and seagrass cover classification. The overview maps are provided as high-resolution pdfs that may be printed in A0 and displayed at an enlarged scale on a desktop computer. Such maps were provided for the baseline and are presented in this report for comparison purposes (see report Ballhorn et al. 2016). The highest image resolution of the data we analyze in this study is the RapidEye imagery. The spatial resolution of RapidEye imagery is 6.5 m, resampled to 5 m (resampled by the data provider). Being the dataset with the highest resolution, it defines the MMU (minimum mapping unit). It is the specific size of the smallest feature that is being reliably mapped in a study. The MMU can be defined by 3x3 pixels, which means would mean (6.5mx3) x (6.5mx3) = 380,25m². This only allows to generate an accuracy in this scale, meaning that any results in hectares may only be given with an accuracy of the first decimal after the dot (corresponding 1.000m²).

Baseline Classification 2015

Table 5 gives an overview of the remote sensing data used for the mangrove and seagrass classification during the baseline measurement in year 2015. Images with different acquisition dates within the year 2015 were used to get a preferably cloud free coverage of the study area.

Table 5: Overview of remote sensing data used for the mangrove and seagrass classification during the baseline measurement in 2015.

Rapid Eye		
Amount tiles	**Acquisition date**	**Cloud cover within study area (%)**
6 (level 3A)	2015-11-01	0
Landsat 8		
Amount images	**Acquisition date**	**Cloud cover within study area (%)**
1	2015-11-01	0

Figure 12 and Figure 13 show the results from the mangrove and seagrass cover classification for the baseline completed in 2015.

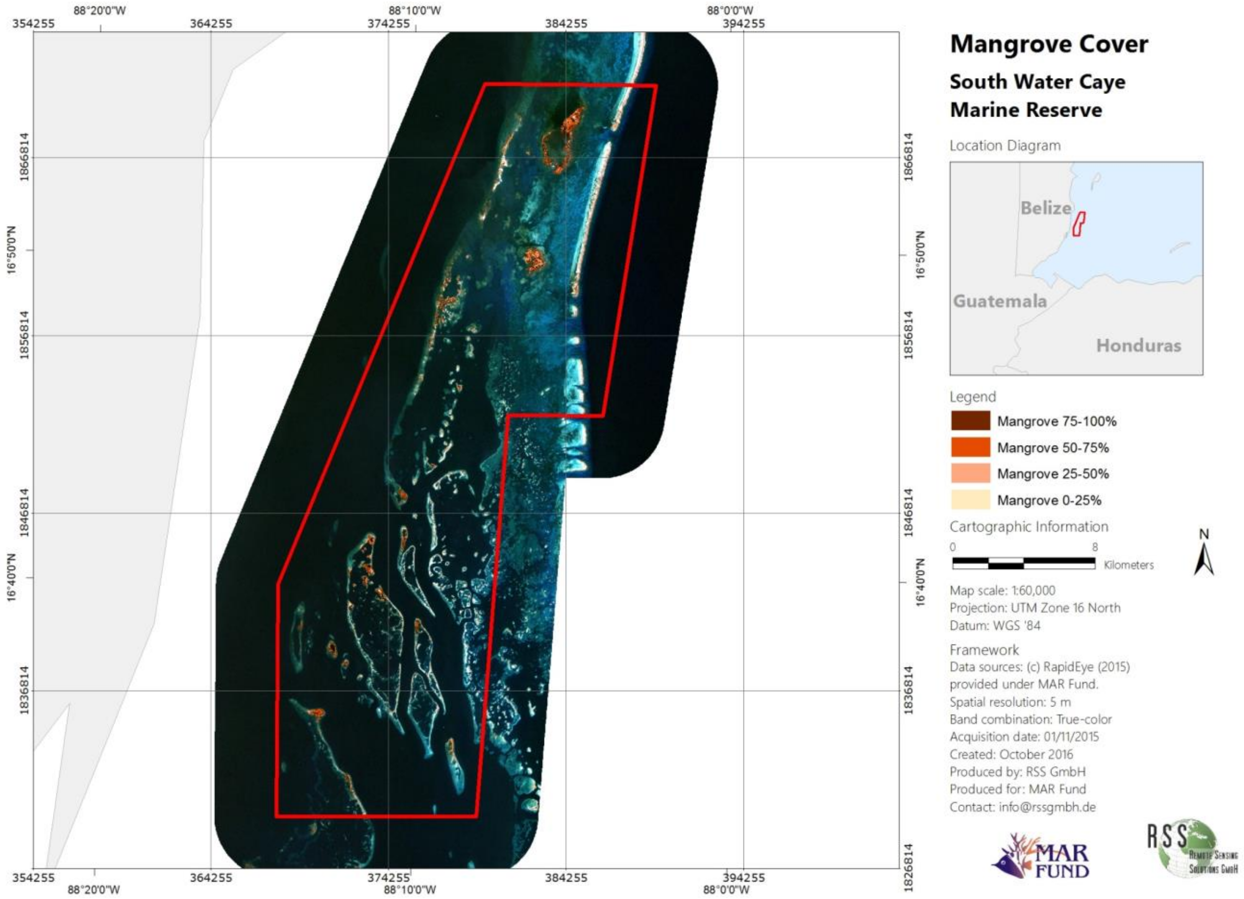


Figure 12: Mangrove cover classification for the South Water Caye Marine Reserve from 2015. The four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%) are shown over RapidEye imagery from 2015. In the upper right diagram, the location of the South Water Caye Marine Reserve within Belize is displayed (red).

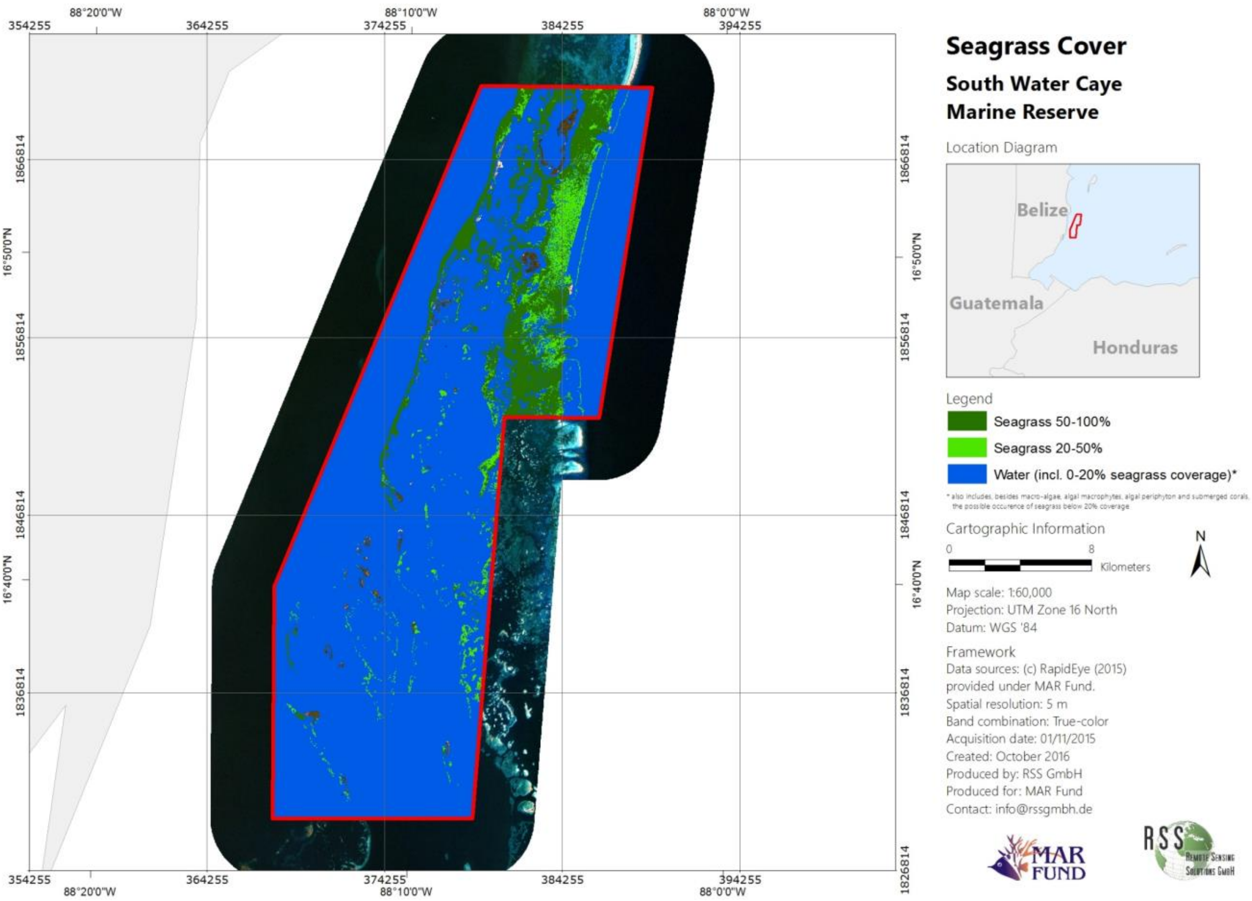


Figure 13: Seagrass cover classification for the South Water Caye Marine Reserve from 2015. The three aquatic classes (Water incl. 0-20% seagrass coverage, 20-50%, and 50-100% seagrass coverage) are shown over RapidEye imagery from 2015. In the upper right diagram, the location of the South Water Caye Marine Reserve within Belize is displayed (red).

