Establishing the baseline for seagrass and mangrove area cover in five Marine and Coastal Priority Protected Areas within the Meso-American Reef area

South Water Caye Marine Reserve
Belize

Contract Services No. 17-2015 "Conservation of Marine Resources in Central America Phase II" Financial Agreement 2010 66 836

Final Report – October 2016

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1. Introduction

The Mesoamerican Reef Fund (MAR Fund) was created 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. It is comprised of four founder funds, representing each of the MAR countries: Protected Areas Conservation Trust (PACT) in Belize, Foundación de los Recursos Naturales y Ambiente (FCG) in Guatemala, Fundación Biosfere (FB) in Honduras and Mexican Fund for the Conservation of Nature (FMCN) in Mexico.

The main focus of MAR Fund's grants programme is the development of an interconnected network of priority conservation areas. Simultaneously, MAR Fund seeks to address issues that directly affect the integrity and health of the network.

As part of the functional network programme for marine and coastal protected areas, implementation of the project "Conservation of Marine Resources in Central America – Phase II" is underway. This project supports best management practices and community participation in the conservation and sustainable use of coastal and marine resources in the initial network of protected areas within MAR. Funded by the German Government through Kreditanstalt für Wiederaufbau or KfW, the project is governed by both the Financial Contribution Contract signed on April 30, 2013 by MAR Fund and KfW and a separate agreement signed on August 29, 2013.

The project will seek 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 MAR. 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.

Total contributions for the project come to €6.2 million. KfW contributes €5 million. Protected areas and beneficiaries will contribute €1,231,938, while the remainder of the budget will come from existing budgets for the protected areas and from funds provided by the MAR Fund and its members.

The project will last five years from July 2015.

The following objectives are defined:

(a) Main objective

To contribute to conservation of the ecological functions of the Mesoamerican Reef System

(b) Project objective

To consolidate selected Marine and Coastal Protected Areas (MCPA) in the project's region and to ensure the conservation and sustainable use of marine and coastal resources in the medium term

The project area is bounded by the Mesoamerican Reef System (MAR), shared between Mexico, Belize, Guatemala and Honduras. These coastal and marine ecosystems 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.

Consequent monitoring of ecosystems in the MAR is inevitable for preventing the continuing rapid loss of those habitats. Many studies and initiatives have demonstrated the high potential of remote sensing techniques for assessing coastal habitats like seagrass canopies (Dekker et al. 2006, Mumby et al. 1997) or mangroves (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 objective of this study was to establish the actual extent of the mangroves' and seagrass' extent within five Marine and Coastal Priority Protected Areas (MCPA) in the Mesoamerican Reef area based on RapidEye and Landsat 8 satellite imagery recorded in 2015:

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 present report describes the procurement, preprocessing and classification of high resolution RapidEye and Landsat 8 imagery for the project area MCPA **South Water Caye Marine Reserve**, Belize. RSS - Remote Sensing Solutions GmbH - generated mangrove and seagrass cover maps that represent the 2015 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 can be used as input for an up-to-date (2015) baseline. The baseline is required to determine, if following two main objective indicators of the MAR Fund have been accomplished at the end of the project:

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

These two main objective indicators are impact indicators and are used to measure the overall positive impact in each area through the implementation of the project.

2. Objectives

The objectives of the study are:

- Derivation of a reliable up-to-date (2015) baseline coverage using actual RapidEye and Landsat 8 satellite imagery
- Application of consistent state of the art 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) from the year 2015 – assessed at a reliable quality and comparable methodology
  - Seagrass area in the South Water Caye Marine Reserve (Belize) from the year 2015 – assessed at a reliable quality and comparable methodology

The coverage assessment will serve as a baseline for future investigations of MAR Fund's 5-year project "Conservation of Marine Resources in Central America". The baseline for the two ecosystem engineers will serve as initial datasets that could be used as a temporal reference to evaluate the success of the project. In the fifth year of the project, there will be a second monitoring in order to measure the project achievement using the indicators established. The primary evaluation point will be the mangrove and seagrass cover as compared to the baseline established in 2015.

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). It is located 18 km east of the mainland and has a size of 47,703 ha (Walker 2009, Figure 1).

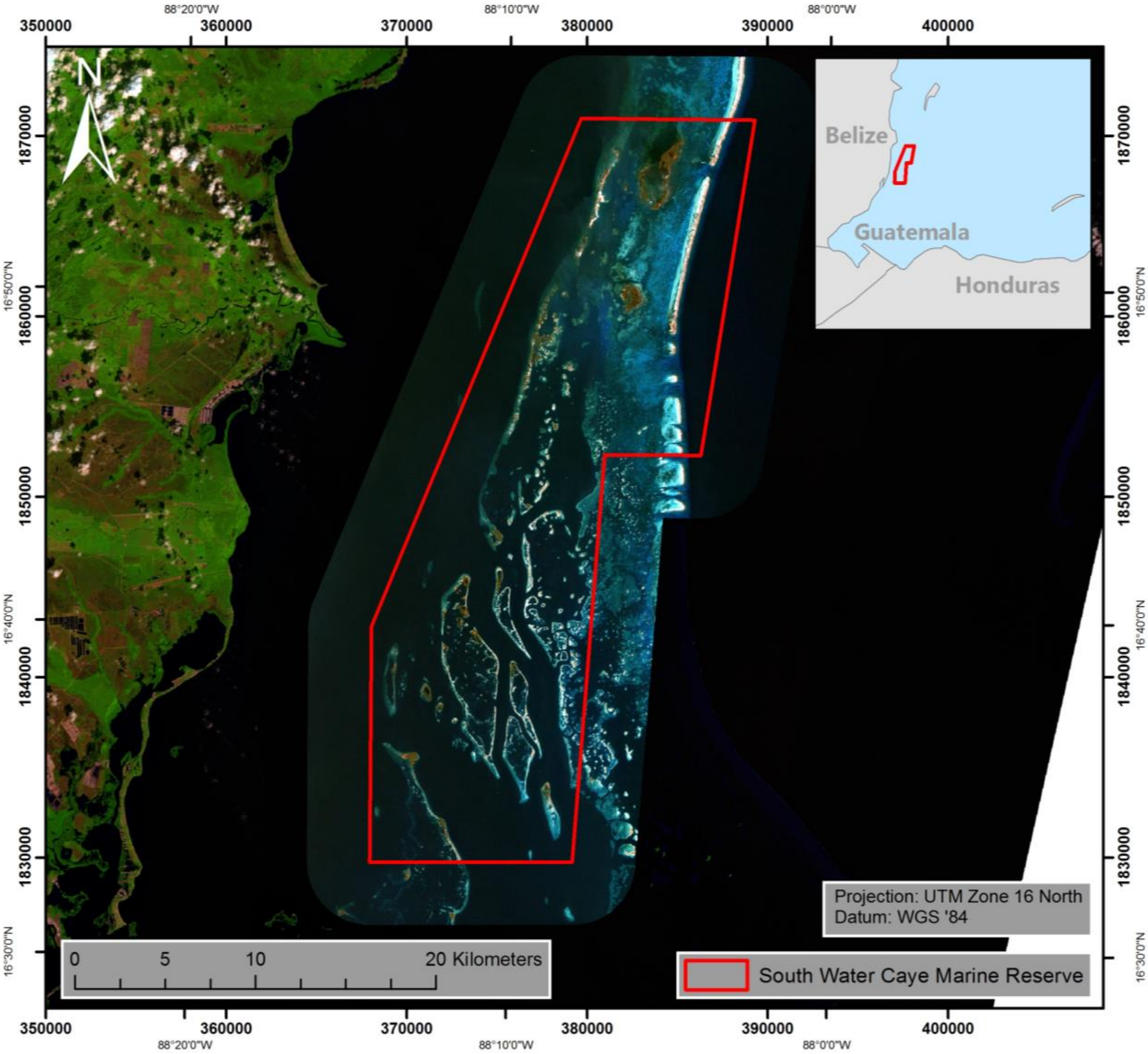


Figure 1: Overview of the South Water Caye Marine Reserve (Belize). True-color RapidEye imagery (01/11/2015) superimposed on Landsat 8 data (01/11/2015; bands: short wavelength infrared (band 6), near infrared (band 5), and red (band 4). The border of South Water Caye Marine Reserve is displayed in red.

Of the coastal marine ecosystems, mangroves and seagrass meadows are considered to be among the most productive (McField and Kramer 2007; Wabnitz 2007).

The South Water Marine Reserve is the largest marine protected area in Belize (Walker 2009). Due to its national, regional and international importance, this marine reserve was established by the Fisheries Department in 1996, under the Fisheries Act (Walker 2009). This designation fulfilled the requirements of the UNESCO and as one of seven protected areas, in the same year, it was declared as part of the Belize Berrier Reef System World Heritage Site (Walker 2009).

Baseline studies of mangrove and seagrass distribution are important as damages in these ecosystems have direct and indirect negative consequences on different environmental services such as: breeding areas for fish populations, as well as reproduction, refuge, nesting or growth for different species. The areas represent a valuable source of organic matter, ensure beach stability, and capture and stabilize the formation of sediments. Profound knowledge of existence, quantity, quality, and distribution of mangroves and seagrass is indispensable to suggest adequate laws, develop strategic plans and cost / benefit assessments.

4. Data and Methods

4.1 Remote Sensing Data

Two sources of remote sensing data were used:

<u>RapidEye constellation</u>

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). Its spatial resolution is 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 the Earth's surface since February 2009.

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

<table>
<tr><th>Mission Characteristics</th><th colspan="2">Information</th></tr>
<tr><td>Number of satellites</td><td colspan="2">5</td></tr>
<tr><td>Spacecraft lifetime</td><td colspan="2">Over 7 years</td></tr>
<tr><td>Orbit altitude</td><td colspan="2">630 km in sun-synchronous orbit</td></tr>
<tr><td>Equator crossing time</td><td colspan="2">11:00 am local time (approximately)</td></tr>
<tr><td>Sensor type</td><td colspan="2">Multi-spectral push broom imager</td></tr>
<tr><td rowspan="3">Spectral bands</td><td colspan="2">Capable of capturing all of the following spectral bands:</td></tr>
<tr><td>Band Name</td><td>Spectral Range (nm)</td></tr>
<tr><td>Blue
Green
Red
Red edge
NIR</td><td>440-510
520-590
630-685
690-730
760-850</td></tr>
<tr><td>Ground sampling distance (nadir)</td><td colspan="2">6.5 m</td></tr>
<tr><td>Pixel size (orthorectified)</td><td colspan="2">5 m</td></tr>
<tr><td>Swath width</td><td colspan="2">77 km</td></tr>
<tr><td>On board data storage</td><td colspan="2">Up to 1,500 km of image data per orbit</td></tr>
<tr><td>Revisit time</td><td colspan="2">Daily (off-nadir) / 5.5 days (at nadir)</td></tr>
<tr><td>Image capture capacity</td><td colspan="2">5 million km^2/day</td></tr>
<tr><td>Camera dynamic range</td><td colspan="2">12 bit</td></tr>
</table>

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).

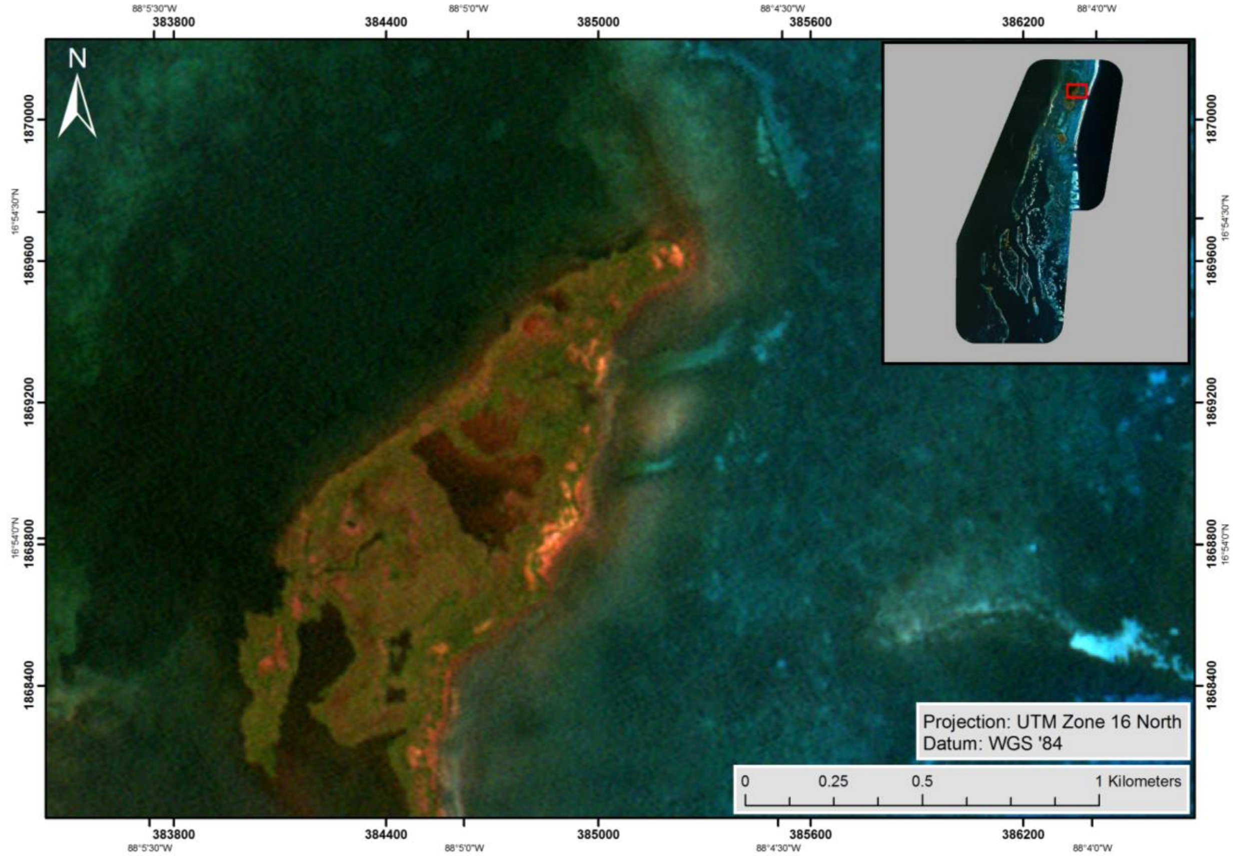


Figure 2: Subset of a RapidEye image (true-color) showing the spatial detail in land cover. The red rectangle in the upper right image shows the location of the subset within the South Water Caye Marine Reserve.

In the present study Level 3A RapidEye imagery was used. This orthorectified product is provided as 25 km by 25 km tiles. Radiometric, sensor and geometric correction is applied to the data (Table 2). More detailed information on the data product is provided in the Satellite Imagery Product Specification from Planet Labs available at:

https://www.planet.com/assets/themes/planet/pdf/1601.RapidEye.Image.Product.Specs_Jan16_V6.1_ENG.pdf (February 2016)

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 01/11/2015 was used for the mangrove and seagrass classification of the South Water Caye Marine Reserve. Figure 3 displays this almost cloud free imagery.

