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

Sandy Bay-West End Special Protection Area, Honduras

Report

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1. Introduction

The Mesoamerican Reef (MAR) complex is stretching from Mexico to Honduras. Coastal and marine ecosystems are remarkably biologically rich and provide a variety of ecosystem services to the adjoining nations Mexico, Belize, Guatemala, and Honduras. Ecosystem services include e.g. shelter from tropical storms, reef fisheries, a wealth of biodiversity, a prosperous tourism industry or the provision of building materials. Besides coral reefs, mangrove and seagrass habitats are a precious part of the coastal ecosystem. Objective of this study was to establish the actual coverage of the Mangroves' and Seagrass' extent in four Marine and Coastal Priority Protected Areas (MCPA) in the Mesoamerican Reef area.

Actual coverage of the mangroves and seagrass meadows in four MCPAs was assessed using satellite imagery recorded in 2013. This coverage assessment was implemented in the framework of the project "Conservation of Marine Resources in Central America" (total volume: € 6.3 million, thereof € 5 million from KfW). This project aims to support 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 the Fund for the Mesoamerican Reef System (MAR Fund).

Consequent monitoring of ecosystems in the MAR is inevitable for preventing the continuing rapid loss of those habitats. Many studies and initiatives proved the high potential remote sensing techniques for assessing coastal habitats like seagrass canopies (Dekker et al. 2006, Mumby et al. 1997) or mangroves (Green at al. 2004, Kuenzer 2011), health status and potential stress parameters in coastal ecosystems. Mapping those ecosystems via remote sensing using aerial and satellite sensors has shown to be more cost-effective than fieldwork (Mumby et al. 1999). The ecological values of mangroves and seagrass meadows in most tropical countries have been recognized as valuable natural resources.

The four MCPAs are the areas of investigation:

1. Yum Balam Protection Area for Flora and Fauna, Mexico
2. Port Honduras Marine Reserve, Belize
3. Punta de Manabique Wildlife Refuge, Guatemala
4. Sandy Bay-West End Special Protection Area, Honduras

The available information on seagrass and mangrove coverage is based on several assessment methodologies and different 'quality' frameworks as shown by Wild (2013). The 2013 technical report 'Analytical summary of available information on mangrove and seagrass data from protected areas & Proposal for establishing the baseline for seagrass and mangrove area cover' concludes: *In order to accurately assess comparative baseline seagrass and mangrove cover in all four MCPAs identical methods need be used. Such methods need to be adjusted to quantify seagrass cover despite the ongoing turbidity problems.* As most critical the various dates of the area assessments are seen (Wild 2013).

The present report describes the procurement, preprocessing and classification of high resolution RapidEye and Landsat 8 imagery for the project area MCPA **Sandy Bay-West End Special Protection Area**, Honduras. RSS - Remote Sensing Solutions GmbH generated mangrove and seagrass cover maps that represent the 2013 cover status in the project area at a high spatial and thematic level of detail. These mangrove and seagrass cover maps, generated at fine scales, which also provide information on different density classes, can be used as input for up-to-date (2013) baseline. The baseline is required to determine, at the end of the project, if following two main objective indicators of the MAR Fund have been accomplished:

- 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 (2013) baseline coverage using actual RapidEye 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 Sandy Bay-West End Special Protection Area (Honduras) of the year 2013 – assessed at a reliable quality and comparable methodology
  - Seagrass area in the Sandy Bay-West End Special Protection Area (Honduras) of the year 2013 – assessed at a reliable quality and comparable methodology

The coverage assessment will serve as 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 data sets 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 exercise to measure the achievement of the indicators established. The primary evaluation point will be the mangrove and seagrass cover over the baseline established in 2013.

3. Project Area

The Sandy Bay-West End Special Protection area is situated on the island of Roatan (Honduras), which is part of the Bay Islands, and has a size of 2,154ha (Figure 1).

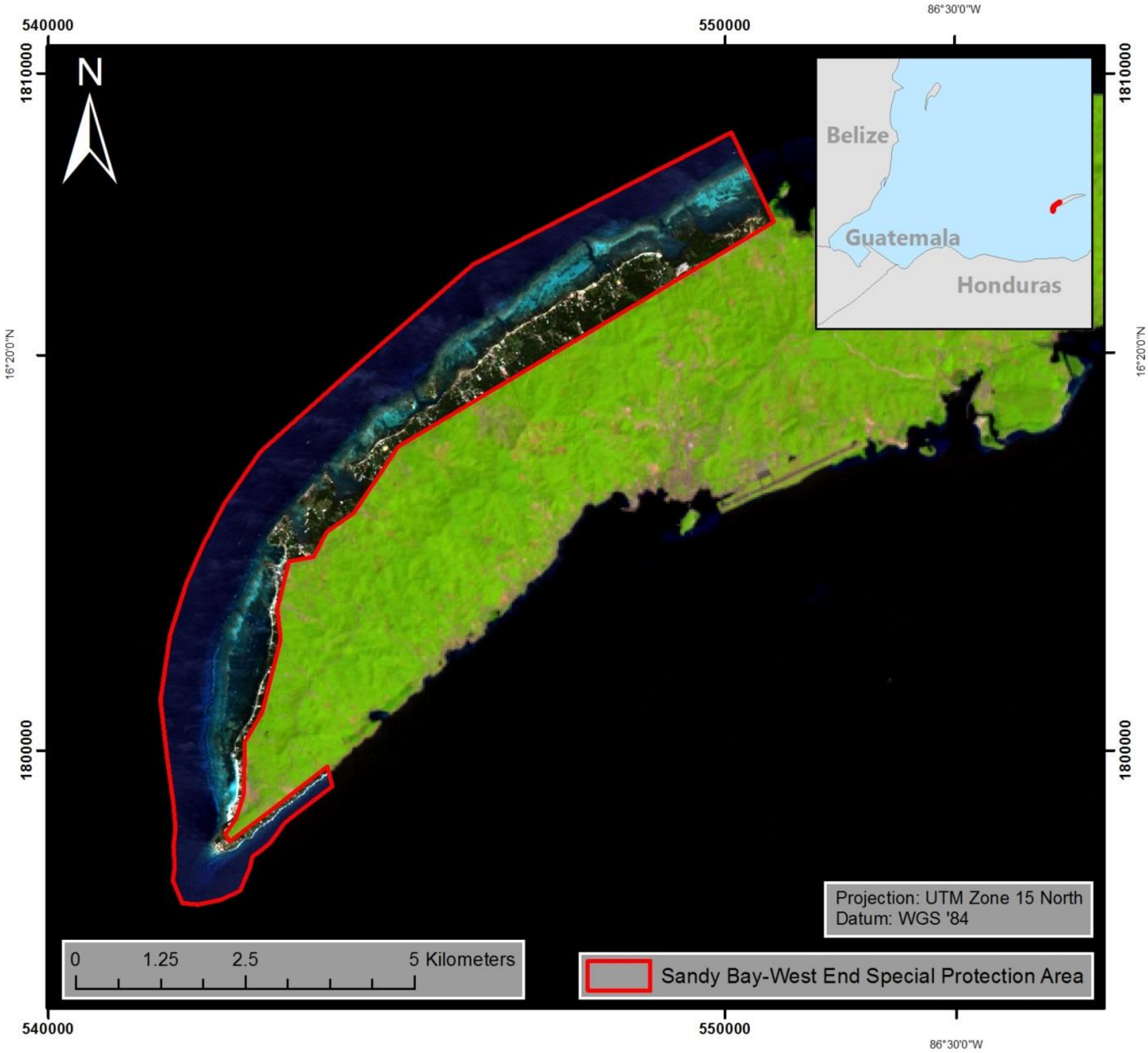


Figure 1: Overview of the Sandy Bay-West End Special Protection Area, Honduras. True-color RapidEye tiles (three tiles from 22/02/2013) superimposed on Landsat 8 data (26/09/2013; bands: short wavelength infrared (band 6), near infrared (band 5), and red (band 4). The border of Sandy Bay-West End Special Protection Area, Honduras, is shown 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).

As the Island of Roatan has a strong tourist sector, the mangroves and seagrass meadows in this area are threatened by coastal infrastructural development. Therefor baseline studies of mangrove and seagrass distribution are important as damages in 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 capture-, stabilization-, and formation of sediments. 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.

4. Data and Methods

4.1 Remote Sensing Data

Under the given framework conditions, two 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). Its spatial resolution is 6.5m, which is resampled to 5m 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 77km-wide swaths extending at least 1,500km 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: BlackBridge).

Number of Satellites	5
Number of Spectral Bands	5
Wavelength	440 - 510 nm (blue) 520 - 590 nm (green) 630 - 685 nm (red) 690 - 730 nm (red- edge) 760 - 850 nm (NIR)
Pixel Resolution **Dynamic Range**	6,5 m 12 bit
Ground sampling distance (nadir) **Pixel size (orthorectified)**	6.5 m 5 m
Swath Width **On board data storage**	77 km 1500 km of image data per orbit
Revisit Time	Daily (off-nadir) / 5.5 days (at nadir)
Equator Crossing	11:00 AM (approximately)
Aquisition Capability	4 Mio. km^2/day

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).

