Stichting Wageningen Research
Centre for Fisheries Research (CVO)

Possibilities of high-resolution optical satellite imagery to detect intertidal mussel and oyster beds

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Possibilities of high-resolution optical satellite imagery to detect intertidal mussel and oyster beds

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Summary

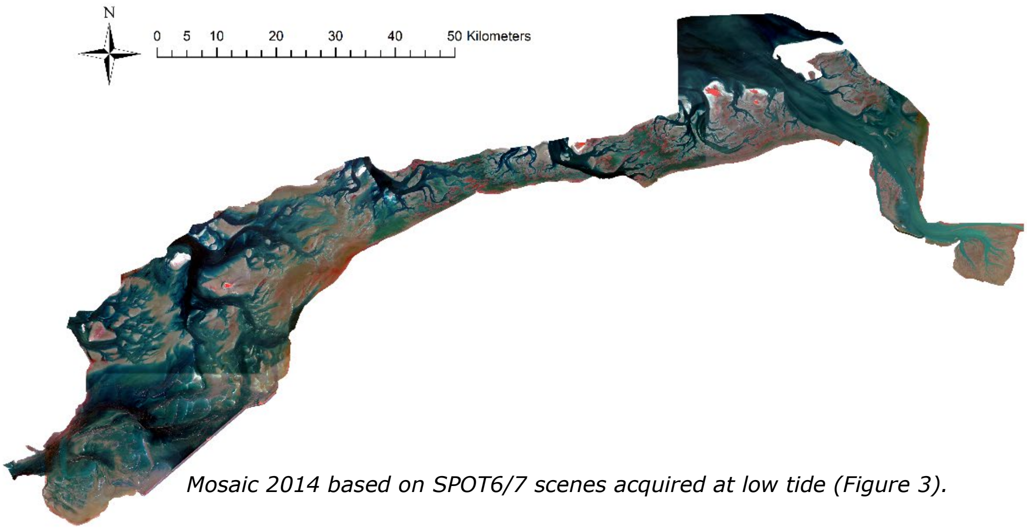
Within the WOT Fisheries - Shellfish programme, mussel and oyster beds in the Wadden Sea are mapped every spring by ground surveys, after an inspection flight has confirmed the presence or absence of existing and new seed beds. The problem is that the field work involved is very time consuming due walking around each mussel and oyster bed with a hand-held GPS. Due to time constraints, not all beds can be visited every year. In this report it is being investigated if the efficiency of the WOT mussel and oyster bed survey can be improved using optical satellite imagery and which sources of satellite data classification methods are most efficient to detect and delineate all beds, including news ones. So, our aim is to identify, or even classify, all mussel and/or oyster beds in the Wadden Sea on basis of satellite imagery in preparation of the field survey. The number of freely available satellite sensors and recorded imagery has increased enormously over the last years which increases the chance now to find cloud-free optical imagery during low tide (two important prerequisites). These prerequisites were a problem before that frustrated the use of optical satellite imagery for mussel and oyster bed surveys.

So, a first challenge was to find out if it is possible to gather cloud-free imagery for the entire Wadden Sea at low tide for every year from 2014 – 2017 (we started the project in 2017). Many different sources of high resolution optical satellite imagery can be downloaded freely from the NSO satellite data portal (http://www.satellietbeeld.nl/ and/or https://www.satellietdataportaal.nl/) by Dutch citizens. For very detailed studies such as the delineation and study of specific mussel and oysters beds the use of very high-resolution satellite data is preferred, such as TripleSat (Example 1) or Superview (respectively 80 and 50 cm resolution).

TripleSat false-colour image with 80 cm spatial resolution and delineation from the WOT field survey (black line) (from Figure 1).

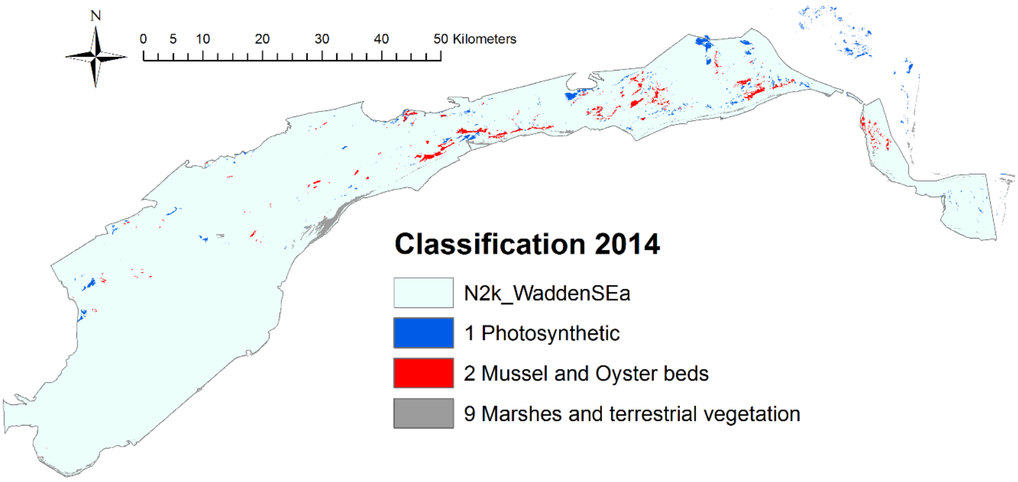
The structure and composition of individual beds is clearly visible with these super high resolutions. A disadvantage of these super high-resolution satellite sensors is that the revisit time is lower than for example SPOT6/7 or Sentinel 2. So, it means a lower chance to find imagery at low tide that is moreover cloud-free.

Therefore, for an operational monitoring of mussel and oyster beds in the entire Wadden Sea, now and in the future, the use of SPOT6/7 or Sentinel 2 is preferred. In this report, the detection of mussel and oyster beds using satellite imagery is based on the fact that parts of most mussel and oyster beds are covered with algae, as shown by the red colours in the false-colour TripleSat image above. This means that the location beds can be detected through the photosynthetic activity of these algae, using easily available spectral vegetation indices such as NDVI. The simplest, fastest and best classification method were therefore based on thresholding NDVI imagery (decision tree classifier) in combination with knowledge from the WOT surveys on the existing mussel beds (mussel bed frequency maps of Troost *et al.*, 2015) and visual post-processing. Sometimes we have missed an existing mussel bed that is present in the mussel bed frequency maps of Troost *et* *al.*, 2015. For example, some of the mussel beds are still under water during acquisition time due to their specific location and the reflection values in the image are therefore skewed and misclassified. By visual inspection we can still detect the mussel or oyster bed by its specific structure, as shown in the picture above, but not anymore by its pixel values. On the other hand, we have sometimes classified mussel and/or oyster beds that are not present in the frequency maps (Troost *et al.*, 2015) and therefore we must perform a visual check to see whether based on its structure if it is really a mussel and/or oyster bed. So, the specific structure of a mussel and/or oyster bed plays an important role in the visual detection and delineation. Object based image analysis is a way to incorporate the structure in an automatic manner in the classification process, which we tested as well in this report. However, we discovered that the fine-tuning and tweaking of the object-based image analysis is so time consuming that thresholding NDVI imagery in combination with visual post-processing is much faster and robust. The figure below shows the mosaic for the year 2014 based on SPOT6/7 scenes acquired at low tide and the final classification 2014 based on decision tree classifier using the NDVI.



Mosaic 2014 based on SPOT6/7 scenes acquired at low tide (Figure 3).

The accuracy of the mussel and/or oyster bed classifications was determined by using the WOT survey data as ground truth data for the years 2014 – 2017. The overall accuracy was high, 96%-98% due to a high agreement in absence and presence of mussel and/or oyster beds, and can be considered a very good result. Nevertheless, a critical comment is that agreement in absence overruled the presence in mussel and/or oyster beds in terms of accuracy. Looking at the presence of the beds the user's and producer's accuracy did not exceed 55% accuracy for any year. Producer's Accuracy is a measure of omission error and User's Accuracy is measure of commission error. These low accuracies are mainly due to partial disagreement in delineation of mussel and/or oyster beds in most locations between the ground truth data and the classified imagery. The delineation of an individual mussel or oyster bed is not necessarily better based on ground surveys by walking with a handheld GPS around a bed compared to a remotely sensed based classification of a bed. To be able to discern which beds are correctly classified and which beds are false positives (and in fact are e.g. benthic diatoms of sand mason worms), or false negatives (e.g. due to submersion) visual interpretations by field experts are still necessary. For example, in the field survey of 2018, an oyster bed was detected based on indications from the classified satellite imagery that was not known before. This bed had not been detected for several years in a row, while it must have been present for at least three years based on the size of the oysters. This shows that not all the mussel and oyster beds are identified well during the field survey, and it confirms the added value of satellite imagery classifications and makes an objective accuracy assessment of the classifications sometimes complicated. Moreover, after the identification of all mussel and oyster beds the super higher resolution satellite imagery such as Superview can be used to analyse the structure and composition of individual beds.



The final classification 2014 based on decision tree classifier using NDVI (Figure 12).

1 Introduction

1.1 Problem definition

Within the long-term operational project WOT Shellfish, mussel and oyster beds are being mapped in the Wadden Sea every spring by walking around the beds with a hand-held GPS. This after an inspection flight has confirmed the presence or absence of existing and new seed beds. The methods used are described in more detail by Van den Ende *et al.* (2017). The field work involved is time consuming and not all beds can be visited every year. The use of satellite imagery can increase the efficiency of the survey through an improved focus on beds that have changed, but a method that can readily be implemented has not yet been developed. Meanwhile, the number of satellite sensors and acquisition dates has enormously increased over the past decade which will increase the chance to find cloud-free imagery during low tide. The challenge is to find cloud-free imagery at low tide for the entire Wadden Sea and for every year in the period 2014 – 2017. Most of the satellite imagery can be accessed for Dutch citizens through the National Satellite Data Portal, see also https://satellietdataportaal.nl/, including many very high resolution satellite imagery as TripleSat and PlanetScope.

1.2 Background

Funded by KBWOT, Davaasuren *et al.* (2013) used multispectral (Formosat-2 satellite) and radar (ERS-2 and Radarsat-2 satellites) and Nieuwhof *et al.* (2015) used radar (TerraSAR-X and Radarsat-2) data to try and map mussel beds. Both gave results for only a limited number of mussel/oyster beds and compared these with contours mapped within WOT Shellfish. The Radarsat-2 results were promising but lower density parts of beds were not detected. Therefore, the comparison needs to be extended to a variety of beds with different compositions (mussel/oyster), algae cover, densities, and with different substrates ranging from highly muddy to firm sandy. This way we can assess under which circumstances Remote Sensing (RS) gives reliable results, so that we can focus the field work on area's that are less reliably detected by RS. Contours mapped in the field are available for the entire survey period since 1994 but satellite data are not. We will only use satellite data with the highest resolution presently available (< 10m) and go as far back in time as these are available. Expected results include: 1) a distribution map for the entire Wadden Sea for mussel and/or oyster beds created from satellite data for each year in the period 2014 -2017; 2) with an overlay of the contours mapped in the field, 3) an overview of circumstances under which beds are detected with an acceptable precision, 4) an analysis of differences in cover estimate between techniques and advice on how to solve or mitigate this, and 5) a plan on how to implement the method in the WOT survey.

1.3 Objective of the project

Earlier studies (Davaasuren *et al.* 2013 (KBWOT); Nieuwhof *et al.* 2015) show the potential of satellite imagery. We want to build further on this knowledge and create mussel and oyster bed maps for the entire Wadden Sea on a yearly basis using high resolution multispectral imagery that have recently become available. By comparing satellite derived mussel and oyster bed classification with the contours mapped in the field we will identify circumstances where satellite data can give reliable results. Also, different classification methods are being tested to see which methods are most reliable and robust to be implemented for the entire Wadden Sea.

Based on synoptic information from high resolution satellite imagery the number of beds to be visited annually might be better targeted and reduced in number, first leading to a higher accuracy of the estimated total area of mussel and oyster beds, and eventually to a reduction in fieldwork needed.

1.4 Research questions and structure of the report

The main research questions are:

1. What optical satellite images are available and suitable for detection of mussel beds?
2. What methods are available for automatic classification of satellite images, suitable for detection of mussel beds, and how well do classification results fit to field reference data?

These two main research questions are addressed in separate chapters in which methods and results are described and discussed. These two chapters are followed by a general discussion, conclusions, and recommendations for implementation of satellite images in the annual shellfish surveys.

2 Availability and suitability of satellite images

2.1 Acquisition of satellite imagery

A wide range of images from satellite sensors have been acquired that are freely available for Dutch citizens through the national satellite data portal, by http://www.satellietbeeld.nl/ (from 1st of October 2019 onwards) and/or from https://satellietdataportaal.nl/ (from 01-03-2013 till onwards) of Netherlands Space Office (NSO). Copernicus high resolution satellite imagery, such as the SENTINEL-1 RADAR and SENTINEL-2 optical imagery can be freely downloaded from https://scihub.copernicus.eu or https://apps.sentinel-hub.com/eo-browser.

In principle we are only interested in satellite imagery with a spatial resolution of 10 meter or more detailed, since coarser spatial resolution will not be very useful to detect the scattered and fragmented mussel beds. The amount and types of satellite imagery available in the National Satellite Data Portal (NSD) has been changing over time, but the Table below reflects quite will the types of optical satellite sensors that can be freely downloaded by Dutch citizens from the sites mentioned above. Recently, Superview satellite imagery with a maximum detail of 50 cm resolution has been added but was not yet available when this study was performed.

Table 1. Overview of the types of freely downloadable satellite imagery from the NSD and satellietbeeld.nl (source: Spaceoffice.nl). Updated on 2nd of September 2019.

Satellite	Period	Spectral bands	Spatial Resolution (m)
SuperView	2019 – now	Panchromatic	0.5
SuperView	2019 – now	Blue, Green, Red, NIR	2.0
TripleSat	2017 - 2018	Panchromatic	0.8
TripleSat	2017 - 2018	Blue, Green, Red, NIR	3.2
PlanetScope	2017 - 2018	Blue, Green, Red, NIR	3.1
RapidEye	2017	Blue, Green, Red, Red-Edge, NIR	5.0
SPOT 6/7	2014 - 2016	Panchromatic	1.5
SPOT 6/7	2014 - 2016	Blue, Green, Red, NIR	6.0
Formosat-2	2012 - 2014	Panchromatic	2.0
Formosat-2	2012 - 2014	Blue, Green, Red, NIR	8.0
UK-DMC-2	2012 - 2016	Green, Red, NIR	22.0
Deimos-1	2012 - 2016	Green, Red, NIR	22.0
SPOT 6/7	April 2014 - 2016	Blue, Green, Red, NIR	6.0

2.1.1 Sentinel-2

The European Sentinel-2 is an Earth Observation mission developed by the European Space Agency (ESA) as part of the Copernicus Programme to perform terrestrial observations in support of services such as forest monitoring, land cover changes detection, and natural disaster management. It consists of two identical satellites, Sentinel-2A and Sentinel-2B. Sentinel-2 data are acquired on 13 spectral bands in the VNIR and SWIR:

- four bands at 10 m: Band 2 (Blue band, 496.6 nm), Band 3 (Green band, 560 nm), Band 4 (Red band, 664.5 nm), and Band 8 (VNIR band, 864.8 nm)
- six bands at 20 m: Band 5 (VNIR, 703.9 nm), Band 6 (VNIR, 740.2 nm), Band 7 (VNIR, 782.5), Band 8a (VNIR, 864.8nm), Band 11 (SWIR, 1613.7 nm), and Band 12 (SWIR, 2202.4 nm)
- three bands at 60 m: Band 1 (Ultra Blue, 443.nm), Band 9 (SWIR, 945 nm), and Band 10 (SWIR, 1373.75 nm)

Sentinel-2A and 2B have together a global revisit time of approximately every five days. The swath width is 290 km.

Table 2. Spectral information Sentinel-2 at 10-meter spatial resolution.

Sentinel-2 10 m	Spectral band	Range in spectrum (nm)
Multispectral	B2: Blue	497 (bandwidth 98)
	B3: Green	560 (bandwidth 45)
	B4: Red	665 (bandwidth 38)
	B8: NIR	835 (bandwidth 145)

2.1.2 *SPOT 6 en 7*

The European SPOT 6 and SPOT 7 from Airbus are designed to cover wide areas in a record time, making it possible to regularly update national map series free from the constraints imposed by seasonal conditions. The constellation covers up to 6 million km^2 every day, an area larger than the entire European Union. Four weather forecasts per day are integrated automatically into the tasking process to optimize efficiency. As a result, 60% of images have less than 10% cloud cover (see also http://www.intelligence-airbusds.com). The swath width is 60 km which makes them very suitable for detailed monitoring at national level. But only twice per month an image was available in the NSD from April 2014 - 2016.

Table 3. Spectral information SPOT 6/7.

SPOT 6/7 type	Spectral band	Range in spectrum (nm)
Multispectral	B1: Blue	450 – 520
	B2: Green	530 – 590
	B3: Red	625 – 695
	B4: NIR	760 – 890
Panchromatic	P: Panchromatic	450 -745

2.1.3 *RapidEye*

RapidEye was built to offer a large-area coverage, frequent revisit intervals, high resolution and multispectral capabilities. The RapidEye constellation consists of five satellites to acquire high resolution imagery daily. The swath width is 77 km. The spatial resolution is 6.5 meter at nadir (straight below the satellite). Rapid Eye was available in the NSD for 2017 and 2018.

Table 4. Spectral information RapidEye.

RapidEye	Spectral band	Range in spectrum (nm)
Multispectral	B1: Blue	440 – 510
	B2: Green	520 – 590
	B3: Red	630 – 685
	B4: Red-Edge	690 – 730
	B5: NIR	760 – 850

2.1.4 *PlanetScope*

The Planet (USA) operates the recently new PlanetScope (PS) and RapidEye (RE) Earth-imaging constellations. Each PlanetScope satellite is a CubeSat 3U form factor (10 cm by 10 cm by 30 cm). The complete PlanetScope constellation of > 50 satellites, called Dove constellation, will be able to image the entire Earth every day (equating to a daily collection capacity of 150 million km²/day), see also https://www.planet.com. The swath width is 25 km. From March 2017 till September 2017 the Netherlands will be covered every two weeks. The spatial resolution is 3.7 meter at nadir.

Table 5. Spectral information PlanetScope.

PlanetScope	Spectral band	Range in spectrum (nm)
Multispectral	B1: Blue	420 – 530
	B2: Green	500 – 590
	B3: Red	610 – 700
	B4: NIR	770 – 900

2.1.5 *TripleSat*

The constellation comprises three identical optical EO satellites from India, which makes it possible to target anywhere on Earth once per day, is offering <1m high-resolution imagery products for the panchromatic product and 3.2 meter for the multispectral imagery with a 23.4km swath, see also http://www.21at.com.cn/en/TripleSatConstellation/. Since March 2017 the imagery is available once in the 2 months for the entire Netherlands. The downloadable TripleSat imagery are already pansharpened by combining the panchromatic with the multispectral image, leading a multispectral image with 80 cm resolution.

Table 6. Spectral information TripleSat.