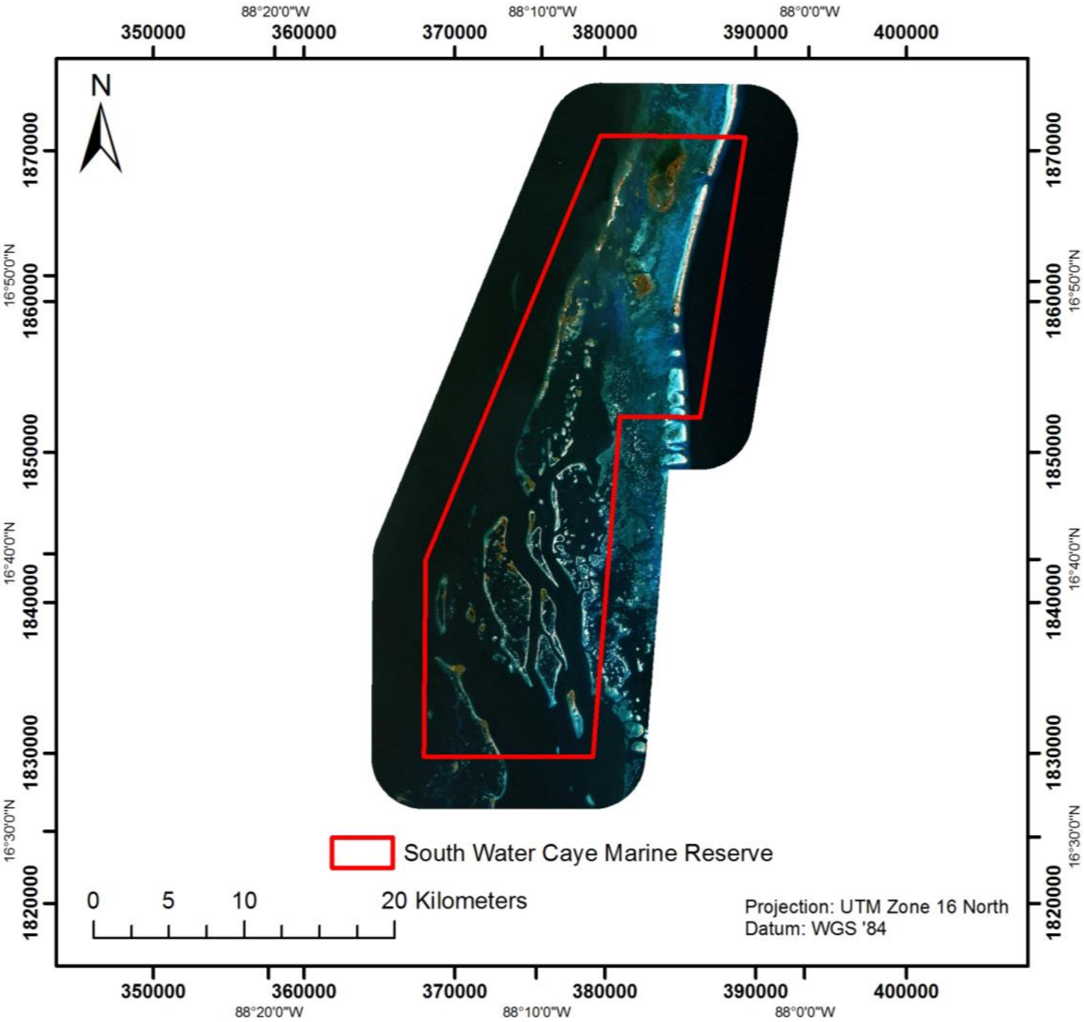


Figure 3: True-color RapidEye imagery (01/11/2015) used for the mangrove and seagrass mapping.

Landsat 8

Landsat 8 covers 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 Earth (USGS 2014). Landsat 8 orbits the earth at 705 km altitude. They cross every point on the Earth once every 16 days. The OLI 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 provided at: https://landsat.usgs.gov/landsat8.php. 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 2011) (Figure 4).

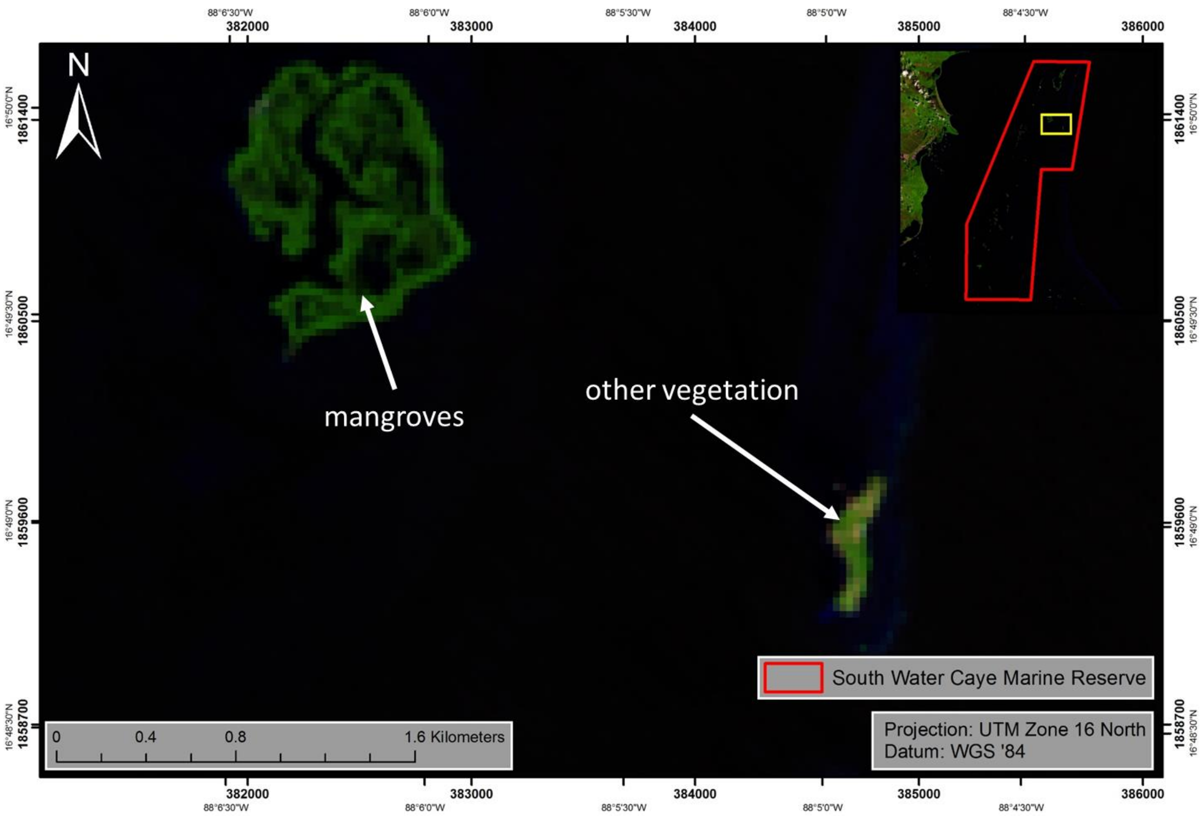


Figure 4: Subset of a Landsat 8 imagery (bands: short wavelength infrared (band 7), near infrared (band 5), and red (band 4) showing that mangroves can be differentiated from other vegetation types. The yellow rectangle in the upper right image shows the location of the subset within the South Water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

The Landsat 8 archive was checked and the most appropriate imagery (01/11/2015) downloaded (lowest cloud cover: 17.50%). Figure 5 shows the acquired Landsat 8 data for the South Water Caye Marine Reserve.

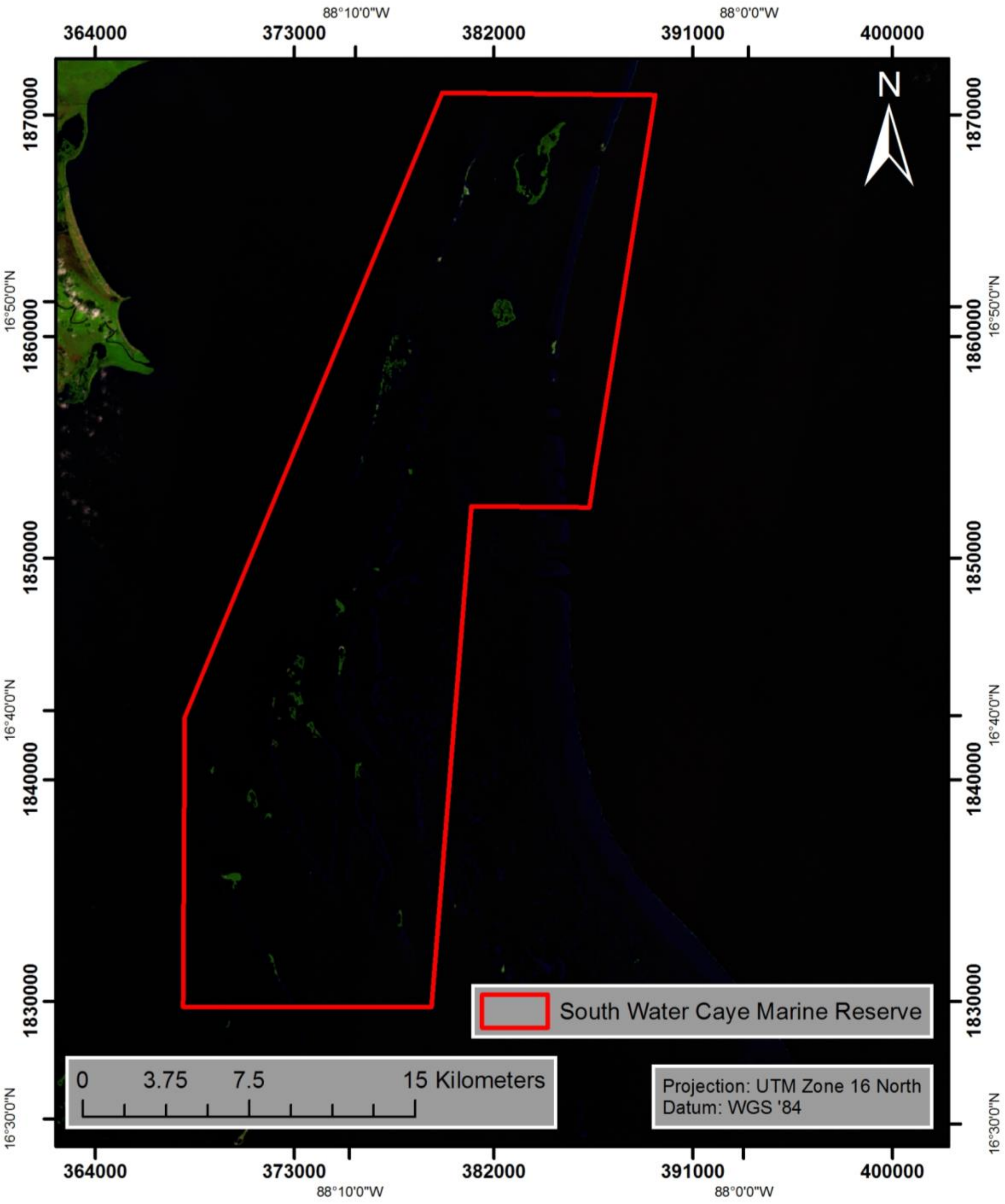


Figure 5: Landsat 8 scene (01/11/2015; bands: short wavelength infrared (band 7), near infrared (band 5), and red (band 4) used for the mangrove and seagrass mapping.

4.2 Data Preprocessing

An essential preprocessing step was the removal of atmospheric effects that influence the signal, induced by water vapour 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 segment-based rule-set classification method. The atmospheric correction was applied to each image using 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 data of the satellite data
- Selection of sensor (RapidEye or Landsat 8) and corresponding calibration file
- Atmospheric file: tropical maritime
- Satellite and sun geometry from the metadata of the satellite data
- Ground elevation: 0 km

Landsat 8 product specifications state that the OLI has a has a geolocation uncertainty of less than 12 m circular error (Table 3). Visual analysis showed that the Landsat 8 data had an excellent geometrical fit with the RapidEye data so no geometrical co-registration was necessary.

4.3 Mangrove and Seagrass Maps

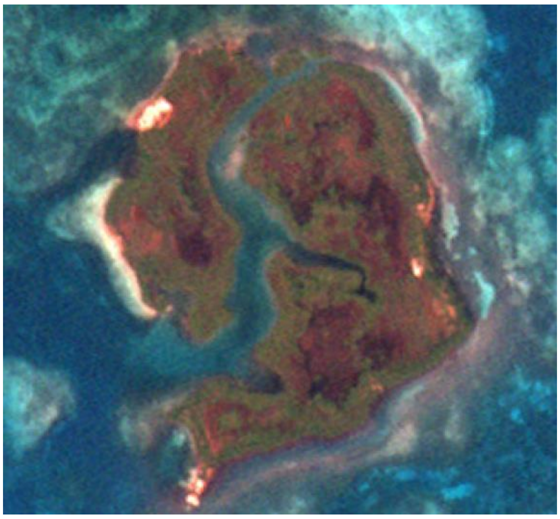
The basic classification method was an object-based image analysis approach using eCognition software (Trimble Geospatial, Munich, Germany). This methodology classifies spatially adjacent and spectrally similar groups of pixels, so called image objects, rather than individual pixels of the image. Traditional 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. Improved spatial resolution of remote sensing systems has resulted 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 underlying idea has been subject to numerous investigations since the 1970's (Haralick and Joo 1986, Kartikeyan et al. 1995, Kettig and Landgrebe 1976)

The first step of the object-oriented approach is a segmentation of the imagery to generate image objects, where neighbouring pixel clusters are combined into an image object. Here the spectral reflectance, as well as texture information and shape indicators are analysed for generating the objects. The attributes of the image objects (such as spectral reflectance, texture or the Normalized Difference Vegetation Index 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 sets 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 (Figure 6):

- **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



RapidEye satellite image

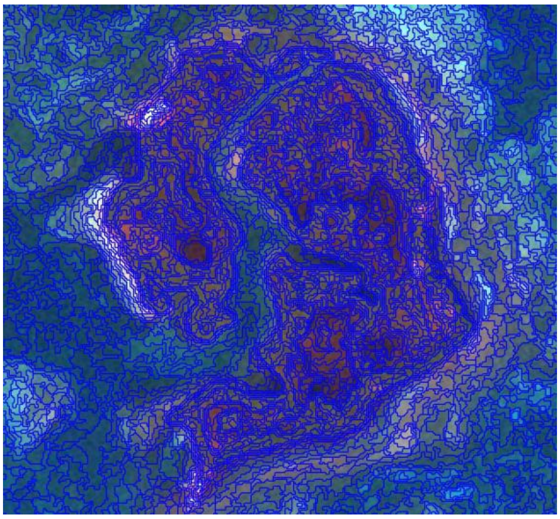
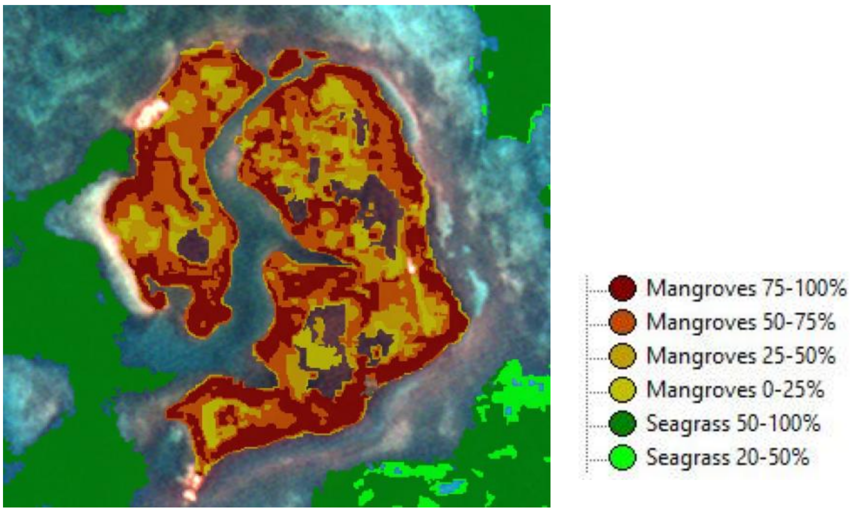


Image segmentation



Classification based on image object attributes

Figure 6: Example of the basic procedures of an object-based image analysis. The input image dataset (top) is first segmented into homogeneous image objects (middle) which are then assigned to predefined classes according to decision rules (down).

The first step in the classification process is the definition of the class hierarchy on the basis of the classification scheme. In total, 7 *ecological* classes were defined:

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

Originally a classification scheme stratifying 25% levels of coverage, meaning 0-25%, 25-50%, 50-75% and 75-100% seagrass coverage was proposed. The conducted analyses showed that such a fine distinction is not implementable with serious scientific standards. Due to turbidity of the ocean, esp. 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 silt, decaying plant and animal matter, industrial waste as well as sewage (Figure 7). Therefore the classification scheme concerning aquatic habitats was adjusted to three classes: Water including 0-20% seagrass coverage, 20-50% and 50-100% seagrass coverage.

The spatial and spectral resolution of the RapidEye satellite data does not allow to go into further detail. Further the analyses showed that it was not possible to detect seagrass unambiguously below 20% coverage. The class water also includes, besides macro-algae, algal macrophytes, algal periphyton and submerged corals, the possible occurrence of seagrass below 20% coverage (Figure 8).