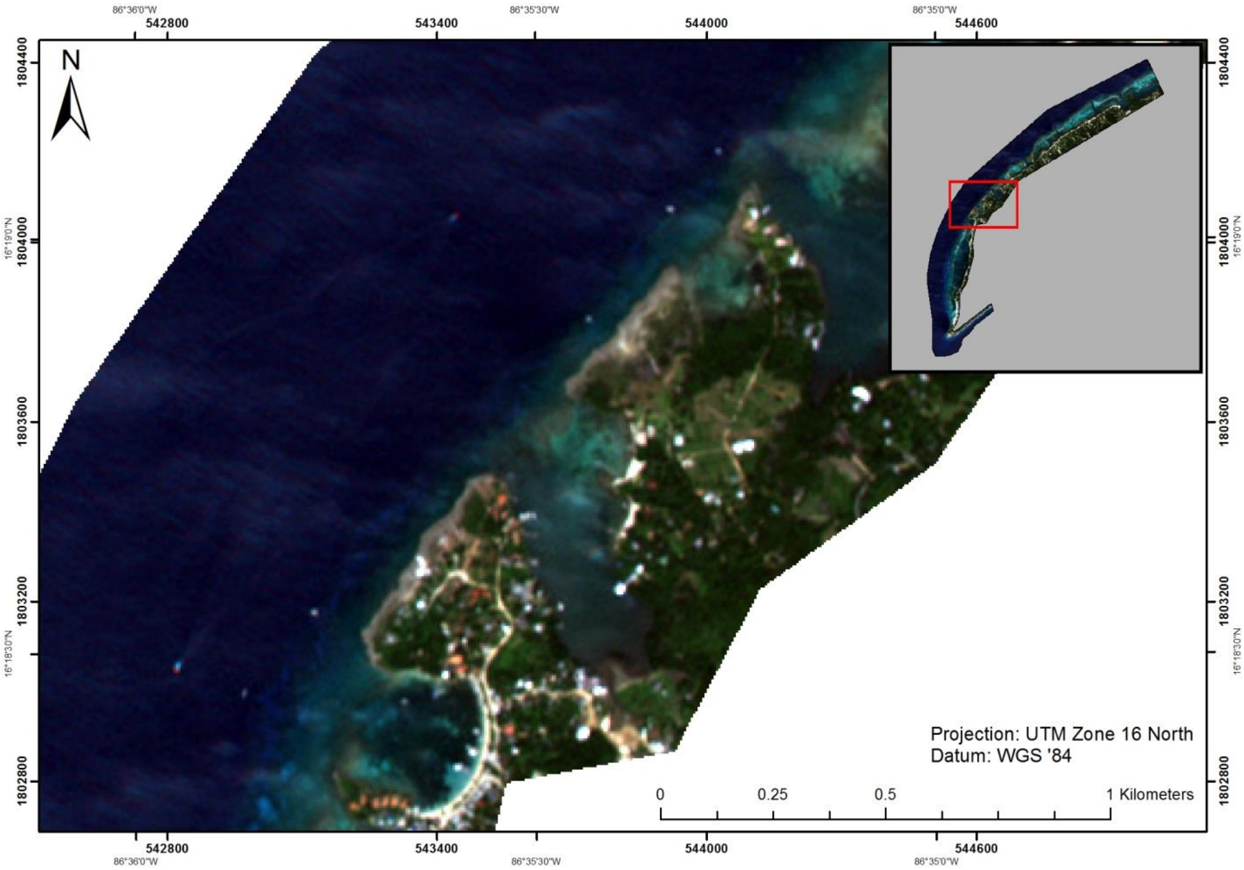


Figure 2: Subset of a RapidEye image (true-color) showing the spatial detail in land cover. The red rectangle in the upper right image shows the location of the subset within the Sandy Bay-West End Special Protection Area.

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

http://www.blackbridge.com/rapideye/upload/RE_Product_Specifications_ENG.pdf (March 2014)

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

Three Level 3A RapidEye tiles were used for the mangrove and seagrass classification of the Sandy Bay-West End Special Protection Area (three tiles from 22/02/2013). Figure 3 displays these almost cloud free tiles.

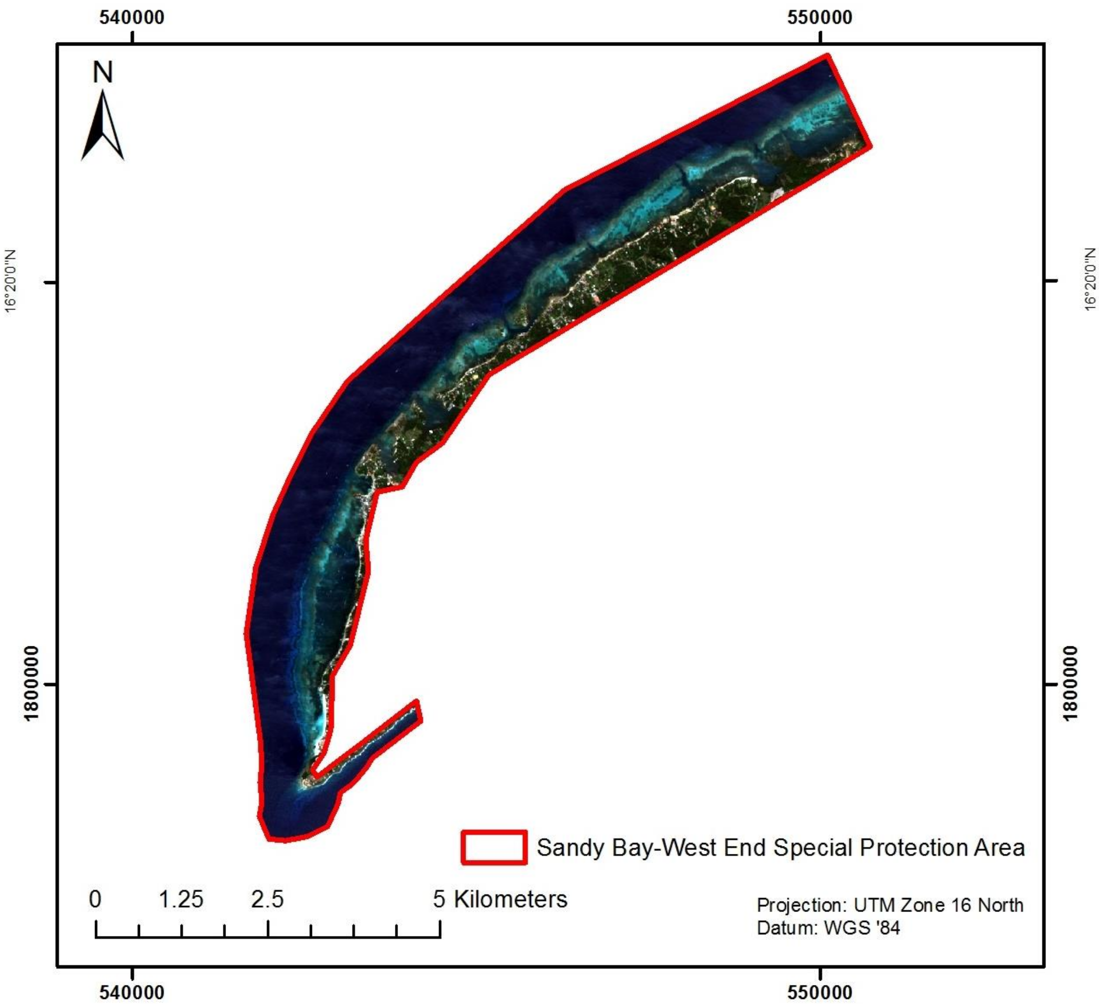


Figure 3: True-color RapidEye tiles (three tiles from 22/02/2013) used for the mangrove and seagrass mapping.

Landsat 8

Landsat satellites 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 kilometers 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 meter resolution and one panchromatic band at 15 meters. 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 profound information on Landsat 8 data is given 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).

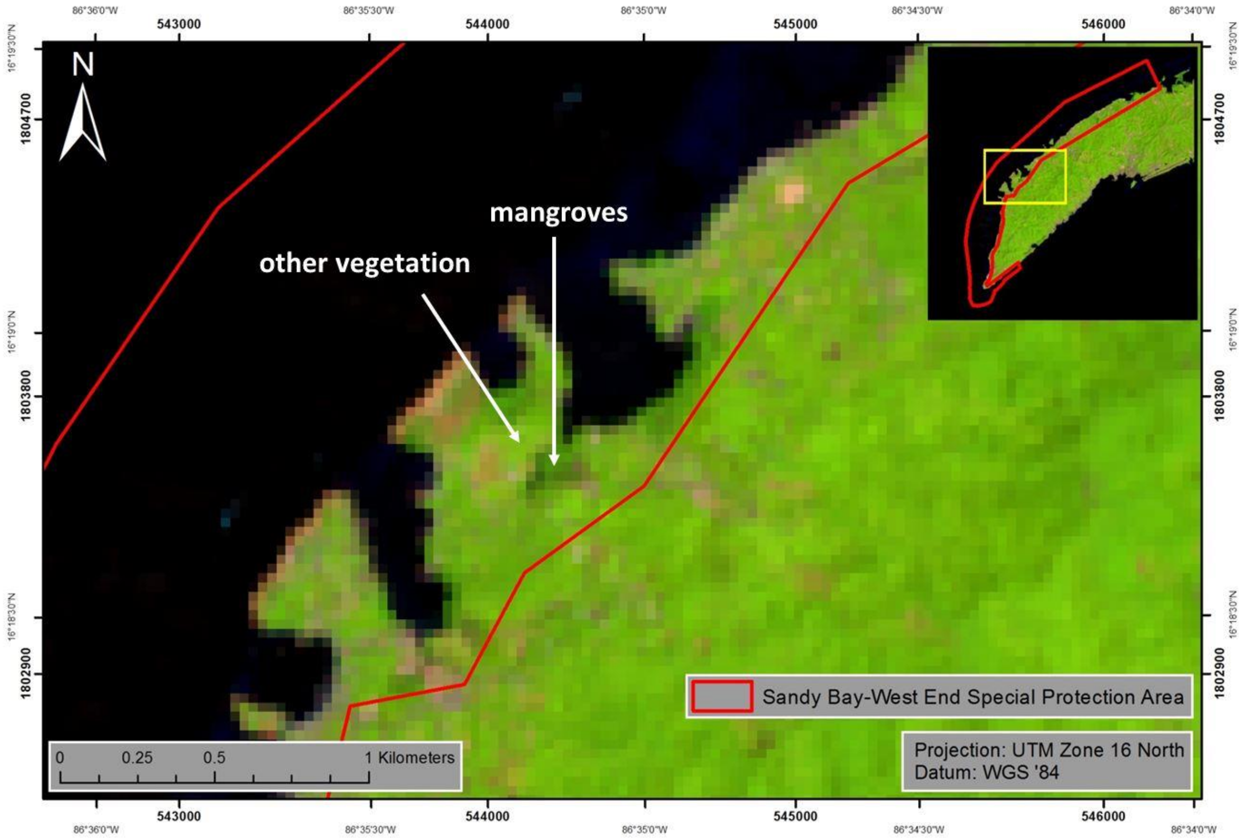


Figure 4: Subset of a Landsat 8 imagery (bands: short wavelength infrared (band 6), near infrared (band 5), and red (band 4) showing that mangroves can be differentiated from other vegetation types. The yellow rectangle in the upper right image shows the location of the subset within the Sandy Bay-West End Special Protection Area.

The Landsat 8 archive was checked and the most appropriate imagery (lowest cloud cover in project area) was downloaded (26/09/2013; scene cloud cover 6.87%). Figure 5 shows the acquired Landsat 8 data for the Sandy Bay-West End Special Protection Area.