TripleSat type	Spectral band	Range in spectrum (nm)
Multispectral	B1: Blue	440 - 510
	B2: Green	510 - 590
	B3: Red	600 - 670
	B4: NIR	760 - 910
Panchromatic	P: Panchromatic	450 - 650

2.1.6 *Comparison of optical satellite sensors*

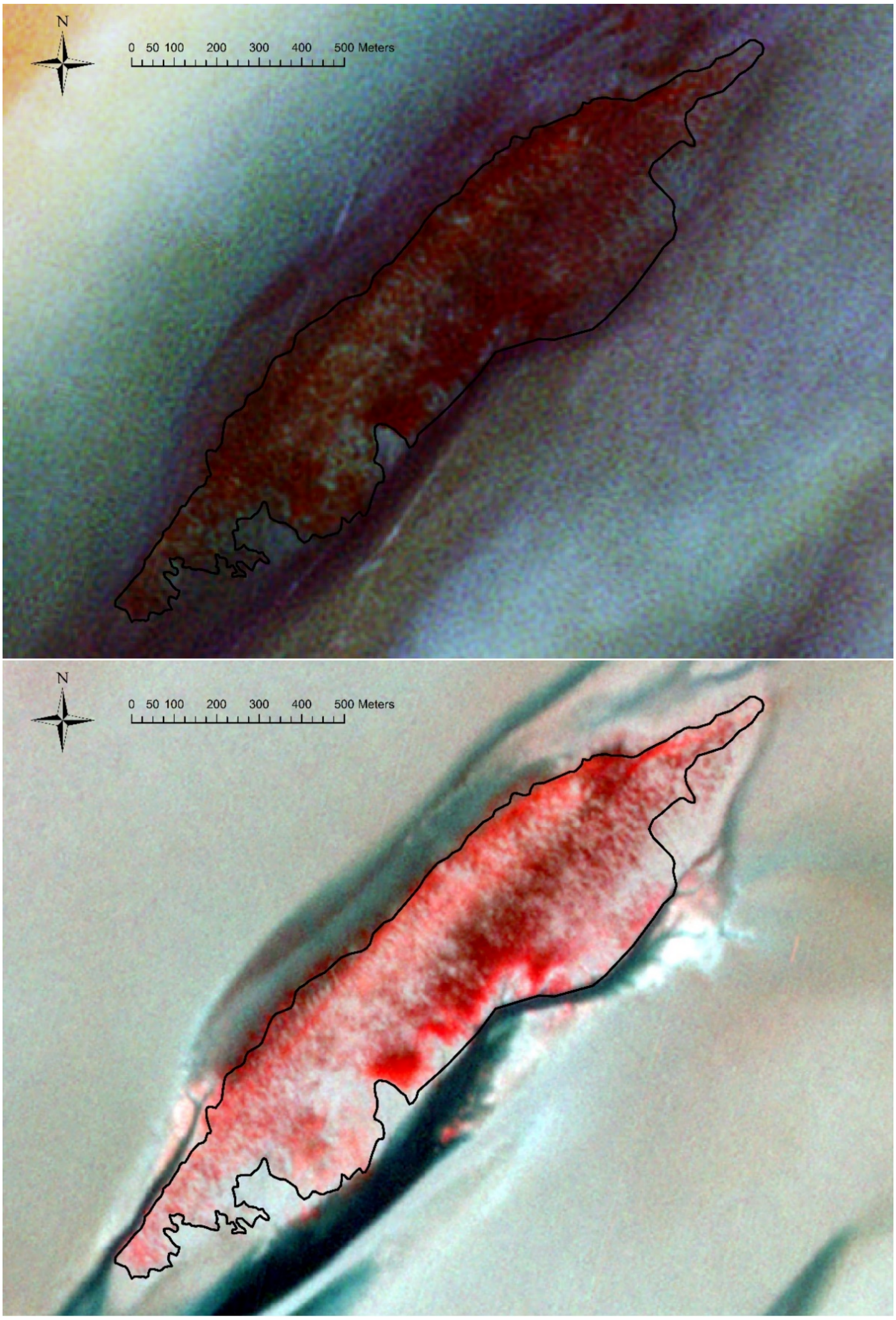
In this section we compare visually the different available optical sensors with a spatial resolution between 80 cm and 10 m, for one mussel bed to detect differences in the quality of the images. In all examples we show false-colour images since it reflects better the photosynthetic activity of all algae and seaweeds. These lifeforms reveal to a large extent the location of the mussel and oyster beds, since these beds are often covered by algae and seaweeds due to their rich structure. Moreover, the image texture, caused by the 3D structure of the bed, is also typical for a mussel or oyster bed and helps as well to identify them, especially on higher resolution satellite imagery, as one can clearly see in the figure below in June.

Sentinel 2A– 10m

SPOT6 – 6m

Rapid Eye 5 – 5m

PlanetScope – 3m



TripleSat – 0.8m

Figure 1. Visual comparison of main satellite sensors Sentinel 2A, SPOT 6, Rapid Eye 5, PlanetScope and TripleSat at a detailed level in June, but still for different spatial resolutions. The polygon (black outline) is the result from the WOT field survey. Almost all sensors can be used for delineation, but the composition and structure of the mussel bed is best seen at highest spatial resolution of TripleSat (resolution merge).

From Figure 1 it becomes clear that sensors like SPOT6/7 and Sentinel 2 give a better spectral reflectance for the mussel bed than RapidEye (RE5). But at the same time, SPOT 6/7 and RapidEye have a higher spatial resolution than Sentinel 2. So, from this aspect we would prefer SPOT6/7 over Sentinel-2. However, from the visual comparison in Figure 1 there does not seem to be so much difference between 6-meter SPOT and 10-meter S2A. Nevertheless, for the mussel bed classification for the entire Wadden sea we slightly preferred to use the SPOT-6/7 over Sentinel 2. So, for the classification of all mussel and/or oyster beds we used SPOT6/7 imagery from the years 2014, 2015 and 2016. However, in the future Sentinel-2 might be used again since this data will be available for the long term and certainly freely available. Besides, for the year 2017 we used Rapid Eye satellite imagery since we did not have SPOT data for that year, and Rapid Eye has a better spatial resolution than S2A. In fact, we would have preferred to use PlanetScope data for 2017, but we were not able to cover the complete Wadden Sea for that year due to cloud-contaminated PlanetScope imagery. For the same reason we could not use TripleSat. In general, we need a very high revisit time to acquire cloud-free optical data. And from Figure 1 it is clear that SPOT is preferred above Rapid Eye.

Zooming in at details of the mussel bed in Figure 2, TripleSat (3SAT) with 80 cm resolution does look much more impressive than the SPOT imagery with 6m resolution. The advantage of TripleSat over PlanetScope is that the pansharpened product of TripleSat has a resolution of 80 cm compared to 3-meter resolution of PlanetScope. The 80 cm makes a big difference for detailed investigation. See the example in Figure 2 which gives a visual comparison between SPOT and TripleSat imagery.

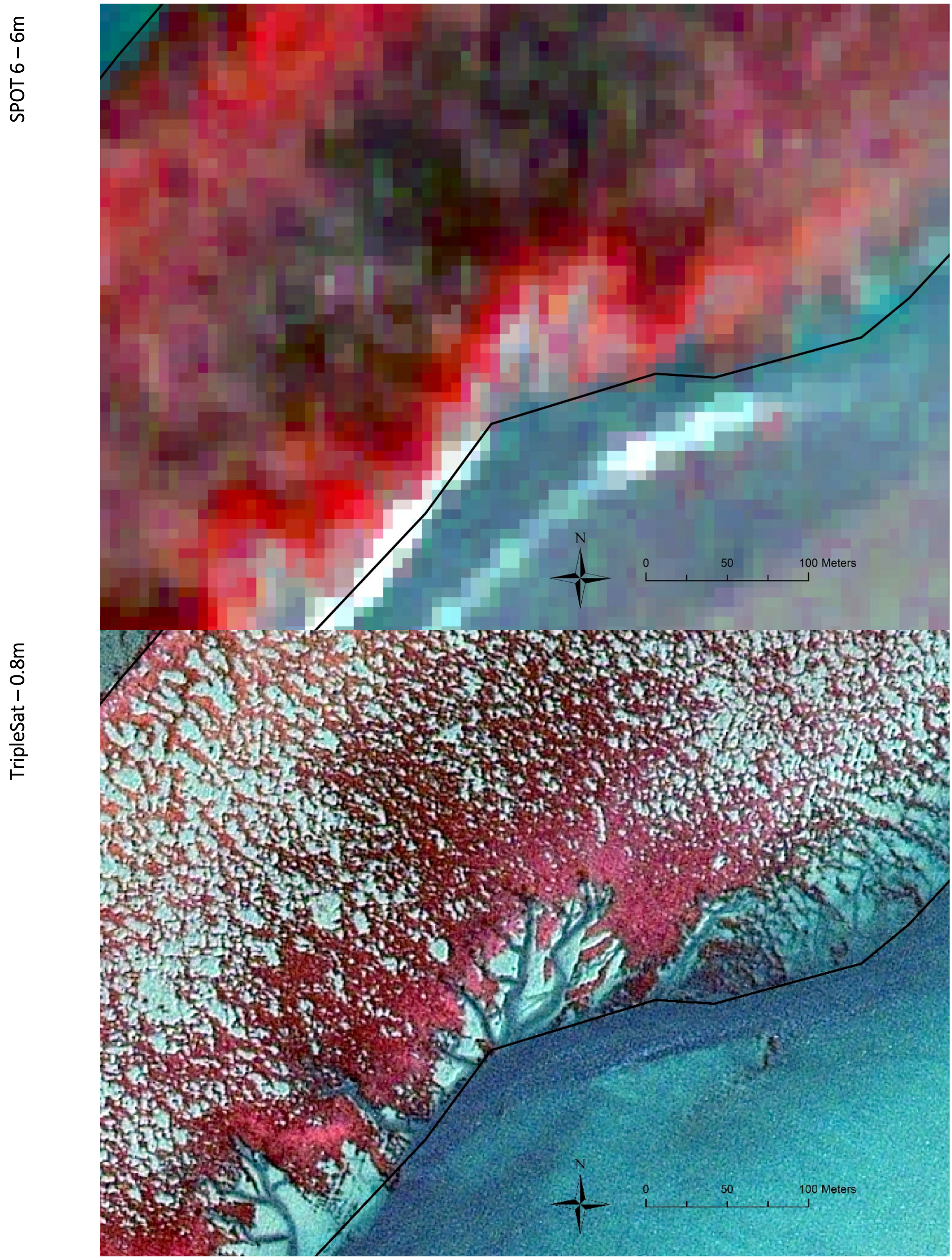


Figure 2. Visual comparison of the details in a mussel bed seen with 6 meter (SPOT 6) or 80 cm spatial resolution (TripleSat).

Concluding, for detailed and local studies we prefer to use satellite data at the highest spatial resolution such as TripleSat (or Superview which is now available), while for a complete cloud-free coverage of the

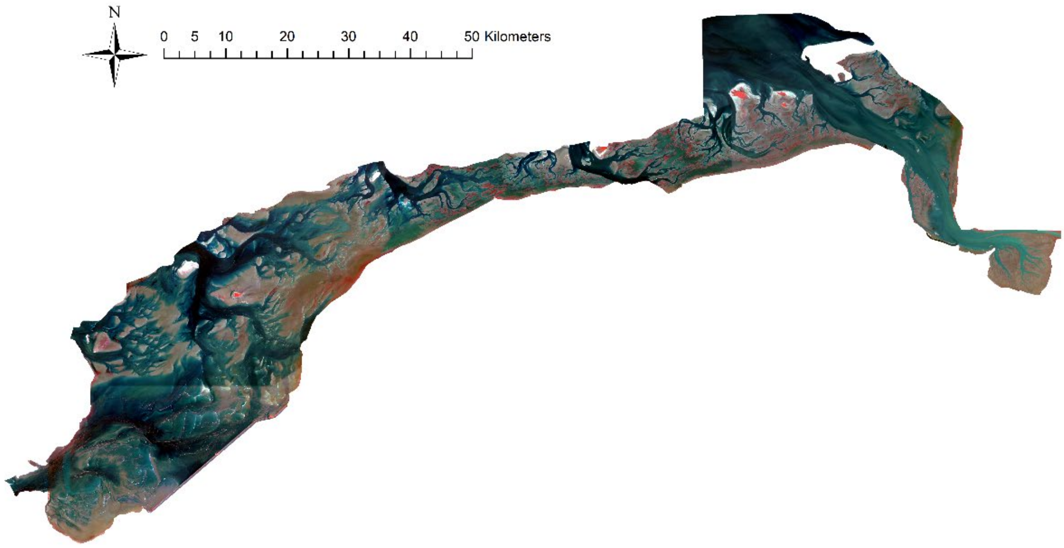
Wadden Sea on a yearly basis, we prefer to use SPOT6/7 at 6-meter resolution or else Sentinel 2 at 10-meter resolution.

An important notice is that we only selected satellite imagery that had been recorded during low tide with a minimum of cloud contamination. Nevertheless, the actual height of the tide will change by the exact acquisition day and time of the satellite. Meaning that in practise we still had to deal with a varying low water level, also due to variation in the exact height of the mussel beds, that affects image interpretation or classification.

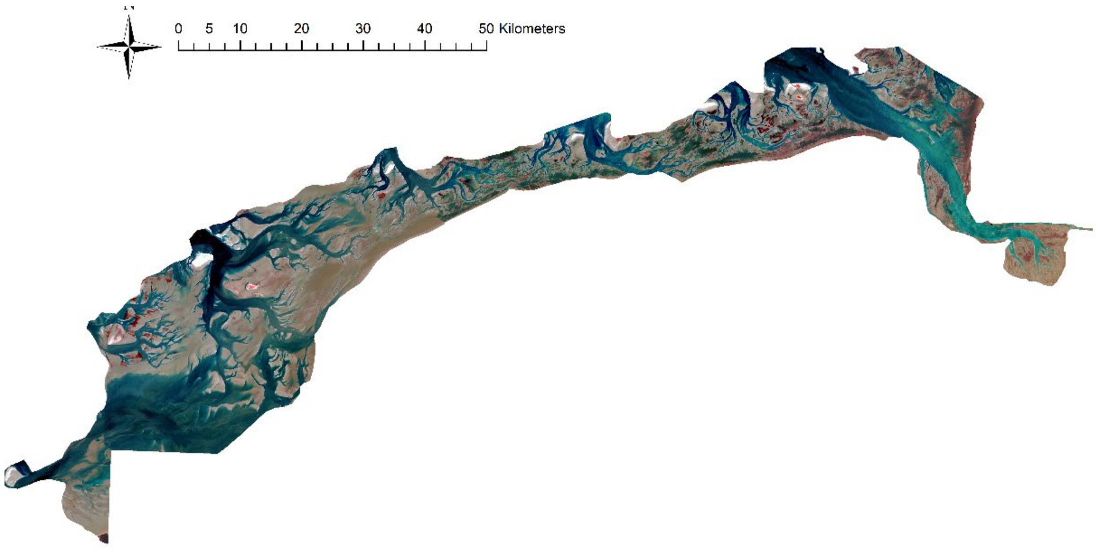
2.1.7 *Satellite mosaics for the Wadden Sea (2014-2017)*

It is nice to have cloud-free satellite imagery acquired during low tide over the Wadden Sea, but the proof is in eating the pudding by collecting cloud-free imagery over the entire Wadden Sea at low tide for subsequent years that enables the monitoring of the dynamics of the mussel beds. Therefore, we took up this challenge and succeeded for the targeted years 2014, 2015, 2016 and 2017 (Figure 3).

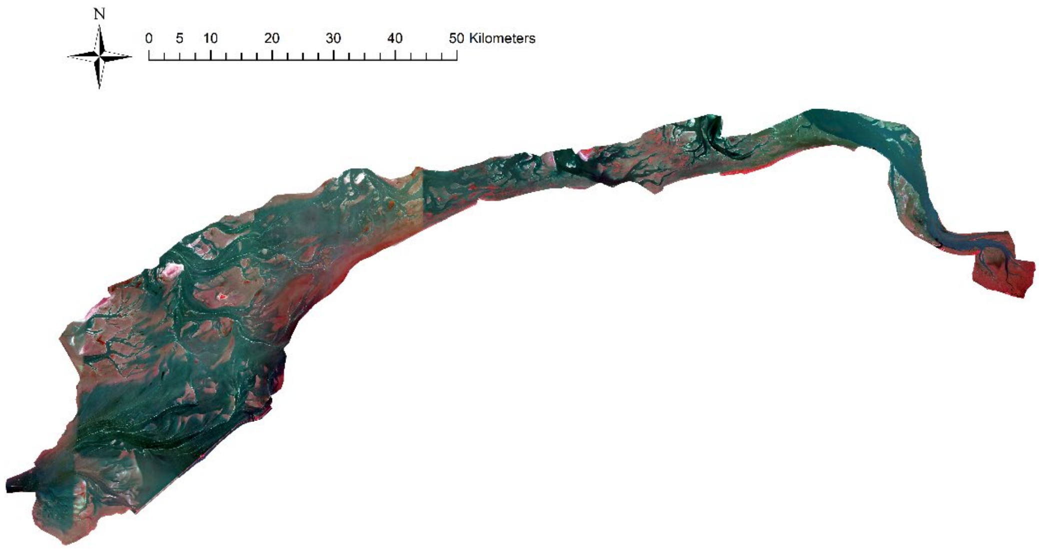
A. 2014 (SPOT6/7)



B. 2015 (SPOT6/7)



C. 2016
(SPOT6/7)



D. 2017
(RapidEye)

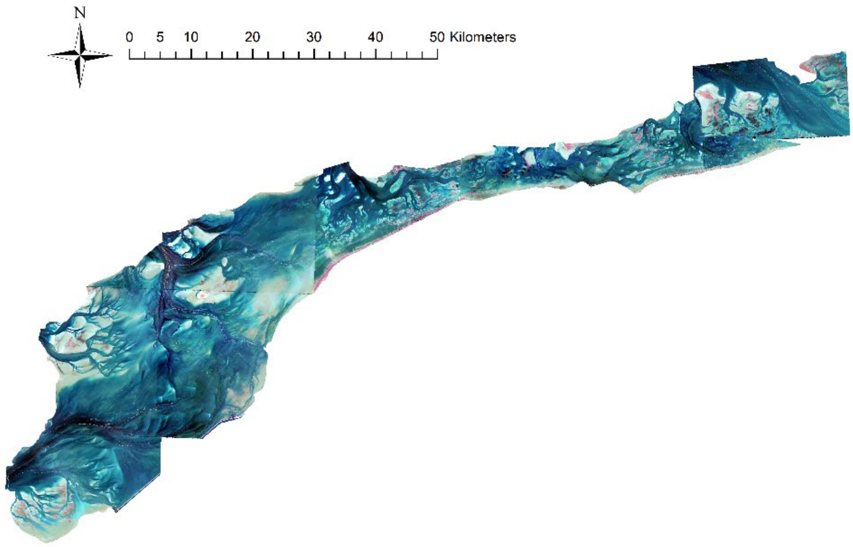


Figure 3. The compiled full coverage mosaics for the entire Wadden Sea for the years 2014 (A), 2015 (B), 2016 (C) and 2017 (D), based on scenes (A-C SPOT6/7 and D RapidEye) acquired during low tide.