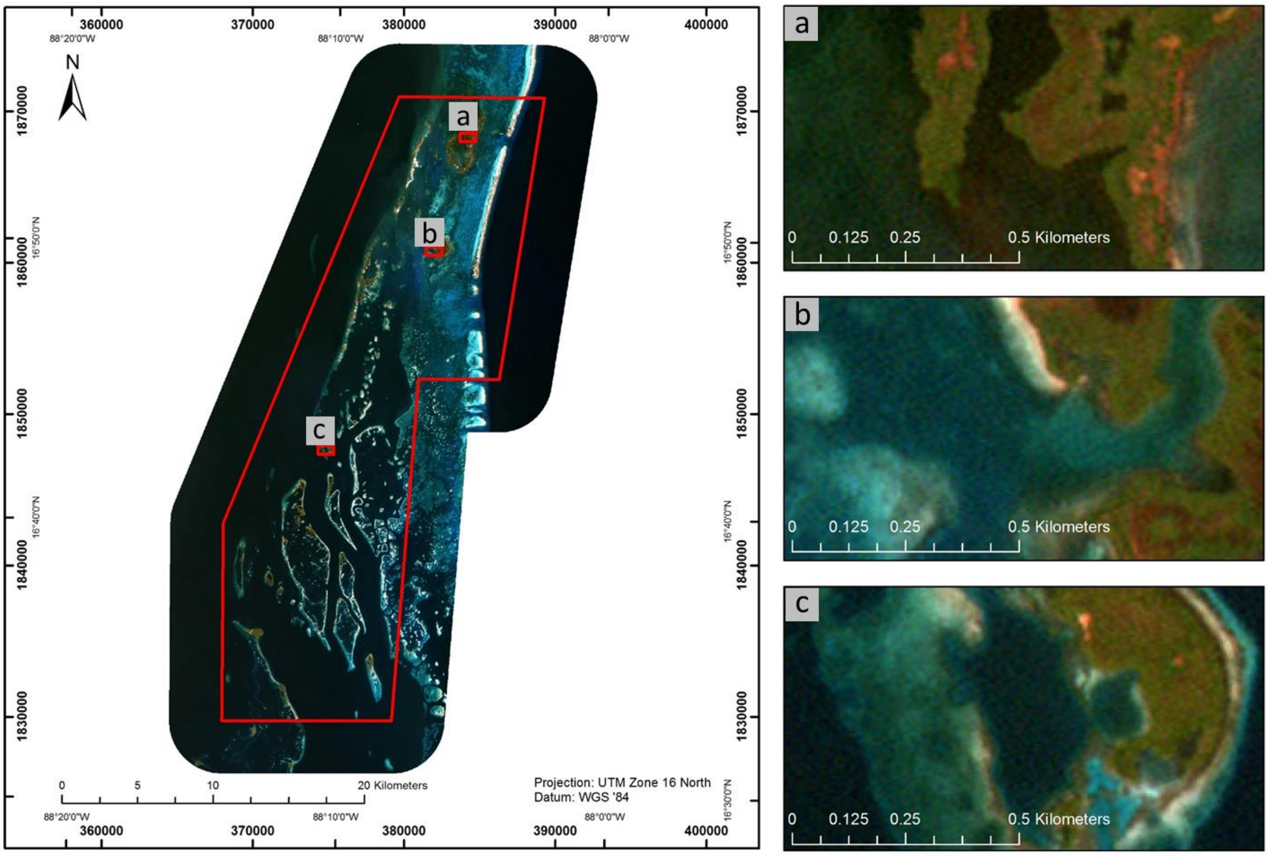


Figure 7: Examples for strong turbid sea within the project area. Here it was not possible to detect 4 density classes for seagrass. True-color RapidEye imagery (01/11/2015).

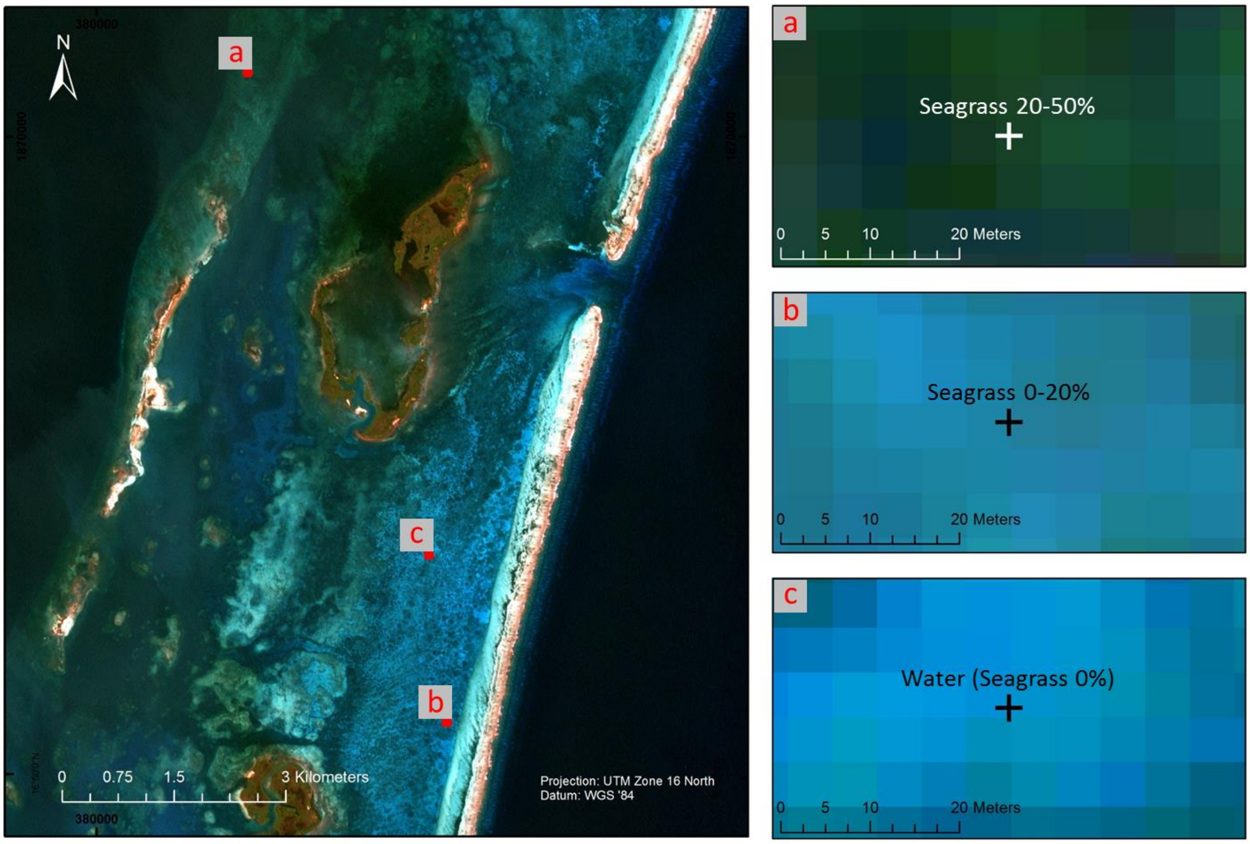


Figure 8: Examples of seagrass classes recorded in the field (a, b and c) compared to RapidEye imagery. It is clearly visible that the classes Seagrass 0-20% and Water (seagrass 0%) are not distinguishable in the RapidEye imagery. Whereas the class Seagrass 20-50% is distinguishable from the Water class. RapidEye image is not capable to unambiguously detect seagrass cover below 20%. Satellite data with a better radiometric and geometric resolution allows a finer detection of seagrass coverage, but is connected to considerably higher costs and consequently other problems.

Figure 9 illustrates the hierarchical structure of the classification scheme, each ecological class is represented by the colours of the final maps (Figures 10-13 and 16-17).

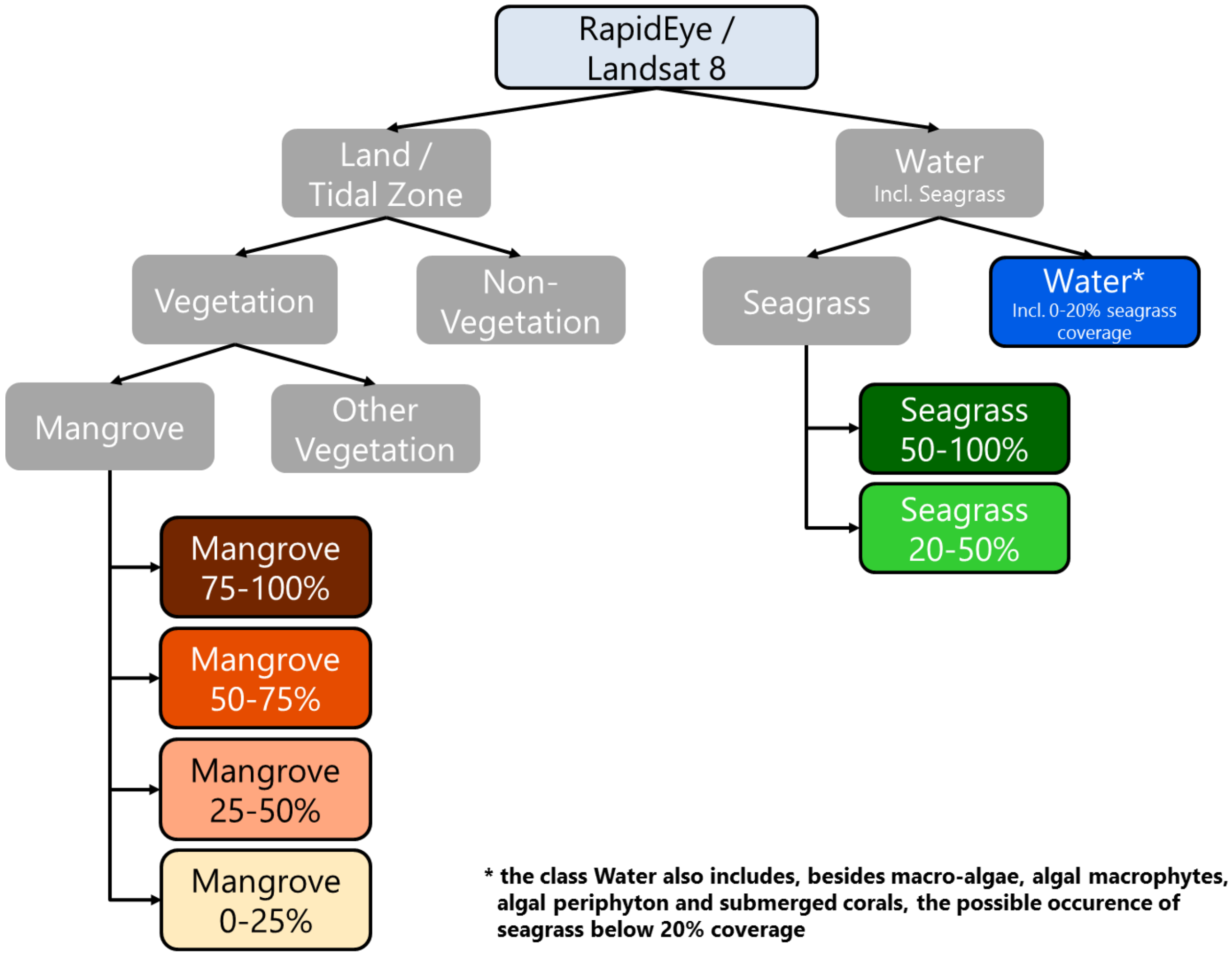


Figure 9: Classification scheme of the mangrove and seagrass cover classification of the South Water Caye Marine Reserve. Grey boxes without frame represent parent classes, framed boxes represent the final classes with the associated colour from the land cover maps (Figures 10-13 and 16-17). It is important to note 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 9.

The classification rule-set works in a hierarchical manner from coarse to fine thematic details. On the first hierarchy level, a 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. This final Water class also includes, besides macro-algae, algal macrophytes, algal periphyton and submerged corals, the possible occurrence of seagrass below 20% coverage.

On the third hierarchy level the vegetated objects were distinguished into Mangrove and Other Vegetation according to their spectral properties. Here also spectral properties from the Landsat 8 data was incorporated in the classification process as especially the two short-wave infrared and near infrared bands have shown to be very helpful in differentiating mangroves from other vegetation (Figure 4) (Chen et al. 2013, Kuenzer et al. 2011).

Mangrove was 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, spectral bands, and spectral indices used. Further, the statistical parameters of the feature objects for the different classes are shown.

5. Results

Figures 10 to 13 show the results for the mangrove and seagrass cover classification. Once without zonation and once with the zones (general use, conservation and preservation).

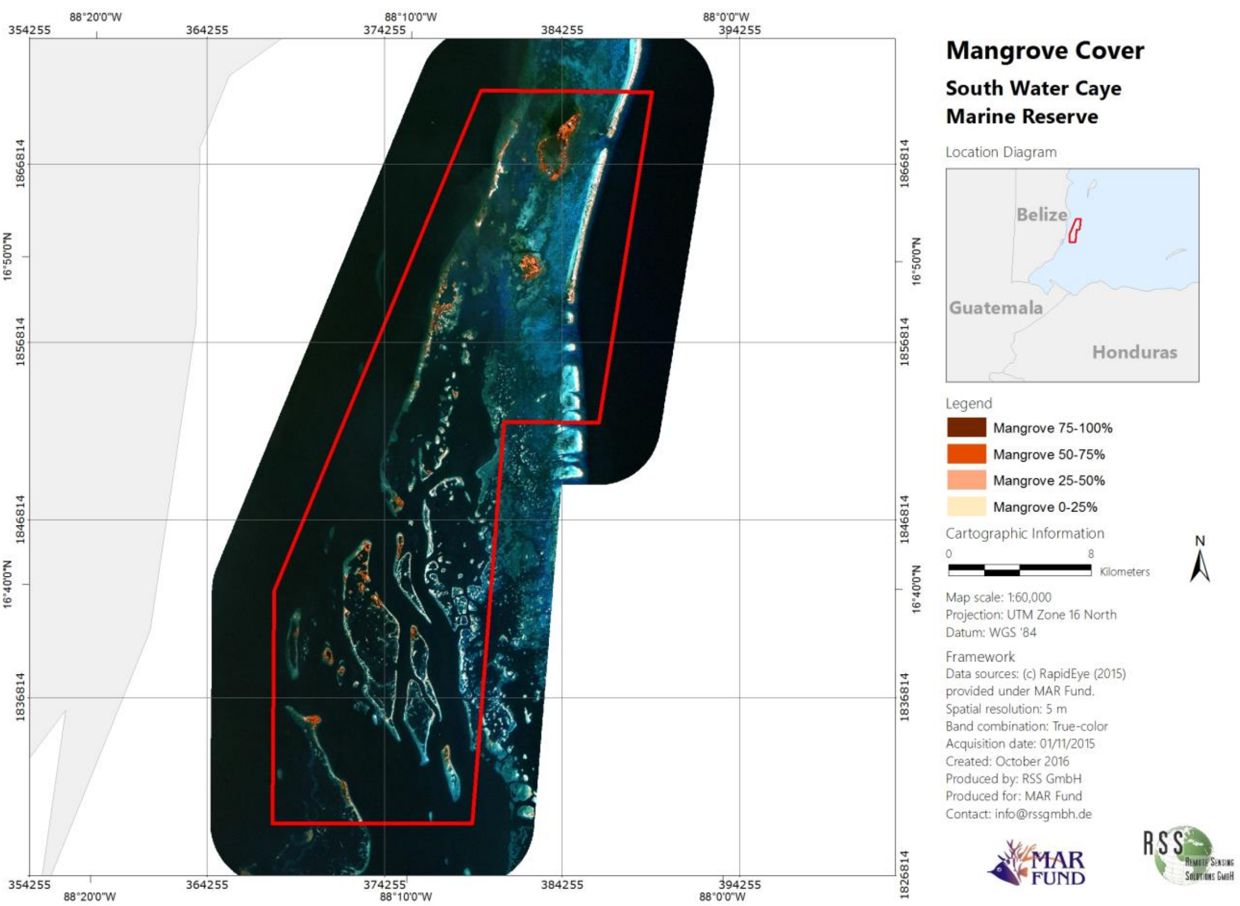


Figure 10: Mangrove cover classification for the South Water Caye Marine Reserve. Shown are the four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%). In the upper right diagram the location of the South Water Caye Marine Reserve within Belize is displayed (red).