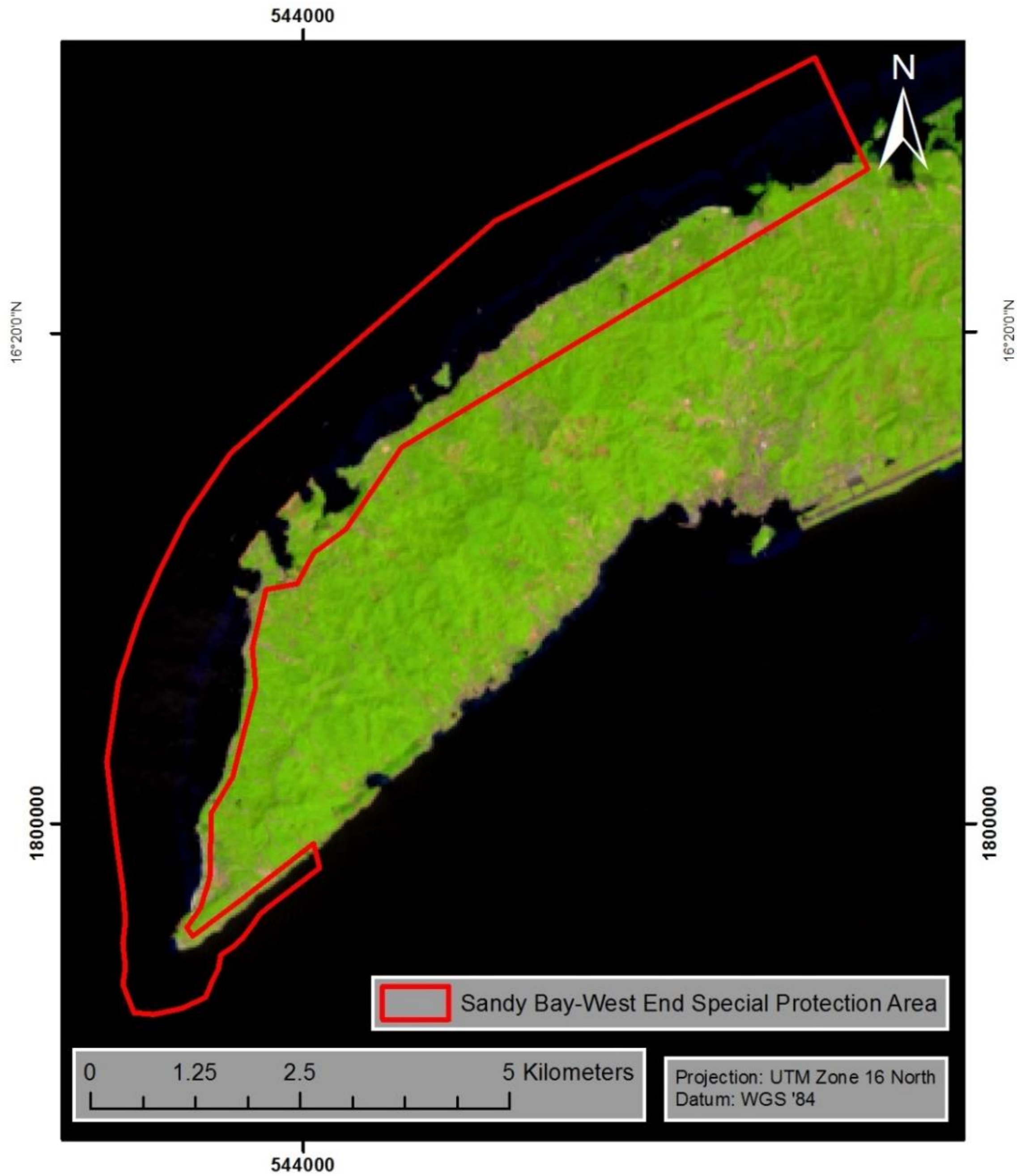


Figure 5: Landsat 8 scene (26/09/2013; bands: short wavelength infrared (band 6), near infrared (band 5), and red (band 4) used for the mangrove and seagrass mapping.

4.2 Data Preprocessing

The first preprocessing step was the removal of atmospheric effects that influence the signal, induced by water vapour and aerosols in the atmosphere, seasonal differences in illumination angles. This preprocessing step results in the calibration of the data leading to 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 semi-automatic segment-based rule-set classification method to be applied subsequently. 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). 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 Landsat8) and corresponding calibration file
- Atmospheric file: tropical maritime
- Satellite and sun geometry from the metadata of the satellite data
- Ground elevation: 0km

Landsat 8 product specifications state that the OLI has a 12m circular accuracy (Table 3). Visual analysis showed that the Landsat 8 data had a good geometrical fit with the RapidEye data so no geometrical co-registration was necessary.

As a basis for the mangrove and seagrass classification, a RapidEye image mosaic was generated.

4.3 Development of 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. Improving the spatial resolution of remote sensing systems, 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 neighbouring pixel clusters to 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 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 (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

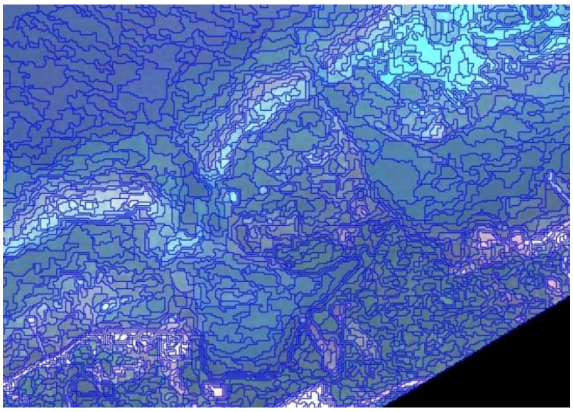
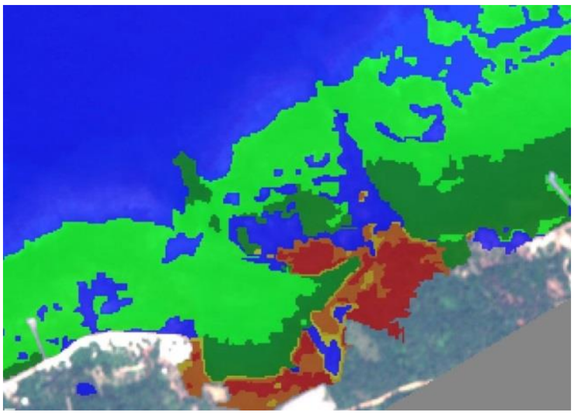


Image segmentation



Classification

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, 6 *ecological* classes were defined:

4 mangrove density classes:

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

2 seagrass density classes:

1. 0-50%
2. 50-100%.

Due to turbid sea, sun glint, missing field data or deep seagrass meadows it was not possible to differentiate 4 seagrass density classes as originally planned. (Figure 7).

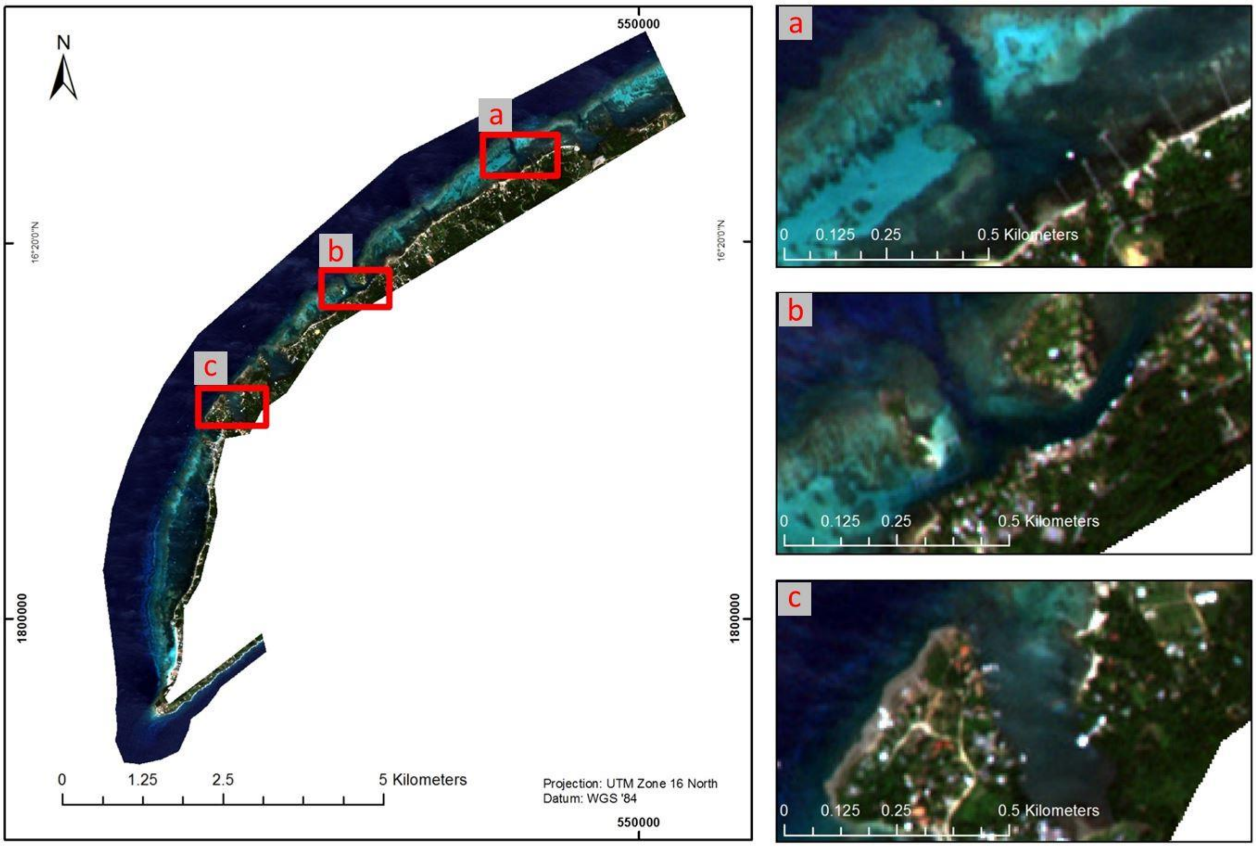


Figure 7: Examples for strong turbid sea within the project area. Here it was not possible to detect 4 density classes for seagrass.

Figure 8 illustrates the hierarchical structure of the classification scheme, each *ecological* class is represented by the colors of the final maps (Figures 9-11).