Table 6 displays the spatial extent of the mangrove and seagrass classes completed for the baseline in 2015 (see Ballhorn et al. 2016).

Table 6: Spatial extent of the different ecological classes classified for the baseline in 2015 in the South Water Caye Marine Reserve. The percentage of the total mangrove/seagrass cover and the percentage of the total South Water Caye Marine Reserve area are also shown per class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total study area (47,703 ha) (%)
Mangrove 75-100%	154.8	37.0	0.3
Mangrove 50-75%	158.1	37.8	0.3
Mangrove 25-50%	73.0	17.5	0.2
Mangrove 0-25%	32.0	7.7	0.1
Sum Mangrove	**417.9**	**100.0**	**0.9**
Seagrass 50-100%	4,847.6	71.9	10.2
Seagrass 20-50%	1,891.7	28.1	4.0
Sum Seagrass	**6,739.2**	**100.0**	**14.1**

Final Classification 2018

Table 7 gives an overview of the remote sensing data used for the mangrove and seagrass classification during the final measurement in year 2018. Images with different acquisition dates within the year were used to get a preferably cloud free coverage of the study area.

Table 7: Overview of remote sensing data used for the final measurement (2018) for mangrove and seagrass classification.

Rapid Eye		
Amount tiles	**Acquisition date**	**Cloud cover within study area (%)**
4 (level 3A)	2018-01-08	5
Sentinel-2		
Amount images	**Acquisition date**	**Cloud cover within study area (%)**
1	2019-03-13	0
Landsat 8		
Amount images	**Acquisition date**	**Cloud cover within study area (%)**
1	2019-01-28	0

Figure 14 and Figure 15 show the results for the final measurement (2018) for mangrove and seagrass cover classification.

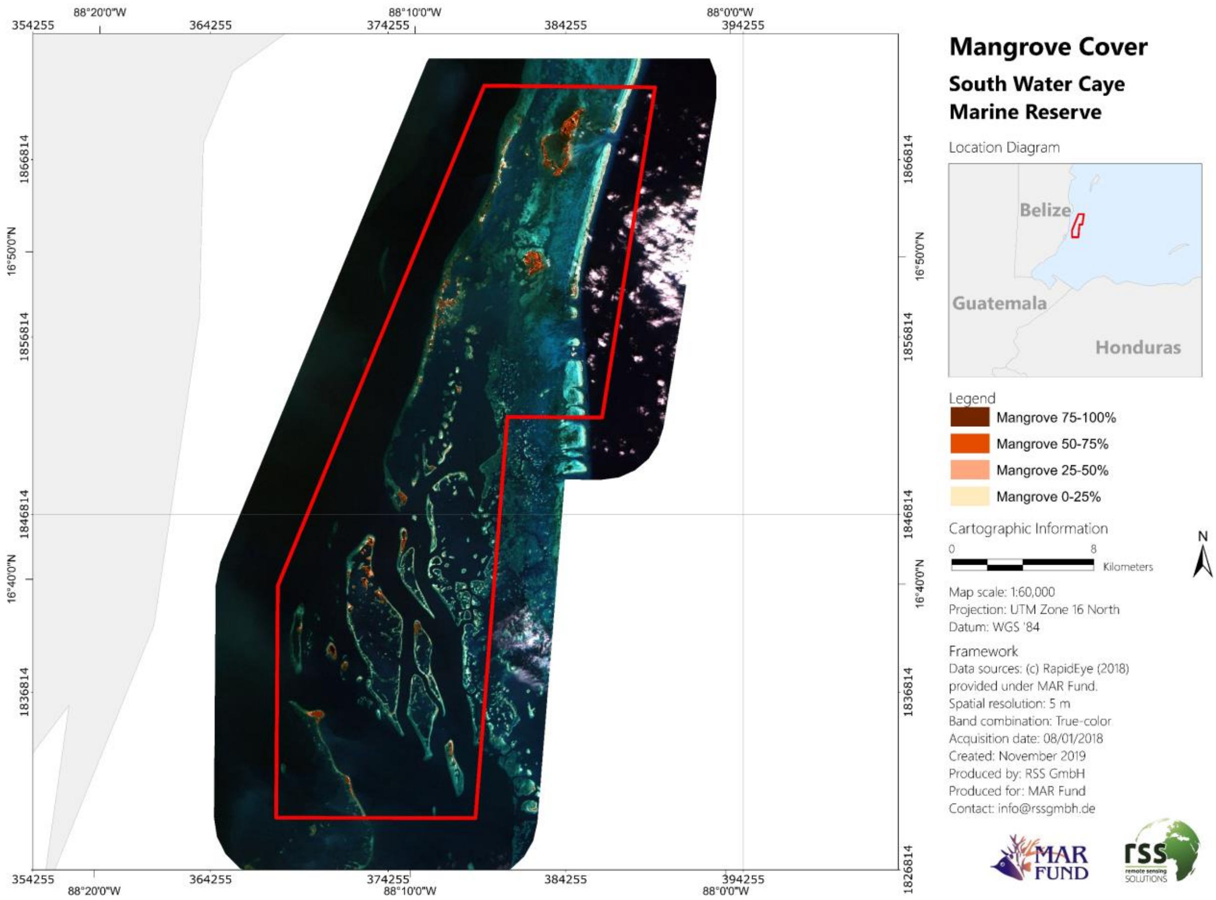


Figure 14: Mangrove cover classification for the South Water Caye Marine Reserve from 2018. The four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%) are shown over RapidEye imagery from 2018. In the upper right diagram, the location of the South Water Caye Marine Reserve within Belize is displayed (red).

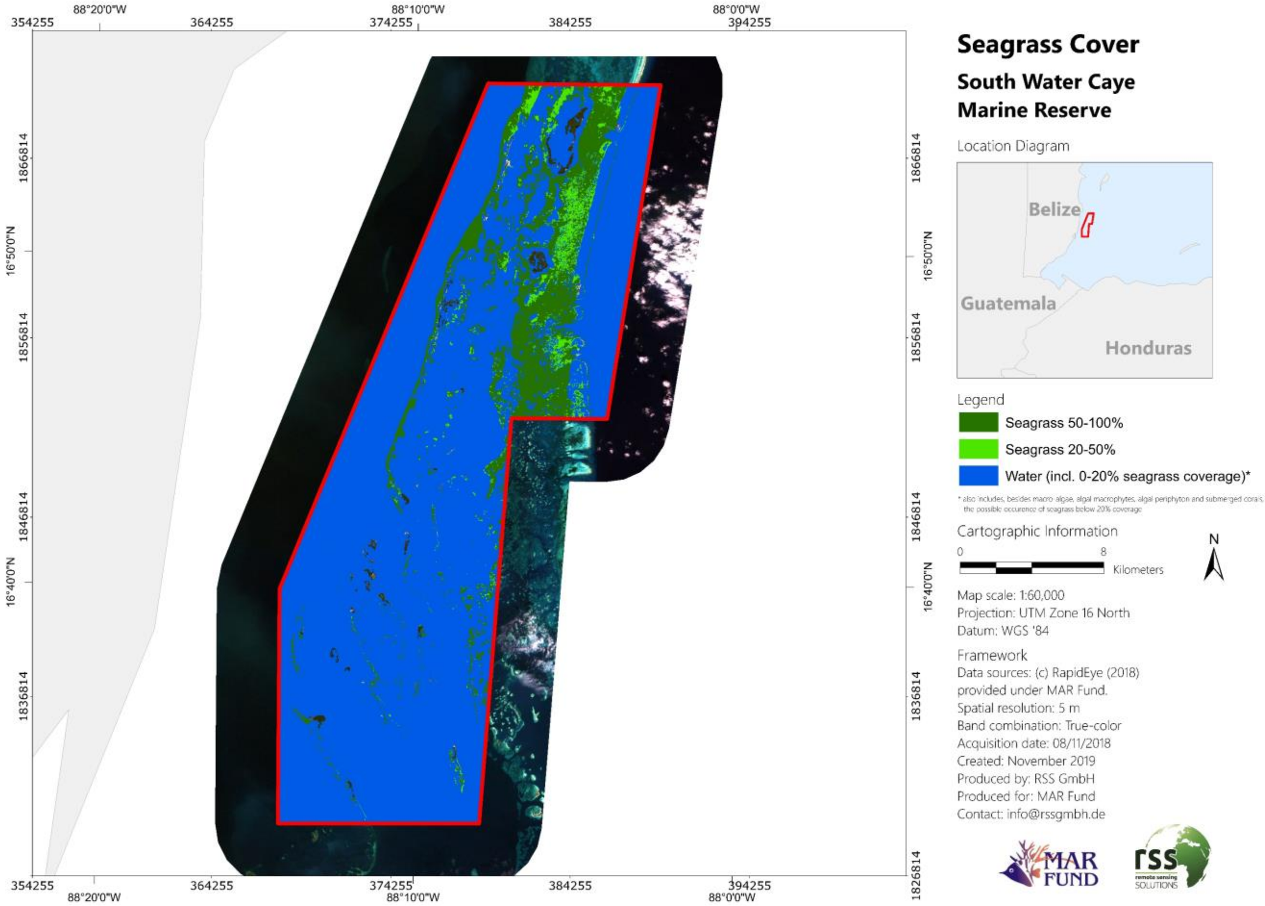


Figure 15: Seagrass cover classification for the South Water Caye Marine Reserve from 2018. The three aquatic classes (Water incl. 0-20% seagrass coverage, 20-50%, and 50-100% seagrass coverage) are shown over RapidEye imagery from 2018. In the upper right diagram, the location of the South Water Caye Marine Reserve within Belize is displayed (red).