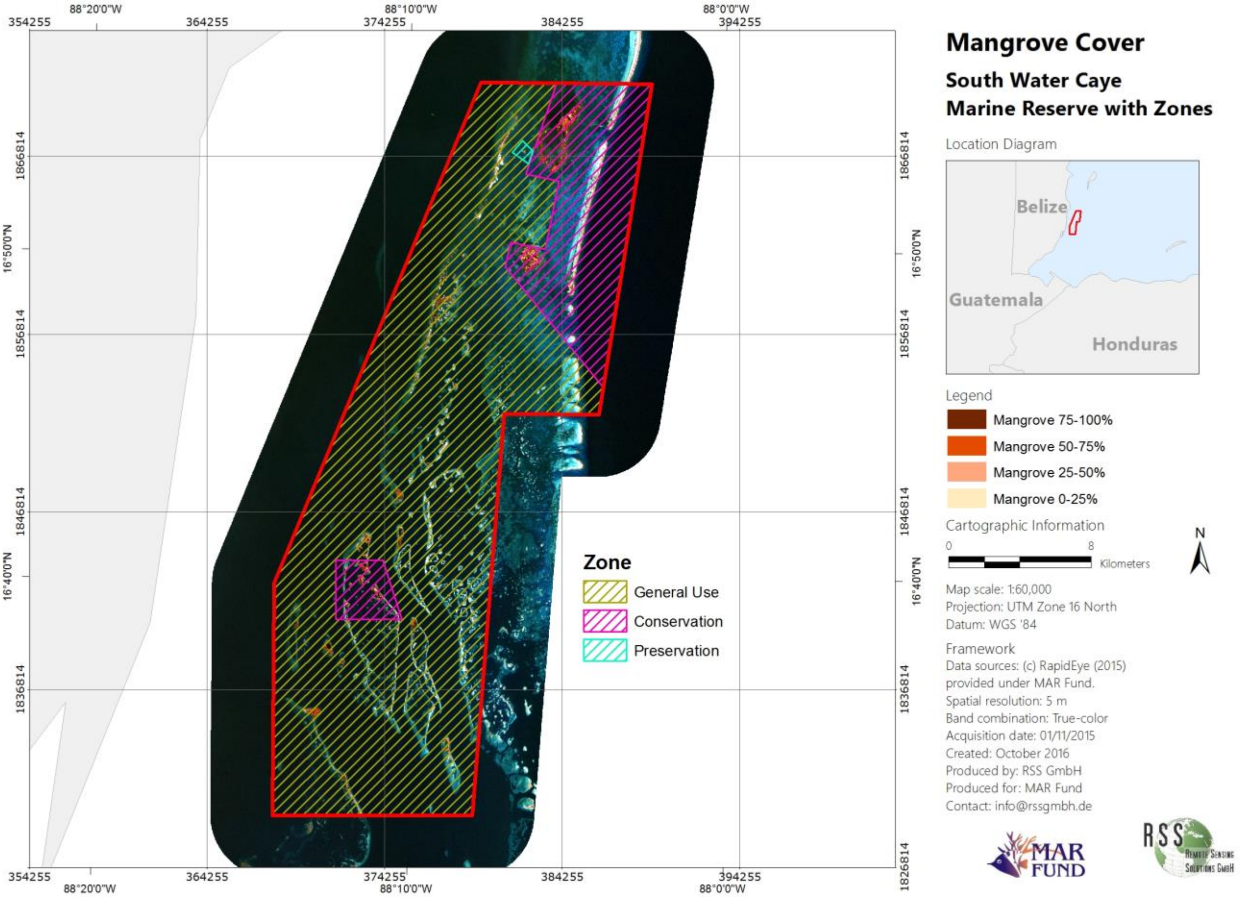


Figure 11: Mangrove cover classification for the South Water Caye Marine Reserve. Shown are the four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%). In the upper right diagram the location of the South Water Caye Marine Reserve within Belize is displayed (red). This map additionally displays the zones (general use, conservation and preservation).

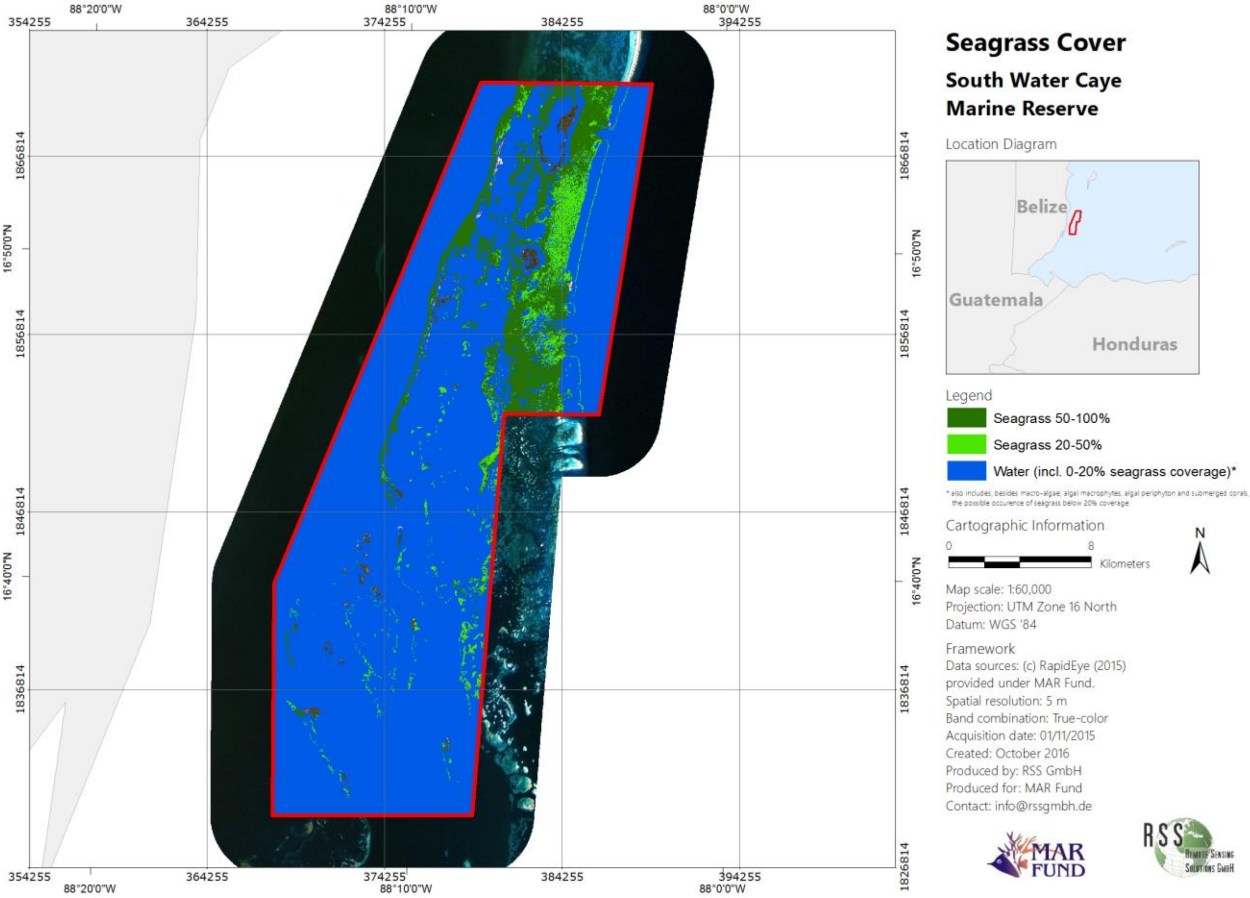


Figure 12: Seagrass cover classification for the South Water Caye Marine Reserve. Shown are the three acquatic classes (Water incl. 0-20% seagrass coverage, 20-50%, and 50-100% seagrass coverage). In the upper right diagram the location of the South Water Caye Marine Reserve within Belize is displayed (red).

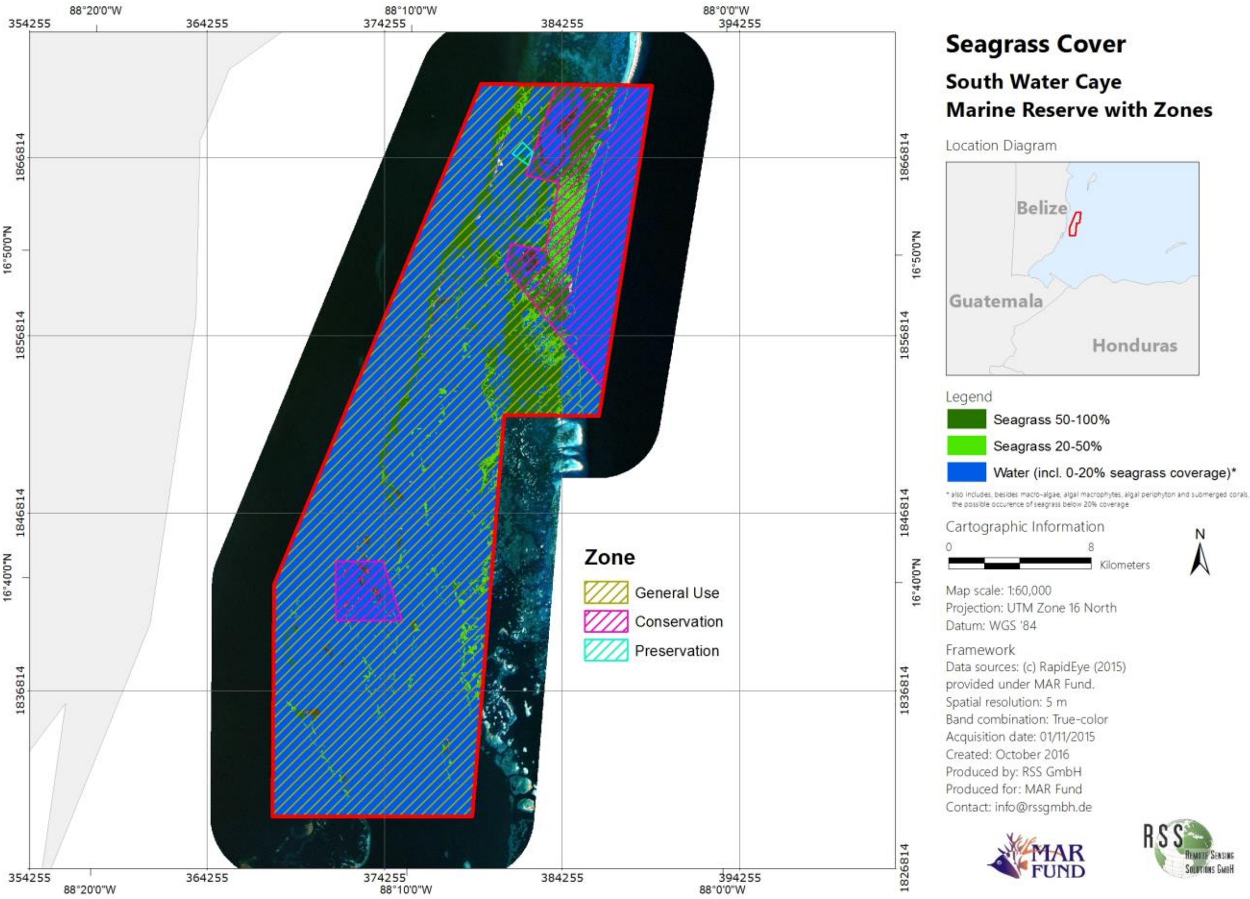


Figure 13: Seagrass cover classification for the South Water Caye Marine Reserve. Shown are the three acquatic classes (Water incl. 0-20% seagrass coverage, 20-50%, and 50-100% seagrass coverage). In the upper right diagram the location of the South Water Caye Marine Reserve within Belize is displayed (red). This map additionally displays the zones (general use, conservation and preservation).

The South Water Caye Marine Reserve has a total area of 47,703 ha of which 155 ha (0.3%) are covered by the class Mangrove 75-100%, 158 ha (0.3%) by Mangrove 50-75%, 73 ha (0.2%) by Mangrove 25-50%, 32 ha (0.1%) by Mangrove 0-25%, 4,848 ha (10.2%) by Seagrass 50-100%, and 1,892 ha (4.0%) by Seagrass 20-50% (Table 4). The dominant class within the mangrove area with 37.8% is Mangrove 50-75%, followed by Mangrove 75-100% with 37.0%, Mangrove 25-50% with 17.5%, and Mangrove 0-25% with 7.7% (Table 4). The class Seagrass 50-100% with 71.9% was more abundant that the class Seagrass 20-50% with 28.1% (Table 4).

Table 4: Spatial extent of the different ecological classes classified in the South Water Caye Marine Reserve. Also shown is the percentage of the total mangrove/seagrass cover and the percentage of the total South Water Caye Marine Reserve for each class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total South Water Caye Marine Reserve (47,703 ha) (%)
Mangrove 75-100%	155	37.0	0.3
Mangrove 50-75%	158	37.8	0.3
Mangrove 25-50%	73	17.5	0.2
Mangrove 0-25%	32	7.7	0.1
Sum Mangrove	**418**	**100.0**	**0.9**
Seagrass 50-100%	4,848	71.9	10.2
Seagrass 20-50%	1,892	28.1	4.0
Sum Seagrass	**6,739**	**100.0**	**14.2**

The graphs in Figures 14 and 15 display the spatial extent of the different ecological classes classified in the South Water Caye Marine Reserve. The colours represent the colours of each class in the final maps (Figures 10-13 and 16-17).

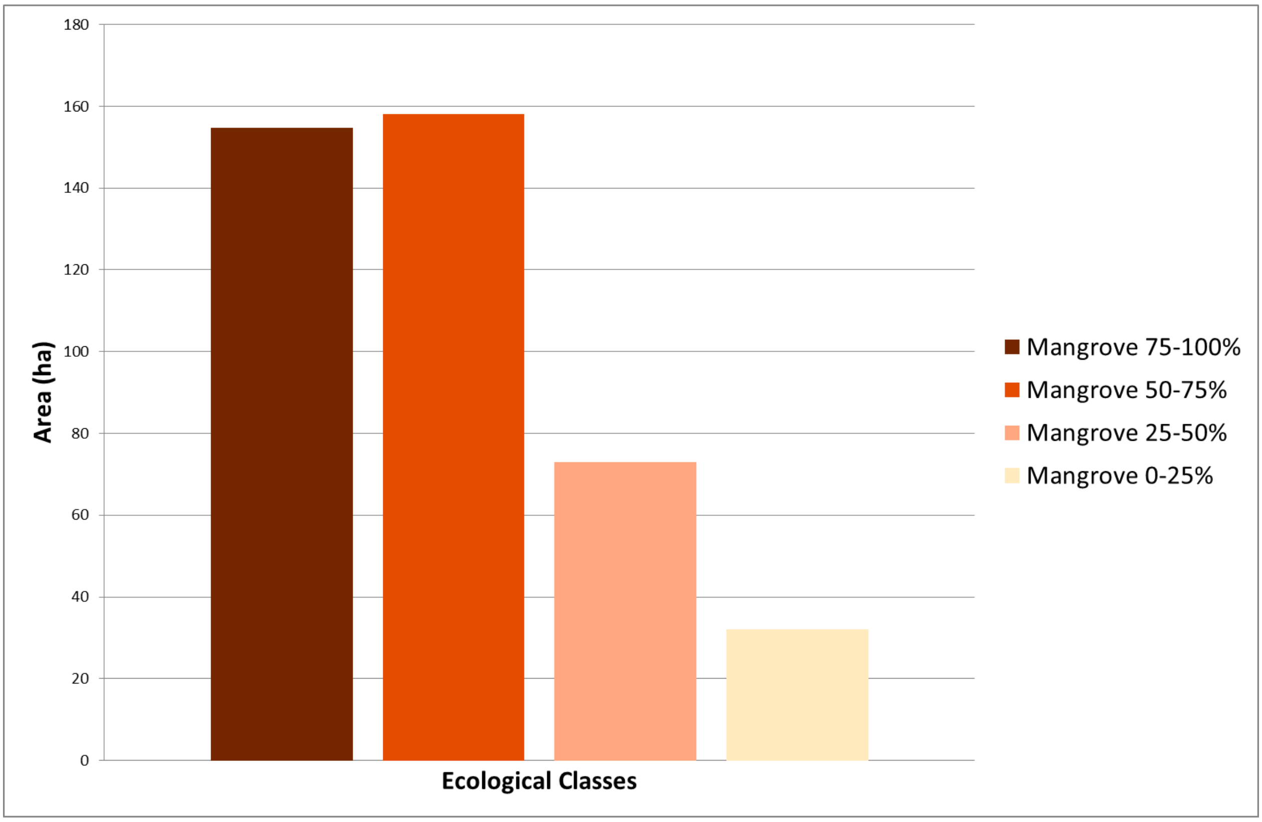


Figure 14: Spatial extent of the diffent mangrove density classes within the South Water Caye Marine Reserve. The colours represent the colours used in the land cover maps (Figures 10-13 and 16-17).