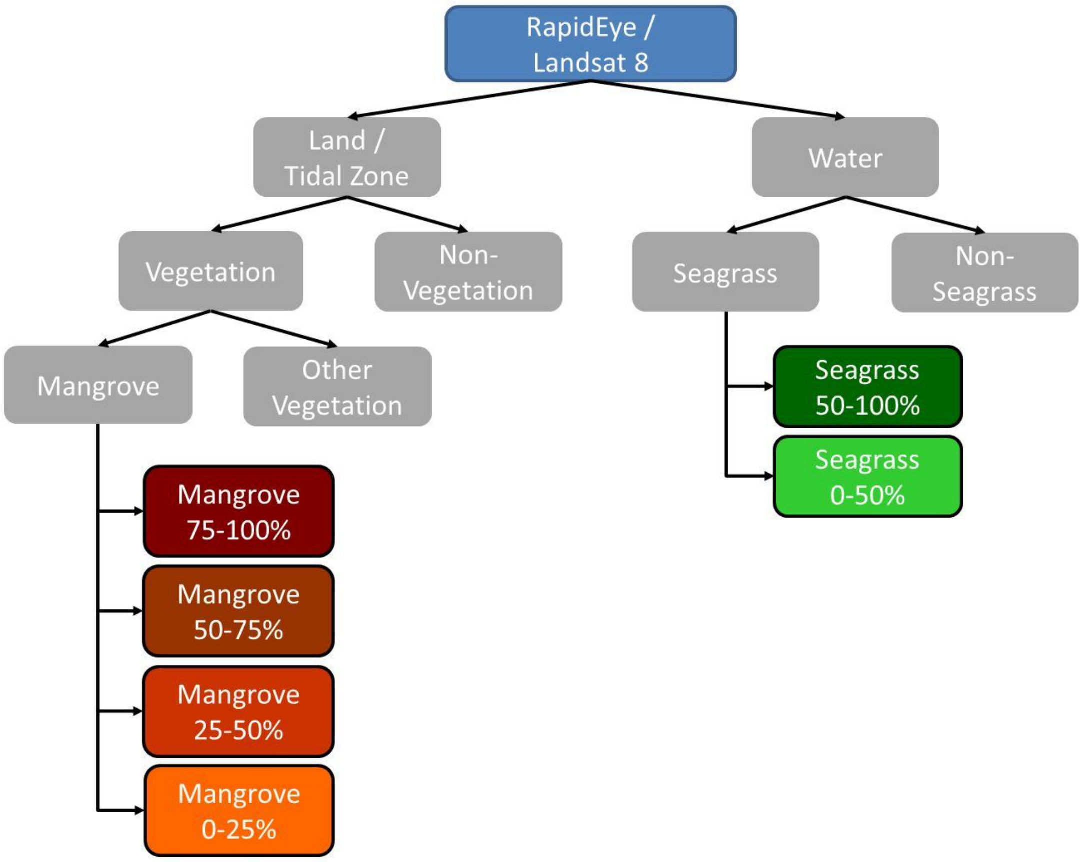


Figure 8: Classification scheme of the mangrove and seagrass cover classification of the Sandy Bay-West End Special Protection Area. Grey boxes without frame represent parent classes, framed boxes represent the final classes with their color as used in the land cover maps (Figures 9-10 and 13-14).

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 8.

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 was conducted based on spectral thresholds.

On the next level of the hierarchy, all land/tidal zone objects were discriminated into vegetated and non-vegetated objects according to their spectral properties. Water was discriminated into seagrass and non-seagrass objects based on their spectral and textural properties.

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 wavelength 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 0-25%) and seagrass into 2 density classes (50-100% and 0-50%) based on spectral and texture properties of these classes, as well as visual interpretation of the image.

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 used and the statistical parameters of the feature objects for the different classes.

5. Results

Figures 9 and 10 show the results for the mangrove and seagrass cover classification.

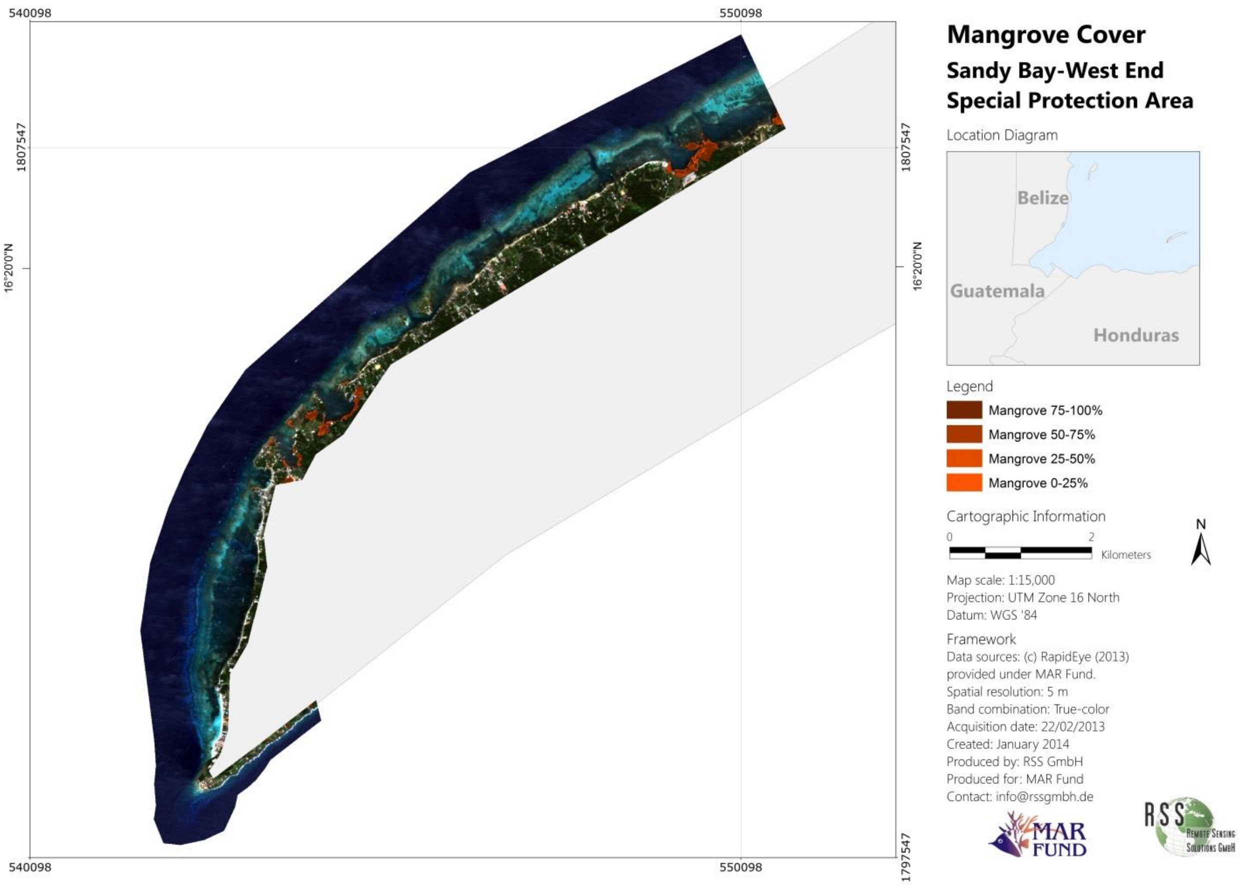


Figure 9: Mangrove cover classification for the Sandy Bay-West End Special Protection Area. Shown are the four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%). In the upper right diagram the location of the Sandy Bay-West End Special Protection Area within Honduras is displayed (red).

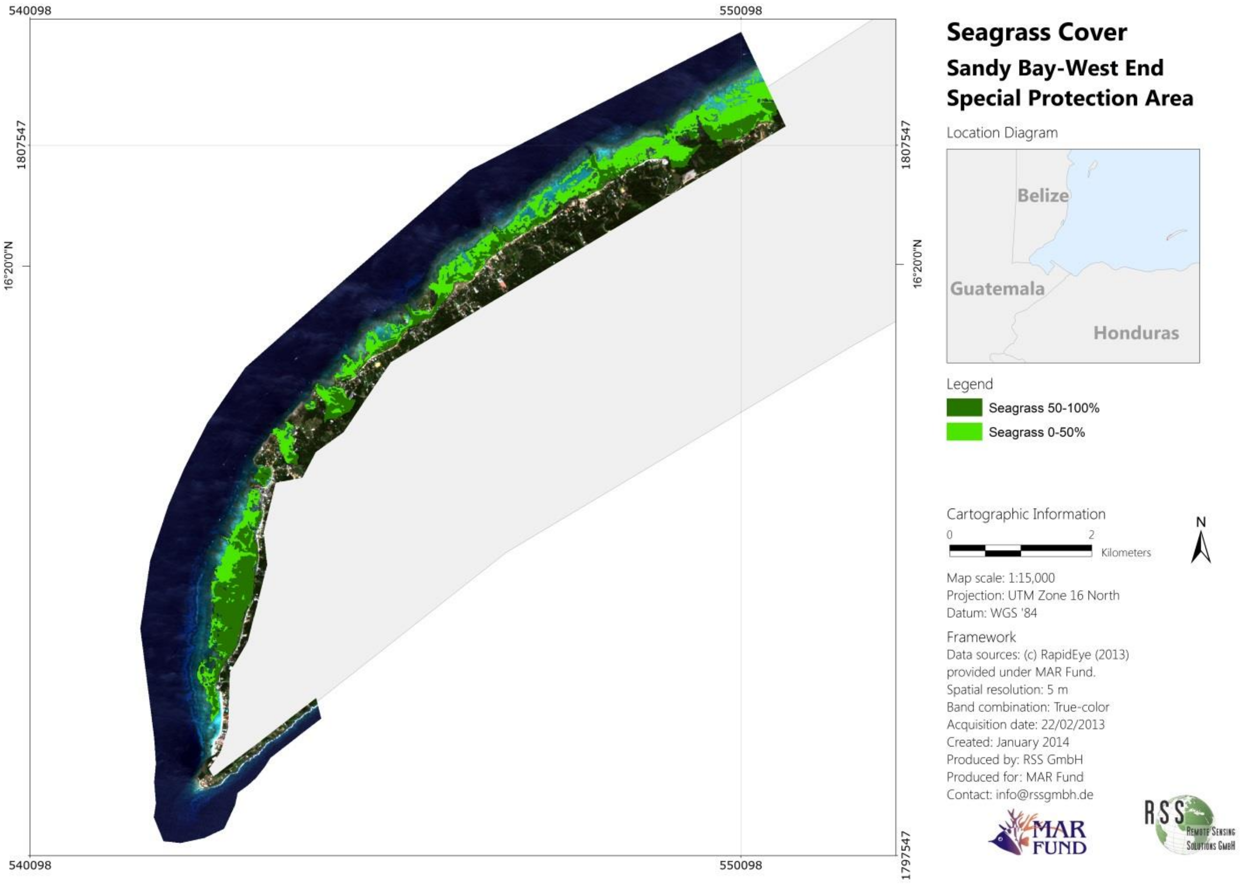


Figure 10: Seagrass cover classification for the Sandy Bay-West End Special Protection Area. Shown are the two seagrass density classes (0-50%, and 50-100%). In the upper right diagram the location of the Sandy Bay-West End Special Protection Area within Honduras is displayed (red).

The Punta de Manabique Wildlife Refuge has a total area of 2,154ha of which 12ha (0.6%) are covered by the class Mangrove 75-100%, 9ha (0.4%) by Mangrove 50-75%, 2ha (0.1%) by Mangrove 25-50%, 1ha (0.1%) by Mangrove 0-25%, 141ha (6.5%) by Seagrass 50-100%, and 191ha (8.9%) by Seagrass 0-50% (Table 4). The dominant class within the mangrove area with 48.9% is Mangrove 75-100%, followed by Mangrove 50-75% with 35.8%, Mangrove 25-50% with 9.7%, and Mangrove 0-25% with 5.6% (Table 4). The class Seagrass 0-50% with 57.6% was more abundant that the class Seagrass 50-100% with 42.4% (Table 4).