Table 8 displays the spatial extent of the mangrove and seagrass classes for the final measurement in 2018.

Table 8: Spatial extent of the different ecological classes classified for the final measurement in 2018 in the South Water Caye Marine Reserve. Also shown are the percentage of the total mangrove/seagrass cover and the percentage of the total South Water Caye Marine Reserve area for each class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total study area (47,703 ha) (%)
Mangrove 75-100%	255.2	52.6	0.5
Mangrove 50-75%	105.4	21.7	0.2
Mangrove 25-50%	65.1	13.4	0.1
Mangrove 0-25%	59.3	12.2	0.1
Sum Mangrove	**485.0**	**100.0**	**1.0**
Seagrass 50-100%	5,742.5	82.4	12.0
Seagrass 20-50%	1,227.3	17.6	2.6
Sum Seagrass	**6,969.9**	**100.0**	**14.6**

The graphs in Figure 16 and Figure 17 display the spatial extent of the ecological classes classified within South Water Caye Marine Reserve for the final measurement in 2018. The chart colors correspond to the class colors in the final maps (Figures 12 &14 and 13 & 15).

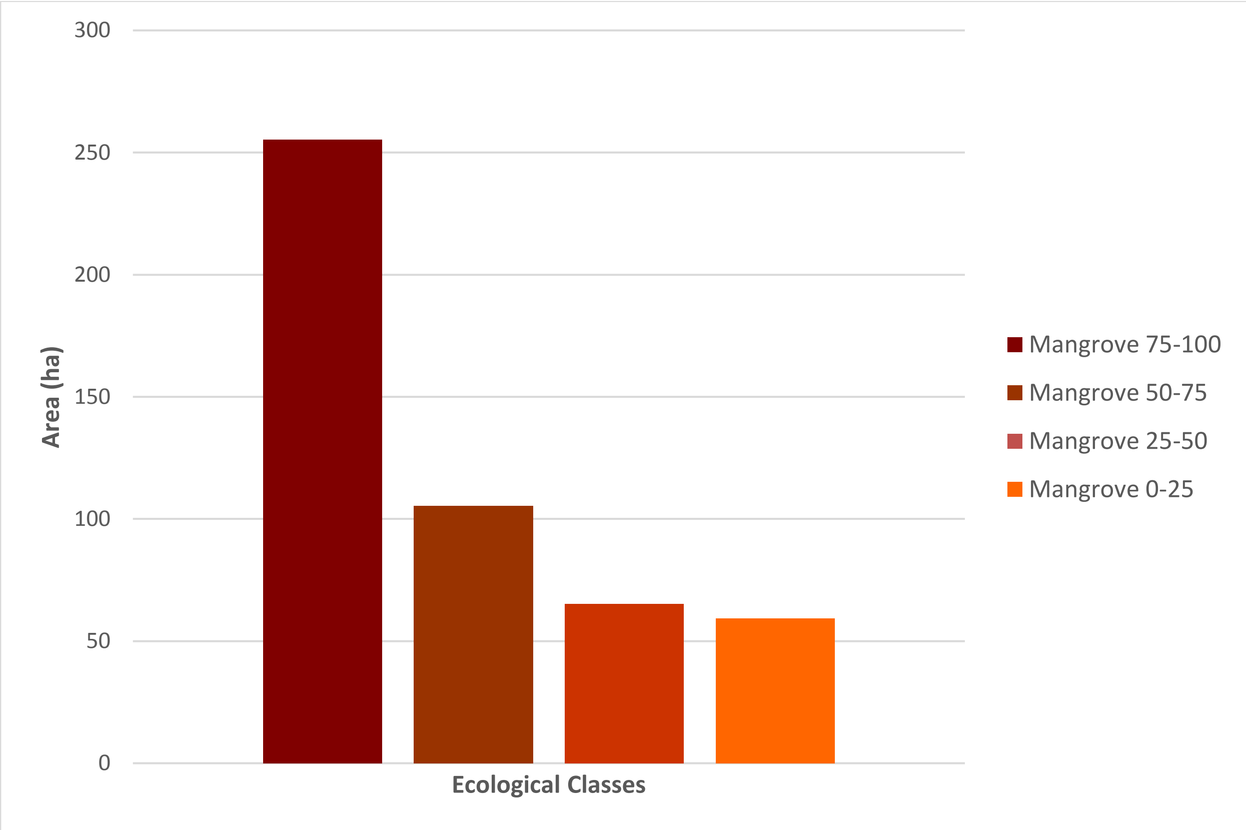


Figure 16: Spatial extent of the different mangrove density classes within the South Water Caye Marine Reserve from the final measurement in 2018. Colors correspond to those used in Figures 12 & 14.

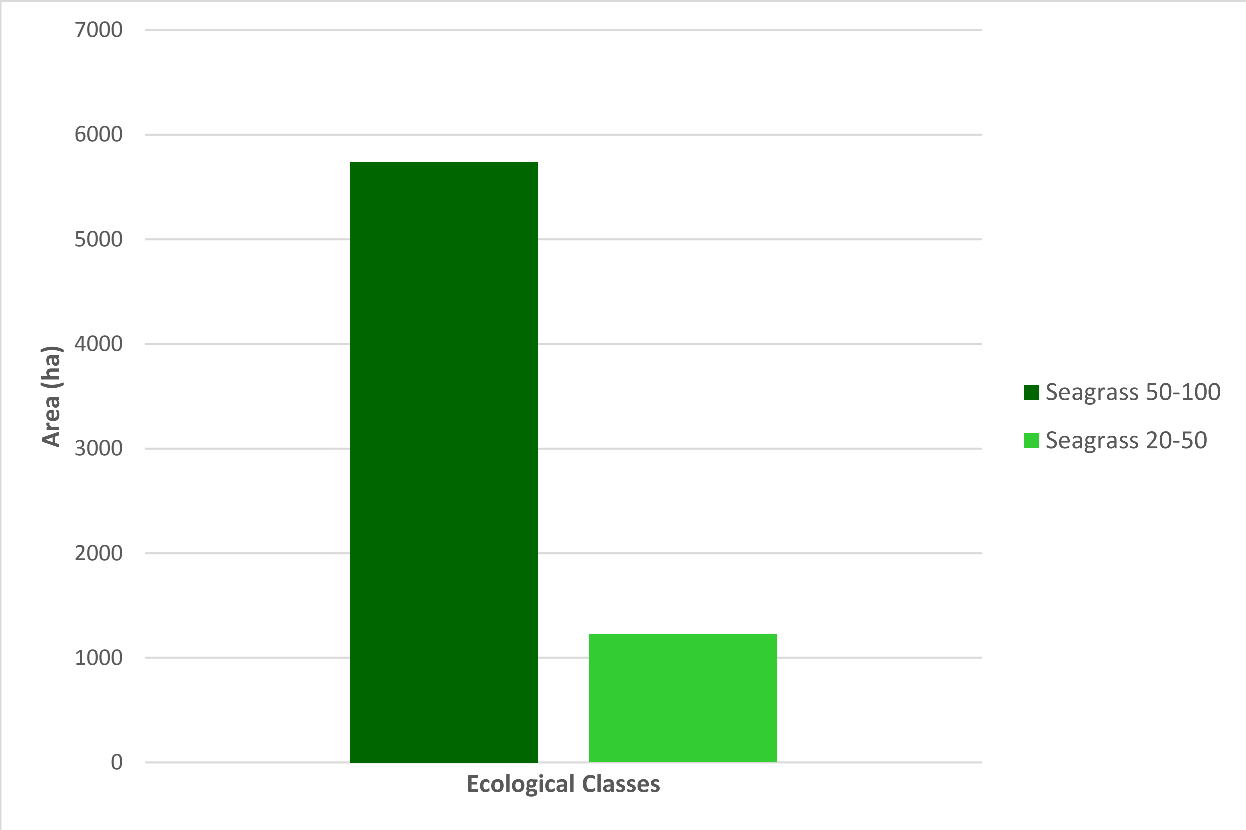


Figure 17: Spatial extent of the different seagrass density classes within the South Water Caye Marine Reserve from the final measurement in 2018. Colors correspond to those used in Figures 13 & 15.