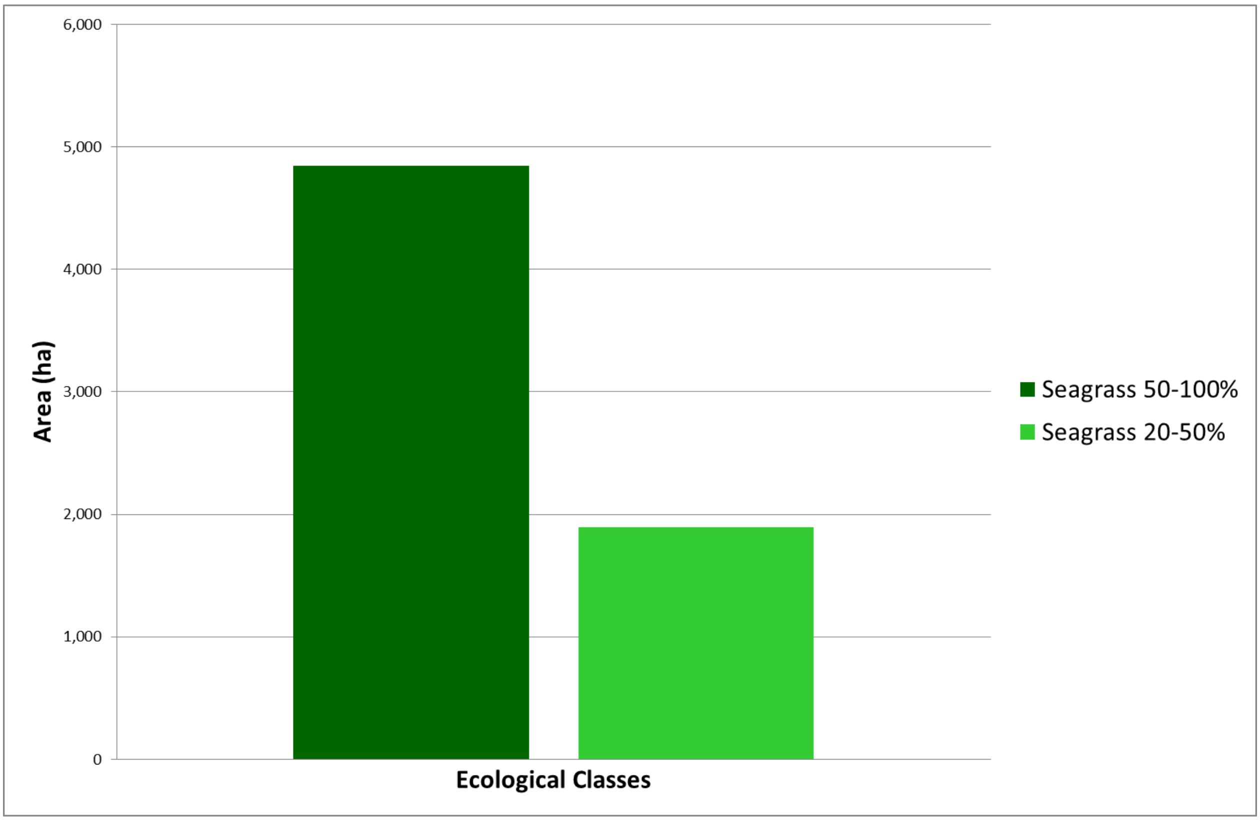


Figure 15: Spatial extent of the diffent seagrass density classes within the South Water Caye Marine Reserve. The colours represent the colours used in the land cover maps (Figures 10-13 and 16-17).

Tables 5-7 show how these ecological classes are distributed among the different zones (general use, conservation and preservation) of the South Water Caye Marine Reserve.

Table 5: Spatial extent of the different ecological classes classified in the South Water Caye Marine Reserve located in the general use zone. Also shown is the percentage of the total mangrove/seagrass cover and the percentage of the total South Water Caye Marine Reserve for each class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total South Water Caye Marine Reserve (47,703 ha) (%)
Mangrove 75-100%	60	14.3	0.1
Mangrove 50-75%	65	15.7	0.1
Mangrove 25-50%	28	6.7	0.1
Mangrove 0-25%	13	3.2	0.0
Sum Mangrove	**166**	**39.7**	**0.3**
Seagrass 50-100%	3,252	48.3	6.8
Seagrass 20-50%	1,015	15.1	2.1
Sum Seagrass	**4,267**	**63.4**	**8.9**

Table 6: Spatial extent of the different ecological classes classified in the South Water Caye Marine Reserve located in the conservation zone. Also shown is the percentage of the total mangrove/seagrass cover and the percentage of the total South Water Caye Marine Reserve for each class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total South Water Caye Marine Reserve (47,703 ha) (%)
Mangrove 75-100%	95	22.8	0.2
Mangrove 50-75%	93	22.2	0.2
Mangrove 25-50%	45	10.8	0.1
Mangrove 0-25%	18	4.4	0.0
Sum Mangrove	**251**	**60.1**	**0.5**
Seagrass 50-100%	1,564	23.2	3.3
Seagrass 20-50%	877	13.0	1.8
Sum Seagrass	**2,441**	**36.2**	**5.1**

Table 7: Spatial extent of the different ecological classes classified in the South Water Caye Marine Reserve located in the preservation zone. Also shown is the percentage of the total mangrove/seagrass cover and the percentage of the total South Water Caye Marine Reserve for each class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total South Water Caye Marine Reserve (47,703 ha) (%)
Mangrove 75-100%	0.0	0.00	0.00
Mangrove 50-75%	0.1	0.03	0.00
Mangrove 25-50%	0.2	0.04	0.00
Mangrove 0-25%	0.5	0.12	0.00
Sum Mangrove	**0.8**	**0.19**	**0.00**
Seagrass 50-100%	31.4	0.47	0.07
Seagrass 20-50%	0.5	0.01	0.00
Sum Seagrass	**31.9**	**0.47**	**0.07**

Figures 16 and 17 show an impact area of potential future land cover change within the South Water Caye Marine Reserve.

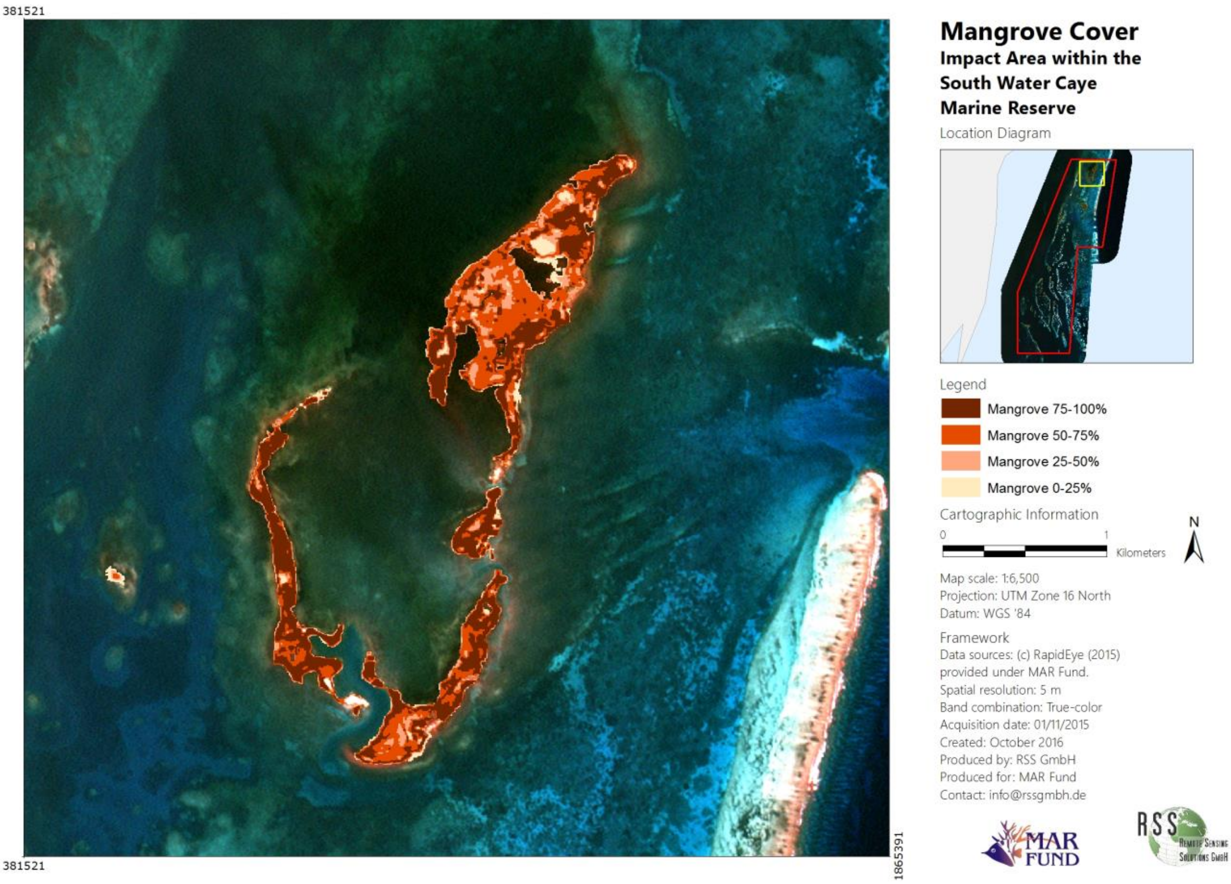


Figure 16: Impact area of potential future land cover change within the South Water Caye Marine Reserve. Displayed are the four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%). In the upper right diagram the location of this impact area within the South Water Caye Marine Reserve is displayed (yellow).

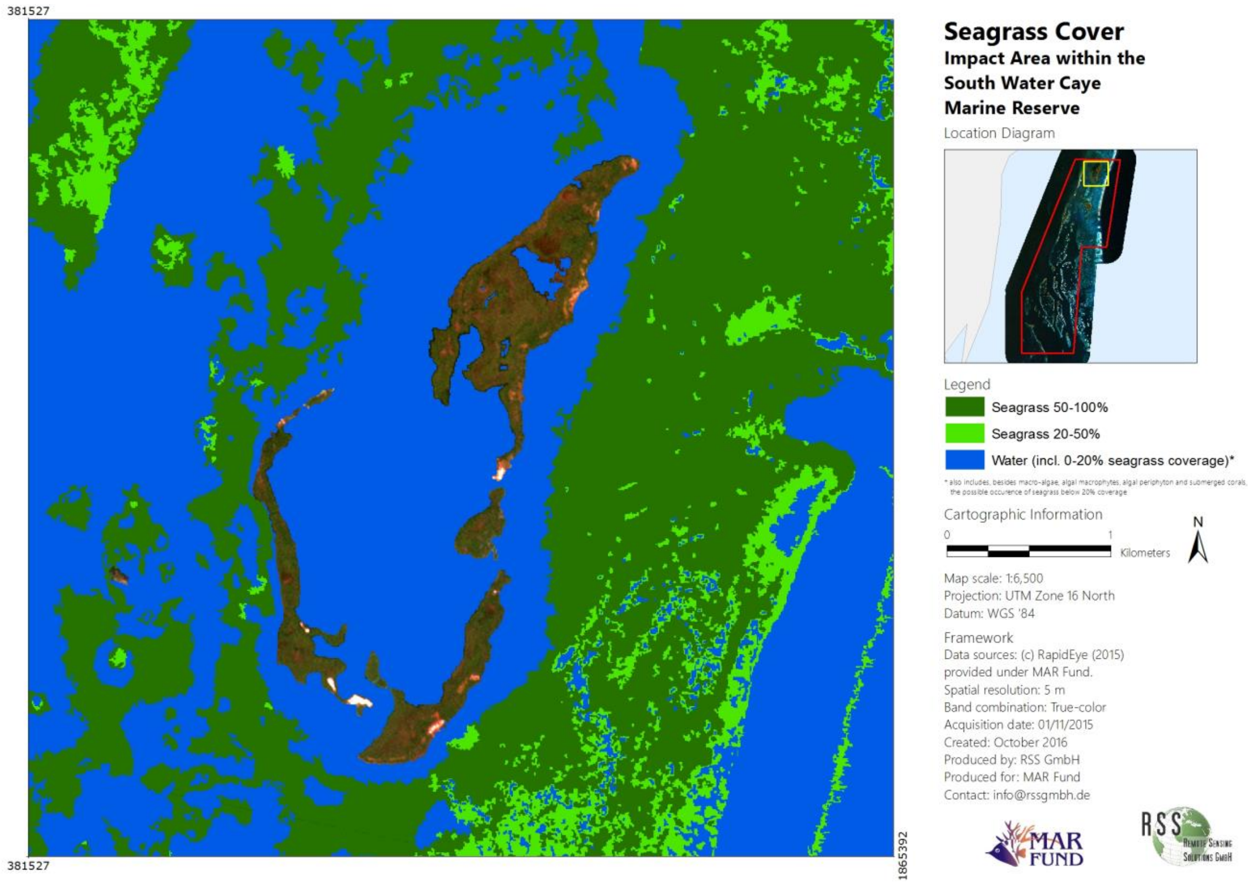


Figure 17: Impact area of potential future land cover change within the South Water Caye Marine Reserve. Displayed are the three acquatic classes (Water incl. 0-20% seagrass coverage, 20-50%, and 50-100% seagrass coverage). In the upper right diagram the location of this impact area within the South Water Caye Marine Reserve is displayed (yellow).

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 error matrix. Ground truth data points were collected directly by local experts of the project partner institute South Water Caye Marine Reserve. The ground truth campaign was planned in close 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 80 sites (4 quadrat measurements per site) (Figure 18). Each site was sampled by taking a GPS point exactly where the first quadrat was dropped, and 3 following quadrats were measured within a 50 m area (defined as 20 kicks) surrounding the first point.

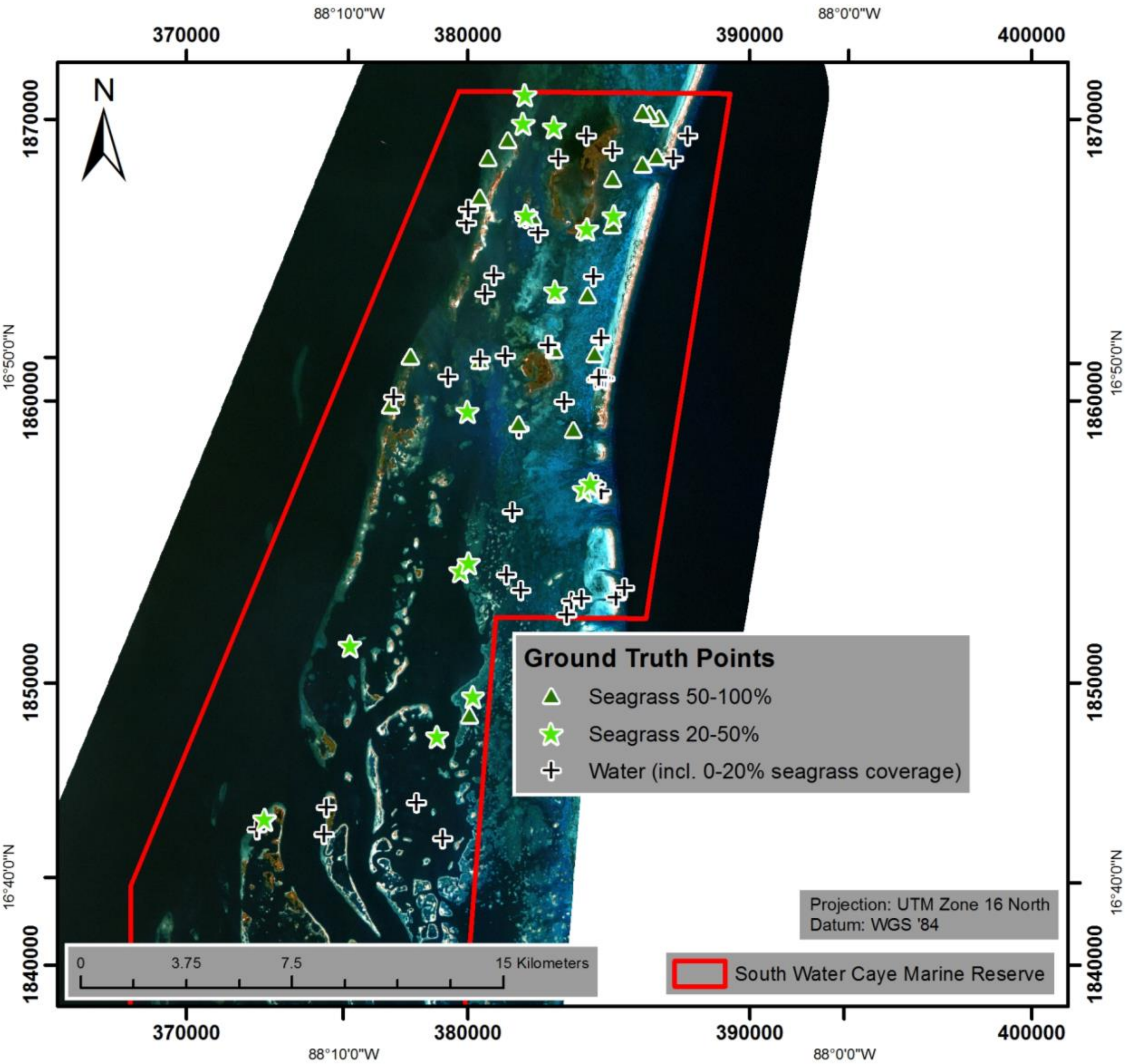


Figure 18: Location of the 80 ground truth data points collected by the local experts of the project partner institute South Water Caye Marine Reserve. Only seagrass cover and water points were requested.