Supporting the monitoring of mussel beds based on high resolution satellite imagery for the entire Dutch Wadden Sea has proven to be possible in terms of acquisition of cloud-free optical satellite imagery at low tide for the years 2014-2017. However, in future years with possible extreme cloud coverage it might not always be possible to have a complete coverage. However, we assume at this moment that the period 2014-2017 has on average weather conditions like the coming years. Moreover, the number of satellites and associated imagery is still increasing, making it more likely to find cloud-free imagery.

Table 7. List of satellite images used in the compilation of full coverage mosaics as shown in Figure 3. All SPOT images were taken around 10.15 hours am.

Year of Mosaic	Sensor type	List of individual scenes
2014	SPOT6 (6m)	SPOT6_MS_**20140904**1023270_RDnew_WAD.dat SPOT6_MS_**20140904**1023270_S_RDnew_WAD.dat SPOT6_MS_**20140904**1024080_RDnew_WAD.dat SPOT6_MS_**20140918**1015442_RDnew_WAD.dat SPOT6_MS_**20140918**1016195_RDnew_WAD.dat
2015	SPOT6 (6m)	SPOT6_MS_**20150611**_135u_wad.dat SPOT6_MS_**20150611**_138u_wad.dat SPOT6_MS_**20150611**_142u_wad.dat SPOT6_MS_**20150611**_145u_wad.dat
2016	SPOT6/7 (6m)	S6_ORTHO_137-01_**2016.09.08**_RD_WAD.dat S6_ORTHO_147-01_**2016.09.13**_RD_WAD.dat S6_ORTHO_178-01_**2016.11.25**_RD_WAD.dat S7_ORTHO_022-01_**2016.04.01**_RD_WAD.dat S7_ORTHO_337-01_**2016.02.16**_RD_WAD.dat
2017	RapidEye-5 (5m)	RE1_**20170604**_3263808_RD_WAD.dat RE1_**20170619**_3163722_RD_WAD.dat RE2_**20170531**_3263708_RD_WAD.dat RE3_**20170601**_3163723_RD_WAD.dat RE3_**20170601**_3263707_RD_WAD.dat RE3_**20170601**_3263807_RD_WAD.dat RE5_**20170525**_3163520_RD_WAD.dat

The list of acquired imagery in Table 7 are only part of the downloaded and processed imagery, and concern only those images that have been used for the classification of mussel and/or oyster beds (next chapter) and can be considered as the best imagery available. It should be noted that the best acquisition periods differ over the years. The most favoured acquisition period seems to be April – June. This is the period of the year that the mussel and oyster beds reveal themselves already by the amount of brown algae that is photosynthetically active (red colours in the false colour satellite imagery). While later in the year also many sand banks reveal themselves as photosynthetically active by for example the amount of diatoms and algae. This could cause an increase of mistakes in the classification of mussel beds, even though mussel and oyster beds show a different structure.

2.2 Potential to distinguish mussels, oysters and other structures

2.2.1 Field reference data on homogeneous areas

In addition to the annual mapping of the contours of mussel and oyster beds, extra reference data were collected during the WOT survey of 2016. Several polygons were delineated which had a homogeneous cover by any of several different types of habitats: mussel bed, oyster bed, aggregation of empty shells, aggregation of sand mason worms, etc. In the section below, an overlay is made with very detailed TripleSat (80 cm) imagery to visually check whether these structures are recognizable on the TripleSat images and whether they have unique spectral signatures that enables classification.

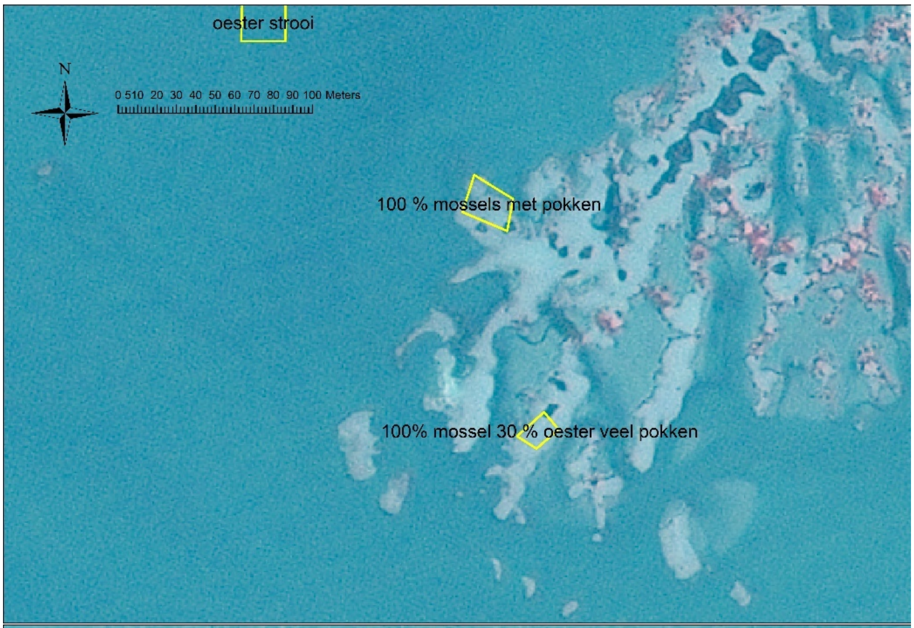
2.2.2 Visual comparison with field reference

Although the number of reference measurements of homogenous objects were too limited in number to make a thorough analysis, we made a simple overlay these reference measurements with the different types of satellite imagery. For this purpose, we overlaid very detailed TripleSat imagery (80 cm resolution) with the delineated polygons from the field (as a shapefile 'referentievlakken_2016').

A.

Homogenous reference objects from top to bottom:

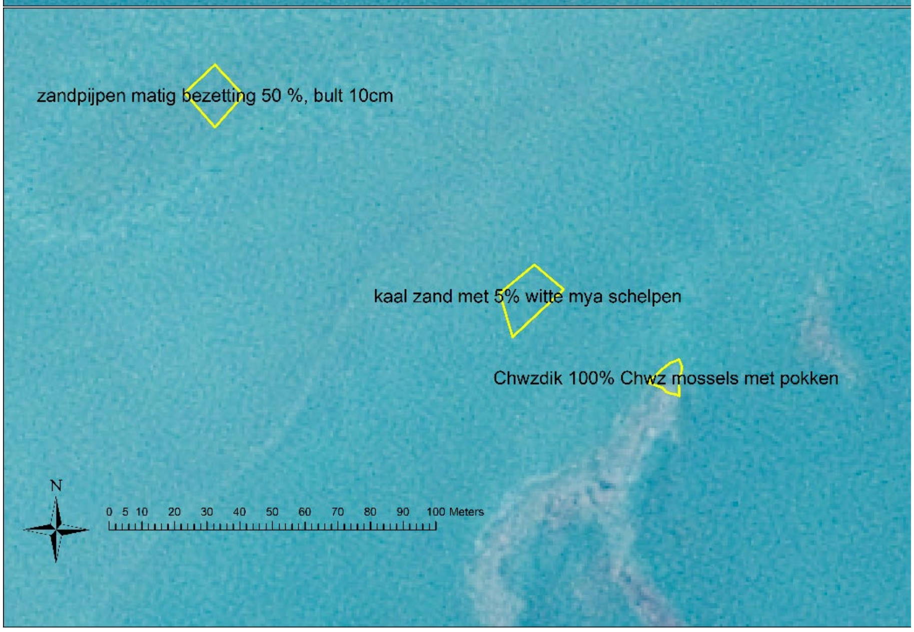
- *scattered oysters*
- *100% mussels with barnacles*
- *100% mussels with 30% oysters and barnacles*



B.

Homogenous reference objects from top to bottom:

- *Sand mason (worm) reef with 50% coverage*
- *Bare sand with 5% white shells (of Mya arenaria)*
- *100% mussels with barnacles*



C.

Homogenous reference objects from top to bottom:

- *100% sand mason worms*
- *100% sand mason worms*

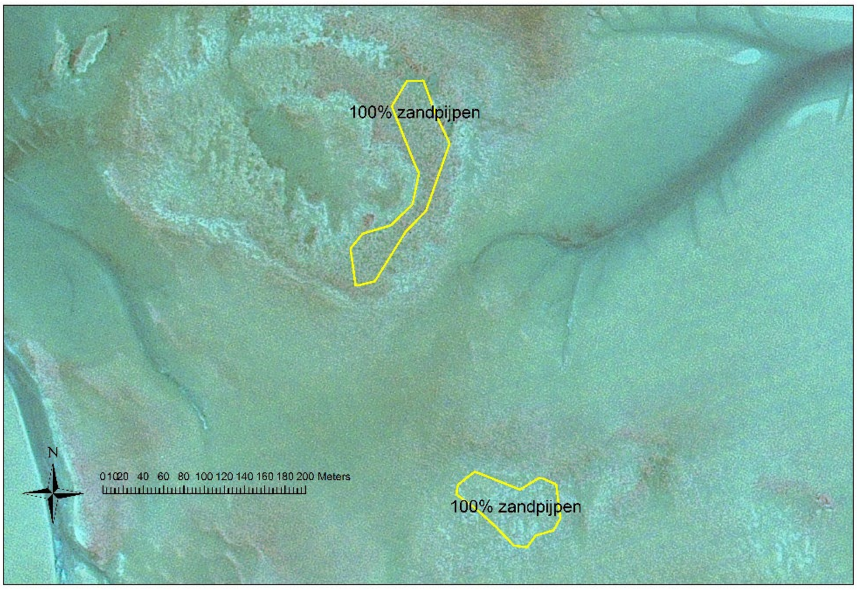


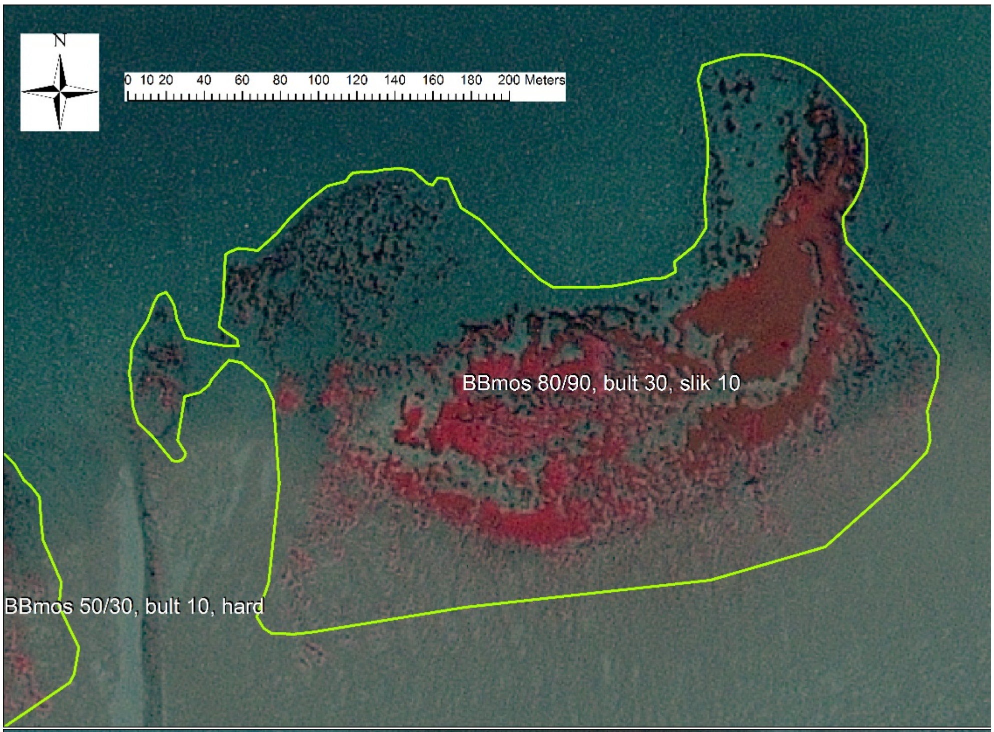
Figure 4 Comparison of different components of mussel and oyster beds using homogenous reference objects for the year 2016 made during the WOT survey and 80 cm resolution TripleSat imagery for the same year.

These examples indicate that even with very high-resolution satellite imagery it will be hard or impossible to distinguish mussels from oysters. Although reefs of sand mason worms (*Lanice conchilega*) might be detectable from oyster /mussel beds since they have a structure that is much finer than those of oyster or mussel beds (own field observations).

In the examples below in Figure 5, the mussel and/or oyster beds as a combined class seem to be well distinguishable from other classes.

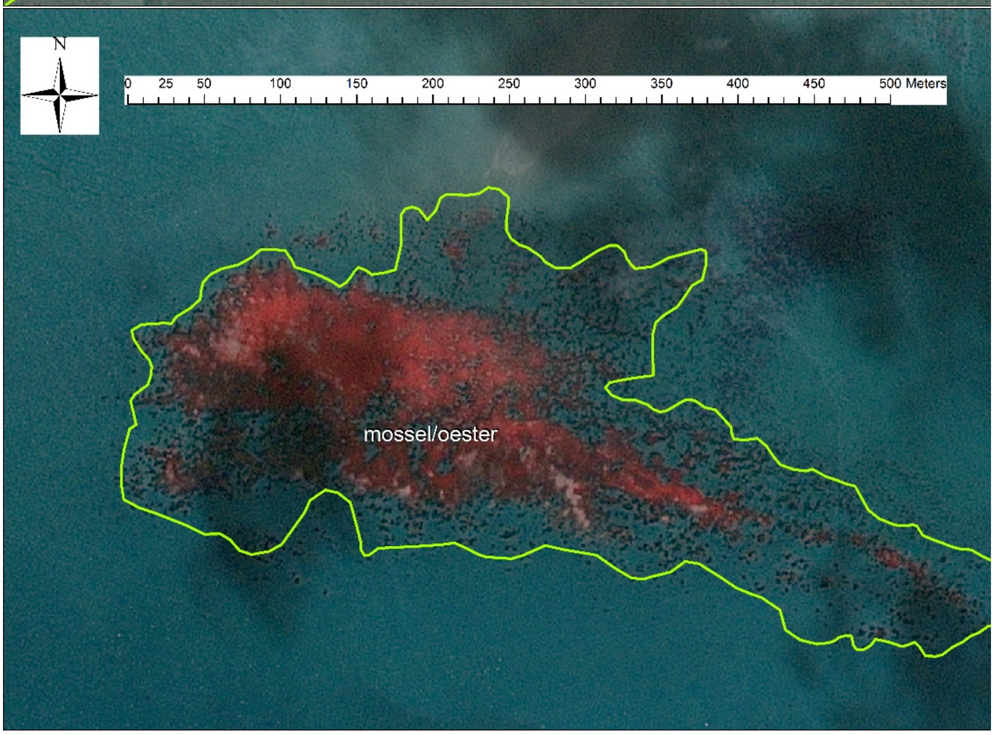
A.

Mussel bed on a TripleSat image of 2017.



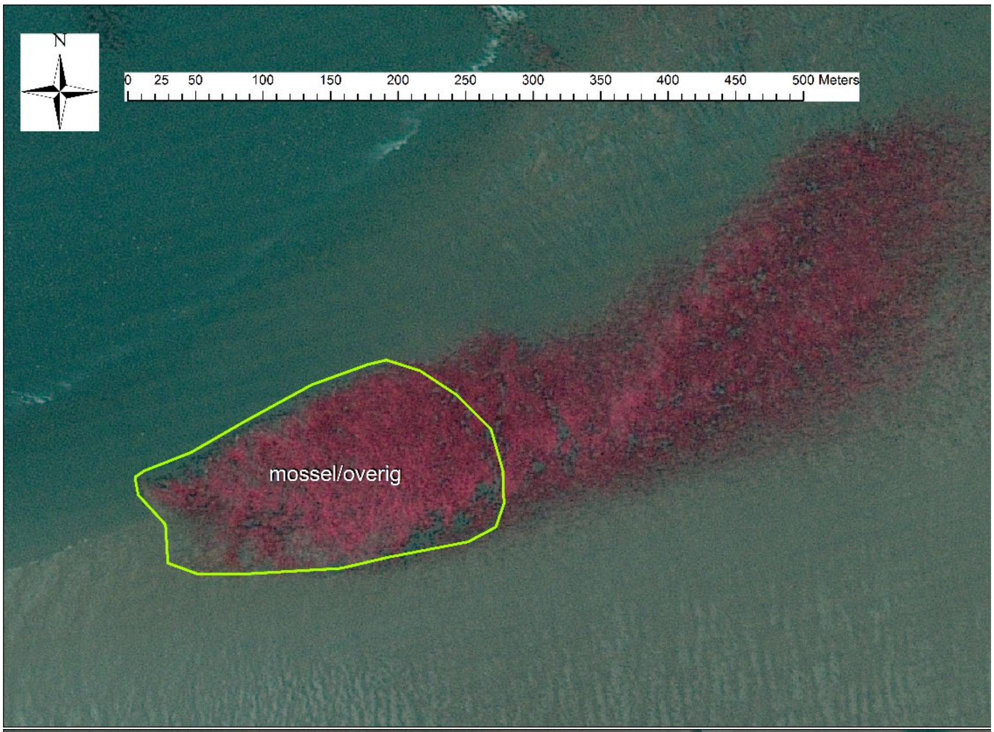
B.

Mixed bed with mussels and oysters on a TripleSat image of 2017.



C.

Mussel bed on a TripleSat image of 2017. Part of the bed was not delineated due to a high water level.



D.

Not a mussel of oyster bed. It misses the typical structure and is much smoother in its texture.

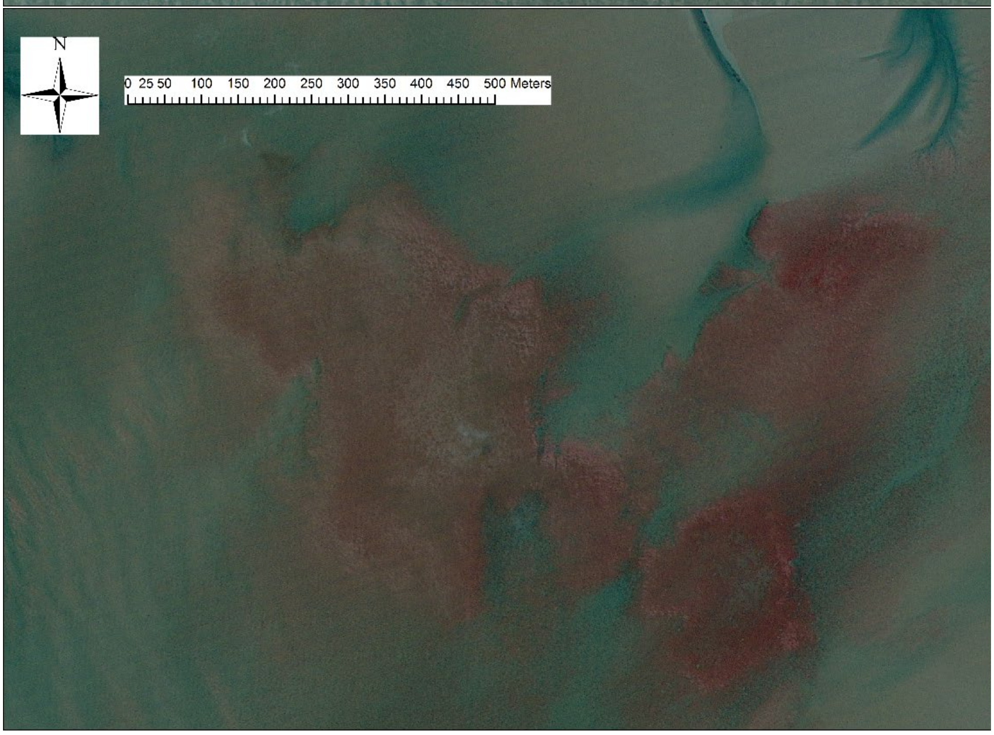


Figure 5 Examples of mussel beds (A-C) and another structure (D) as can be recognised on satellite images. Green lines are the field contours as mapped in the field survey of the same year (white text describes the bed composition in jargon). Structure D might be diatoms or sand mason worms.