Change analysis

Total mangrove cover and total seagrass cover were recorded to measure the changes between the baseline done in 2015 and the measurement done in 2018

Table 9: Combined overview of respective class areas between the baseline and measurement, as taken from Table 6 and Table 8.

Ecological Class	Area (ha)		Percentage of total mangrove/seagrass cover (%)		Percentage of total study area (%)	
	2015	2018	2015	2018	2015	2018
Mangrove 75-100%	154.8	255.2	37.0	52.6	0.3	0.5
Mangrove 50-75%	158.1	105.4	37.8	21.7	0.3	0.2
Mangrove 25-50%	73.0	65.1	17.5	13.4	0.2	0.1
Mangrove 0-25%	32.0	59.3	7.7	12.2	0.1	0.1
Sum Mangrove	**417.9**	**485.0**	**100.0**	**100.0**	**0.9**	**1.0**
Seagrass 50-100%	4,847.6	5,742.5	71.9	82.4	10.2	12.0
Seagrass 20-50%	1,891.7	1,227.3	28.1	17.6	4.0	2.6
Sum Seagrass	**6,739.2**	**6,969.9**	**100.0**	**100.0**	**14.2**	**14.6**

Table 10: Total change between the baseline (2015) and final measurement (2018), provided in hectares, the percent change within all mangrove or seagrass classes, and percent change within the total study area. Please note that these are rounded values.

Ecological Class	Change in area (ha)	Change within total mangrove/seagrass cover (%)	Change in total study area (%)
Mangrove 75-100%	100.4	20.7	0.2
Mangrove 50-75%	-52.7	-10.9	-0.1
Mangrove 25-50%	-7.9	-1.6	0.0
Mangrove 0-25%	27.3	5.6	0.1
Sum Mangrove	**67.1**	**13.8**	**0.1**
Seagrass 50-100%	894.9	12.8	1.9
Seagrass 20-50%	-664.4	-9.5	-1.4
Sum Seagrass	**230.5**	**-3.3**	**0.5**

Table 10 shows the absolute numbers of area change assessed in the measurement of 2018 compared to 2015. The first column of Table 10 shows the changes in area Both Mangroves and Seagrass areas increase tremendously. Total Mangrove increase amounts approx. 70 ha whereas the increase in seagrass amounts approx. 230 ha. It should be noted that in both mangrove and seagrass the 'best' coverage class (75%-100%) have a large increase compared to 2015. However, seagrass meadows show ecological fluctuations and constantly vary in coverage.

A more detailed assessment of the overall class changes between these two measurements can be seen in the Change Matrix shown in Table 11.

The values of Table 11 were generated by intersecting the classifications of 2015 and 2018. The results of the intersection are displayed in a correspondence matrix, which is the de facto method for reporting land cover changes over two time periods. The table should be read horizontally (from left to right) for the land cover detected in 2015 and vertically (top to bottom) for the assessed land cover of the year 2018. The different colors of the cells represent whether no change, loss, degradation or regeneration occurred within the mangrove or seagrass classes. The legend at the bottom of the table displays, which color represents which change process. Congalton (1991) describes the background of accuracy assessment of remote sensing imagery and set standards in accuracy assessment methodology.

Table 11: Detailed change matrix of the different land covers between the baseline (2015) and the final measurement (2018), provided in hectares (ha).

		Classification 2018 (ha)								
		Land / Tidal Zone	**Mangrove 0-25**	**Mangrove 25-50**	**Mangrove 50-75**	**Mangrove 75-100**	**Seagrass 20-50**	**Seagrass 50-100**	**Water**	**Sum**
Classification 2015	**Land / Tidal Zone**	**16.7**	10.4	11.5	6.1	1.9	0.2	0.2	26.1	73.1
	Mangrove 0-25		**9.8**	**13.6**	**5.5**	**1.3**			**1.9**	32.1
	Mangrove 25-50		**6.2**	**16.6**	**37.4**	**12.8**			**0.0**	73.0
	Mangrove 50-75		**4.3**	**11.6**	**41.9**	**100.2**			**0.0**	158.0
	Mangrove 75-100		**0.8**	**3.4**	**12.0**	**138.6**				154.8
	Seagrass 20-50						**829.0**	**1062.5**	**0.2**	1,891.7
	Seagrass 50-100						**260.3**	**4587.0**	**0.2**	4,847.5
	Water	**7.8**	**27.7**	**8.5**	**2.4**	**0.5**	**137.8**	**92.8**	**40,194.8**	40,472.3
	Sum	24.6	59.2	65.2	105.3	255.3	1,227.3	5,742.5	40,223.2	47,702.6

	No Change
	Loss/Deforestation
	Degradation
	Gain/Reforestation
	Regeneration

Each density class is defined as:

- Deforestation (or loss) is the change of one of the density classes (either mangrove or seagrass) to a non density class (water or land/tidal zone).
- Degradation is the change of a density class (mangrove or seagrass) to a lower density class of the same land cover.
- Reforestation (or gain) is defined as the change from a non density class (water or land/tidal zone) to a density class of either mangrove or seagrass.
- Regeneration is the change of a lower density class (either mangrove or seagrass) to a higher density class.

Mangrove reforestation and regeneration is clearly demonstrated between the baseline and the final measurement, as well as overall seagrass gain and regeneration in the same time frame.

Table 12: Summarized changes between baseline (2015) and final measurement (2018) in hectares (ha).

Change Class	Area (ha)
Mangrove Deforestation	1.9
Mangrove Degradation	38.3
Mangrove Reforestation	69.0
Mangrove Regeneration	170.8
Seagrass Loss	0.4
Seagrass Degradation	260.3
Seagrass Gain	231.0
Seagrass Regeneration	1,062.5
Seagrass to Mangrove	0.00
Mangrove to Seagrass	0.00
Land / Tidal Zone to Water	26.1
Water to Land / Tidal Zone	7.8
No Change	45,834.9

As seen in Table 12, both mangrove reforestation and mangrove regeneration show that MAR Fund's activities led to positive developments between 2015 and 2018. Mangrove reforestation and Regeneration exeeds Mangrove Deforestation and Degradation in the sama time period. The change of statistics also indicate an overall increase in seagrass coverage during this time. It should be noted that seagrass meadows are often difficult to detect due to turbid waters and bad weather conditions. This, together with natural seasonal fluctuations in seagrass coverage, indicate that the statistics in Table 12 should be interpreted with caution. The present study corresponds an assessment at on point of time. The inter seasonal and interannual are not assessed. Sea grasses respond to natural light variations, salinity, acidity, human pressure, turbidity, marine pests and many more. The dynamic nature of seagrass meadows in response to natural environmental variation complicates the identification of changes caused by humans

Mangrove degradation is also fairly high (38.3 ha) but appears to be spatially scattered throughout the study area and thus is likely due to natural variations and/or detection error. The loss of seagrass (0,4 ha) is explainable with differeing image data quality and varying turbidity levels between 2015 and 2018, and has been observed for other MAR Fund study sites.

Figure 18 displays areas of land cover change between 2015 and 2018 within the South Water Caye Marine Reserve.