As this ground truth data collection did not reach the sufficient amount of 50 points per class, additional samples of the original data (RapidEye imagery) were analyzed (Congalton and Green 1999). A random sample of additional 320 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 8 shows the amount of samples per class collected in the field and the amount collected in the original satellite imagery (RapidEye).

Table 8: Amount of ground truth samples per class collected in the field and collected 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%	22	28	**50**
Seagrass 20-50%	16	34	**50**
Land/Tidal Zone	0	50	**50**
Water**	42	8	**50**
Sum	**80**	**320**	**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.

Several statistical measures for the accuracy (overall accuracy, Kappa coefficient's of agreement, producer's and user's accuracy per class) were calculated. Tables 9 and 10 show the detailed results of the accuracy assessment. An **overall accuracy of 82.3%** with a **Kappa coefficient of 0.80** was realized.

Table 9: Confusion matrix per class by the use of 50 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%	**39**	9	1	1	-	-	-	-	**50**
Mangrove 50-75%	-	**42**	5	3	-	-	-	-	**50**
Mangrove 25-50%	-	-	**46**	4	-	-	-	-	**50**
Mangrove 0-25%	-	1	9	**40**	-	-	-	-	**50**
Seagrass 50-100%	-	-	-	-	**33**	11	-	6	**50**
Seagrass 20-50%	-	-	-	-	-	**46**	-	4	**50**
Land/Tidal Zone	-	-	4	1	-	-	**45**	-	**50**
Water*	-	-	-	-	3	9	-	**38**	**50**
Sum	**39**	**52**	**65**	**49**	**36**	**66**	**45**	**48**	**400**

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

Table 10: Producer's and User's Accuracy per class.

Class	Producer's Accuracy	User's Accuracy
Mangrove 75-100%	100.0%	78.0%
Mangrove 50-75%	80.8%	84.0%
Mangrove 25-50%	70.8%	92.0%
Mangrove 0-25%	81.6%	80.0%
Seagrass 50-100%	91.7%	66.0%
Seagrass 20-50%	69.7%	92.0%
Land/Tidal Zone	100.0%	90.0%
Water*	79.2%	76.0%

* 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 imagery from 01/11/2015 (GeoTIFF)
- Original Landsat 8 image from 01/11/2015 (GeoTIFF)
- Preprocessed RapidEye image mosaic from 01/11/2015 (GeoTIFF), XML-Metadata
- Preprocessed Landsat 8 image from 01/11/2015 (GeoTIFF), XML-Metadata
- Mangrove cover classification (Shapefile and Layerfile), XML-Metadata
- Seagrass cover classification (Shapefile and Layerfile), XML-Metadata
- Mangrove maps (with/without zonation) in A0 (pdf and ArcGIS .mxd-file), XML-Metadata
- Seagrass maps (with/Without zonation) 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

Shortcomings and Recommendations

Difficult ecological parameters made the detection of seagrass challenging. Here actual ground truth data, taken directly at the site of investigation, improved reliability and quality of the provided maps. More field data could be integrated in the development of the classification algorithms and the assessment of reliable object properties.

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 is free of charge.

However, the use of higher resolution image data would improve the quality and reliability of such a mapping. This is true in terms of spectral validity and stability of the remote sensing data, but most of all concerning the scale of the maps. For example, the modern WorldView-2 satellite records image data in eight spectral bands and at 1.8 m spatial resolution.

Another option which requires specialized skills of the consultant but provides, according to our experience, the best 'quality/price' ratio: a flight campaign recording high resolution image data over the MCPAs with a modern, air-based camera sensor, like UltraCam (http://www.microsoft.com/ultracam/en-us/default.aspx) or Intergraph's Z/I Imaging Digital Mapping Camera (DMC, http://www.ziimaging.com/en/zi-dmc-iie-camera-series_20.htm). The processing, correction and orthorectification of these data is operational and readily available, in contrast to very high resolution satellite data. Compared to satellite imagery, airborne data is recorded at stable atmospheric conditions with spatial resolutions from 10 cm to 50 cm, depending on the application, optimal weather and sea wave conditions may be chosen, guaranteeing highest image quality standards. The correction of illumination effects during the flight campaign is operational.

A flight campaign recording data over the four MCPAs may be implemented in one or two campaign days at costs much lower than hires satellite data, but improved spatial and radiometrical quality.

References

Atkinson, P. M. and Lewis, P. (2000). Geostatistical classification for remote sensing: an introduction. Computer & Geosciences, Volume 26, pp.361-371.

Benz, U. C., Hofmann, P., Wilhauk, G., Lingenfelder, I., Heyen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. Isprs J Photogramm 58 (3-4), pp. 239-258.

Chen, C. F., Son, N. T., Chang, N. B., Chen, C. R., Chang, L. Y., Valdez, M., Centeno, G., Thompson, C. A., Aceituno, J. L. (2013). Multi-Decadal Mangrove Forest Change Detection and Prediction in Honduras, Central America, with Landsat Imagery and a Markov Chain Model. Remote Sensing, Volume 5, pp.6408-6426.

Congalton, R.G. (1991). A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. Remote Sens Environ 37(1), pp. 35-46.

Congalton, R.G. and Green, K. (1999). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. CRC Press, Inc., United States of America.

Dekker, A., Brando, V., Anstee, J., Fyfe, S., Malthus, T., Karpouzli, E. (2006). Remote Sensing of Seagrass Ecosystems: Use of Spaceborne and Airborne Sensors. Seagrasses: Biology, Ecology and Conservation 2006, pp. 347-359.

Guindon, B. (1997). Computer-Based Aerial Image Understanding: A Review and Assessment of its Applications to Planimetric Information Extraction from Very High Resolution Satellite Images. Canadian Journal of Remote Sensing, Volume 23, pp.38-47.

Guindon, B. (2000). Combining Diverse Spectral, Spatial and Contextual Attributes in Segment-Based Image Classification. ASPRS 2000 Annual Conference.

Haralick, R. M. and Joo, H. (1986). A Context Classifier. IEEE Transactions on Geoscience and Remote Sensing, Volume 24, pp.997-1007.

Hay, G. J., Niemann, K. O., McLean, G. F. (1996). An object-specific image texture analysis of H-resolution forest imagery. Remote Sensing of Environment, Volume 55, pp.108-122.

Kartikeyan, B., Majumder, K. L., Dasgupta, A. R. (1995). An Expert-System for Land-Cover Classification. IEEE Transactions on Geoscience and Remote Sensing, Volume 33, pp.58-66.

Kartikeyan, B., Sarkar, A., Majumder, K. L. (1998). A segmentation approach to classification of remote sensing imagery. International Journal or Remote Sensing, Volume 19, pp.1695-1709.

Kettig, R. L. and Landgrebe, D. A. (1976). Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects. IEEE Transactions on Geoscience and Remote Sensing, Volume 14, pp.19-26.

Kuenzer, C., Bluemel, A., Gebhardt, S., Quoc, T.V., Dech, S. (2011). Remote Sensing of Mangrove Ecosystems: A Review. Remote Sens., 3, pp. 878-928.

Matsuyama, T. (1987). Knowledge-Based Aerial Image Understanding Systems and Expert Systems for Image-Processing. IEEE Transactions on Geoscience and Remote Sensing, Volume 25, pp.305-316.

McField, M. and Kramer P. R. (Eds.) (2007). Healthy Reefs for Healthy People: A Guide to Indicators of Reef Health and Social Well-being in the Mesoamerican Reef Region. Smithsonian Institution. Available online: http://www.healthyreefs.org/cms/publications/.

Mott, C (2005). Objektorientierte Klassifikationsstrategien zur Erfassung der Landnutzung aus hochauflösenden Fernerkundungsdaten. Technische Universität München. PhD-Thesis.

Mumby, P. J., Green, E. P., Edwards, A. J., Clark. C. D. (1997). Coral reef habitat mapping: how much detail can remote sensing provide? Marine Biology. Volume 130, Issue 2, pp.193-202.

Mumby, P.J., Green, E.P., Edwards, A.J. and Clark, C.D. (1999). The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. Journal of Environmental Management, 55, pp.157–166.

Remote Sensing Handbook for Tropical Coastal Management (2004). E. P. Green, P. J. Mumby, A. J. Edwards, C. D. Clark edited by A. J. Edwards.

Richter, R. and Schläpfer, D. (2011). Atmospheric / Topographic Correction for Satellite Imagery. DLR report DLR-IB 565-02/11, Wessling, Germany, 202 pp.

USGS website assessed in Feb. 2016. http://landsat.usgs.gov/landsat8.php.

Wabnitz, C. C. C., Andrefouet, S., Torres-Pulliza, D., Muller-Karger, F. E., Kramer P. A. (2007). Regional-scale seagrass habitat mapping in the Wider Caribbean Region using Landsat sensors: Applications to Conservation and Ecology. University of British Columbia Fisheries Centre Working Paper Series. Working Paper # 2007-04. 44 pp.

Walker, Z. (2009). South Water Caye Marine Reserve – Management Plan 2010 - 0215. Wildtracks, Belize.

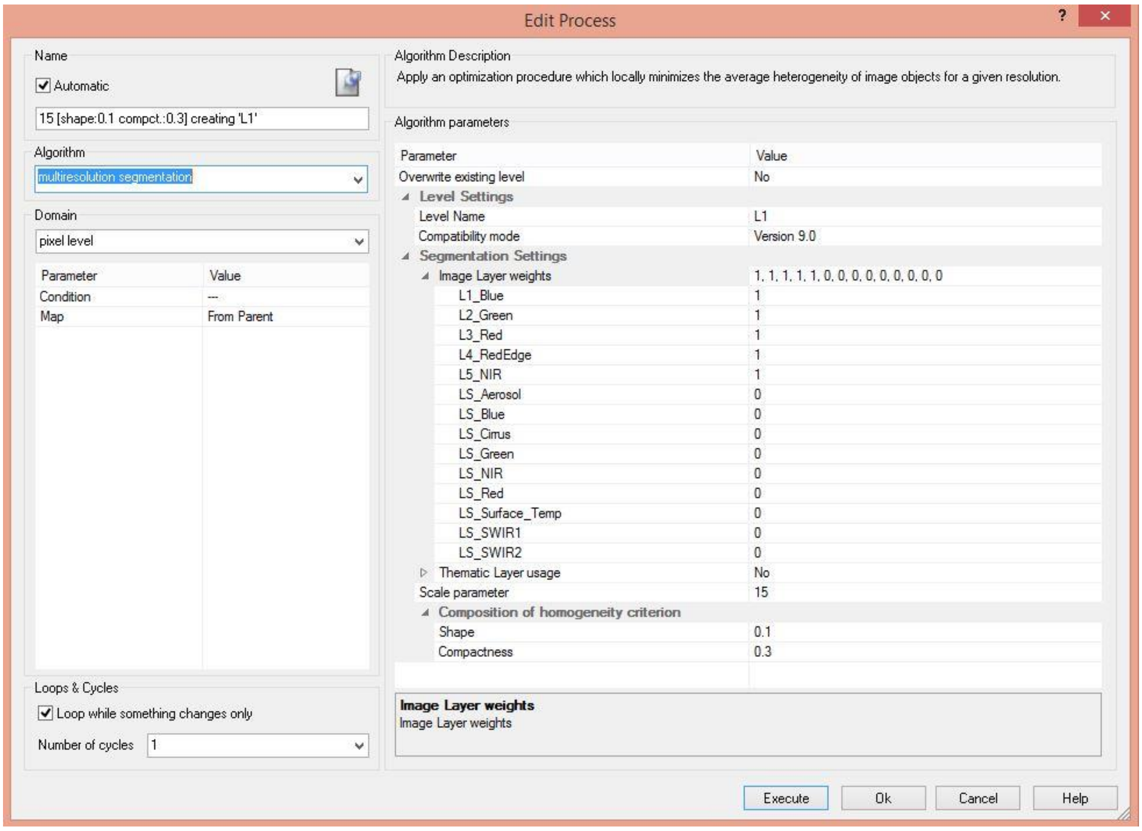
Woodcock, C. E., Strahler, A. H., Jupp, D. L. B. (1988). The use of variograms in remote sensing I: Scene models and simulated images. Remote Sensing of Environment, Volume 25, pp.323-348.

Annex I

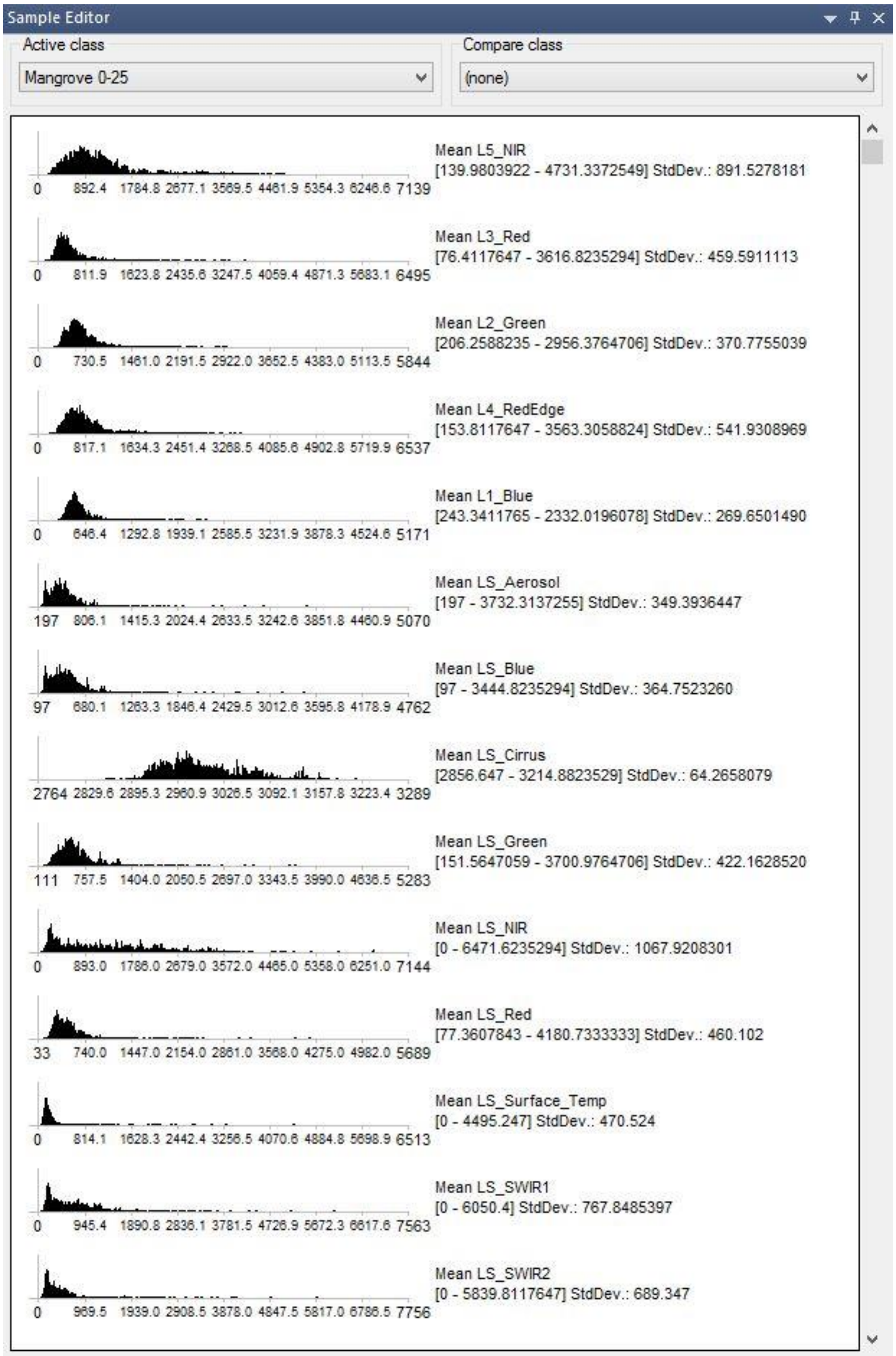
List of Abbreviations for the different spectral bands and indices used