Based on this visual comparison of the different sources of optical high resolution satellite imagery with field data, it seems that it is only possible to classify mussel and oysters beds as a combined class with a sufficient high accuracy, while other classes class such as diatoms, cockles, sandpipes will be difficult to visually classify on basis of high resolution optical satellite imagery with a sufficient high accuracy.

3 Classification of the satellite imagery

3.1 Remote sensing classification methods

This chapter deals with various remote sensing approaches to classify the mussel and/or oyster beds in the entire Wadden Sea by using the SPOT and RapidEye satellite imagery as an input. The different remote sensing classification approaches were amongst others, the calculation of spectral indices useful for the detection of mussel and/or oyster beds, and the use of unsupervised, decision tree classifiers and object-based segmentation techniques. Supervised classification methods are not discussed here since they need ground-truth data for training the classification, while the whole idea is to have a satellite derived mussel and/or oyster bed classification in advance of the WOT Survey, to support the annual WOT field surveys as much as possible.

3.1.1 Calculation of spectral indices

ENVI and other software packages for remote sensing provide the possibility to calculate automatically a wide range of indicators or spectral indices that can be derived from the satellite imagery. The number of spectral indices depends on the number of spectral bands available. A wide array of spectral indices can be calculated for specific purposes. Vegetation reflectance properties are used to derive vegetation indices from reflectance measurements in two or more wavelengths across the optical spectrum to analyse specific characteristics of vegetation, such as total leaf area and water content. ENVI provides the calculation of the following categories of indices: vegetation indices, geology indices, burn indices, and miscellaneous indices. Concerning mussel and or oyster beds we cannot pinpoint directly a specific spectral index. Also due to rapidly changing water conditions between low tide and high tide, the surface reflectance values are changing as well, for example for the sediments saturated or not with water. However, the brown algae that often cover mussel and oyster beds (see Figure 6) are photosynthetically active and can be detected well with spectral vegetation indices (even if the brown algae are slightly under water), which is one way to detect the beds.

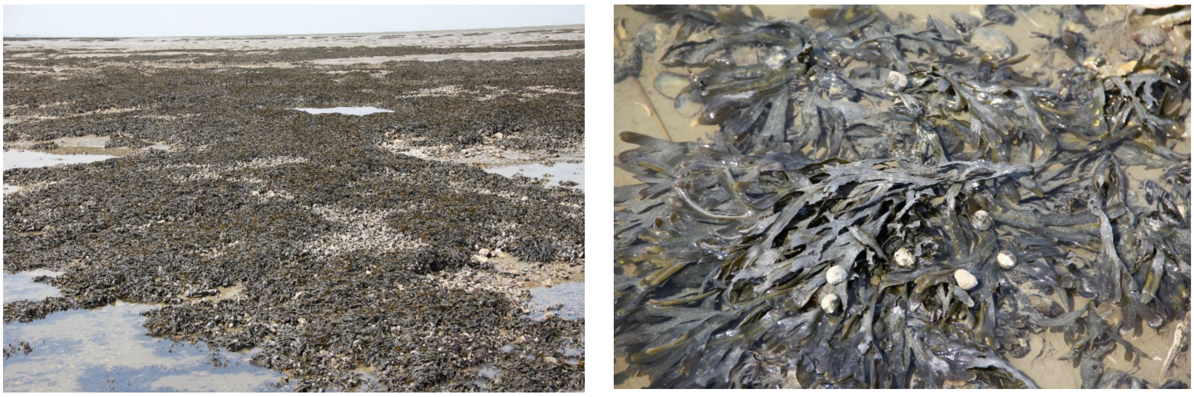
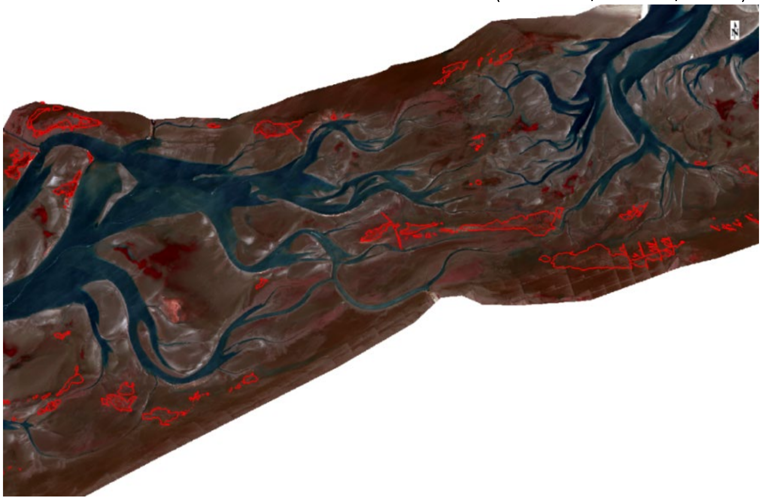


Figure 6. Two pictures of a mussel bed showing the rapidly changing moist conditions and therefore surface reflection values. The brown algae that cover the mussel and/or oyster beds, on the other hand, offer a possibility to detect the bed through their photosynthetic activity, that can be detected well with spectral vegetation indices such as NDVI.

There are many spectral vegetation indices. Next to narrowband greenness, canopy nitrogen, canopy water content, dry or senescent carbon, leaf pigments and light use efficiency, there are many commonly used broadband greenness indices like: Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), Enhanced Vegetation Index (EVI), Global Environmental Monitoring Index (GEMI), Green Atmospherically Resistant Index (GARI), Green Difference Vegetation Index (GDVI), Green Normalized Difference Vegetation Index (GNDVI), Green Ratio Vegetation Index (GRVI), Green

Vegetation Index (GVI), Infrared Percentage Vegetation Index (IPVI), Leaf Area Index (LAI), Modified Non-Linear Index (MNLI), Modified Simple Ratio (MSR), Non-Linear Index (NLI), Optimized Soil Adjusted Vegetation Index (OSAVI), Renormalized Difference Vegetation Index (RDVI), Soil Adjusted Vegetation Index (SAVI), Simple Ratio (SR), Sum Green Index (SGI), Transformed Difference Vegetation Index (TDVI), etc. See also the Appendix in which all spectral indices have been visualised. For more background information, see for example http://www.harrisgeospatial.com/docs/broadbandgreenness.html. Since for mussel bed detection it is quite difficult to decide on any optimal spectral index, we decided to use for our classification purposes, next to the original spectral bands, the Normalized Difference Vegetation Index (NDVI; see figure 7 for an example). We selected the NDVI since it is the best vegetation index for operational use, it is more stable in different atmospheric conditions, and can be easily analysed and integrated). However, since we can dispute which spectral index is the best, in Appendix 1 we give an overview of a wide array of spectral indices that we have calculated for an example of a multi-spectral SPOT image in the Wadden Sea. The reader can in that sense also give his/her own opinion.

SPOT6 IMAGE MULTSPECTRAL FALSE COLOUR (RGB:NIR/GREEN/BLUE) – 11 June 2015



NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI)

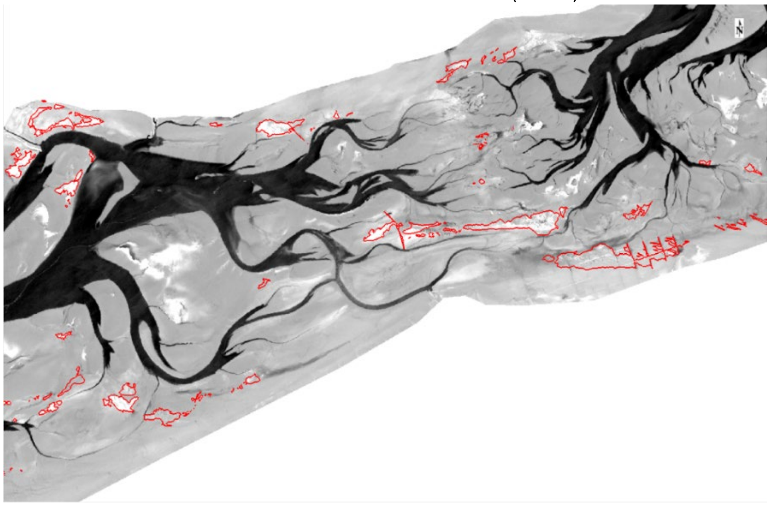
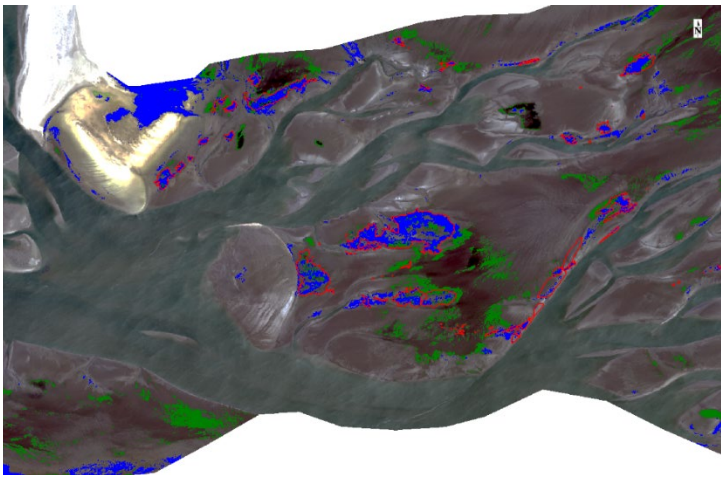


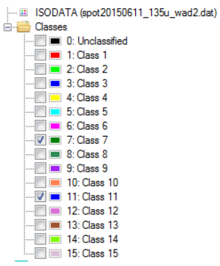
Figure 7. Example of a false-colour SPOT6 image with the derived NDVI below. The polygon (red outline) is the result from the WOT field survey and indicates the location of the mussel and or oyster beds for the year 2015. It's clear that many beds are only partly covered by photosynthetically material, and that not all photosynthetically material reflects mussel and or oyster beds.

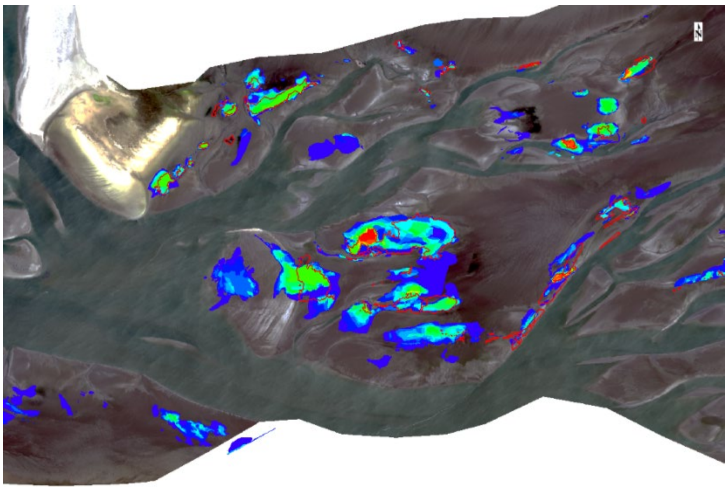
3.1.2 Unsupervised classification

The advantage of unsupervised classifications or clustering is that you can categorize the pixels in a satellite image into different classes without providing training or reference data. There are two main clustering techniques that are often used in unsupervised classifications, namely ISODATA and K-means. K-Means unsupervised classification calculates initial class means evenly distributed in the data space then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates class means and reclassifies pixels with respect to the new means. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached (source: harrisgeospatial.com). The ISODATA algorithm has some further refinements by splitting and merging of clusters (Jensen, 1996). Clusters are merged if either the number of members (pixel) in a cluster is less than a certain threshold or if the centres of two clusters are closer than a certain threshold. Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value and the number of members (pixels) is twice the threshold for the minimum number of members.



ISODATA clustering result with classes 7 and 11 selected as being related to mussel beds





The number of years a mussel bed was present in the periode 1995-2011 (Troost et. Al. 2015)

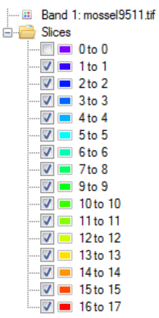


Figure 8. Isodata unsupervised classification compared with field-based mussel bed frequency map of Troost et al. (2015).

The ISODATA algorithm is similar to the k-means algorithm with the distinct difference that the ISODATA algorithm allows for a different number of clusters while the k-means assumes that the number of clusters is known a priori. For this reason, we prefer ISODATA clustering, to explore our imagery for mussel bed detection. Visual comparison of the ISODATA unsupervised classification with the field-based mussel bed frequency map of Troost *et al.* (2015) shows that ISODATA classes 7 and 11 are quite well related with the location of the mussel beds. And so, it shows the potential to identify mussel and oyster beds on basis of high resolution satellite imagery. Nevertheless, clustering techniques are more useful to explore the satellite imagery than to implement a classification for the entire Wadden Sea since it is often difficult to label the spectral classes directly into thematic classes. Supervised classification methods, like maximum likelihood, minimum distance, Mahalanobis distance algorithm, or Spectral Angle Mapper (SAM), are useful to categorize pixels of an image into different classes if we have sufficient reference data. Since we want to identify or classify all mussel and/or oyster beds in the Wadden Sea before the field survey has taken place, we cannot depend on supervised classification methods. Only in case the beds are not dynamic you could suppose the use the data from the WOT field surveys could be used from the years before. However, the beds are dynamics, and therefore we do not deal with supervised classifications in this report. However, we used the information form the former WOT field surveys in the post processing classification chain, explained in a later stage. The best classification alternatives, next to unsupervised classifications, are therefore object-based image classification and/or a decision tree classifier as being discussed in the next sessions.

3.1.3 Object based Image Analysis (OBIA)

Instead of analysing individual pixels as within an unsupervised or supervised classification, Object Based Image Analysis (OBIA) groups pixels into meaningful objects and analyses the objects for classification. On top of the information contained in the individual pixels, objects contain information about the relevant context of a pixel. Alternative to OBIA is to use a moving window to incorporate contextual information of pixel's direct neighbourhoods. Downside of such an approach is that the neighbourhood of a pixel is not necessarily meaningful and thus not necessarily relevant for classification (Stuckens *et al.*, 2000), it does not embrace spatial concepts (Blaschke and Strobl, 2001). Besides this, OBIA gives the user control over the mapping scale and can handle the implicit variability that comes with very high-resolution imagery (Jyothi *et al.*, 2008; Liu and Xia, 2010). More important for applications where reliability is more important than accuracy, OBIA separates the identification from the classification which is in line with the manual approach of delineation of boundaries and the assignment of labels in the field. The user has more control over the final mapping result since it has choices in both steps. It is possible to partially skip the first step for certain regions, to only segment areas which have known changes for subsequent maps. Simultaneously, this means that there should be objective mechanisms to identify objects of the right scale, and consistently assign the correct labels. One of the most common software packages for OBIA, and that we have available, is eCognition Developer of Trimble (version 9.2). The software eCognition Developer offers a collection of algorithms for image analysis, amongst others a variety of segmentation algorithms such as multiresolution segmentation, quad tree or chessboard segmentation. The classification algorithms range from sample-based nearest neighbour, fuzzy logic membership function or specialized context-driven decision tree classifiers (source http://www.ecognition.com).

As an example, we have performed an object-based classification in eCognition developer 9.2. As an input we used a SPOT 6 image of 11th of June 2015 (SPOT20150611_125u_wad2.tif). On this SPOT image with a 6-meter resolution we applied a multiresolution segmentation with the following parameter settings: scale 100; shape 0.4; compact 0.2 and same image layer weight for all four spectral bands. These parameter settings are based on trial and error and on experiences from former projects. After this a spectral difference of 50 was performed to merge all polygons with a similar reflectance. In a following step these polygons were classified into two classes; mussel bed 1 and mussel bed 2. For class

1 we used a decision tree classifier purely based on thresholding the NDVI (NDVI > 0.14). For class 2 we used an additional criterion namely GLCM > 600, next to a NDVI > 0.11. All based on trial and error, using *mussel bed frequency map of Troost et al. 2015* as a reference. GLCM stands for Grey Level Co-occurrence Matrix as measures the texture of a polygon-based algorithm originally described by Haralick et al in 1973.

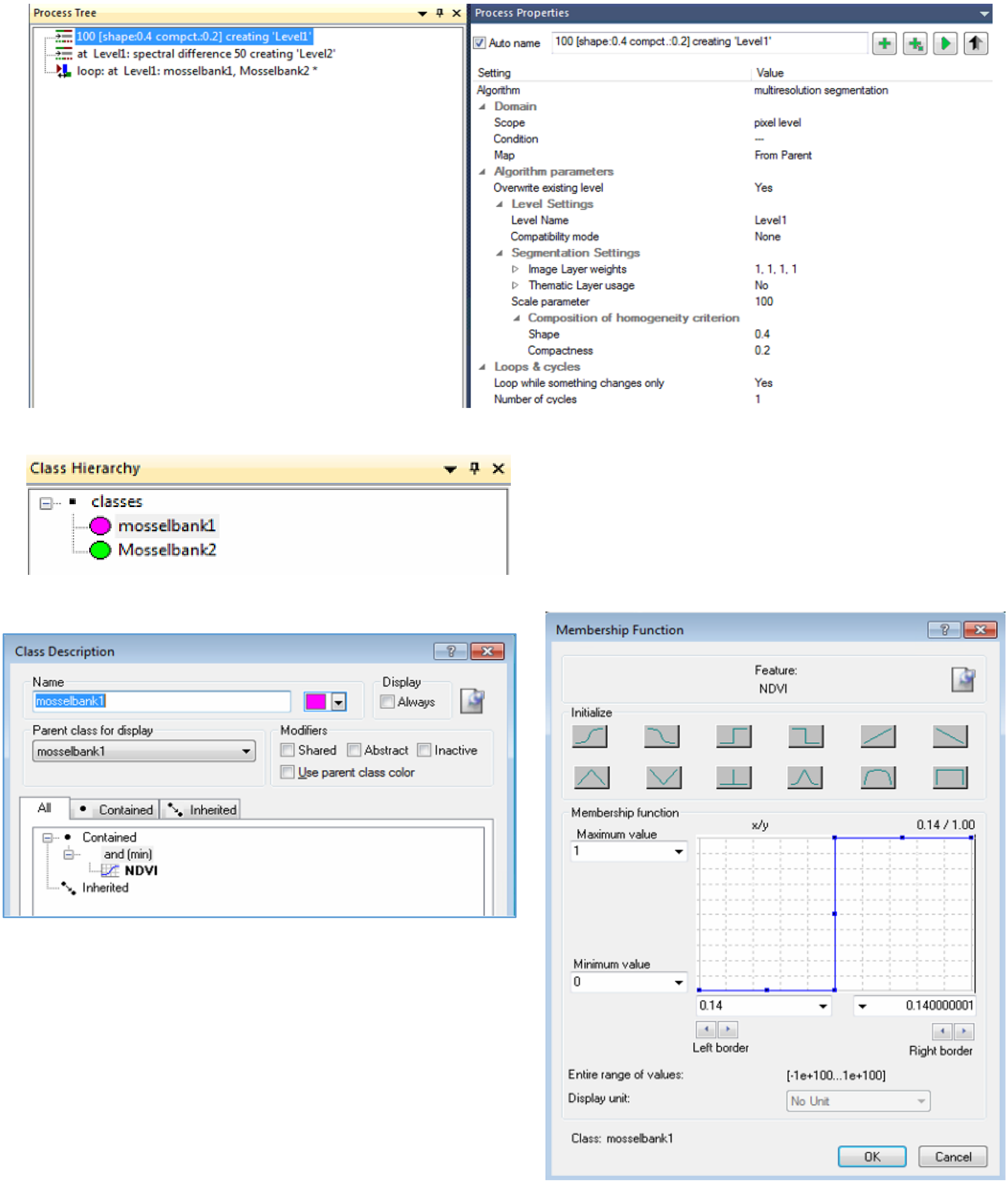


Figure 9. Example of setting up an object classification in eCognition.