Table 4: Spatial extent of the different *ecological* classes classified in the Sandy Bay-West End Special Protection Area. Also shown is the percentage of the total mangrove/seagrass cover and the percentage of the total Sandy Bay-West End Special Protection Area for each class.

Ecological Class	Area (ha)	Percentage of total mangrove/seagrass cover (%)	Percentage of total Sandy Bay-West End Special Protection Area (2,154ha) (%)
Mangrove 75-100%	12	48.9	0.6
Mangrove 50-75%	9	35.8	0.4
Mangrove 25-50%	2	9.7	0.1
Mangrove 0-25%	1	5.6	0.1
Sum Mangrove	**25**	**100.0**	**1.1**
Seagrass 50-100%	141	42.4	6.5
Seagrass 0-50%	191	57.6	8.9
Sum Seagrass	**332**	**100.0**	**15.4**

The graphs in Figures 12 and 13 display the spatial extent of the different *ecological* classes classified in the Sandy Bay-West End Special Protection Area. The colors represent the colors of each class in the final maps (Figures 9-10 and 13-14).

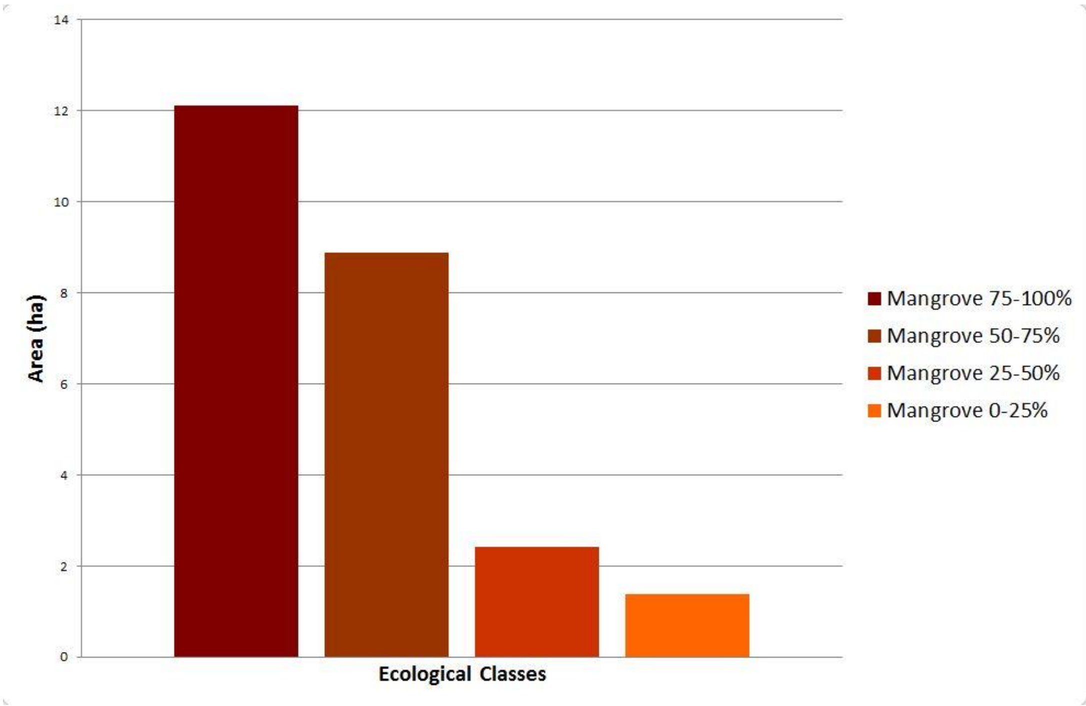


Figure 11: Spatial extent of the diffent mangrove density classes within the Sandy Bay-West End Special Protection Area. The colors represent the colors used in the land cover maps (Figures 9-10 and 13-14).

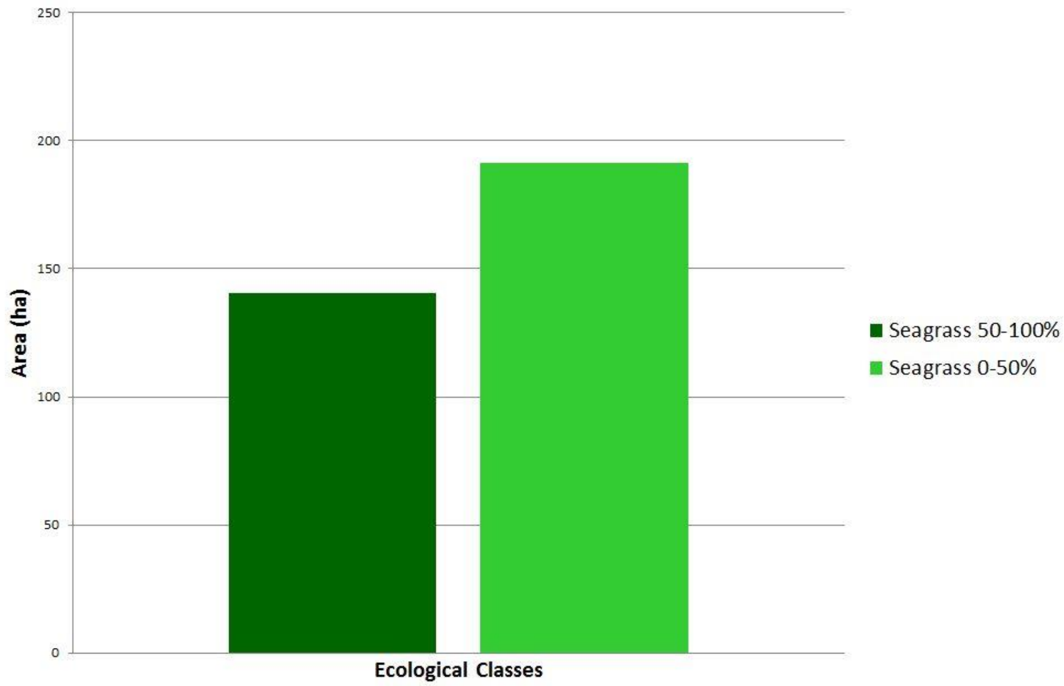


Figure 12: Spatial extent of the diffent seagrass density classes within the Sandy Bay-West End Special Protection Area. The colors represent the colors used in the land cover maps (Figures 9-10 and 13- 14).

Figures 13 and 14 show an impact area of potential future land cover change within the Sandy Bay-West End Special Protection Area. The area is highlighted here, since it it among the few larger, coherent mangrove extents within the Sandy Bay-West End Special Protection Area.

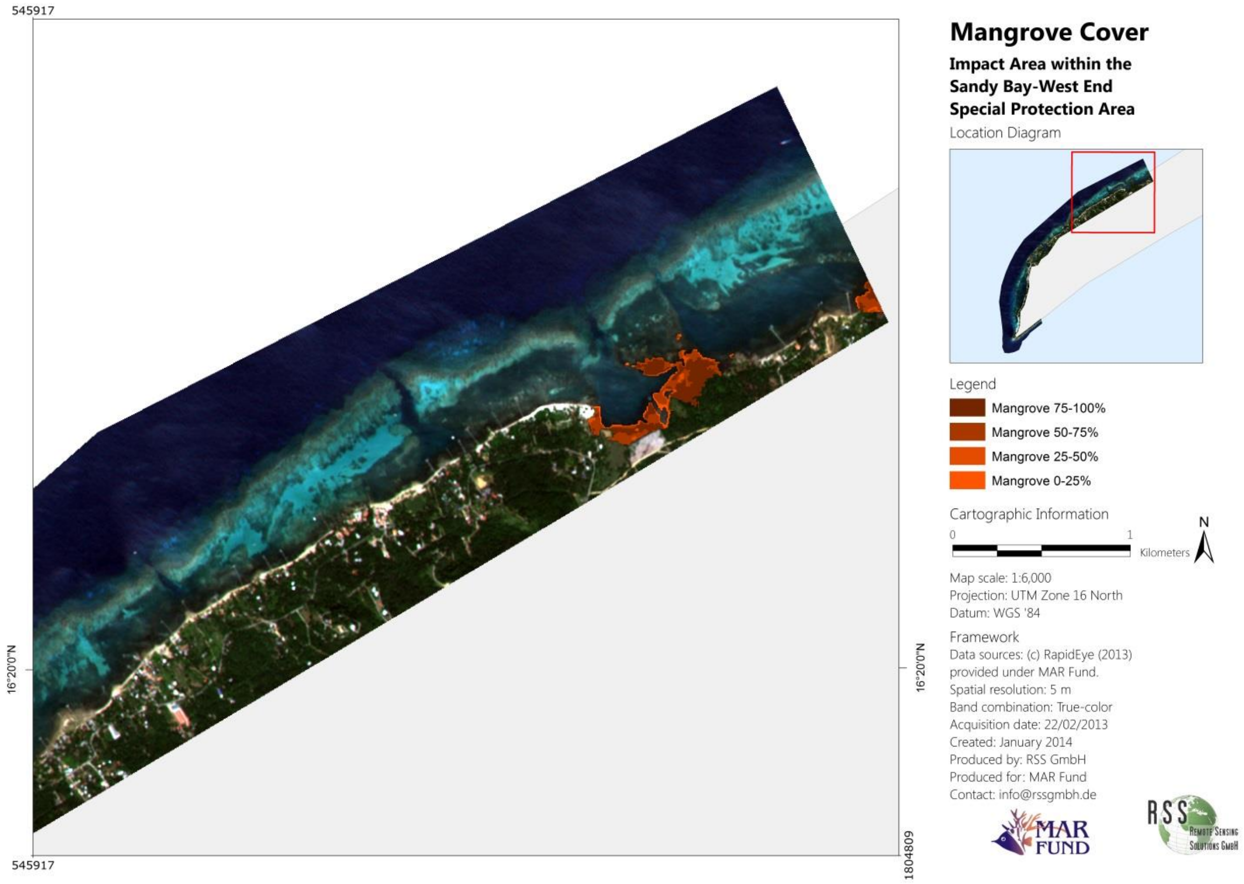


Figure 13: Impact area of potential future land cover change within the Sandy Bay-West End Special Protection Area. Displayed are the four mangrove density classes (0-25%, 25-50%, 50-75%, and 75-100%). In the upper right diagram the location of this impact area within the Sandy Bay-West End Special Protection Area is displayed (red).