Abbreviation	Band/Description	Spectral Range (nm)/Equation
L1_Blue	RapidEye blue	440-510
L2_Green	RapidEye green	520-590
L3_Red	RapidEye red	630-685
L4_RedEdge	RapidEye red edge	690-730
L5_NIR	RapidEye near infrared	760-850
LS_Aerosol	Landsat 8 coastal aerosol	430-450
LS_Blue	Landsat 8 blue	450-510
LS_Cirrus	Landsat 8 cirrus	136-138
LS_Green	Landsat 8 green	530-590
LS_NIR	Landsat 8 near infrared	850-880
LS_Red	Landsat 8 red	640-670
LS_Surface_Temp	Landsat 8 surface temperature	Calculated from the two thermal bands TRIS 1 and TRIS 2
LS_SWIR1	Landsat 8 short wave infrared 1	1,570-1,650
LS_SWIR2	Landsat 8 short wave infrared 2	2,110-2,290
Anthocyanin RI	RapidEye Anthocyanin Reflectance Index	(1/[Mean L2_Green])/(1/[Mean L4_RedEdge])
Chloryphyll Green	RapidEye Chlorophyll Green Index	1/([Mean L5_NIR]/[Mean L2_Green])
Cust_Brightness_RGB	RapidEye Cust Brightness RGB Index	([Mean L1_Blue]+[Mean L2_Green]+[Mean L3_Red])/3
GreenRatio	RapidEye Green Ration Index	([Mean L2_Green]+[Mean L1_Blue])/[Mean L1_Blue]
NDVI	RaipidEye Normalized Difference Vegetation Index	([Mean L5_NIR]-[Mean L3_Red])/([Mean L5_NIR]+[Mean L3_Red])
NDWI_IR	RapidEye Normalized Difference Water Infrared Index	([Mean L2_Green]-[Mean L5_NIR])/([Mean L2_Green]+[Mean L5_NIR])
NDWI_Red_Edge	RapidEye Normalized Difference Water Red Edge Index	([Mean L2_Green]-[Mean L4_RedEdge])/([Mean L2_Green]+[Mean L4_RedEdge])

Segmentation parameters used



Statistical parameters of the feature objects for the class Mangrove 0-25%



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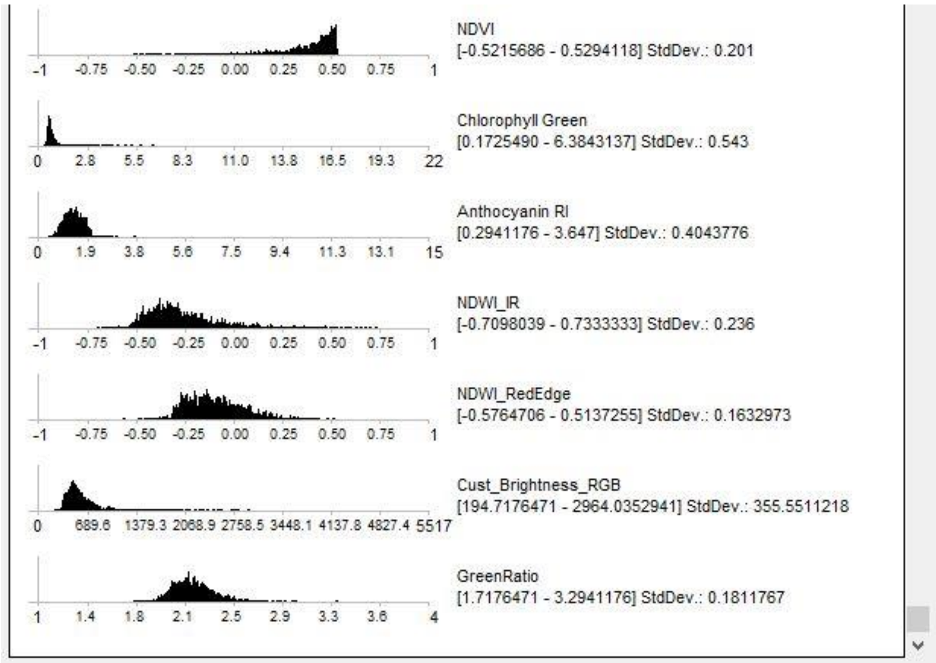
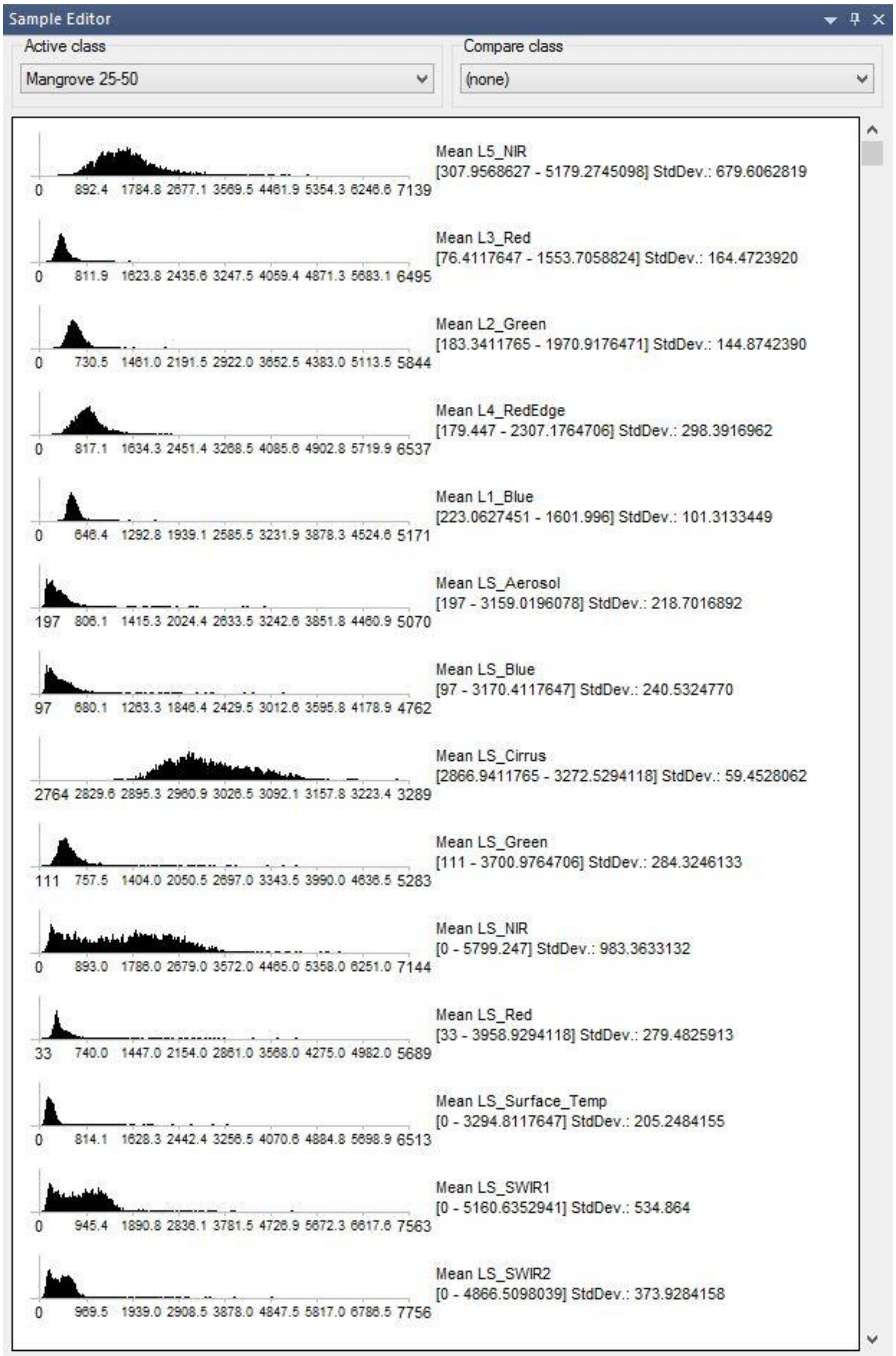


Statistical parameters of the feature objects for the class Mangrove 25-50%



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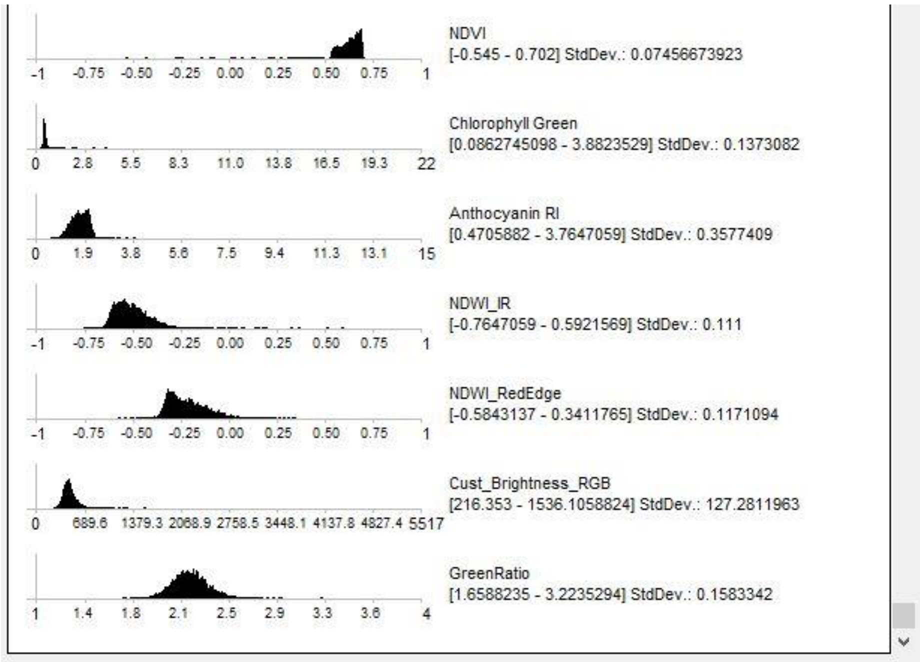
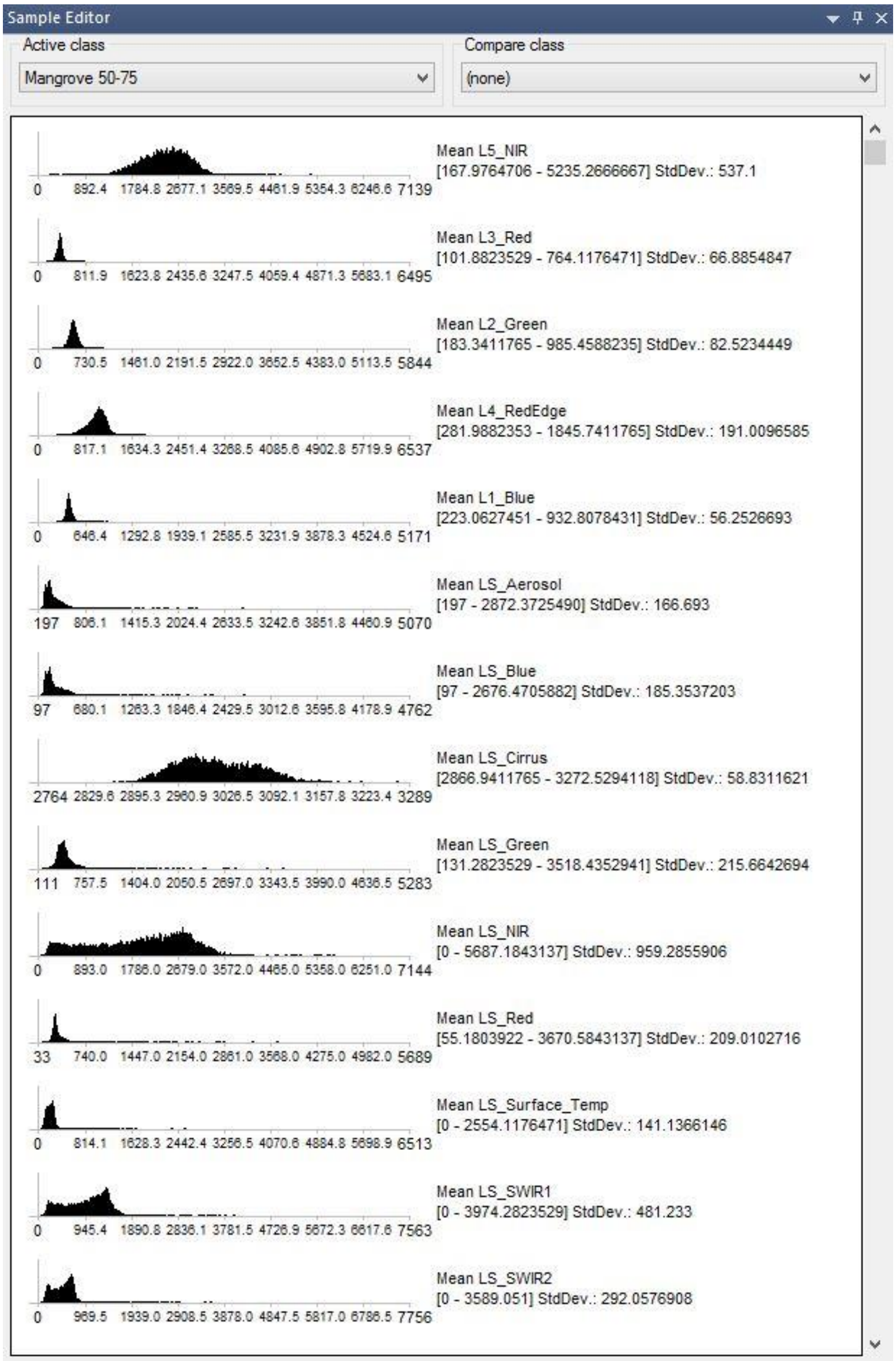


Statistical parameters of the feature objects for the class Mangrove 50-75%



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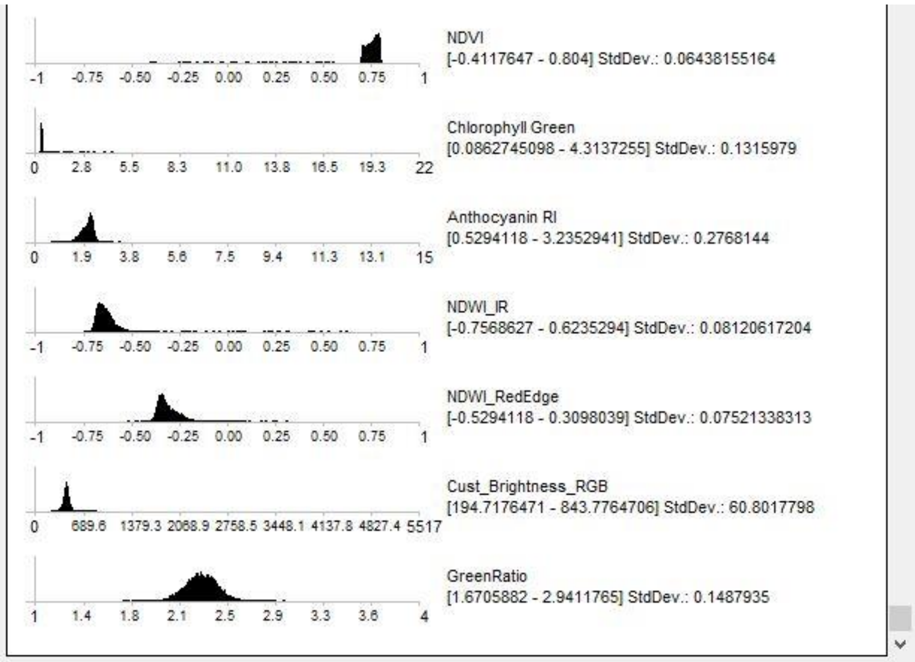