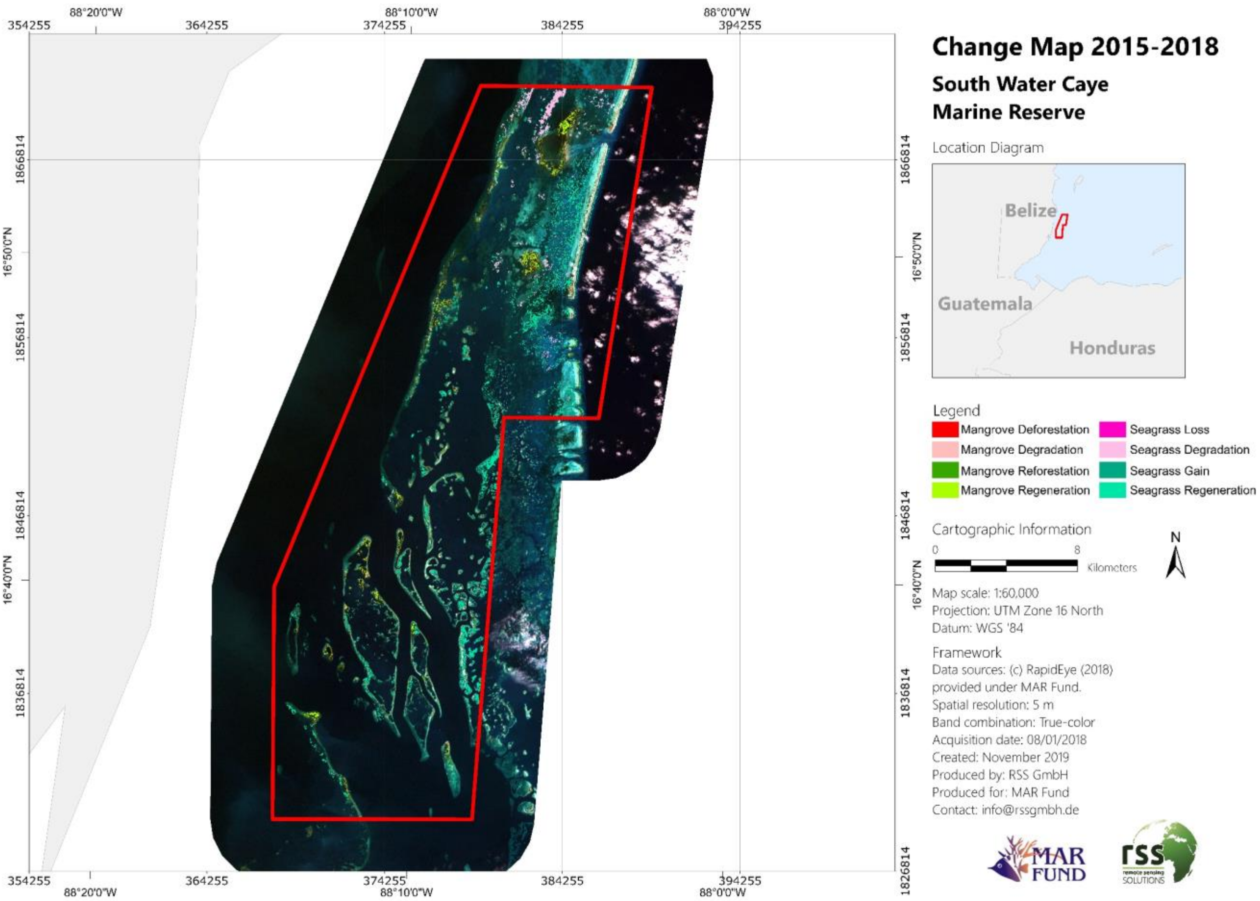


Figure 18: Land cover change map for the period between the years 2015 and 2018. In the upper right diagram, the location of the South Water Caye Marine Reserve within Belize is displayed (red).

Figure 19 displays areas of larger change within the South Water Caye Marine Reserve in more detail.

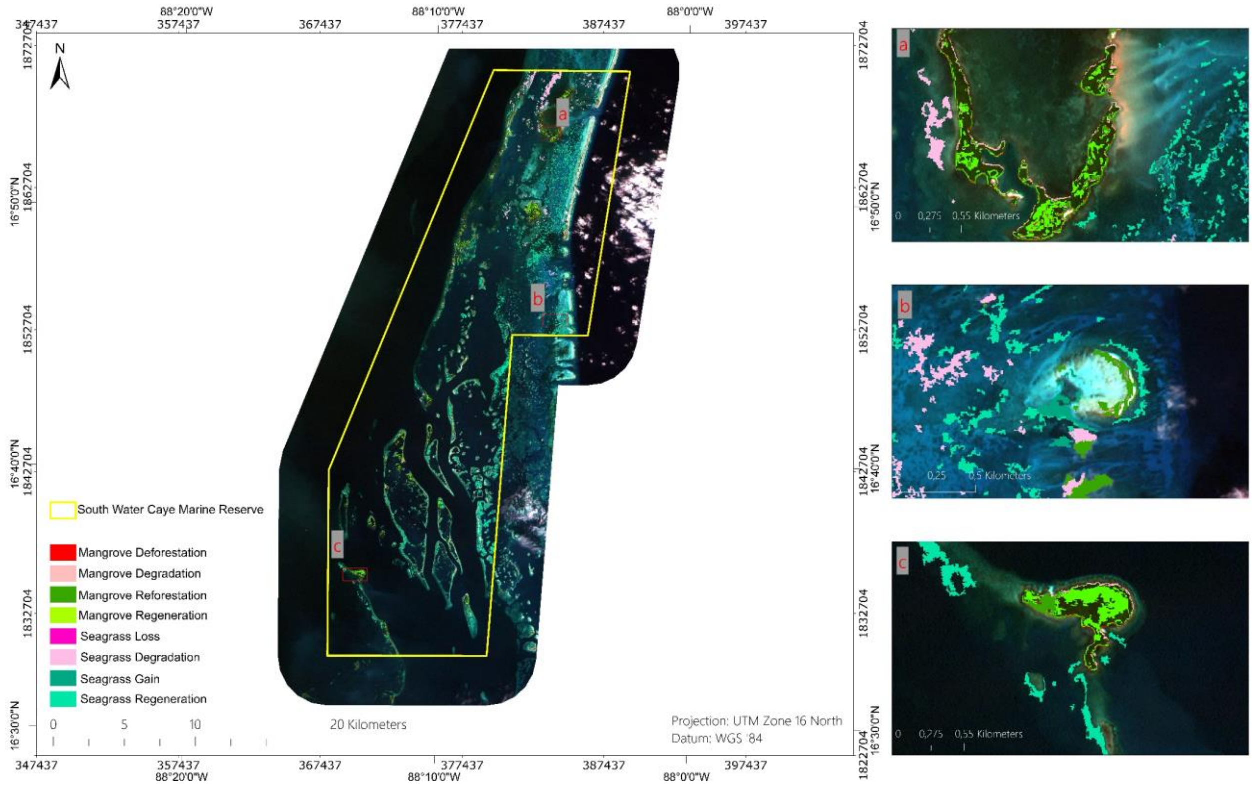


Figure 19: Examples for mangrove and seagrass changes detected between 2015 and 2018. The changes are superimposed on true-color RapidEye imagery (2018-01-08).

Areas of seagrass regeneration and degradation are depicted in Figure 19 a & b. “Seagrass Loss” and “Mangrove Deforestation” were both very seldom occuring classes in this study site (Table). “Seagrass Degradation” occured most often in the norhtern section of the reserve. Examples of mangrove reforestation and regeneration can been observed in Figure 19 a-c. Isolated patches of magrove deforestation and degradation are scattered across the cayes.

Figure and Figure 19 show the potential impact area of future land cover change identified in the 2015 baseline report within the South Water Caye Marine Reserve. The higher mangrove density classes have become more contiguous in the northern section of the area. There is little evidence of negative impacts to mangrove coverage for the identified potential impact area. Relatively little change was detected in the overall coverage of seagrass (Figure 19) but fluctuations between the two density classes (20-50% coverage and 50-100% coverage) are prevalent. One of the dominant seagrass species in the study area, *Thalassia testudinum*, is susceptible to annual die-off and may thus experience natural coverage fluctuations from year to year.

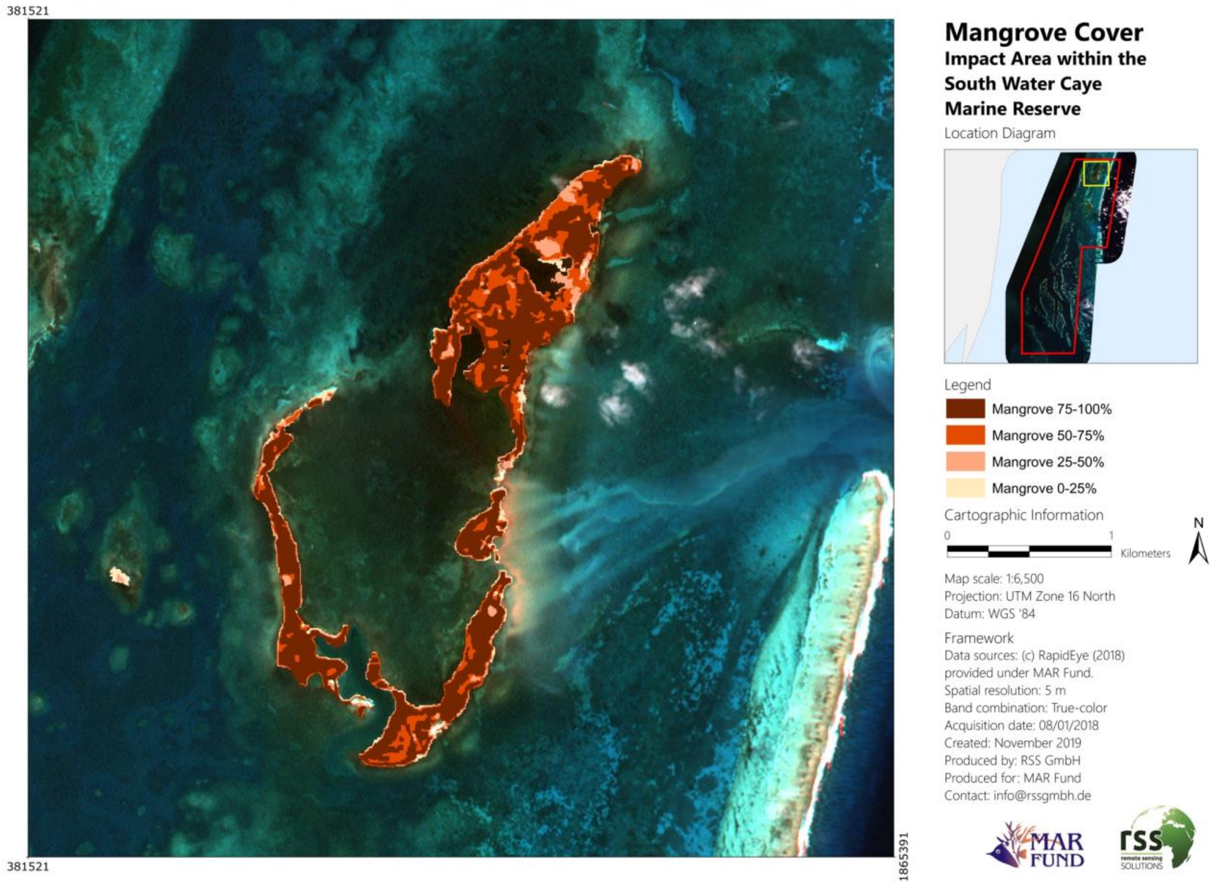


Figure 20: Earlier identified impact area of potential land cover change within the South Water Caye Marine Reserve. Displayed are the four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%). In the upper right diagram, the location of this impact area within the South Water Caye Marine Reserve is displayed (yellow rectangle).