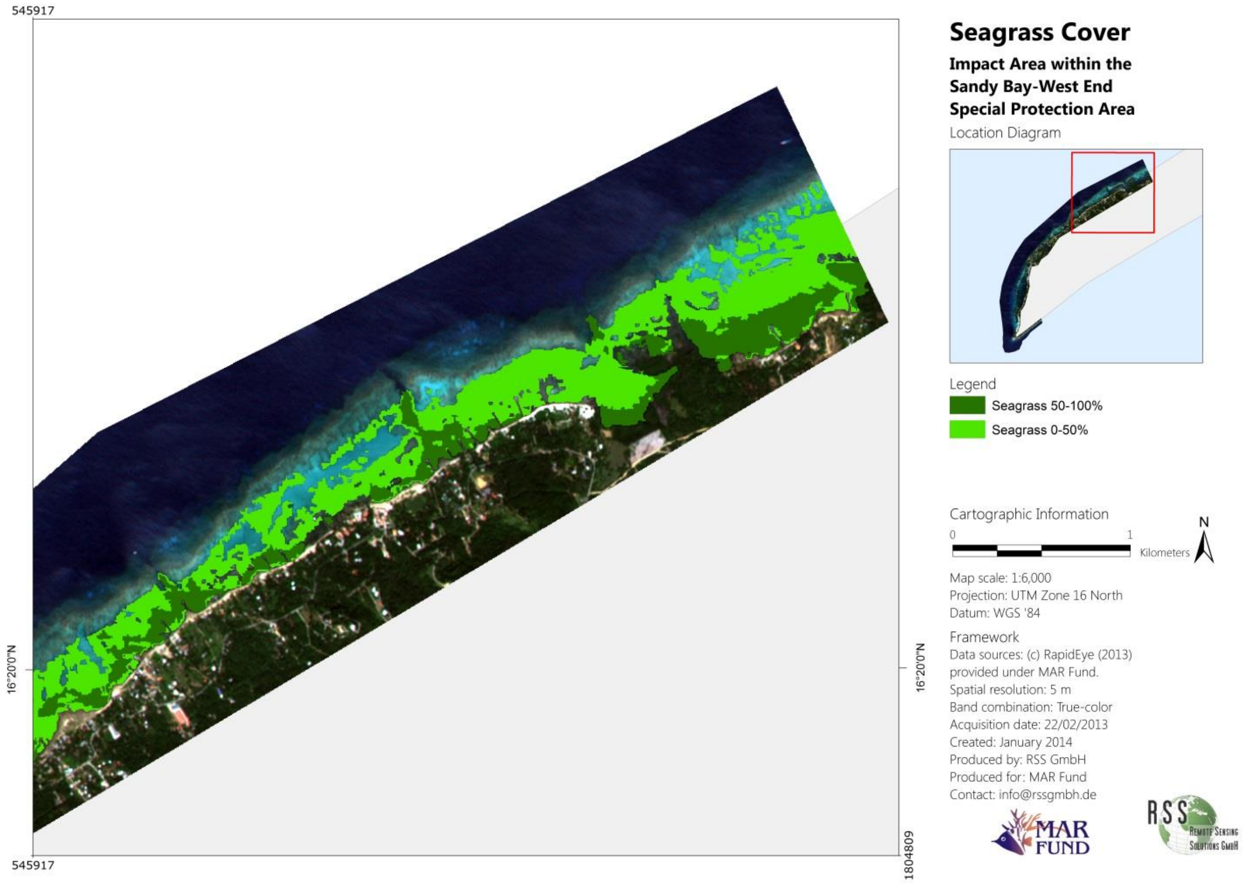


Figure 14: Impact area of potential future land cover change within the Sandy Bay-West End Special Protection Area. Displayed are the two seagrass density classes (0-50%% ane 50-100%). In the upper right diagram the location of this impact area within the Sandy Bay-West End Special Protection Area is displayed (red).

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). Due to a lack of reference data a reinterpretation of samples of the original data in an independent manner is permissible in such a case. A random sample of 240 points (30 points per land cover class: Mangrove 75-100%, Mangrove 50-75%, Mangrove 25-50%, Mangrove 0-25%, Seagrass 50-100%, and Seagrass 0-50%, Land/Tidal Zone, and Water) 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.

Several statistical measures for the accuracy (overall accuracy, Kappa coefficient's of agreement, producer's and user's accuracy per class) were calculated. Tables 5 and 6 show the detailed results of the accuracy assessment. An **overall accuracy of 85.0%** with a **Kappa coefficient of 0.83** was achieved.

Table 5: Confusion matrix per class by the use of 240 reference samples.

Confusion Matrix									
	Validation class								
Classification class	Mangrove 75-100%	Mangrove 50-75%	Mangrove 25-50%	Mangrove 0-25%	Seagrass 50-100%	Seagrass 0-50%	Land/Tidal Zone	Water	Sum
Mangrove 75-100%	**29**	0	1	0	0	0	0	0	**30**
Mangrove 50-75%	3	**26**	1	0	0	0	0	0	**30**
Mangrove 25-50%	0	5	**25**	0	0	0	0	0	**30**
Mangrove 0-25%	0	3	6	**21**	0	0	0	0	**30**
Seagrass 50-100%	0	0	0	0	**30**	0	0	0	**30**
Seagrass 0-50%	0	0	0	0	13	**17**	0	0	**30**
Land/Tidal Zone	0	0	0	0	0	0	**30**	0	**30**
Water	0	0	0	0	0	4	0	**26**	**30**
Sum	**32**	**34**	**33**	**21**	**43**	**21**	**30**	**26**	**240**

Table 6: Producer's and User's Accuracy per class.

Class	Producer's Accuracy	User's Accuracy
Mangrove 75-100%	90.6%	96.7%
Mangrove 50-75%	76.5%	86.7%
Mangrove 25-50%	75.8%	83.3%
Mangrove 0-25%	100.0%	70.0%
Seagrass 50-100%	69.8%	100.0%
Seagrass 0-50%	81.0%	56.7%
Land/Tidal Zone	100.0%	100.0%
Water	100.0%	86.7%

7. Deliverables

- Original RapidEye image from 22/02/2013 (GeoTIFF)
- Original Landsat 8 image from 26/09/2013 (GeoTIFF)
- Preprocessed RapidEye image from 22/02/2013 (GeoTIFF), XML-Metadata
- Preprocessed Landsat 8 image from 26/09/2013 (GeoTIFF), XML-Metadata
- Mangrove cover classification (Shapefile and Layerfile), XML-Metadata
- Seagrass cover classification (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

Shortcomings and Recommendations

Difficult ecological parameters made the detection of seagrass challenging. Here actual ground truth data, taken directly at the site of investigation, would improve reliability and quality of the provided maps. One aspect is, that field data could be used to adequately train the classification algorithms and assess reliable object properties. In addition, accuracy assessment in the postprocessing could be based on objective parameters.

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 definitely 'boost' 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 WorlView-2 satellite records image data in eight spectral bands and at 1.8 m spatial resolution. The price of the data is 30 – 50 times higher compared to RapidEye imagery.

Another option requiring high-professionalism of the consultant 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 unlike highest resolution satellite data readily available. In contrast 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.

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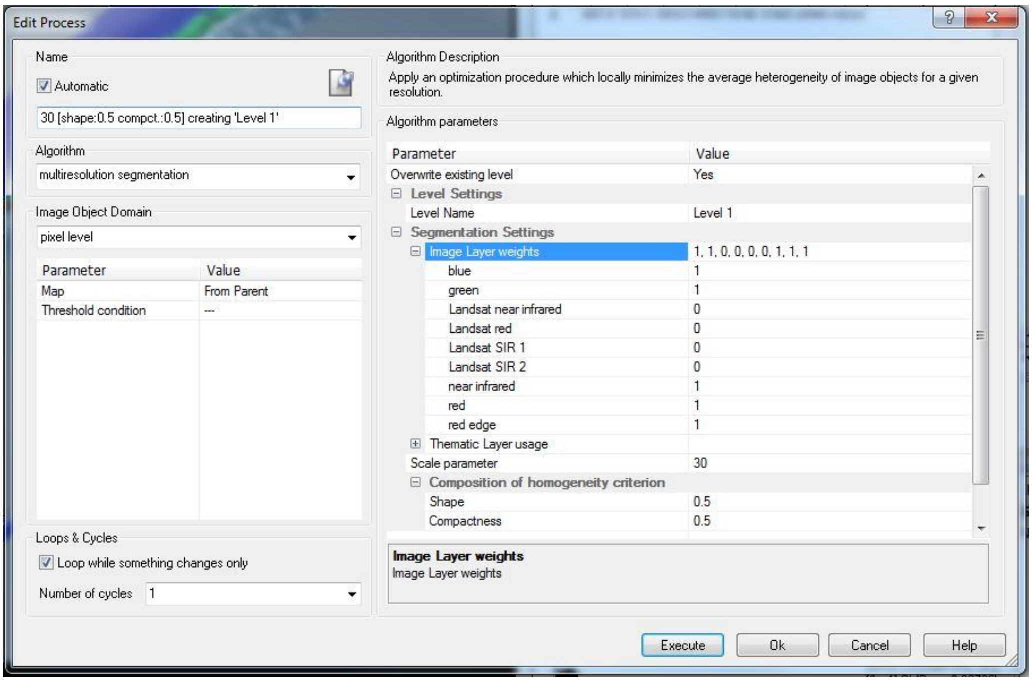
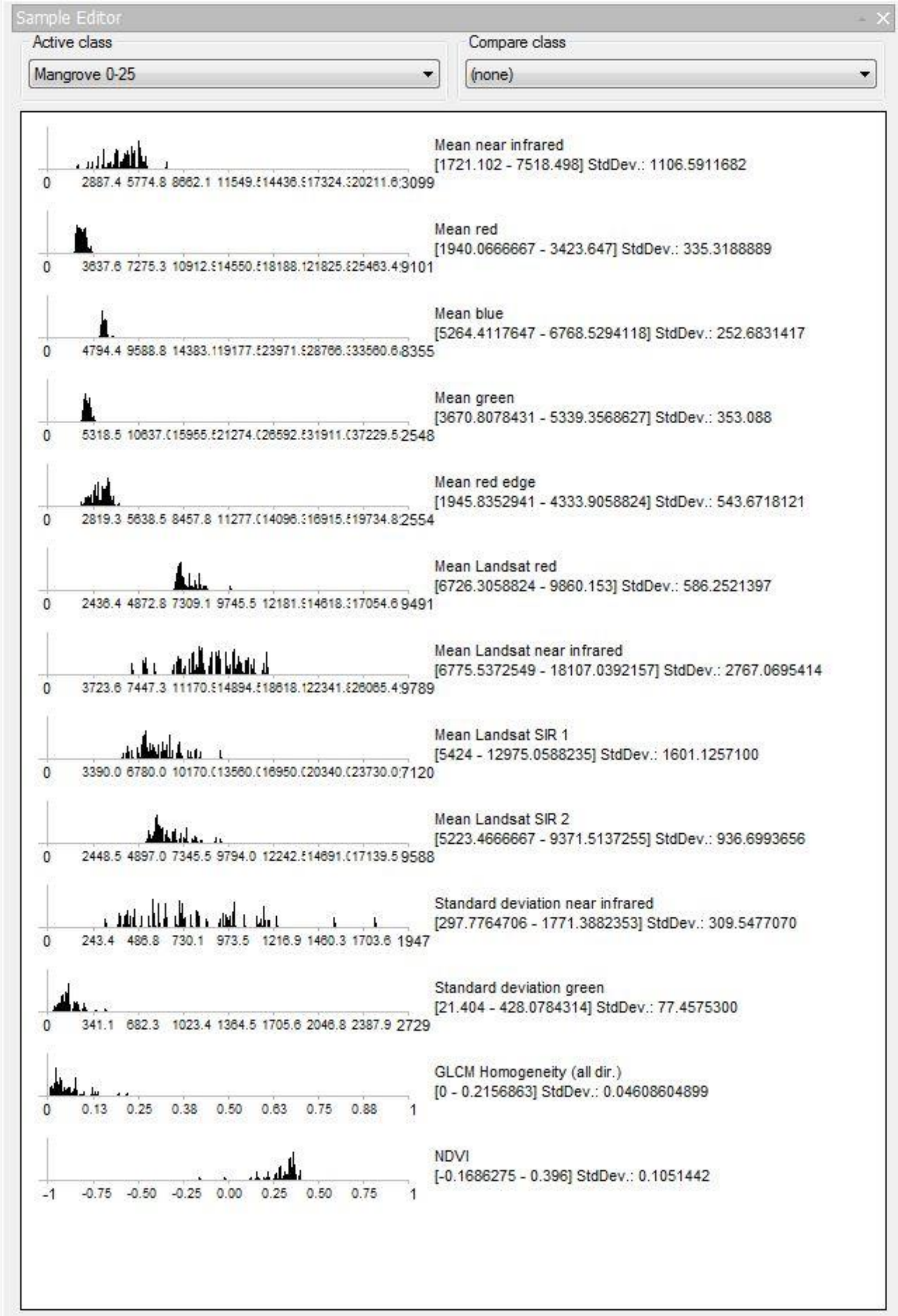
Annex I