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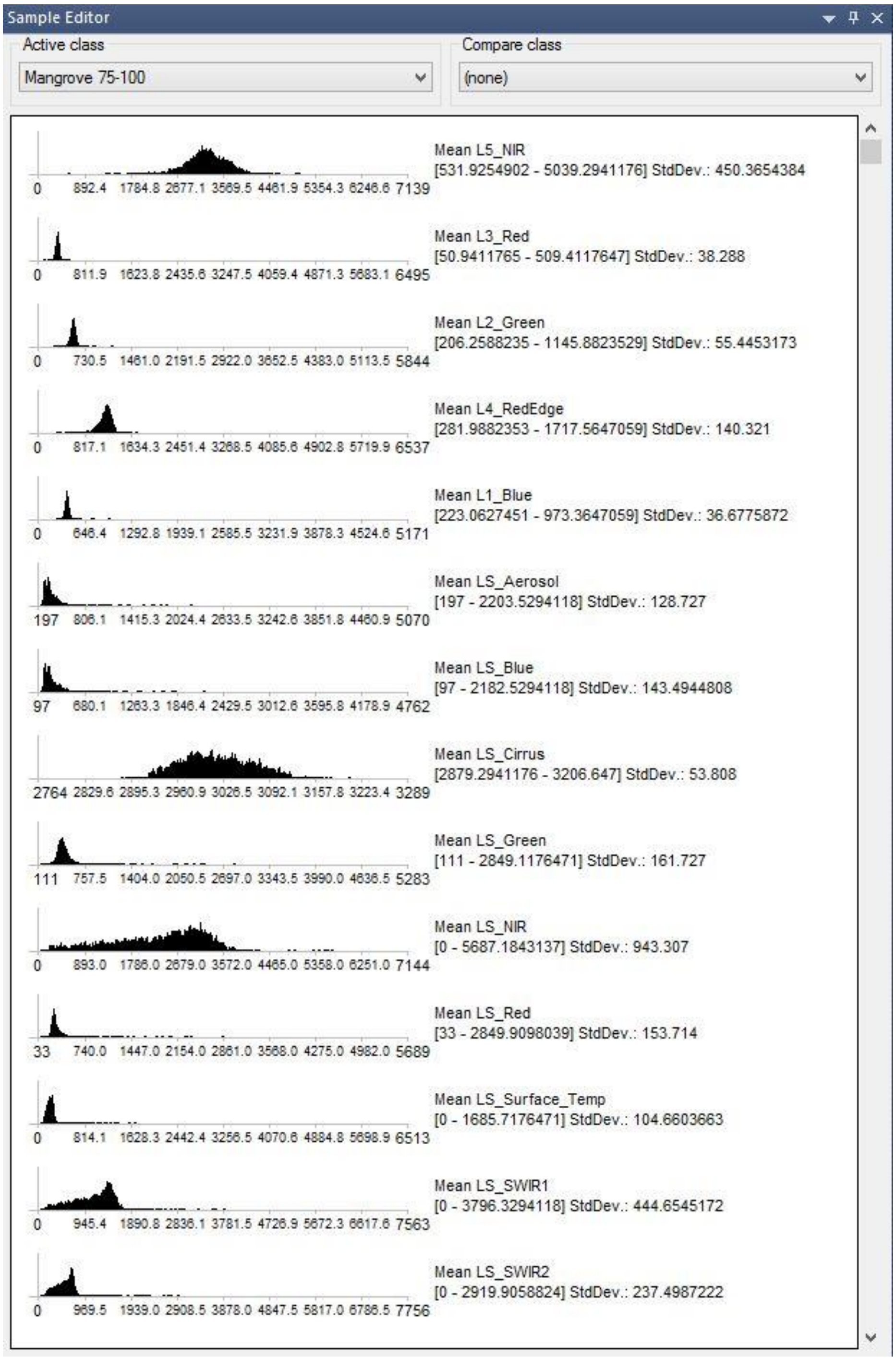
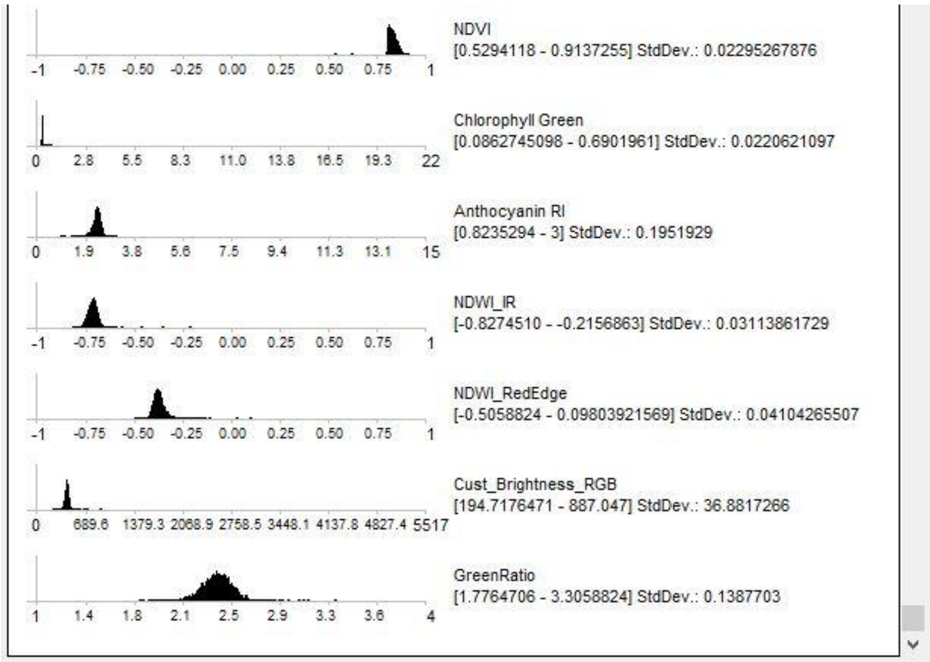
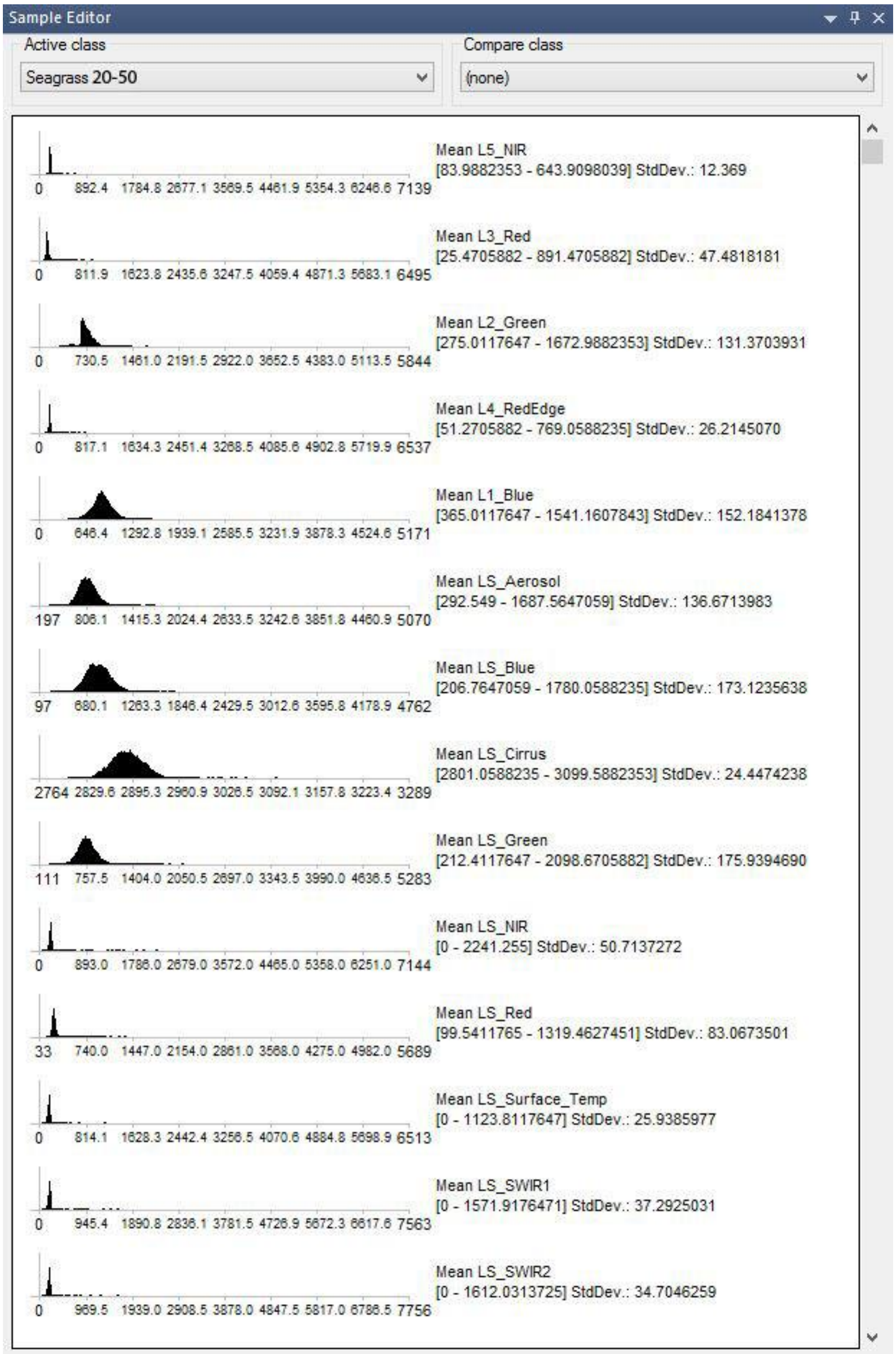


Statistical parameters of the feature objects for the class Mangrove 75-100% cont.



Statistical parameters of the feature objects for the class Seagrass 20-50%



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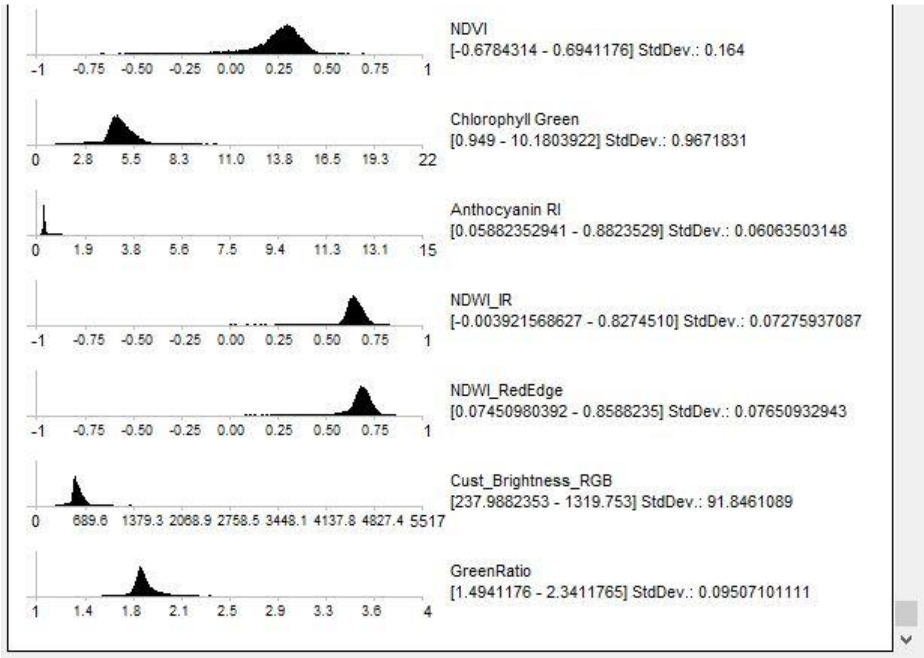

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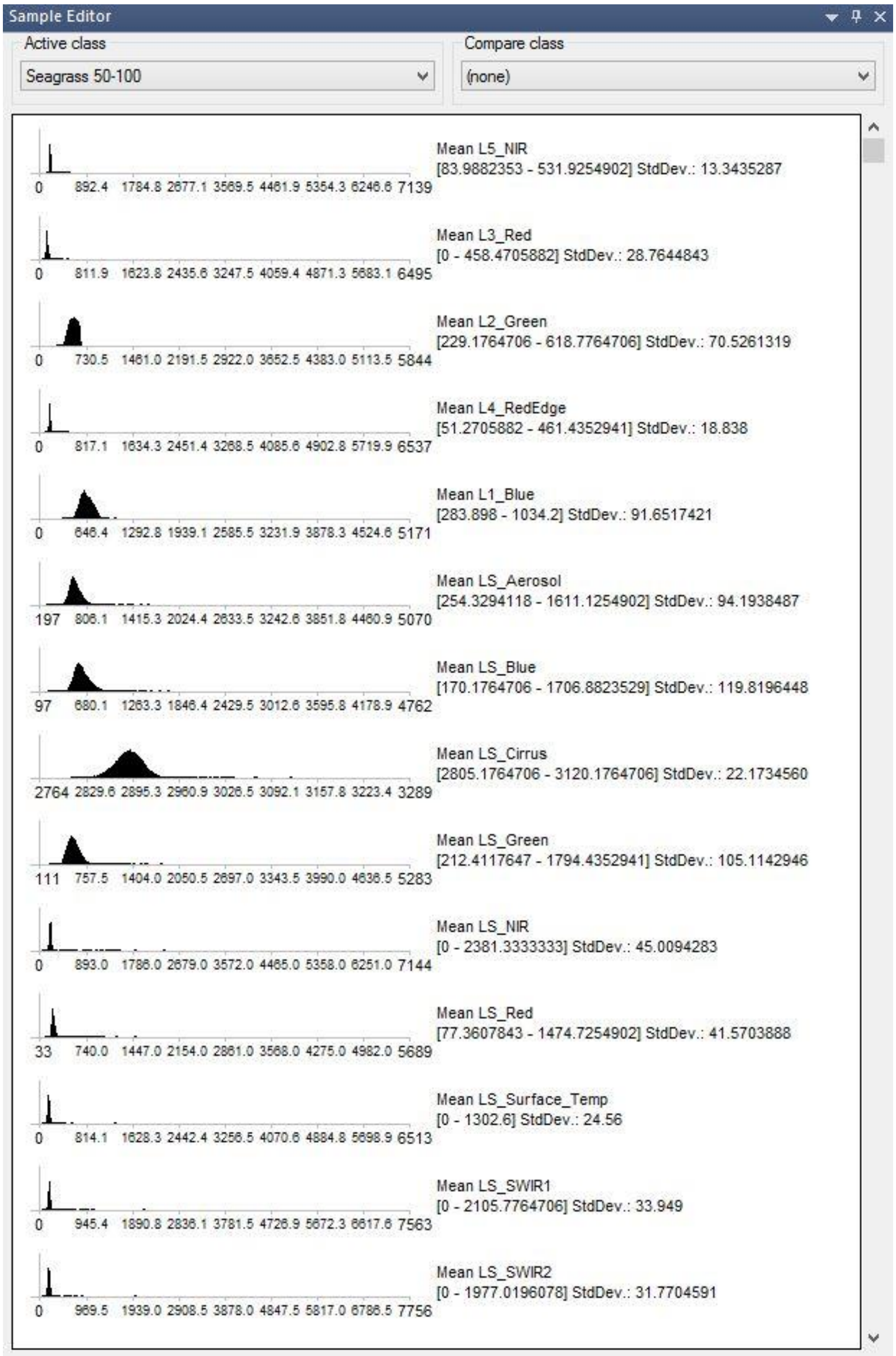

Statistical parameters of the feature objects for the class Seagrass 50-100% cont.