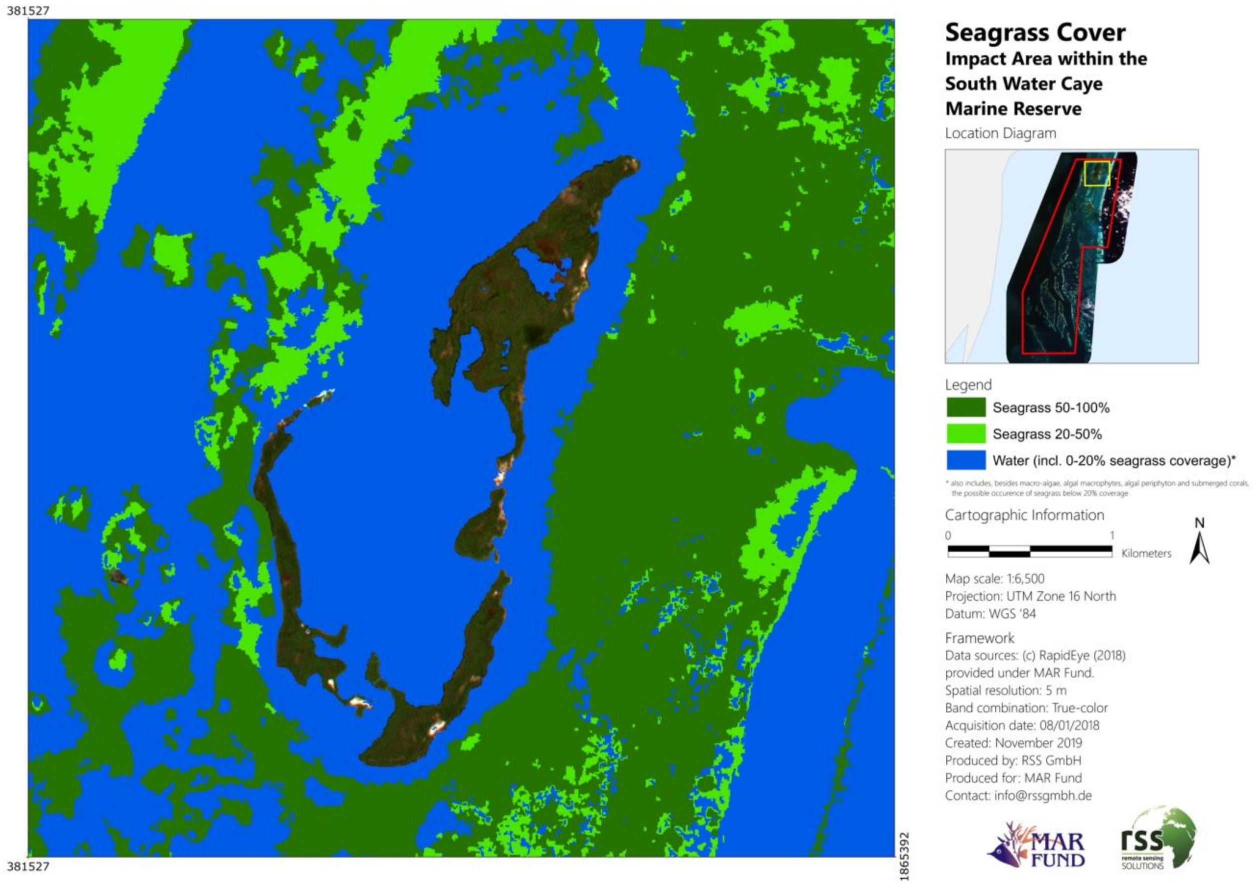


Figure 19: Earlier identified impact area of potential land cover change within the South Water Caye Marine Reserve. Displayed are the three aquatic classes (Water incl. 0-20% seagrass coverage, 20-50%, and 50-100% seagrass coverage). In the upper right diagram, the location of this impact area within the South Water Caye Marine Reserve is displayed (yellow rectangle).

6 Accuracy Assessment

An independent accuracy assessment and verification of the classification results with reference data is an essential component. The accuracy analysis provides a confusion matrix considering user and producer accuracies, the overall accuracy and the kappa index (Congalton 1991). Regarding the amount of ground truth data for this accuracy assessment, a balance between what is statistically sound and what is practicable must be found (Congalton and Green 1999). Congalton and Green (1999) propose as a "rule of thumb" to collect a minimum of 50 samples for each class in the confusion matrix. As the spatial extent of the area is medium large (47,703 ha), it was decided to use 50 samples per class. Ground truth data points were collected directly by the project partner institute for South Water Caye Marine Reserve. The ground truth campaign was planned in cooperation with RSS GmbH. The field data assessment followed a strict protocol provided by RSS GmbH to assure objectivity and scientific validity. Only seagrass cover and water points were requested, and surveys were completed at 30 sites (Figure 20). Field data coverage classes were compared with site photos from the campaign data and, for the few cases where necessary, the coverage class was changed to remain consistent with the coverage classes for all five assessed MAR Fund sites. If a particular coverage class was overrepresented in the final dataset, a set random sample of points was removed to keep validation point totals consistent across all classes.

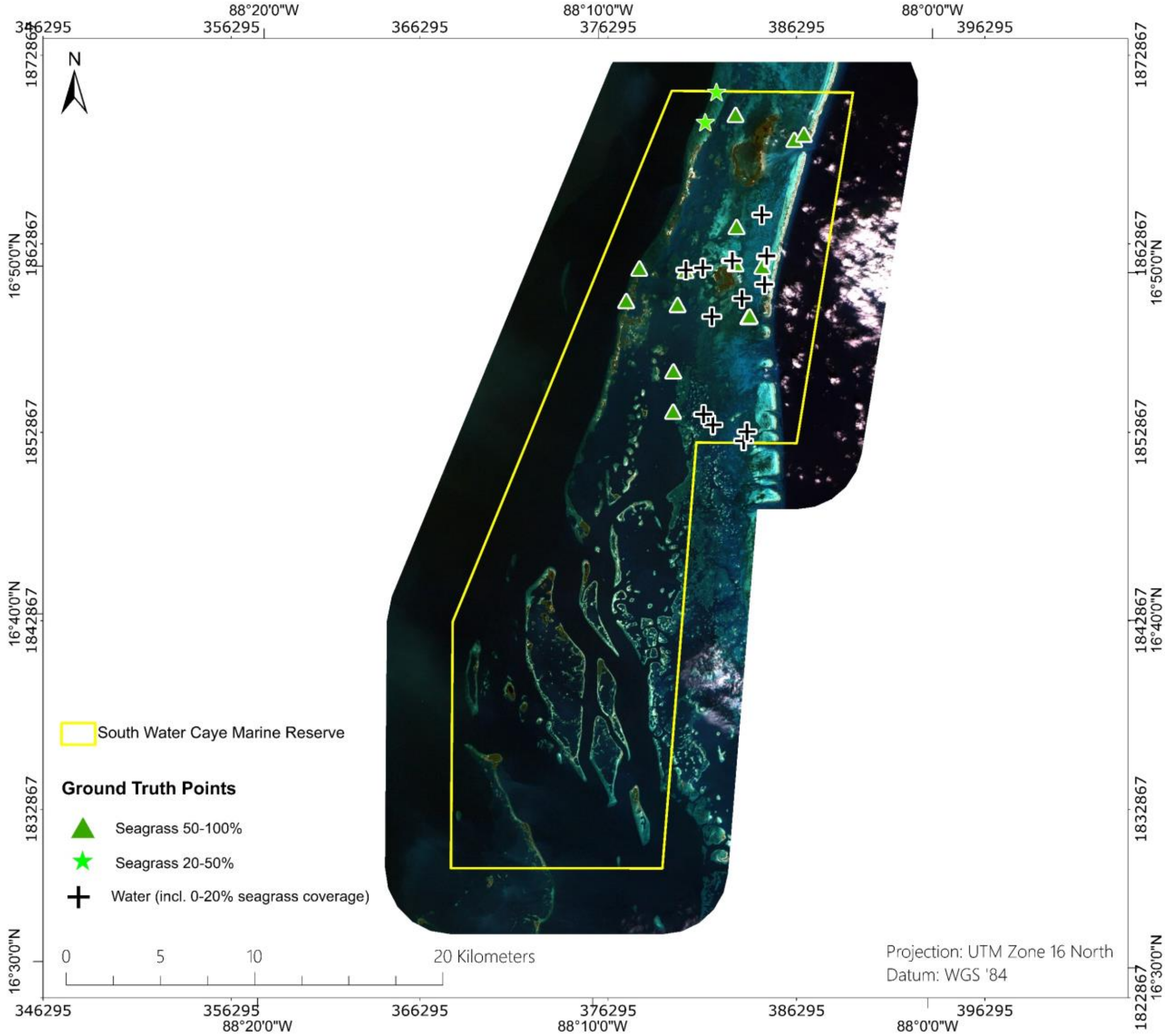


Figure 20: Location of the 30 ground truth data points collected for the South Water Caye Marine Reserve by the local experts of the project partner. Only seagrass cover and water points were requested.