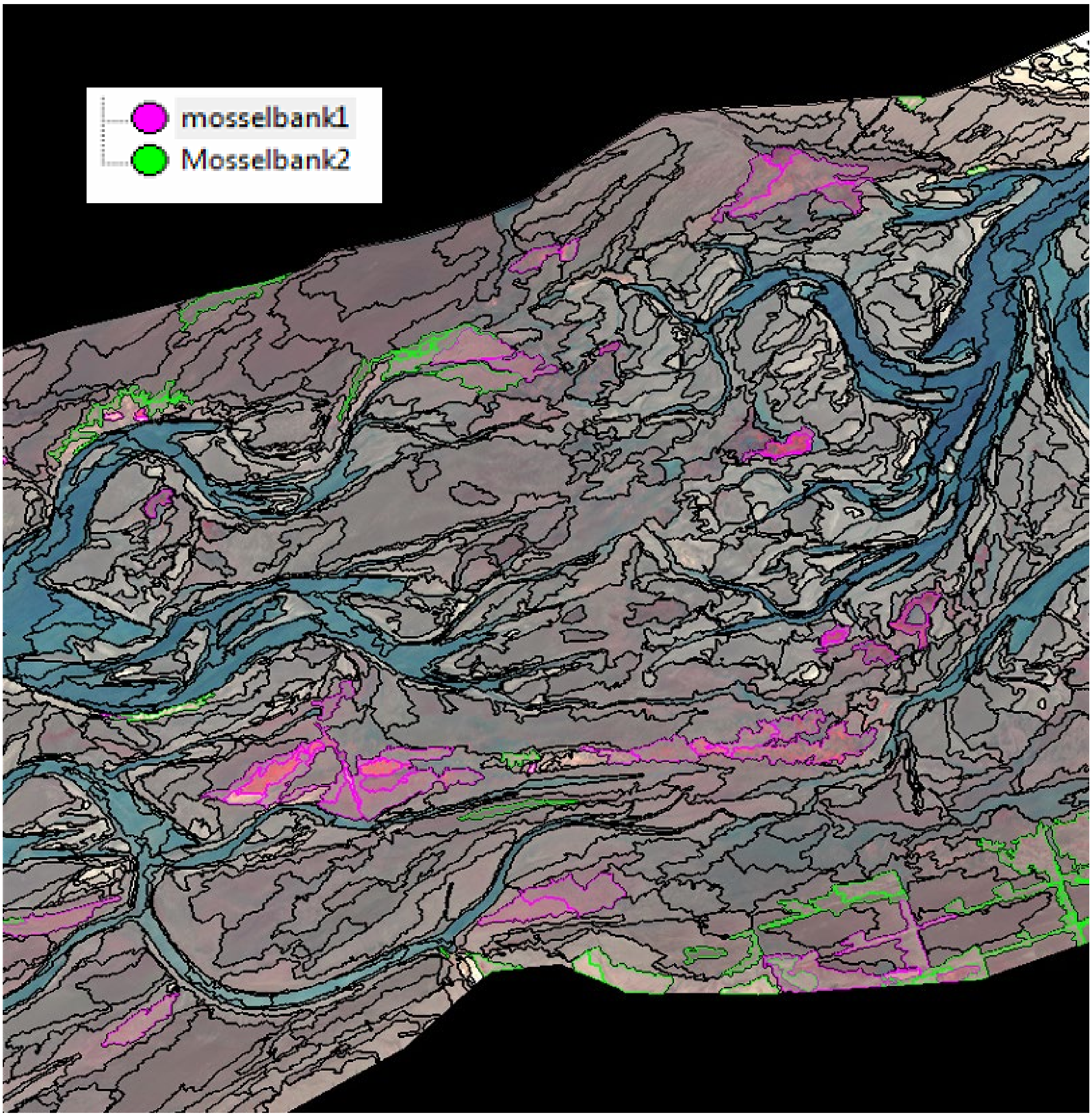
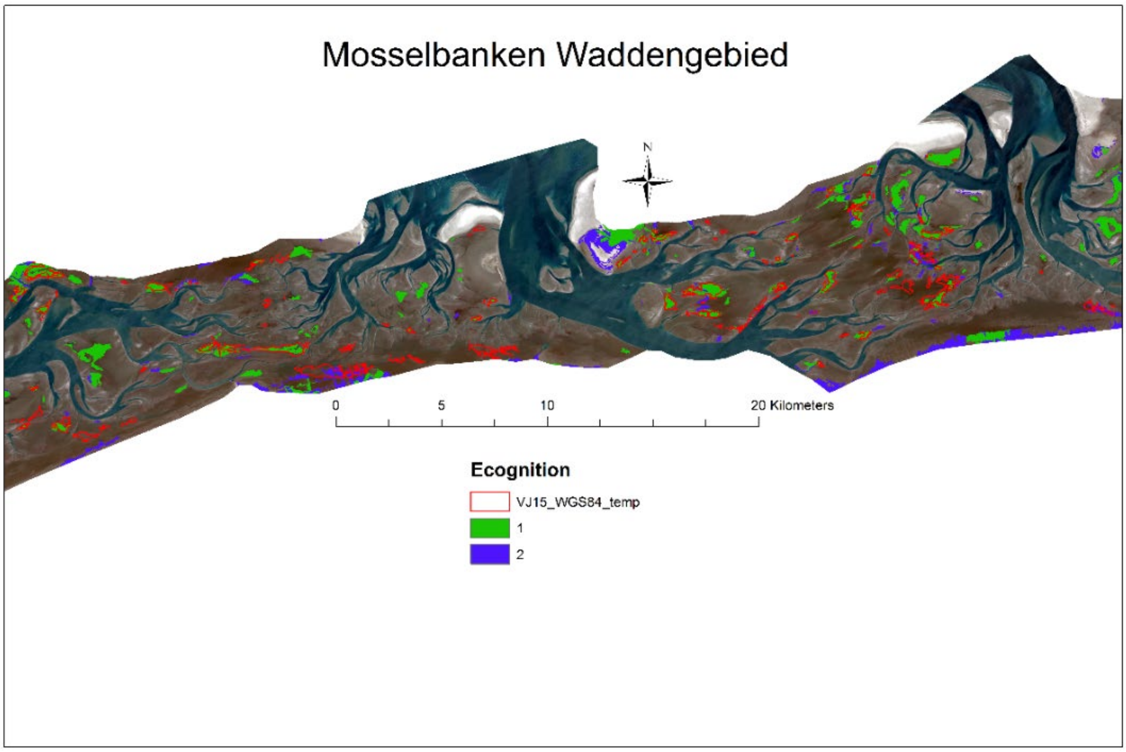


Figure 10. Resulting object classification of mussel beds in eCognition based on a SPOT image and divided into two mussel bed classes with different spectral characteristics.

This object-based classification in eCognition leads to the result shown as shown in Figure 8. It demonstrates an example of setting up an object classification in eCognition.

In Figure 9 the resulting object classification is being compared with the mussel bed frequency map of Troost *et al.* 2015 and the WOT field survey of 2015 that we used as references.



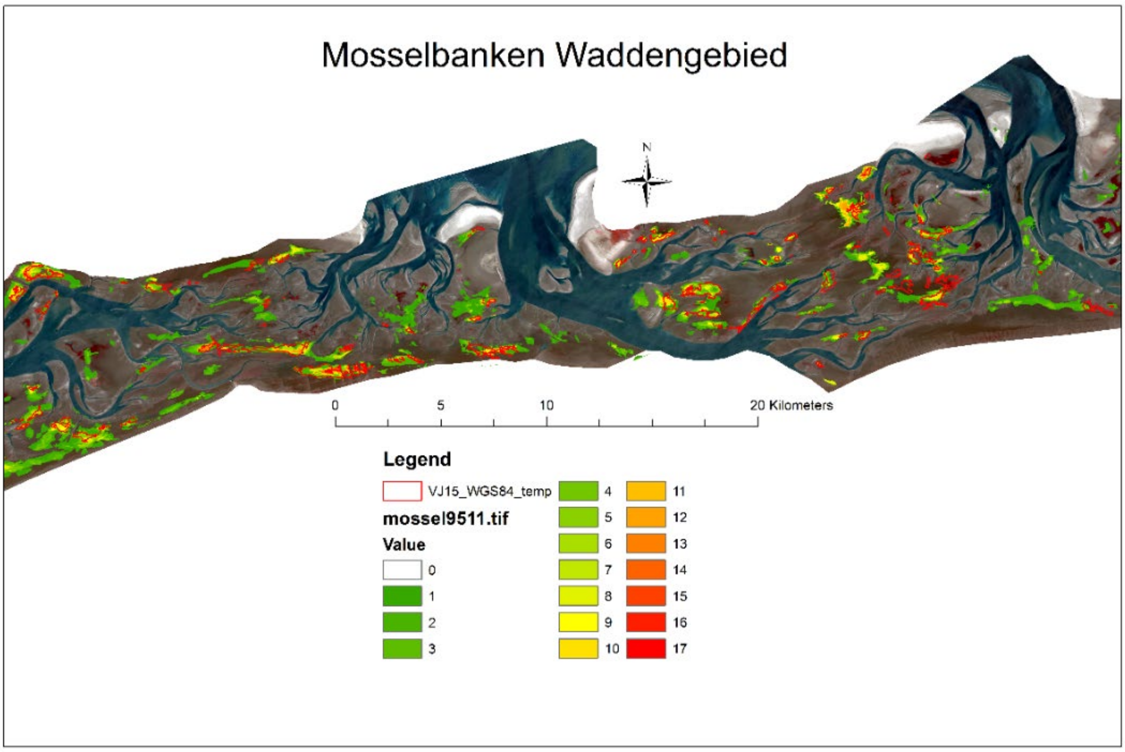


Figure 11. Visual comparison of a simple classification performed in eCognition, with the settings as explained above, with the field-based mussel bed frequency map of Troost et al. 2015 and the WOT field survey of 2015.

The classification results are reasonable but finding the proper thresholds for the decision tree classifiers in eCognition is the most labour-intensive part of the classification since it is based on trial and error using the *mussel bed frequency map of Troost et al. 2015* as a reference. Since executing a proper classification in eCognition is still labour-intensive for the entire Wadden Sea for subsequent years it was decided to explore a simpler decision tree classification based on thresholding NDVI imagery, which in principle can be done in almost any image analysis software package.

3.1.4 Decision tree classification based on thresholding NDVI imagery

To make the classification as simple and as fast as possible we decided to perform the final classification for the entire Wadden Sea and for the four subsequent years 2014 – 2017 based on a simple decision tree classification. The decision tree classification is based on thresholding the NDVI imagery as calculated from the multispectral images. For this purpose, we used the ENVI image analysis software, but any other image analysis software package could be used as well. Within the decision tree we can use any mathematical function (band algebra) on the input spectral bands, and in our case, we used the NDVI imagery as an input for thresholding. For subsequent years we used the following thresholds on the individual NDVI scenes, as shown in Table 8.

Table 8. The thresholds for each individual satellite image used in the NDVI decision tree classification.

Mosaic	Individual images	Thresholds
2014	SPOT6_MS_**20140918**1016195_RDnew_WAD.dat	NDVI gt 0.09 AND NDVI lt 0.50
	SPOT6_MS_**20140918**1015442_RDnew_WAD.dat	NDVI gt 0.09 AND NDVI lt 0.50
	SPOT6_MS_**20140904**1024080_RDnew_WAD.dat	NDVI gt 0.09 AND NDVI lt 0.50
	SPOT6_MS_**20140904**1023270_S_RDnew_WAD.dat	NDVI gt 0.07 AND NDVI lt 0.45
	SPOT6_MS_**20140904**1023270_RDnew_WAD.dat	NDVI gt 0.07 AND NDVI lt 0.40
2015	SPOT6_MS_**20150611**_138u_wad.dat	NDVI gt 0.20 AND NDVI lt 0.50
	SPOT6_MS_**20150611**_135u_wad.dat	NDVI gt 0.18 AND NDVI lt 0.45
	SPOT6_MS_**20150611**_142u_wad.dat	NDVI gt 0.13 AND NDVI lt 0.60
	SPOT6_MS_**20150611**_145u_wad.dat	NDVI gt 0.17 AND NDVI lt 0.60
2016	S7_ORTHO_022-01_**2016.04.01**_RD_WAD.dat	NDVI gt 0.01 AND NDVI lt 0.35
	S6_ORTHO_178-01_**2016.11.25**_RD_WAD.dat	NDVI gt -0.21 AND NDVI lt 0.18 AND ne 0
	S6_ORTHO_137-01_**2016.09.08**_RD_WAD.dat	NDVI gt -0.3 AND NDVI lt 0.0
	S7_ORTHO_337-01_**2016.02.16**_RD_WAD.dat	NDVI gt -0.1 AND NDVI lt 0.1 AND ne 0
	S6_ORTHO_147-01_**2016.09.13**_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.2
2017	RE1_**20170604**_3263808_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.06
	RE1_**20170619**_3163722_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.20
	RE2_**20170531**_3263708_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.10
	RE3_**20170601**_3163723_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.26
	RE3_**20170601**_3263707_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.20
	RE3_**20170601**_3263807_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.30
	RE5_**20170525**_3163520_RD_WAD.dat	NDVI gt 0.0 AND NDVI lt 0.40

As can be seen in Table 8, the thresholds differ per scene. There are various reasons why the thresholds vary, but the first one is due to slightly different wetness conditions. The second reason is the variation in atmospheric conditions (no atmospheric correction was applied). The third reason is that is the seasonality. And the fourth reason is that the types of sensor sometimes differ as is the case for 2017, namely RapidEye instead of SPOT 6/7.

The final results are demonstrated and validated in Paragraph 3.2, and discussed in Chapter 5.

3.2 Post-processing and classification results

After each scene is classified with a decision tree classifier based on its NDVI values, all binary classified images (values 0 and value 1) for a specific year are mosaicked into a full coverage for the Wadden Sea using the ARCMAP command 'mosaic_to_new_raster'. For each 6m pixel the maximum value is being used. This means that if one scene misses a mussel bed, while an overlapping satellite image still has identified the mussel bed, the mosaicked image includes the mussel bed.

Of these preliminary classification results class 1 'Photosynthetic' includes mussel beds, oyster beds, macro-algae, diatoms, salt marshes, but also other terrestrial vegetation if the terrestrial area was not properly masked. Class 1 'Photosynthetic' may also include aggregations of cockles, shells, and sand mason worms (*Lanice conchilega*). In a next geo-processing step class 1 'Photosynthetic' is subdivided into class 2 'Mussel and Oyster beds' based on the mussel and oyster bed frequency maps of Troost *et al.* (2015). In this step class 2 already indicates that the identified photosynthetic pixels might belong to an oyster or a mussel bed. In a third step a visual classification is performed. First, this step includes removal of marshes and terrestrial vegetation from class 2, reclassifying these as class 9 'Marshes and terrestrial vegetation'. This is followed by a better distinction of class 1 'Photosynthetic' and class 2 'Mussel and Oyster beds' based on a visual classification. This visual classification is an important step to better identify class 2 'Mussel and Oyster beds' on basis of the structural, spectral and contextual information of the mussel and or oyster bed.

For the post-processing we used the software package ERDAS IMAGINE is which we can draw Areas of Interest (AOIs) on our classified image and recode all the pixels belonging to a class into another thematic class.

The mussel bed classifications for the subsequent years cannot be used directly to detect changes between years, since the overall classification accuracy of each classification is not yet known. For this reason, an assessment is implemented in Chapter 4. But in general change detection asks for a specific change detection methodology to avoid false positives or negatives. This can be implemented by using the classification of one specific year (base year) and compare the original satellite images for subsequent years to indicate if existing mussel bed has really disappeared.

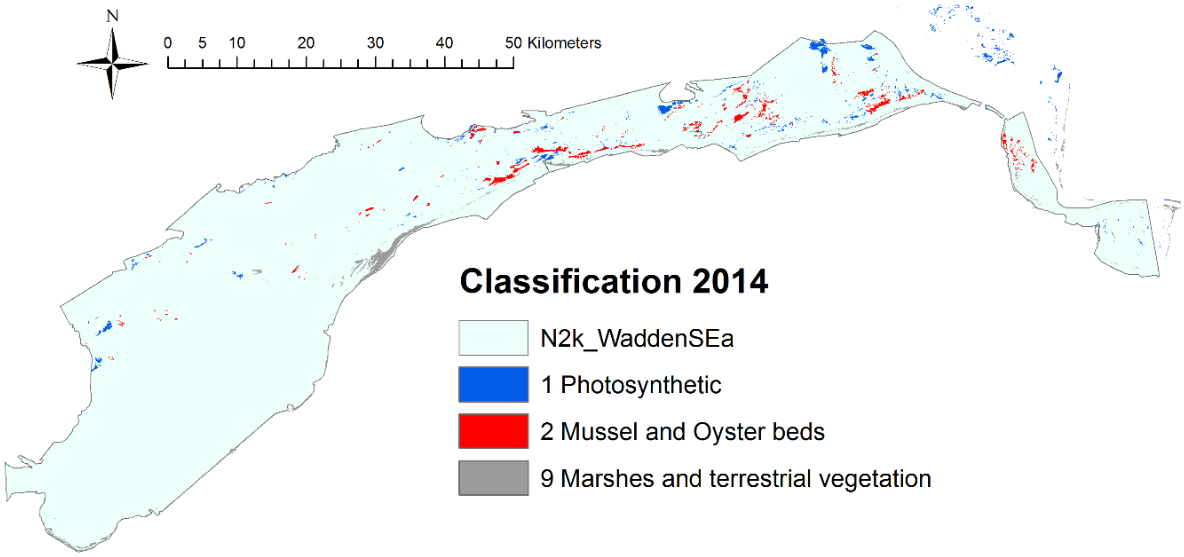


Figure 12 Classification 2014.