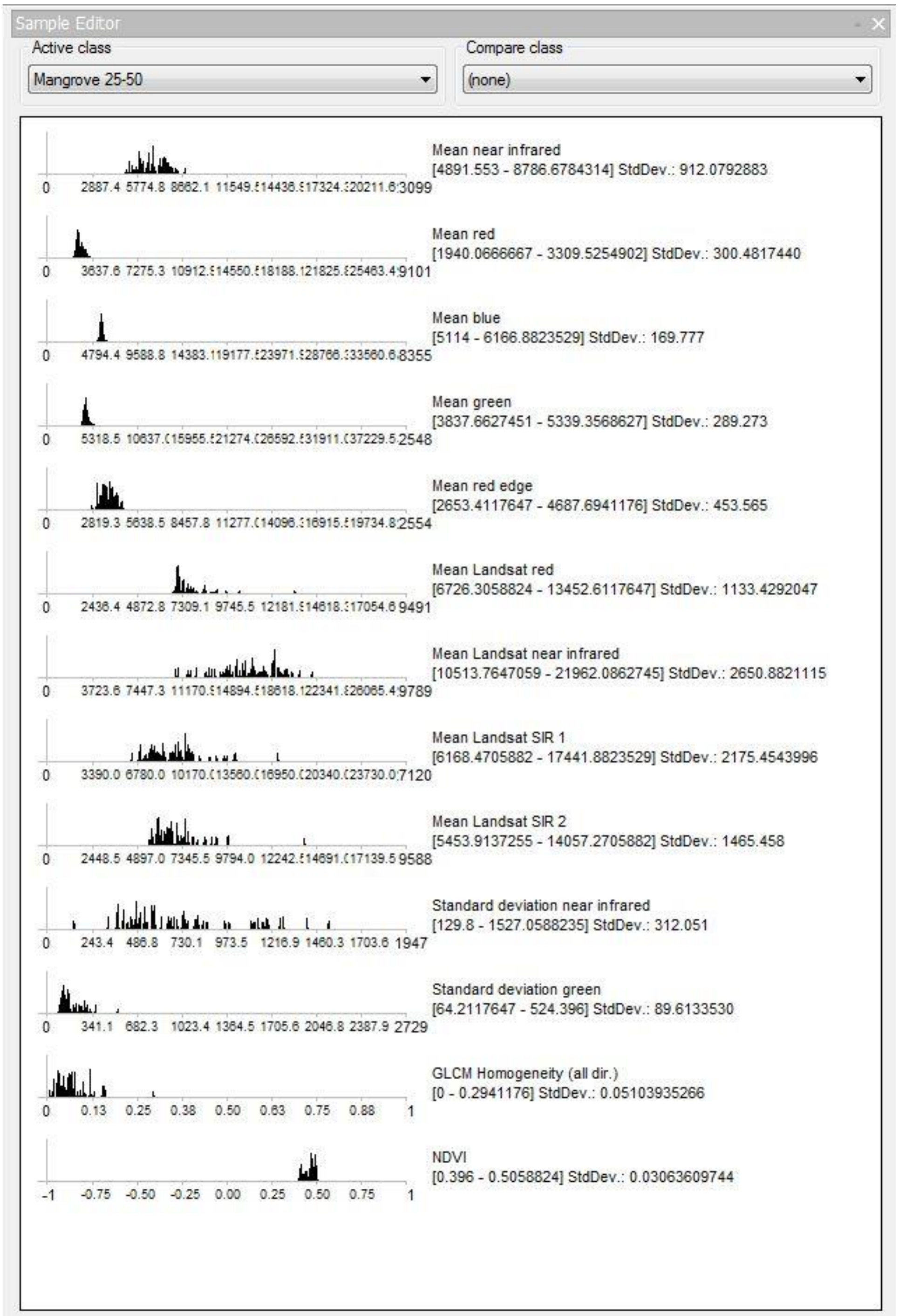
Segmentation parameters used



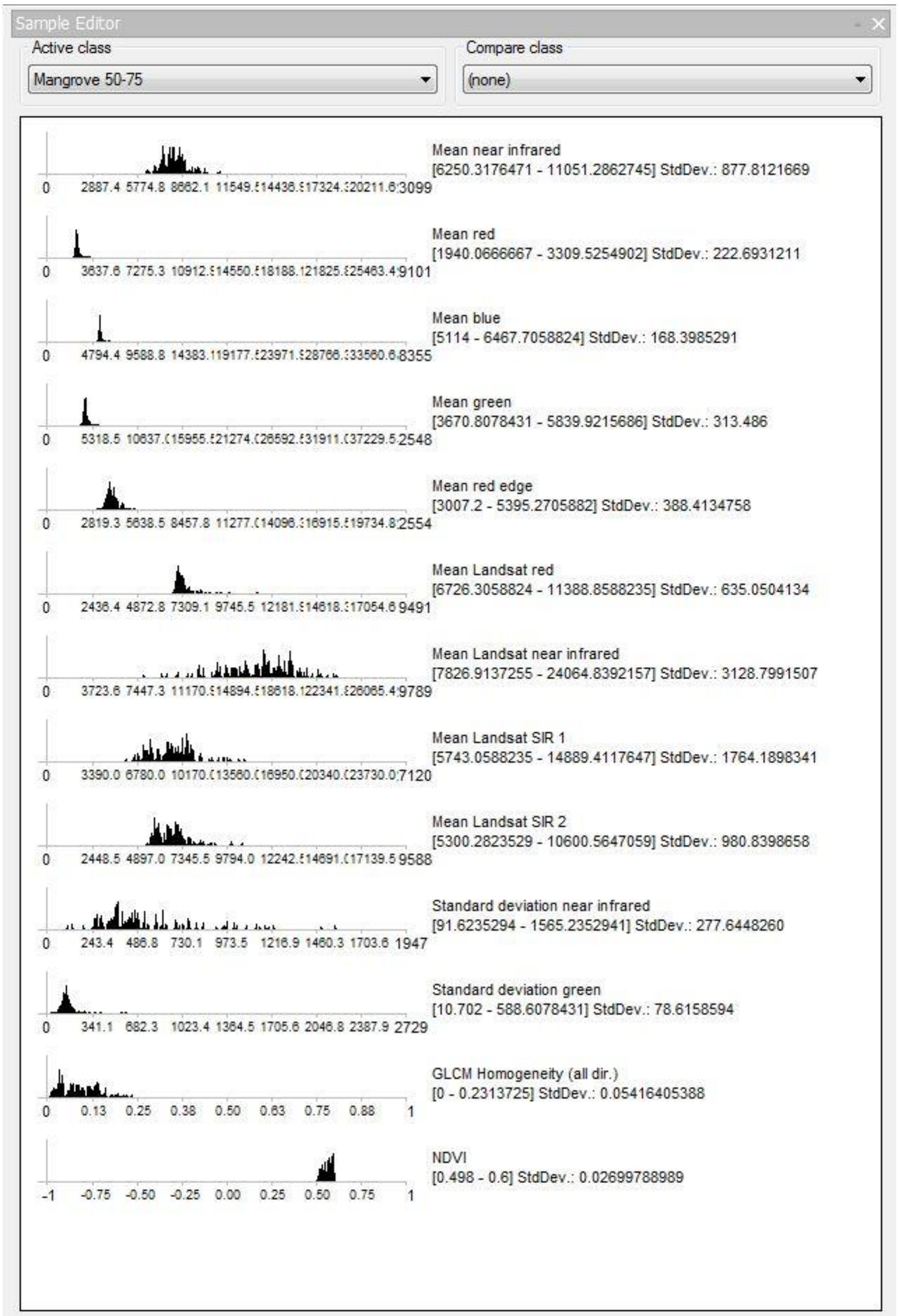
Statistical parameters of the feature objects for the class Mangrove 0-25%