As this ground truth data collection would not reach the sufficient amount of 50 points per class, an additional reinterpretation of samples from the original data (RapidEye imagery) in an independent manner is permissible in such a case (Congalton and Green 1999). A random sample of additional 370 points was selected using ArcGIS, which were afterwards interpreted by an independent remote sensing expert not involved in the classification. Random sampling reduces the risk of bias and allows for an objective assessment of the uncertainty of the estimates. Table 13 shows number of samples per class collected in the field and those collected in the original satellite imagery (RapidEye).

Table 13: Number of ground truth samples per class collected in the field and in the original RapidEye satellite imagery.

Class	Collected in the field	Collected in the imagery*	Sum
Mangrove 75-100%	0	50	**50**
Mangrove 50-75%	0	50	**50**
Mangrove 25-50%	0	50	**50**
Mangrove 0-25%	0	50	**50**
Seagrass 50-100%	14	36	**50**
Seagrass 20-50%	2	48	**50**
Land/Tidal Zone	0	50	**50**
Water**	14	36	**50**
Sum	**30**	**370**	**400**

* Original RapidEye satellite imagery

** The class Water also includes, besides macro-algae, algal macrophytes, algal periphyton and submerged corals, the possible occurrence of seagrass below 20% coverage.

Number of ground truth samples per class collected in the field and in the original RapidEye satellite imagery. The field data were collected by the local experts of Corazol Bay, while the Ground truth data collected in the Rapid Eye imagery were collected by RSS experts. These data were assumed as 'true'' in the accuracy analysis. All ground truth points were chosen randomly, to prove objective results

Several statistical measures for the accuracy (overall accuracy, Kappa coefficient of agreement, producer's and user's accuracy per class) were calculated. Table 14 and Table 15 show the detailed results of the accuracy assessment. An **overall accuracy of 87.3**% with a **Kappa coefficient of 0.88** was achieved.

Table 14: Confusion matrix per class by the use of 400 reference samples

Confusion Matrix									
	Validation class								
Classification class	Mangrove 75-100%	Mangrove 50-75%	Mangrove 25-50%	Mangrove 0-25%	Seagrass 50-100%	Seagrass 20-50%	Land/Tidal Zone	Water*	Sum
Mangrove 75-100%	44	5	1	-	-	-	-	-	50
Mangrove 50-75%	-	40	10	-	-	-	-	-	50
Mangrove 25-50%	-	2	45	3	-	-	-	-	50
Mangrove 0-25%	-	1	-	40	-	2	-	7	50
Seagrass 50-100%	-	-	-	-	40	7	-	3	50
Seagrass 20-50%	-	-	-	-	1	49	-	-	50
Land/Tidal Zone	-	-	-	1	-	-	49	-	50
Water*	-	-	-	-	-	8	-	42	50
Sum	44	48	56	44	41	66	49	52	400

*The class Water also includes, besides macro-algae, algal macrophytes, algal periphyton and submerged corals, the possible occurrence of seagrass below 20% coverage.

Confusion matrix per class by the use of 520 reference samples. The left column shows the respective class, the row from left to right shows the classes of the classification number of reference points. Please consult Congalton (1991) or Foody (2002) for further clarification. The diagonal grey cells display the number of matching samples.

Table 15: Producer's und user's accuracy per class

Class	Producer's Accuracy	User's Accuracy
Mangrove 75-100%	100%	88%
Mangrove 50-75%	83%	80%
Mangrove 25-50%	80%	90%
Mangrove 0-25%	91%	80%
Seagrass 50-100%	98%	80%
Seagrass 20-50%	74%	98%
Land/Tidal Zone	100%	98%
Water*	81%	84%

* The class Water also includes, besides macro-algae, algal macrophytes, algal periphyton and submerged corals, the possible occurrence of seagrass below 20% coverage.

7 Deliverables

- Original RapidEye image from 08/01/2019 (GeoTIFF)
- Original Landsat 8 image from 28/01/2019 (GeoTIFF)
- Original Sentinel-2 imagery from 13/01/2019 (JPEG 2000)
- Preprocessed RapidEye image from 08/01/2019 (GeoTIFF), XML-Metadata
- Preprocessed Landsat 8 image from 28/01/2019 (GeoTIFF), XML-Metadata
- Preprocessed Sentinel-2 image from 13/01/2019 (Band Sequential (.bsq) image file), XML-Metadata
- Mangrove cover classification (Shapefile and Layerfile), XML-Metadata
- Seagrass cover classification (Shapefile and Layerfile), XML-Metadata
- Change 2016 – 2018 (Shapefile and Layerfile), XML-Metadata
- Mangrove map in A0 (pdf and ArcGIS .mxd-file), XML-Metadata
- Seagrass map in A0 (pdf and ArcGIS .mxd-file), XML-Metadata
- Detailed map of hot spots / heavy impact sites / touristic sites (pdf and ArcGIS .mxd-file), XML-Metadata

8 Conclusions and Recommendations

Based on comparison of the 2015 and 2018 measurements (Table 11 and Table 12), the two main objective indicators of the MAR Fund Phase II project were achieved:

- Areas of mangrove in project CMPA 2018 are equal to or greater than the baseline (as assessed in 2015)
- Areas of marine seagrass beds in project CMPA 2018 are equal to or greater than the baseline (as assessed in 2015)

As for the information analized, it can be concluded that:

- Total Mangrove increase amounts approx. 70 ha whereas the increase in seagrass amounts approx. 230 ha. It should be noted that in both mangrove and seagrass th1e 'best' coverage class (75%-100%) have a large increase compared to 2015. However, seagrass meadows show ecological fluctuations and constantly vary in coverage. To improve the outcome of the accuracy assessment activities in future projects, we continue to recommend extending local ground truth activities as much as possible under the project budget.
- This study has shown that seagrass and mangrove coverage can be reliably assessed using actual high-resolution satellite imagery in good quality at low costs. The summarized statistics (Figure 10) lead to the conclusion that Mangrove and Seagrass cover increased in the time between 2015 and 2018.

The general conclusion and recommendations are:

- Data from ground truth campaigns, implemented by local experts, provided an excellent basis for a realistic accuracy assessment and confirms the results of this study.
- This study has shown that seagrass and mangrove coverage can be reliably assessed using actual high-resolution satellite imagery in good quality at low costs. RapidEye archive data costs approx. 1 € per SQKM, whereas Landsat 8 and Sentinel-2 data are free of charge. Planet Lab Inc. announced October of this year that it will continue the highly popular RESA program, which could offer an opportunity to conduct future such studies for a lower price.
- At least 50 samples for each desired class should be collected (Congalton and Green 1999). For larger areas, i.e. in excess of 400,00 ha, at least 75 samples should be collected per desired class (Congalton and Green 1999).
- Acquisition of additional field data, beyond the minimum requirement for ground truthing, would allow for integrated development of the classification algorithms and potentially improve the reliable assessment of object properties.
- Survey by drones have become more prevalent with recent technological advances, making the learning curve for implementation within field campaign activities more feasible following a short (1-2 day) training session. RSS GmbH has already had good success conducting such workshops in Indonesia for peat forest modelling activities. This would allow project partner field teams to more easily collect ground truthing data, especially in areas that are difficult or inaccessible by foot.For future investigations an assessment of the Mangrove's carbon stock would be recommended. By doing so, strong protection arguments could be pinpointed, as the habitat Mangroves is a crucial component of the so-called "blue carbon" (Nellemann, 2009).
- The collection of destructive and non-destructive sampling plots within the Mangrove sites, harvesting, weighing and collecting of above- and belowground (roots) tree components would

provide important facts on the role of Mangroves in a country's carbon stock,- thus why the protection and regeneration of this habitat is indispensable considering climate change and global carbon stock.