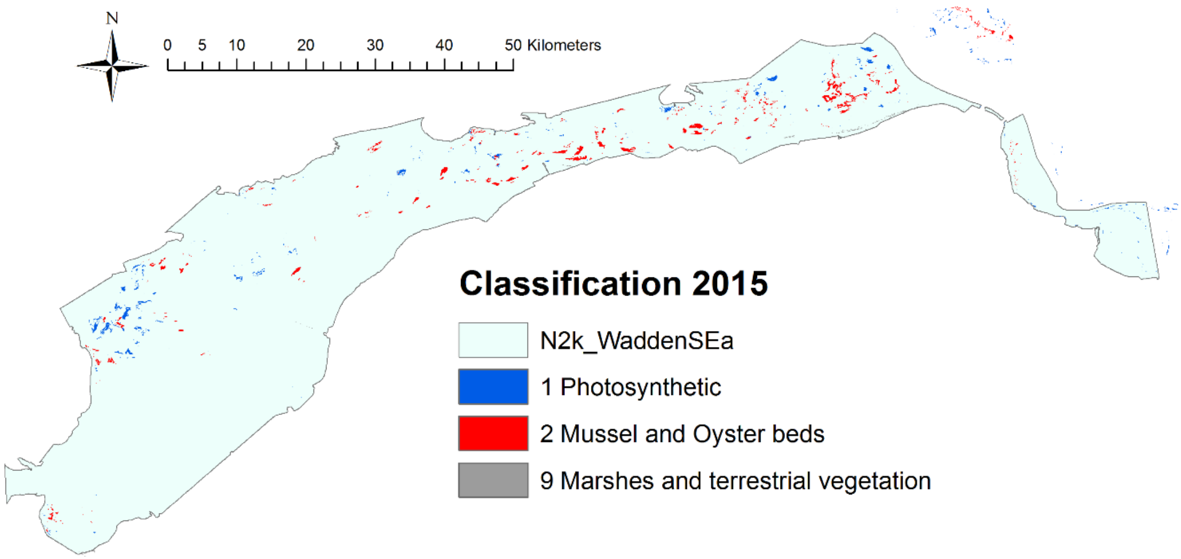


Figure 13 Classification 2015.

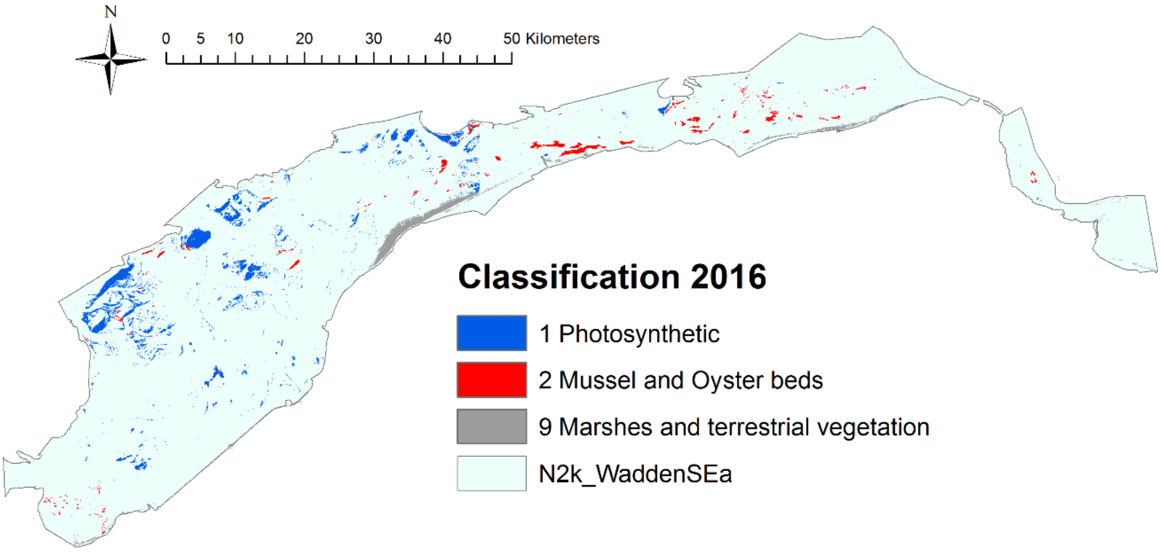


Figure 14 Classification 2016.

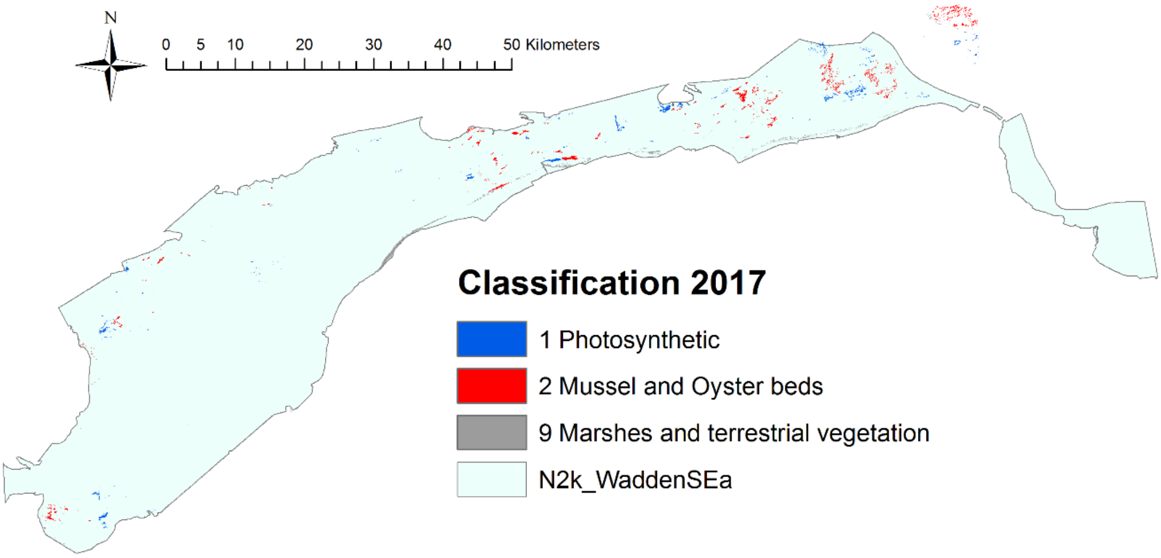


Figure 15 Classification 2017.

4 Accuracy assessment

4.1 Introduction

An assessment of the mussel bed classifications can be implemented on basis of ground truth data as being collected during the WOT surveys for the sub sequential years: 2014 – 2017. For each year a pixel-based comparison can be performed according to classification accuracy assessment method described by Lilesand *et al.* (2008) by preparing a classification error matrix, also known as confusion matrix or contingency table. Error matrices compare, on a category-by-category basis, the relationship between known reference data (ground truth) and the corresponding results of the classification or modelling exercise (Lillesand *et al.*, 2008). Producer's Accuracy is a measure of omission error and User's Accuracy is measure of commission error. Errors of commission result when pixels associated with a class are incorrectly identified as other classes, or from improperly separating a single class into two or more classes. Errors of omission occur whenever pixels that should have been identified as belonging to a particular class were simply not recognized as present. For simplicity we refer to user's accuracy as *reliability* and producer's accuracy as *accuracy*. These are expressed as:

- Reliability: the percentage of the total area classified as "bed" that was identified as such in the field survey. For example, a reliability of 50% means that of the total area classified as "bed" 50% was actually identified as being a mussel or oyster bed in the field survey.
- Accuracy: the percentage of the total area identified as "bed" in the field survey that was classified as such based on the satellite images. For example, an accuracy of 50% means that of the total area that was identified as being a mussel or oyster bed in the field survey, 50% was classified as being a mussel or oyster bed based on the satellite images.

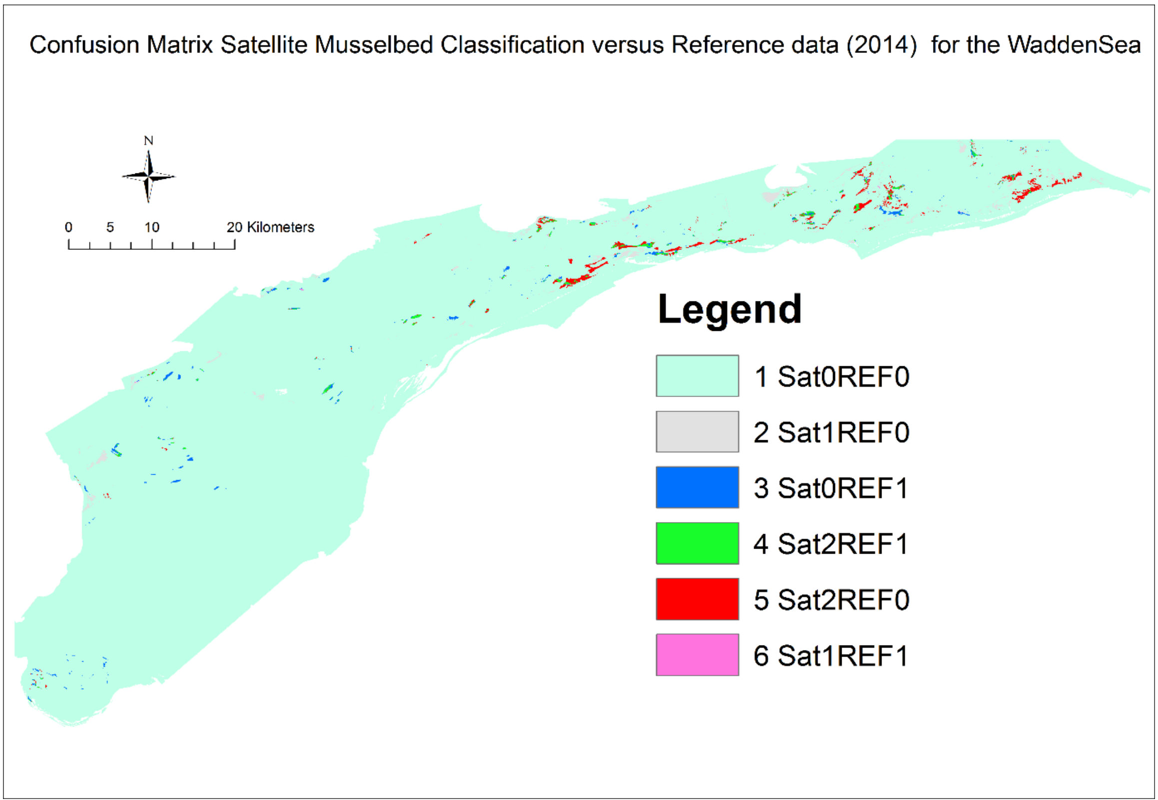
4.2 Ground truth from WOT survey

Within the WOT survey mussel and oyster beds are being mapped every spring in the Wadden Sea using a hand-held GPS, after an inspection flight has confirmed the presence or absence of existing and new seed beds. The methods used are described in more detail by Van den Ende *et al.* (2017). The field work involved is time consuming and not all beds can be visited every year. For each year all ground truth polygons were used that were identified as mussel and/or oyster bed. The mussel and/or oyster beds were lumped into one class since we know beforehand that our remotely sensed classifications are not good enough to separate oyster beds from mussel beds. For this reason, the beds were taken together as one class (class 1). The classified satellite imagery is being assessed for the class 2 mussel and/or oyster beds.

Table 9 Legend ground truth (REF) and classification (Sat).

Class	REF	Sat
0	No bed	No data
1	Mussel or Oyster bed	Photosynthetic
2		Mussel and/or oyster beds

Year 2014



Nr	Sat	REF	Explanation
1	No bed	No data	100% match
2	Algae	No data	Might be a bed covered by algae which may have been missed
3	No bed	Bed	Bed may have disappeared
4	Bed	Bed	100% match
5	Bed	No data	Bed may have been missed
6	Algae	Bed	Bed covered by algae

Figure 16 Confusion matrix visualised for 2014: 1) Sat0REF0: no mussel or oyster bed according to classification and ground truth 2) Sat1REF0: photosynthetic material according to the classification and no mussel or oyster bed according to ground truth, etc.

Table 10 Summary accuracy assessment of mussel and/or oyster bed satellite classification 2014

Sum of Area (ha)	Sat 2014			
REF 2014	0	1	2	Total
0	234438	1813	1812	238063
1	935	32	780	**1747**
Total	235373	1845	**2593**	239811

Reliability[1] (%)	Sat 2014	
REF 2014	0	2
0	**99.6**	69.9
1	0.4	**30.1**
Total	100.0	100.0

Accuracy (%)[1]	Sat 2014		
REF 2014	0	2	Total
0	**98.5**	0.8	100.0
1	53.5	**44.7**	100.0

Reliability (user's accuracy): 30.1%

Accuracy (producer's accuracy): 44.7 %

Overall accuracy: 98.5 %

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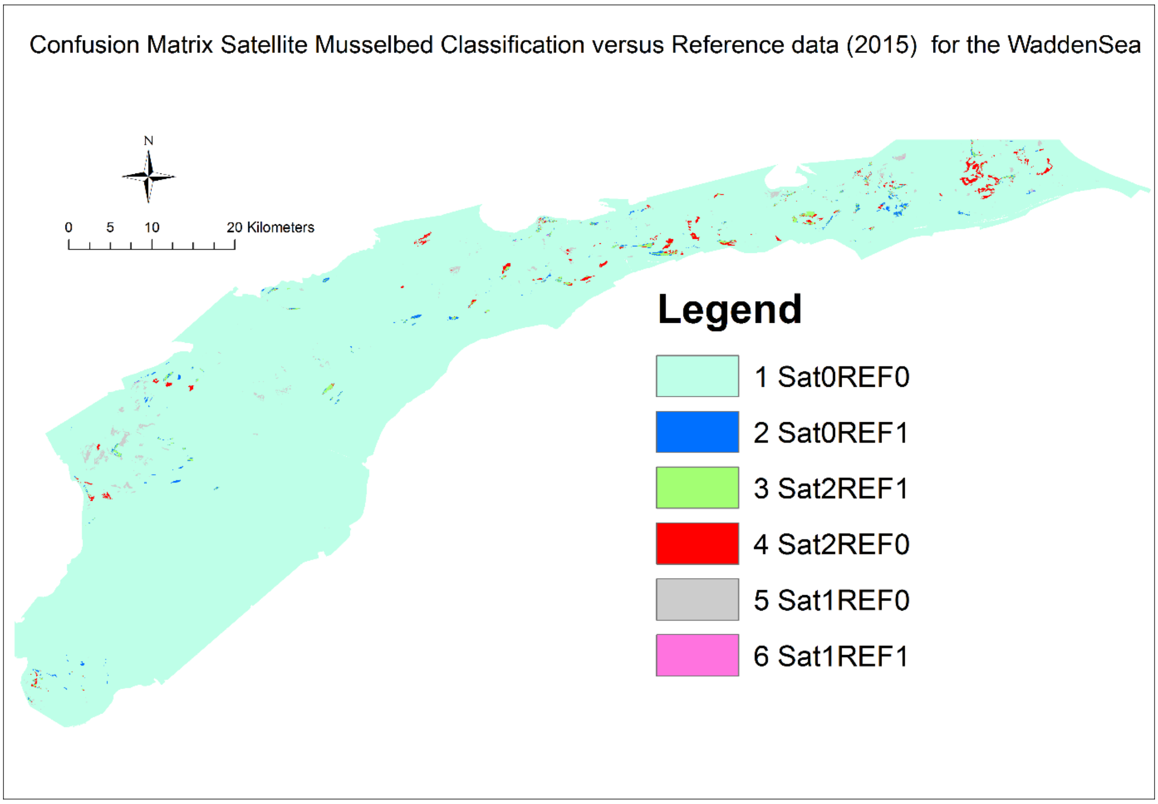
[1] For simplicity we refer to user's accuracy as *reliability* and producer's accuracy as *accuracy*. These are expressed as:

- Reliability: the percentage of the total area classified as "bed" that was identified as such in the field survey. For example, a reliability of 50% means that of the total area classified as "bed" 50% was actually identified as being a mussel or oyster bed in the field survey.
- Accuracy: the percentage of the total area identified as "bed" in the field survey that was classified as such based on the satellite images. For example, an accuracy of 50% means that of the total area that was identified as being a mussel or oyster bed in the field survey, 50% was classified as being a mussel or oyster bed based on the satellite images.

Year 2015



Nr	Sat	REF	Explanation
1	No bed	No data	100% match
2	Algae	No data	Might be a bed covered by algae which may have been missed
3	No bed	Bed	Bed may have disappeared
4	Bed	Bed	100% match
5	Bed	No data	Bed may have been missed
6	Algae	Bed	Bed covered by algae

Figure 17 Confusion matrix visualised for 2015: 1) Sat0REF0: no mussel or oyster bed according to classification and ground truth 2) Sat1REF0: photosynthetic material according to the classification and no mussel or oyster bed according to ground truth, etc.