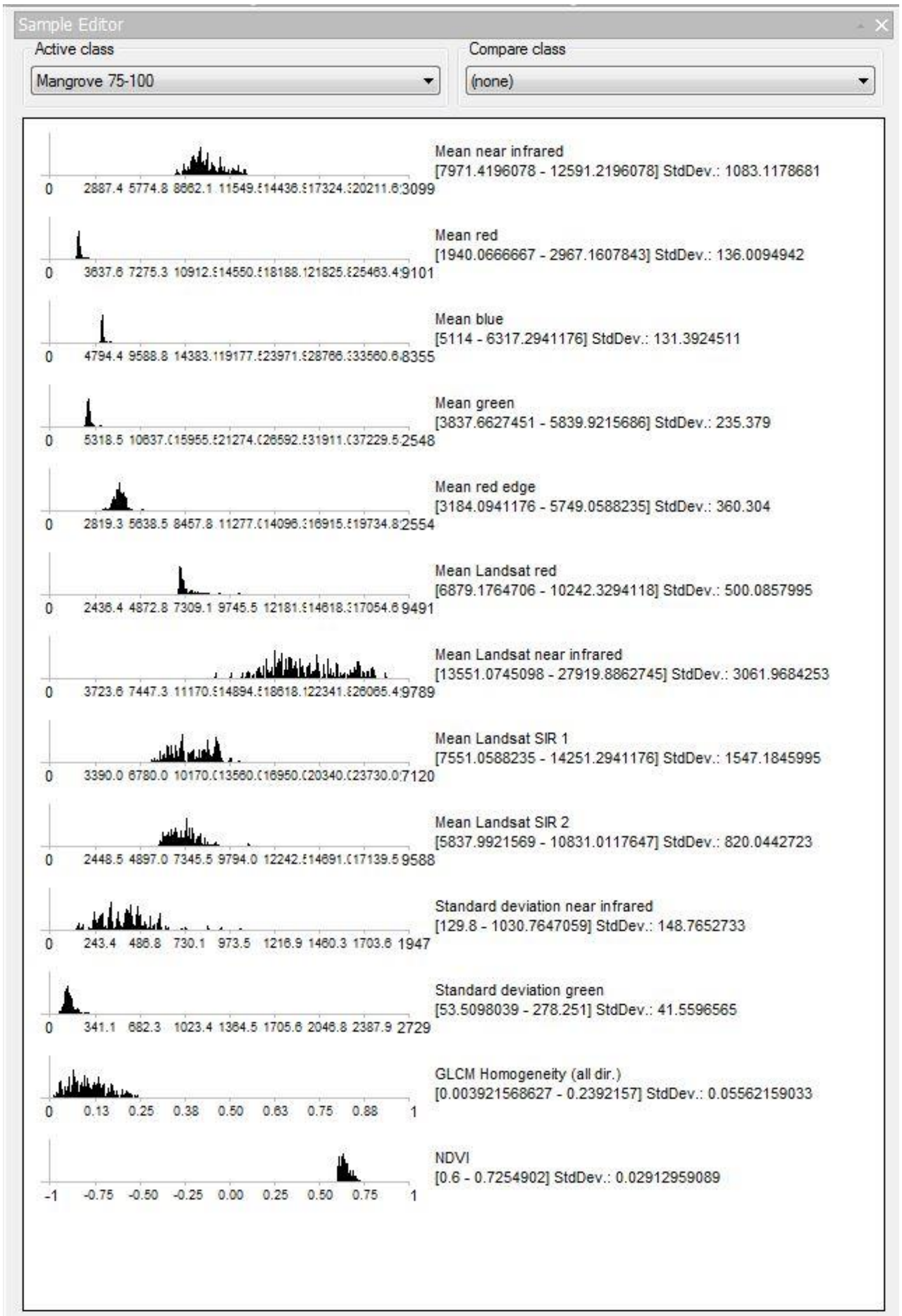
Statistical parameters of the feature objects for the class Mangrove 25-50%



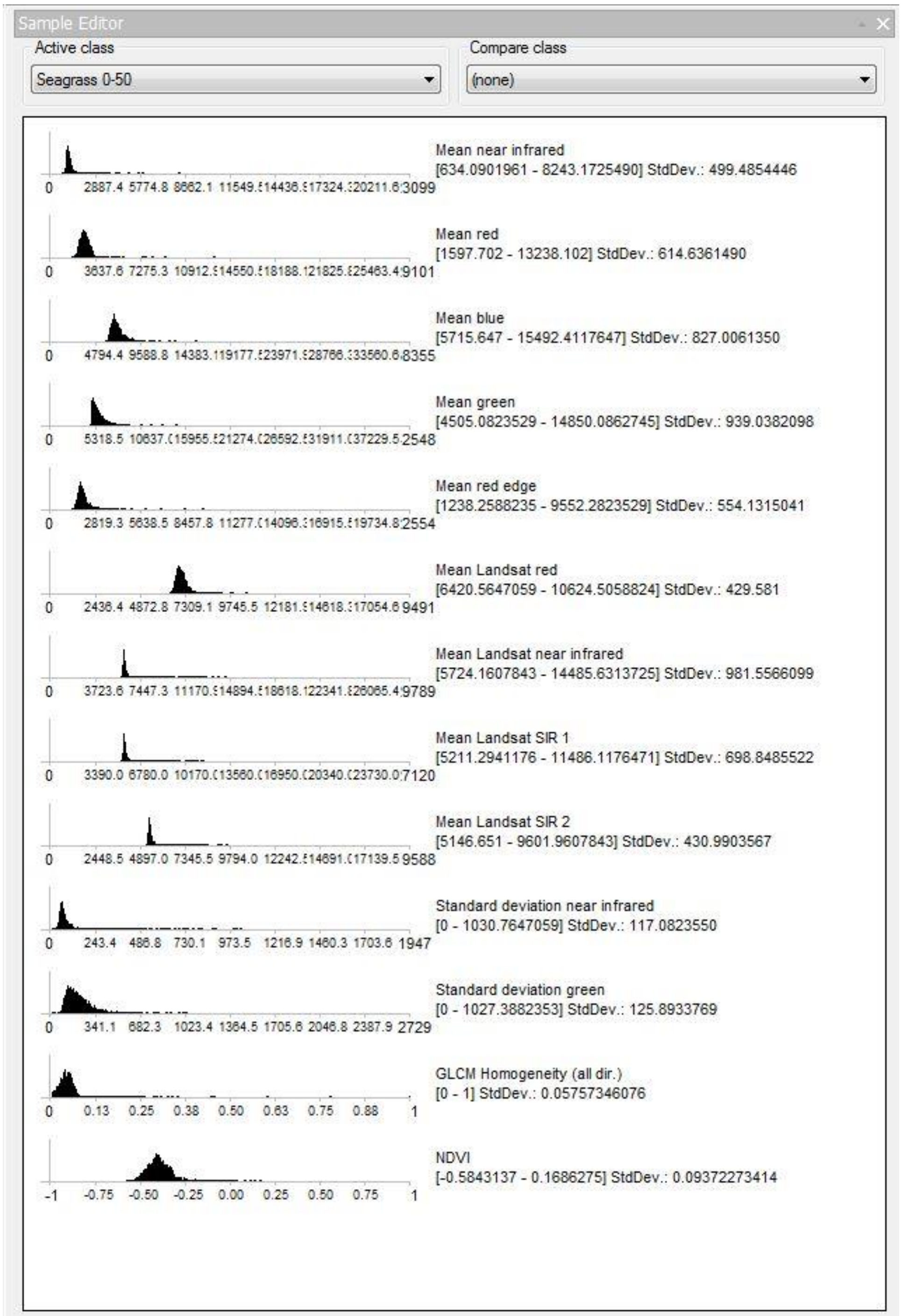
Statistical parameters of the feature objects for the class Mangrove 50-75%



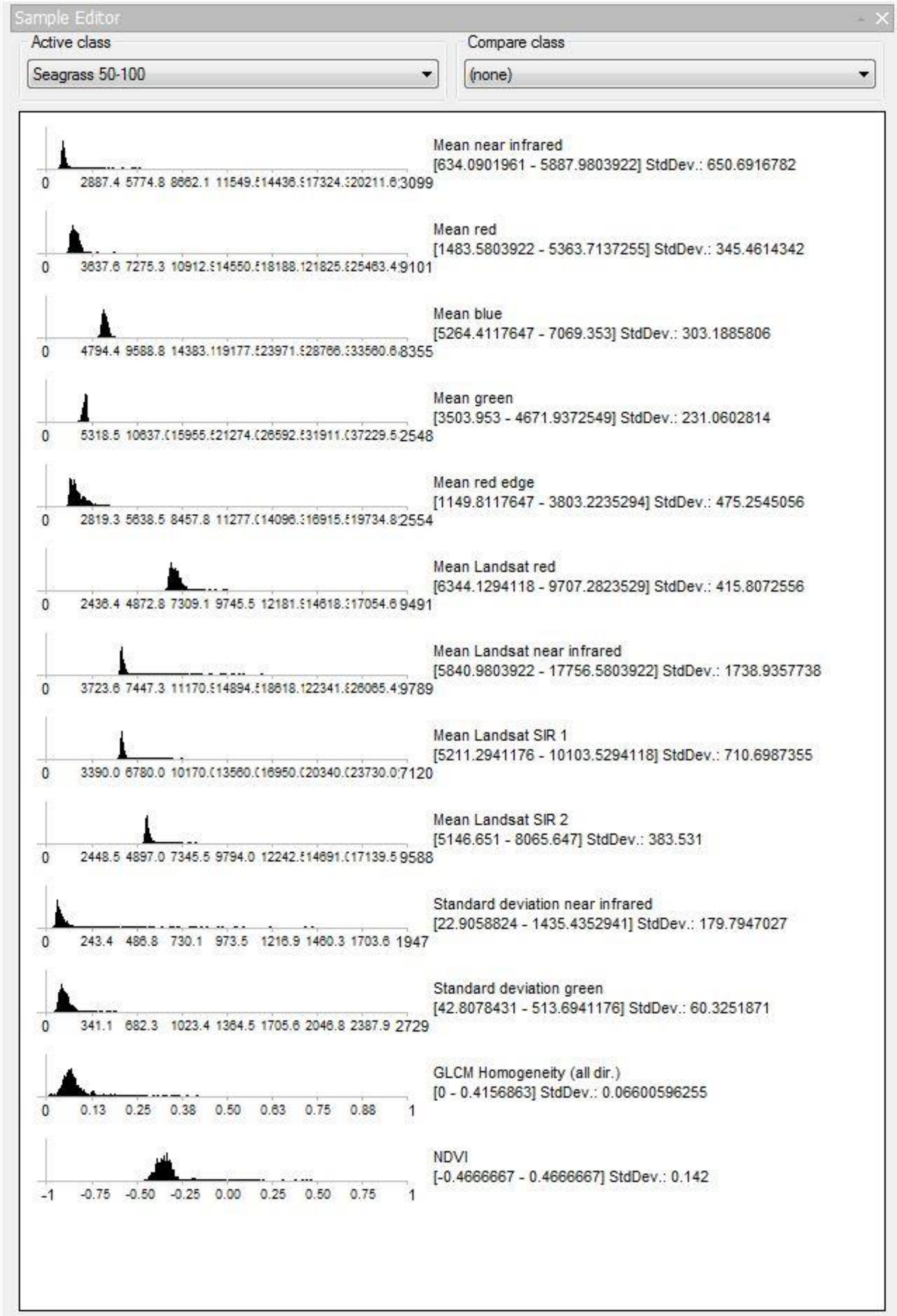
Statistical parameters of the feature objects for the class Mangrove 75-100%



Statistical parameters of the feature objects for the class Seagrass 0-50%



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



Statistical parameters of the feature objects for the class Water