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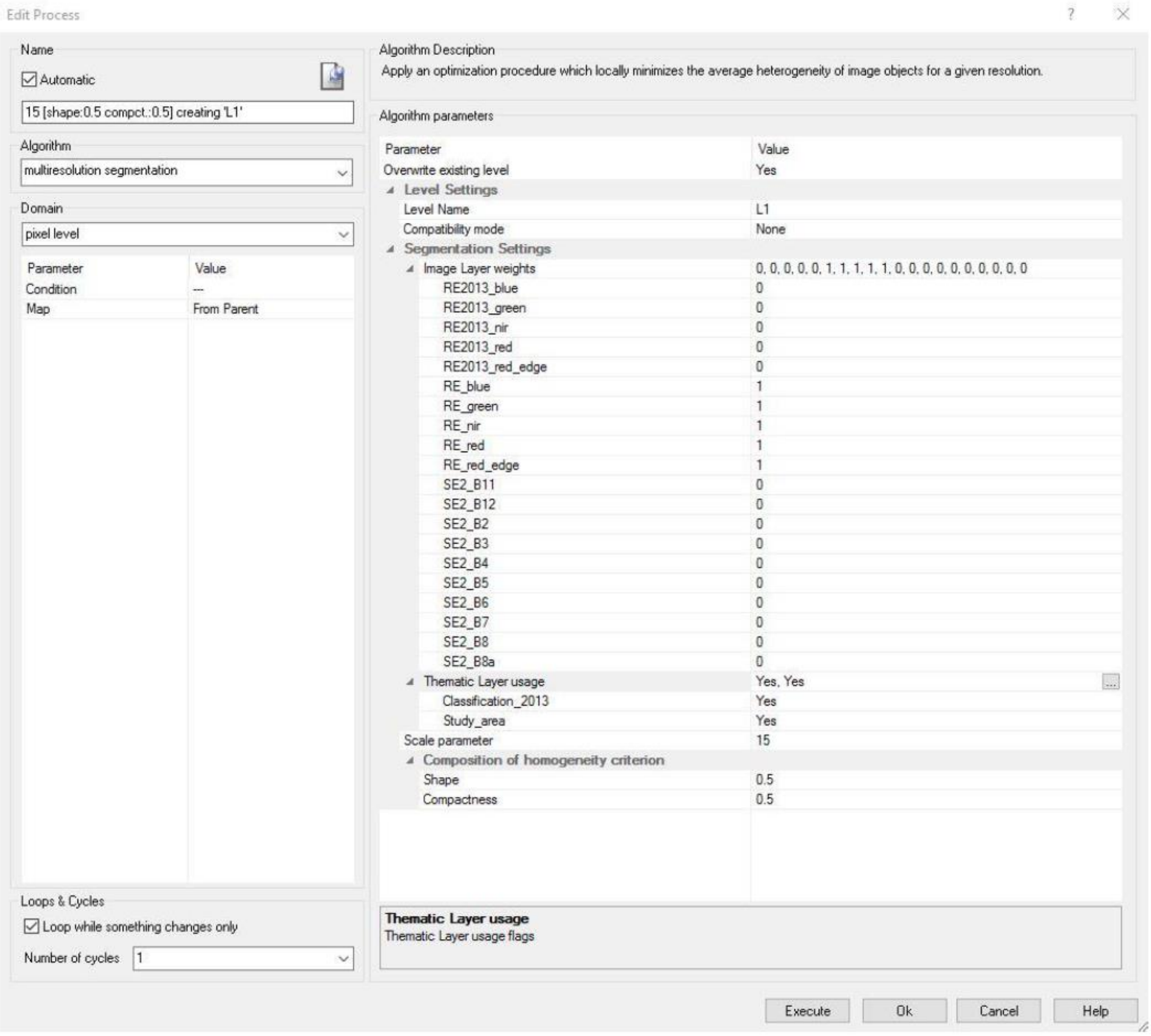
Annex I

List of abbreviations for the different spectral bands and indices used

Abbreviation	**Band/Description**	**Spectral Range/Central Wavelength (nm) or Equation**
RE_blue	RapidEye 2016 blue	440-510
RE_green	RapidEye 2016 green	520-590
RE_red	RapidEye 2016 red	630-685
RE_red_edge	RapidEye 2016 red edge	690-730
RE_nir	RapidEye 2016 near infrared	760-850
SE2_B2	Sentinel-2A Band 2 blue	490
SE2_B3	Sentinel-2A Band 3 green	560
SE2_B4	Sentinel-2A Band 4 red	665
SE2_B5	Sentinel-2A Band 5 vegetation red edge	705
SE2_B6	Sentinel-2A Band 6 vegetation red edge	740
SE2_B7	Sentinel-2A Band 7 vegetation red edge	783
SE2_B8	Sentinel-2A Band 8 near infrared	842
SE2_B8a	Sentinel-2A Band 8a vegetation red edge	865
SE2_B11	Sentinel-2A Band 11 short wavelength infrared	1,610
SE2_B12	Sentinel-2A Band 12 short wavelength infrared	2,190
RE2013_blue	RapidEye 2016 blue	440-510
RE2013_green	RapidEye 2016 green	520-590
RE2013_red	RapidEye 2016 red	630-685
RE2013_red_edge	RapidEye 2016 red edge	690-730
RE2013_nir	RapidEye 2016 near infrared	760-850
Anthocyanin_RI	RapidEye Anthocyanin Reflectance Index	(1/[Mean RE_green])/(1/[Mean RE_red_edge])
Chlorophyll_Green	RapidEye Chlorophyll Green Index	1/([Mean RE_nir]/[Mean RE_green])
Cust_Brightness_RGB	RapidEye Cust Brightness RGB Index	([Mean RE_blue]+[Mean RE_green]+[Mean RE_red])/3
Green_Ratio	RapidEye Green Ration Index	([Mean RE_green]+[Mean RE_blue])/[Mean RE_blue]
NDVI	RaipidEye Normalized Difference Vegetation Index	([Mean RE_nir]-[Mean RE_red])/([Mean RE_nir]+[Mean RE_red])
NDWI_IR	RapidEye Normalized Difference Water Infrared Index	([Mean RE_green]-[Mean RE_nir])/([Mean RE_green]+[Mean RE_nir])
NDWI_Red_Edge	RapidEye Normalized Difference Water Red Edge Index	([Mean RE_green]-[Mean RE_red_edge])/([Mean RE_green]+[Mean RE_red_edge])

Segmentation parameters used



Annex II

Field sheet for terrestrial sample points

LCCS Field Sampling RSS GmbH; Mangroves

Site ID:		Date:	dd.mm.yyyy
Location:		Time:	

Surveyor:	GPS coordinates (UTM or lat/lon):	GPS point Nr.:	Photo Nr.: North East South West Up

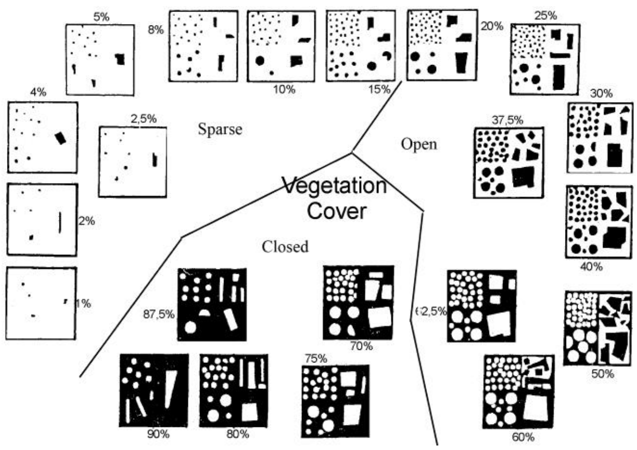
Mangrove coverage (%)	Mangrove species	Mixed w/ sedge or grass	Covered by other trees or palms
		Just y/n	Just y/n

Please assess four mangrove coverage levels
0% - 25%
25% - 50%
50% - 75%
75% - 100%

Please take 5 photos per site, standing at the GPS point
One photo facing north, one facing east, south, west
Fifth photo should be taken directly upwards (ie. pointed at the sky)

*Locations with species taller than mangroves may be unuseable for accuracy assessment.
For a suggested location with more than 75% overgrowth coverage, consider relocating measurement point.

Comments: (anthropogenic impacts, transition zone, proximity to shore, etc.)



Clarification:
Everything which is dark is meant to represent canopy cover. When the background is black, as in the lower quadrats, the white objects then represent gaps in the canopy. Thus dark circles+rectangles can either represent individual trees or a stand of trees that have combined closed coverage, while the white objects represent areas where there is no canopy coverage.

Field sheet for marine sample points

LCCS Field Sampling RSS GmbH; Seagrass

Site ID:		Date:	dd.mm.yyyy
		Time:	
Location:			

Surveyor:	GPS coordinates (UTM or lat/lon):	GPS point Nr.:	Photo Nr.:

Depth (m)	Water clarity	Bottom type	Seagrass	Seagrass coverage (%)	Algae	Overall Coverage (%)
	Such as Secchi depth	e.g. rock, sand, pebble, etc.	Just y/n		Just y/n	

Please assess four seagrass coverage levels
0% - 25%
25% - 50%
50% - 75%
75% - 100%
*Data on species level is not necessary, but you may assess it as well.

Comments:	(anthropogenic impacts, near to river, plot characteristic for surroundings, etc.)

More information
http://coralhealth.spatial.hawaii.edu/research.html
http://gulfsci.usgs.gov/gom_ims/sgpubs.html
https://en.wikipedia.org/wiki/Seagrass

Seagrass Percentage Cover