Table 11 Summary accuracy assessment of mussel and/or oyster bed satellite classification 2015

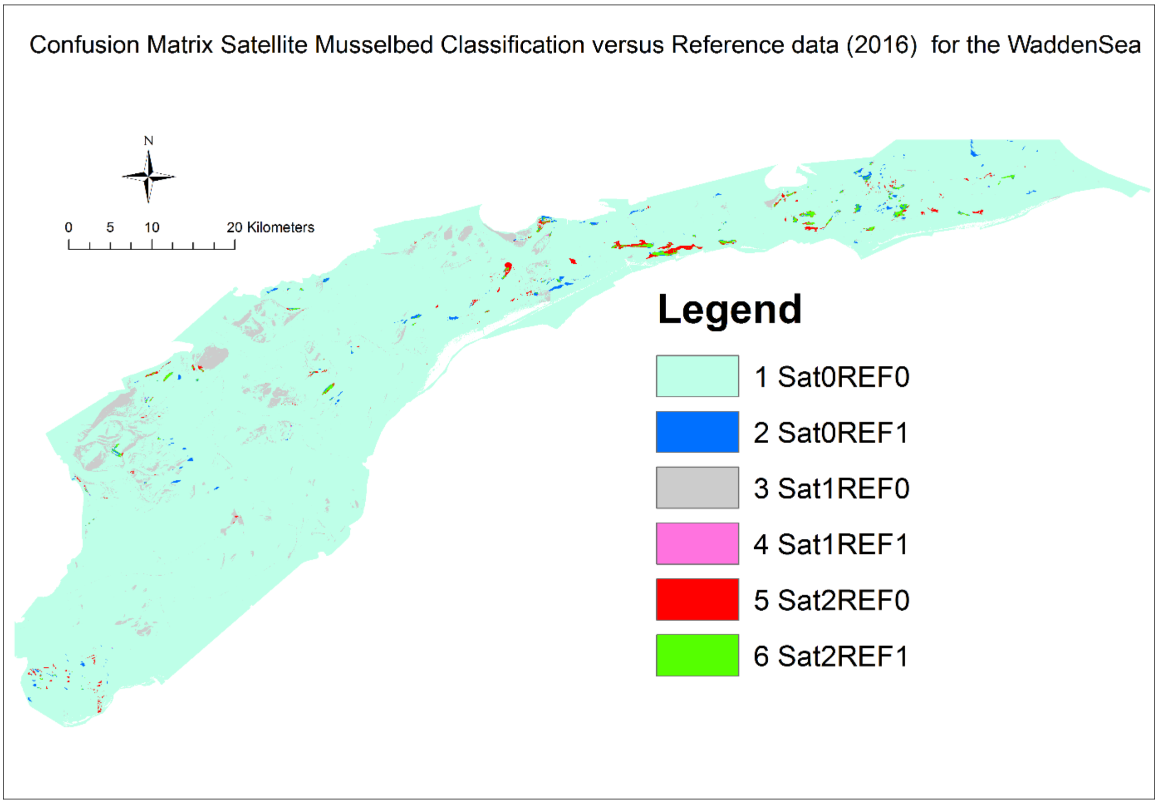
Sum of Area (ha)	Sat 2015			
REF 2015	0	1	2	Total
0	237182	1351	1547	240080
1	834	20	958	**1812**
Total	238016	1371	**2505**	241892

Reliability (%)	Sat 2015	
REF 2015	0	2
0	**99.6**	61.8
1	0.4	**38.2**
Total	100.0	100.0

Accuracy (%)	Sat 2015		
REF 2015	0	2	Total
0	**98.8**	0.6	100.0
1	46.0	**52.9**	100.0

Reliability (user's accuracy): 38.2 %
Accuracy (producer's accuracy): 52.9 %
Overall accuracy: 98.8 %

Year 2016



Nr	Sat	REF	Explanation
1	No bed	No data	100% match
2	Algae	No data	Might be a bed covered by algae which may have been missed
3	No bed	Bed	Bed may have disappeared
4	Bed	Bed	100% match
5	Bed	No data	Bed may have been missed
6	Algae	Bed	Bed covered by algae

Figure 18 Confusion matrix visualised for 2016: 1) Sat0REF0: no mussel or oyster bed according to classification and ground truth 2) Sat1REF0: photosynthetic material according to the classification and no mussel or oyster bed according to ground truth, etc.

Table 12 Summary accuracy assessment of mussel and/or oyster bed satellite classification 2016

Sum of Area (ha)	Sat 2016			
REF 2016	0	1	2	Total
0	227623	8190	1315	237128
1	1118	28	1000	**2146**
Total	228740	8218	**2315**	239274

Reliability (%)	Sat 2016	
REF 2016	0	2
0	**99.5**	56.8
1	0.5	**43.2**
Total	100.0	100.0

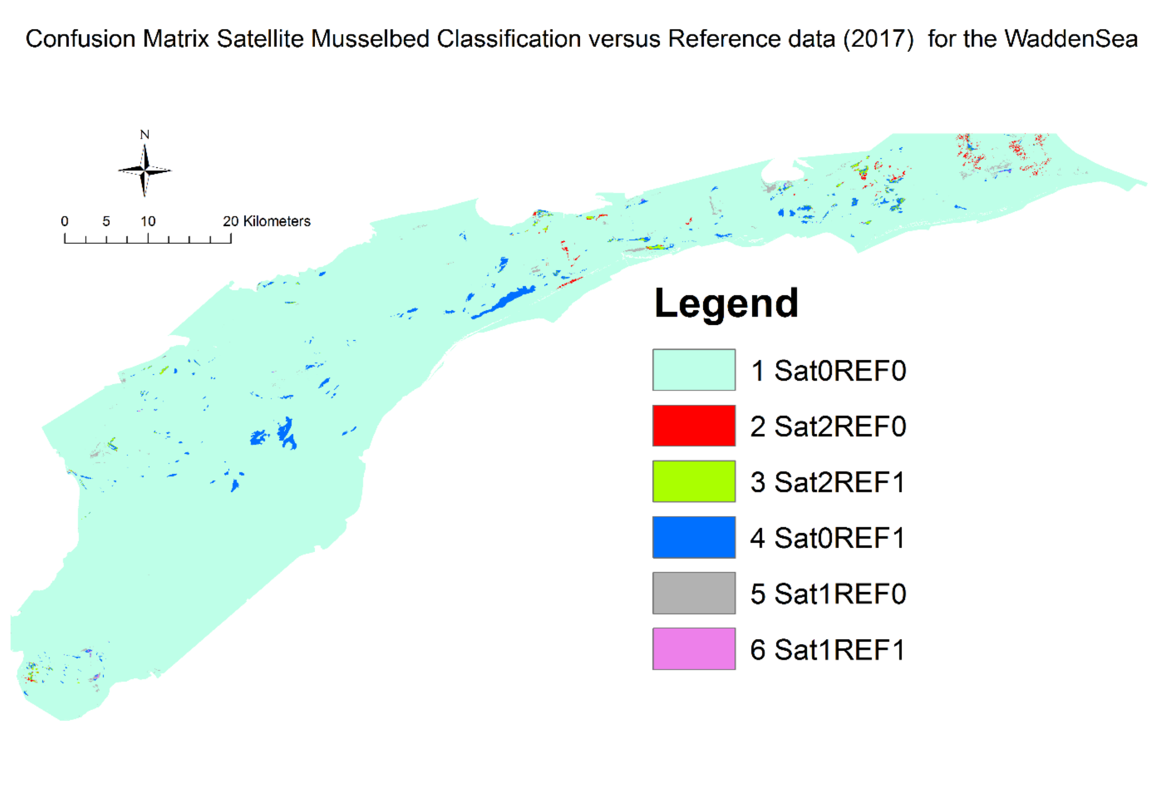
Accuracy (%)	Sat 2016		
REF 2016	0	2	Total
0	**96.0**	0.6	100.0
1	52.1	**46.6**	100.0

Reliability (user's accuracy): 43.2 %

Accuracy (producer's accuracy): 46.6 %

Overall accuracy: 96.0 %

Year 2017



Nr	Sat	REF	Explanation
1	No bed	No data	100% match
2	Algae	No data	Might be a bed covered by algae which may have been missed
3	No bed	Bed	Bed may have disappeared
4	Bed	Bed	100% match
5	Bed	No data	Bed may have been missed
6	Algae	Bed	Bed covered by algae

Figure 19 Confusion matrix visualised for 2017: 1) Sat0REF0: no mussel or oyster bed according to classification and ground truth 2) Sat1REF0: photosynthetic material according to the classification and no mussel or oyster bed according to ground truth, etc.

Table 13 Summary accuracy assessment of mussel and/or oyster bed satellite classification 2017

Sum of Area (ha)	Sat 2017			
REF 2017	0	1	2	Total
0	235947	710	724	237381
1	3337	60	571	**3967**
Total	239284	770	**1294**	241348

Reliability (%)	Sat 2017	
REF 2017	0	2
0	**98.6**	55.9
1	1.4	**44.1**
Total	100.0	100.0

Accuracy (%)	Sat 2017		
REF 2017	0	2	Total %
0	**99.4**	0.3	100.0
1	84.1	**14.4**	100.0

Reliability (user's accuracy): 44.1 %

Accuracy (producer's accuracy): 14.4 %

Overall accuracy: 98.6 %

The accuracy assessment (Table 14 - 13) shows that the reliability (user's accuracy) and accuracy (producer's accuracy) do not exceed for any year the 55%, which is not satisfactory. On the other hand, the overall accuracy is very high, with 96%-98%, for all 4 years (2014-2017). However, this is mainly due to agreement within classification and ground truth data on the absence of mussel and/or oyster beds in most locations. In Chapter 5 we discuss the results in more detail.

Table 14 Summary of the reliability, accuracy and overall accuracy determined for the four years studied: 2014-2017 (2014-2016 SPOT6/7 and 2017 RapidEye).

	Reliability (%)	Accuracy (%)	Overall Accuracy (%)
2014	30.1	44.7	98.5
2015	38.2	52.9	98.8
2016	43.2	46.6	96.0
2017	44.1	14.4	98.6

Reasons for false positives (detected by classification but not in the field) could be the following:

1) There may be a bed present that was not detected in the field because:
    a) It was never detected in the airplane survey or on foot;
    b) It was covered by water during the field survey but not at the time the satellite image was taken;
    c) If the image acquisition is of an earlier date than the field survey: The bed was still present during the time of satellite image acquisition but disappeared before the field survey took place;
2) Another structure than a mussel or oyster bed may give a signal (benthic diatoms, other vegetation, reefs of sand mason worms).

Reasons for false negatives (detected in the field but not by classification) may be the following:

1) If the image acquisition is of a later date than the field survey: the bed may have disappeared after the field survey. The bed may not have been detected because:
    a) it was covered by water during the time of image acquisition;
    b) the classification used did not recognize the signal given by this bed, e.g. because the density of mussels was too low, or because of other, yet unknown, reasons.

5 Discussion and conclusions

5.1 Data availability

A decade ago it was still difficult to acquire satellite imagery during the daytime, at low tide and with no cloud cover. For recent years (2014-2017) we have shown now that it is possible to acquire freely available optical satellite imagery covering the entire Wadden Sea at low tide and with no cloud cover. We have shown that the satellite imagery as available in the national satellite data portal is an additional source of information for the monitoring of mussel and/or oyster beds. Next to the fact that the amount of satellite imagery continues to grow. For example, for Sentinel-2 there are now two satellites 2A and 2B making it possible to acquire satellite imagery on a weekly basis at a resolution of 10 meters.

The most favoured acquisition period seems to be April – June. This is the period of the year that the mussel and oyster beds reveal themselves already by the amount of brown algae that is photosynthetically active (red colours in the false colour satellite imagery). While later in the year also many sand banks reveal themselves as photosynthetically active by for example the amount of diatoms and algae. This could cause an increase of mistakes in the classification of mussel beds at 6-10-meter resolution, even though mussel and oyster beds show a different structure at spatial resolutions <=3m. This might indicate that the use of very high-resolution imagery <=3 m resolution might be attractive but once more due to a lower acquisition frequency of this type of data it is more difficult to find cloud-free imagery at low tide.

Although we have succeeded in acquiring sufficient SPOT and RapidEye optical satellite imagery during the daytime, at low tide with limited amount of clouds, the varying water levels between image acquisition dates are still a complication. This results in a varying surface area of mussel beds that is submerged and therefore not visible, which hampers the automatic classification. This means that in most cases additional visual interpretations of the imagery are needed.

Radar imagery has the advantage that it is not limited to daytime and cloud-free conditions. The spatial and temporal resolution of freely available radar imagery like Sentinel-1 (radar), is similar to Sentinel-2 (optical), with a maximum spatial resolution of 10 meter and complete coverage for the Netherlands every 5 days. However, at the moment at the national satellite portal (https://www.satellietdataportaal.nl/ or http://www.satellietbeeld.nl/) optical data are available with a much higher spatial resolution than for Radar data, namely RADARSAT-2 with 3 meter resolution, while optical Superview satellite data are available with 0,5 meter resolution. Combining both types of imagery may, however, be a logical next step towards implementation of satellite imagery in the annual shellfish surveys.

5.2 Classification methods

Different classifications methods can be exploited for the identification of mussel and /or oyster beds. But in general, all classification methods are hampered by the fact that the spectral differences between the targeted classes are often small and the internal spectral variation of a specific class can be high due to large differences in water content. We failed to differentiate the different oyster from mussel beds. On the other hand, detection of oyster and mussel beds, as one class, is possible but is mainly driven by the presence of (brown) algae that are photosynthetically active. So, the detection of photosynthetically active material can be done most easily based on thresholding NDVI imagery by using a decision tree classifier in combination with the mussel bed frequency maps of Troost *et al.* (2015). Additional visual interpretations of the imagery were still needed to improve the classification, especially for those areas where the beds are still covered by shallow water, and areas where benthic diatoms or seaweeds are concentrated and give signals like those of beds covered by algae.

5.3 Classification accuracy

The overall classification accuracy for the entire Wadden Sea is very high for the four subsequent years and varies between 96-98 % accuracy. However, the reliability (user's accuracy) and accuracy (producer's accuracy) did not exceed 55% for any of the four years studied. This can be considered as a bad result. But concerning the accuracy assessment one must consider as well that not all mussel and oyster beds may have been identified during the field survey for a specific year. The accuracy may therefore be (somewhat) higher than 55%. In the field survey of 2018, an oyster bed was detected based on the satellite imagery classification. This bed had not been detected for several years in a row, while it must have been present for at least three years based on the size of the oysters. This shows that not all the mussel and oyster beds are identified during the field survey, and it confirms the added value of satellite imagery classifications. For this reason, producer's accuracy is a more reliable indicator for the quality of the classifications, but also here we see that only a part of the existing mussel and / or oyster beds has been identified. The mean reason for this is that part of the beds is still under shallow water during the acquisition time of the satellite imagery during low tide. In case the beds are still under water it is very difficult to classify them in an automatic way. Visually they are sometimes still visible but being missed in the automatic classification procedure. Nevertheless, the overall accuracy is very high for the four subsequent years and varies between 96-98 % accuracy. These high overall classification accuracies are due to the fact that for the largest part of the Wadden Sea the classifications and ground truth agree that no beds are existing. The use of true negatives boosts the overall accuracy, and the numbers could be considered as flattered, but on the other hand true negatives are also important.

5.4 Recommendations for implementation in WOT survey

The present study was conducted with the aim of implementing satellite imagery in the annual WOT shellfish stock assessments, more specifically in the annual mapping of intertidal mussel and oyster beds. During the study, the freely available optical satellite images already proved highly useful in finding new mussel and oyster beds, and in focussing the field campaign. The automatic classifications proved to be less suited for mussel bed detection than the human eye, especially concerning beds submerged in shall water. At this moment, satellite imagery is used in addition to the annual inspection flight. Both methods miss some of the mussel and oyster beds present, so combining both methods gives a more complete overview of beds that are new, and beds that have (partially) disappeared. This allows the field campaign to better focus on beds that have changed, instead of beds that remain more constant and of which the contours may therefore be more reliably interpolated. Although at this moment automatic classification has an overall accuracy of 95-99%, mussel and oyster beds are detected with a significantly lower accuracy. To be able to discern which beds are correctly classified and which beds are false positives (and in fact are e.g. benthic diatoms of sand mason worms), or false negatives (e.g. due to submersion) visual interpretations by field experts are still necessary. Methods such as segmentation and semi-automatic classifications, such as decision tree classifier, can support the visual interpretations. Within the remote sensing community machine learning takes a steep learning curve but requires an enormous amount of training data on homogenous targets. And this might not be feasible during the WOT survey. Having to collect a large amount of training data annually, means that remote sensing using optical satellite imagery cannot completely replace field measurements. The goal is, therefore, to make as much use as possible of the optical images themselves, in addition to the methods already used. By doing this, the researchers involved will be trained in their visual interpretation of satellite images and classification results, which may render the inspection flight superfluous in a few years' time.

6 References

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7 Quality assurance

CVO is certified to ISO 9001:2015 (certificate number: 268632-2018-AQ-NLD-RvA). This certificate is valid until December 15th, 2021. The certification was issued by DNV GL Business Assurance B.V

Justification

CVO Report: 20.020
Project number: 4311300049

The quality of this report has been peer reviewed by a colleague scientist and the head of CVO.

Approved by: Dr. Jacob Capelle
Researcher

Signature:

Date: 17 September 2020

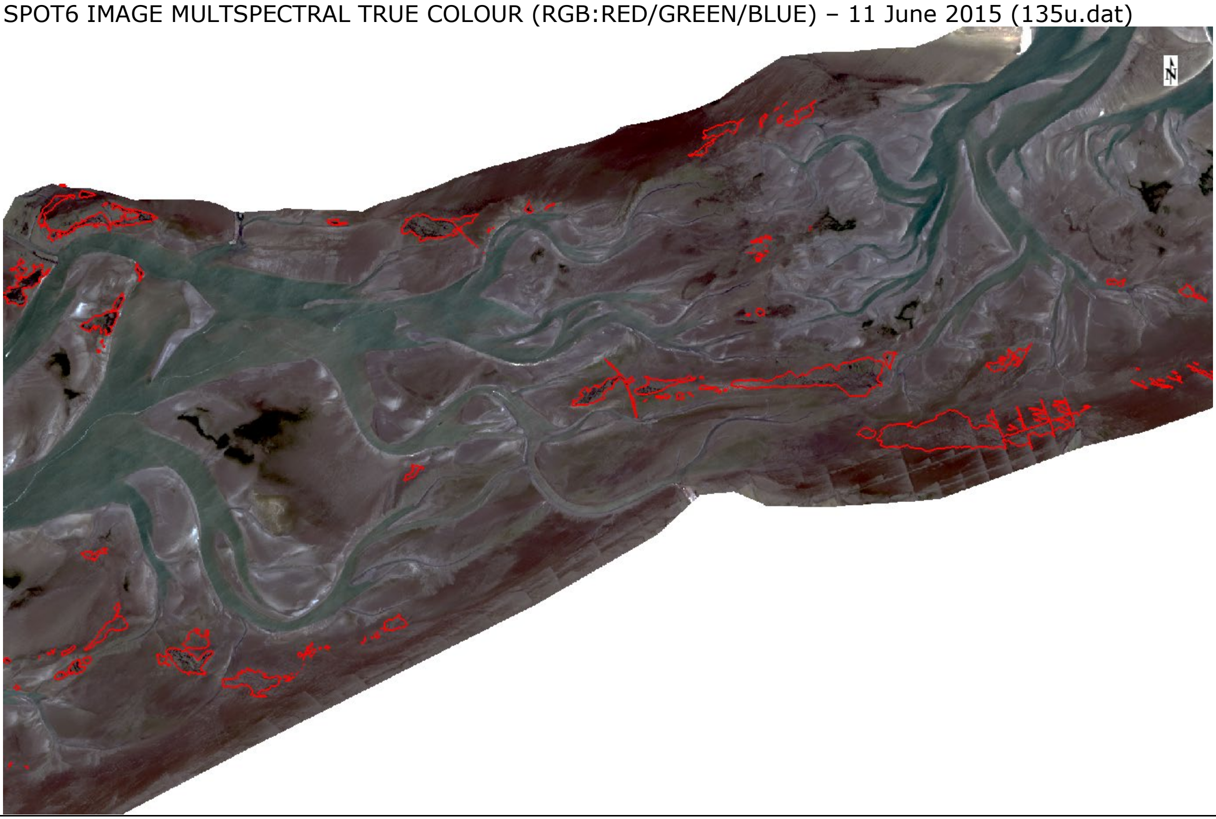
Approved by: Ing. S.W. Veryer
Head Centre for Fisheries Research

Signature:

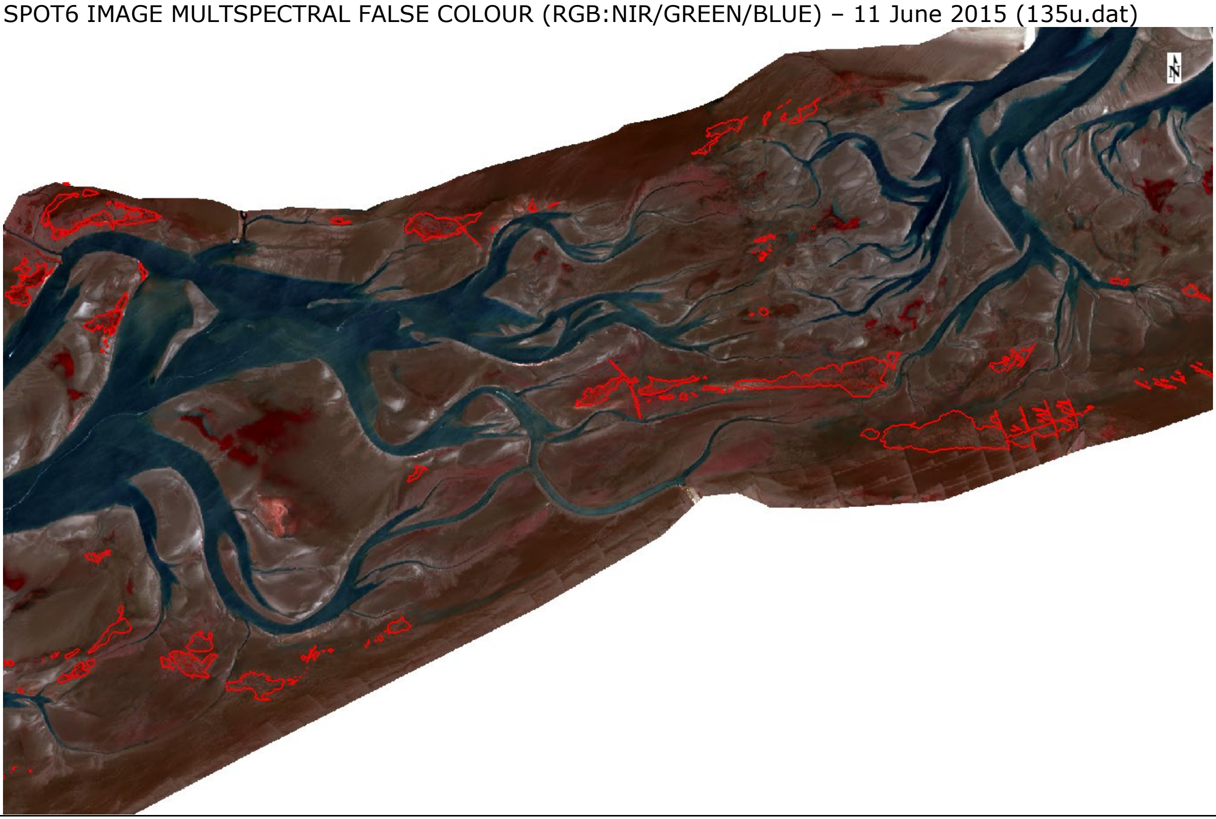
Date: 17 September 2020

Appendix 1 Multispectral indices calculated for the same SPOT image of 11 June 2015

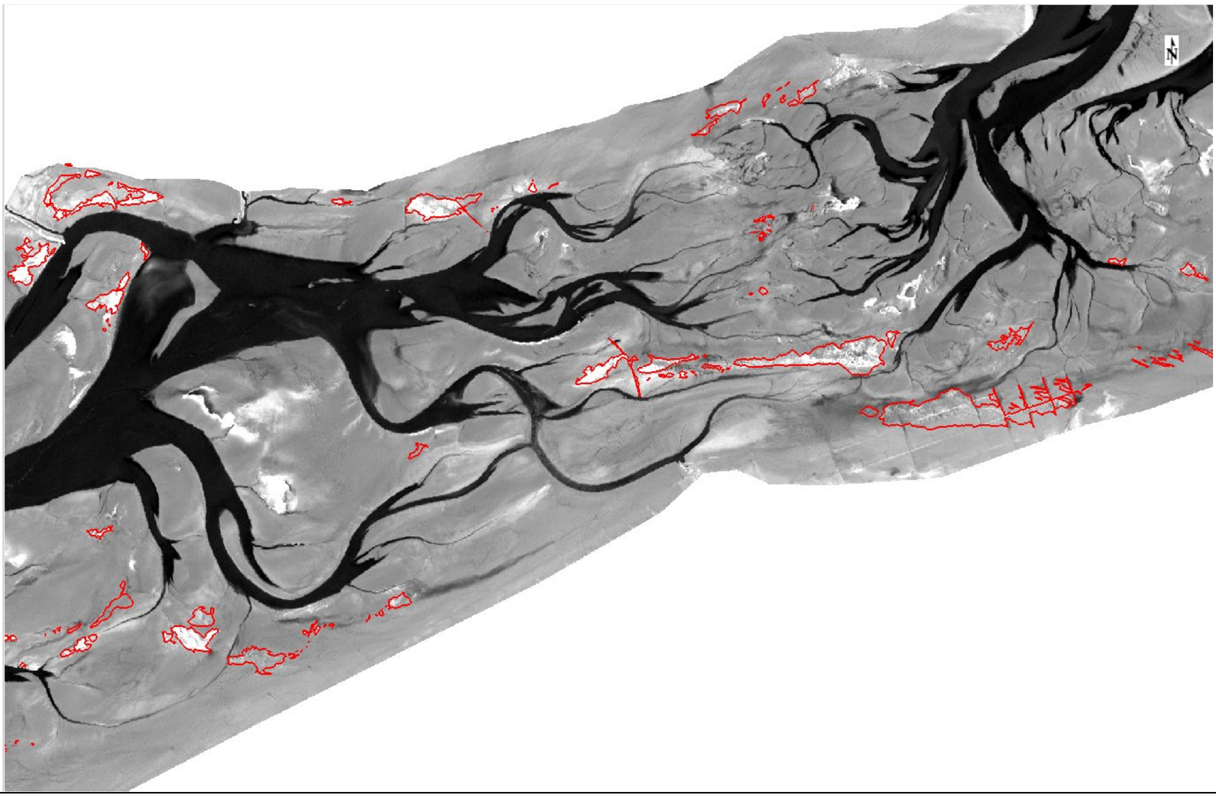
SPOT6 IMAGE MULTSPECTRAL TRUE COLOUR (RGB:RED/GREEN/BLUE) – 11 June 2015 (135u.dat)



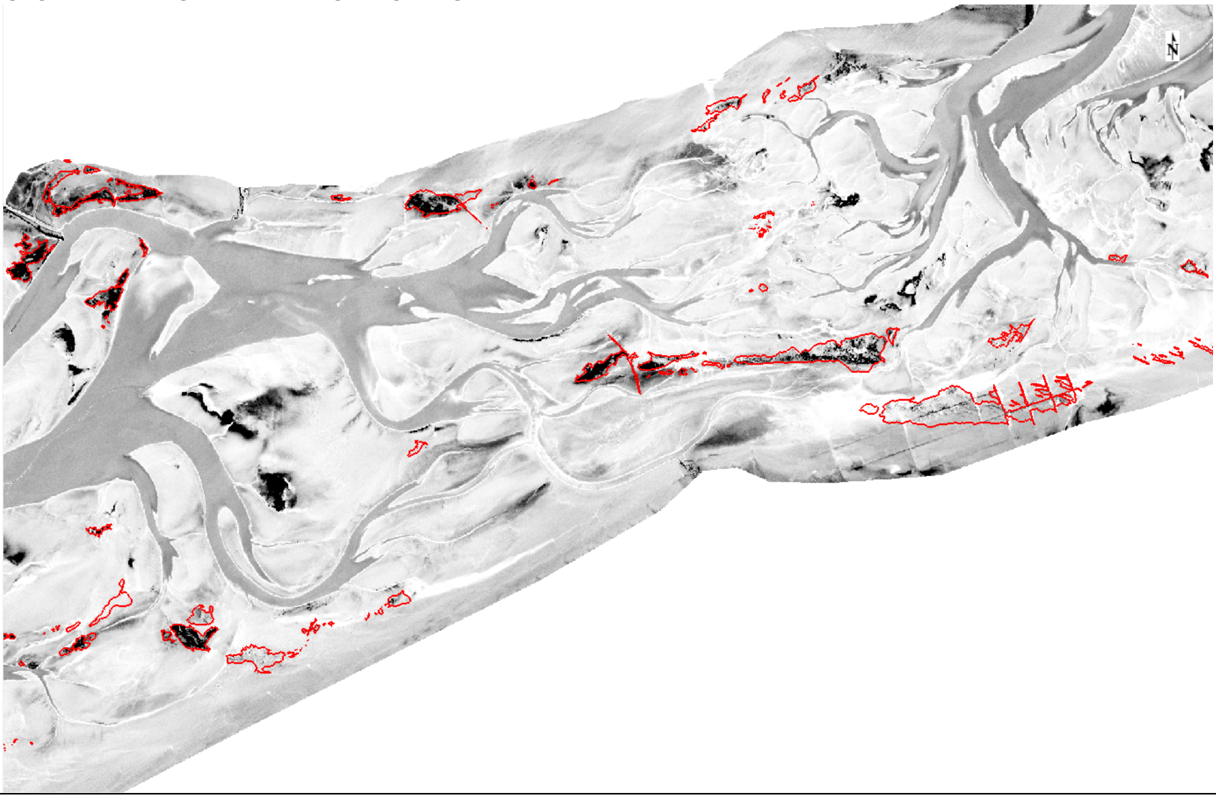
SPOT6 IMAGE MULTSPECTRAL FALSE COLOUR (RGB:NIR/GREEN/BLUE) – 11 June 2015 (135u.dat)



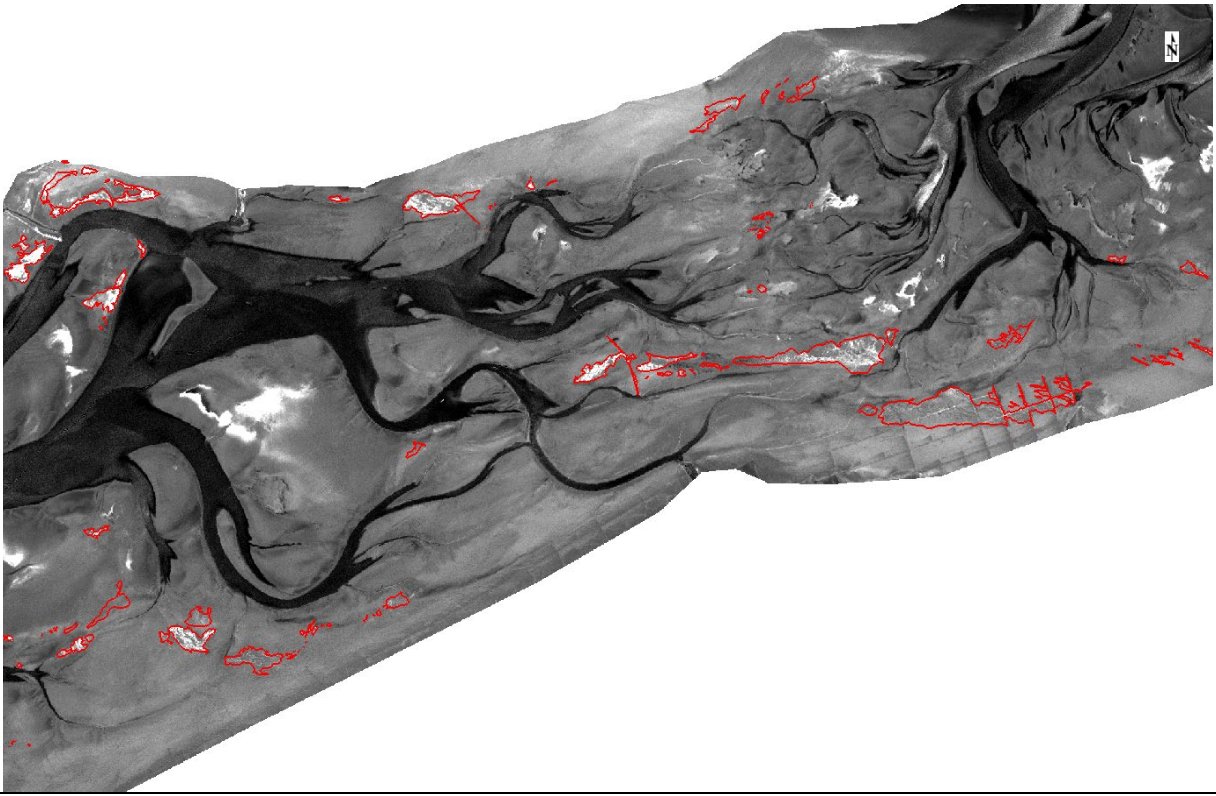
DIFFERENCE VEGETATION INDEX



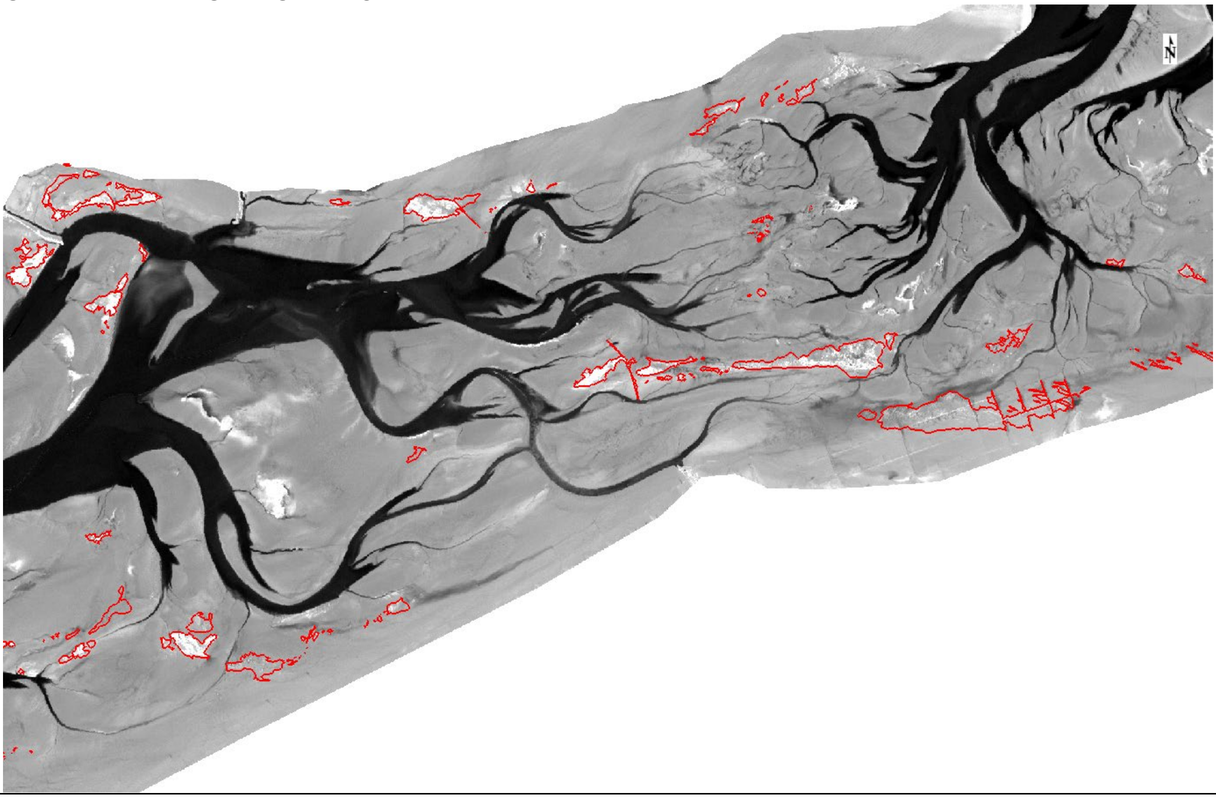
GLOBAL ENVIRONMENTAL MONITORING INDEX



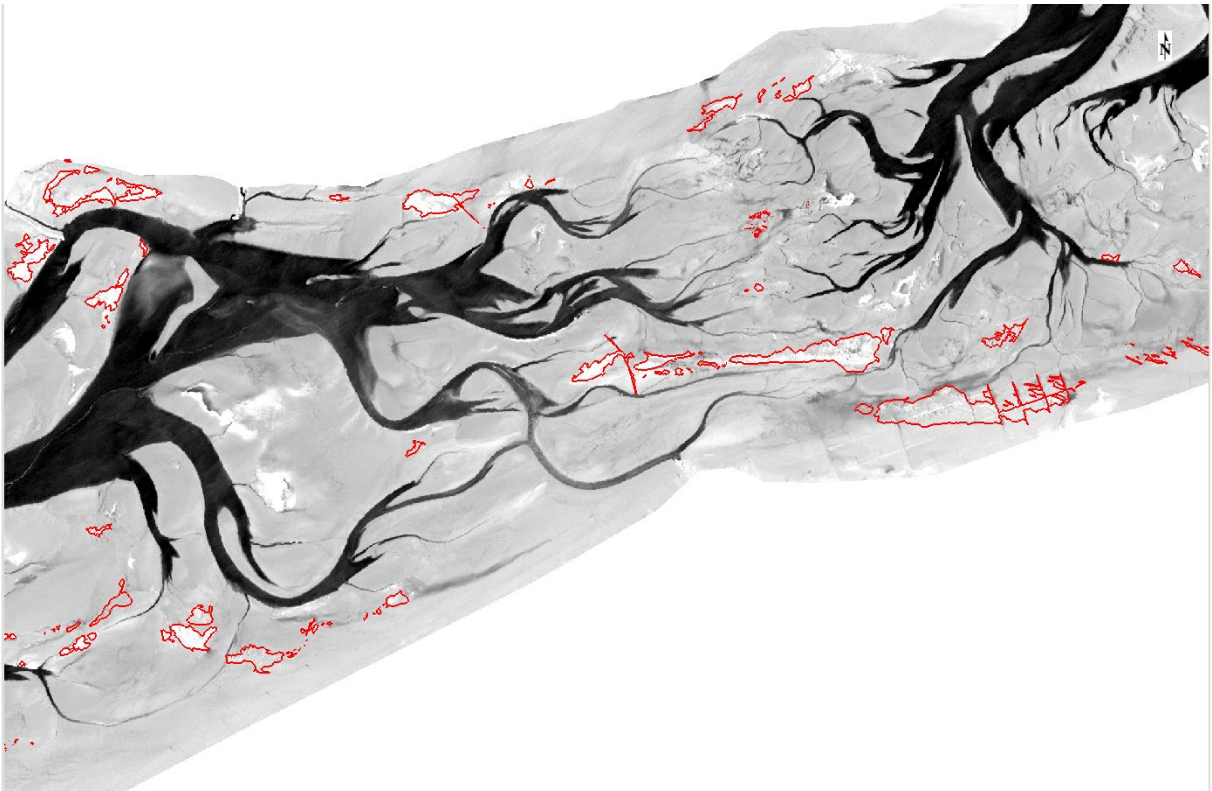
GREEN ATMOSPHERICALLY RESISTANT INDEX



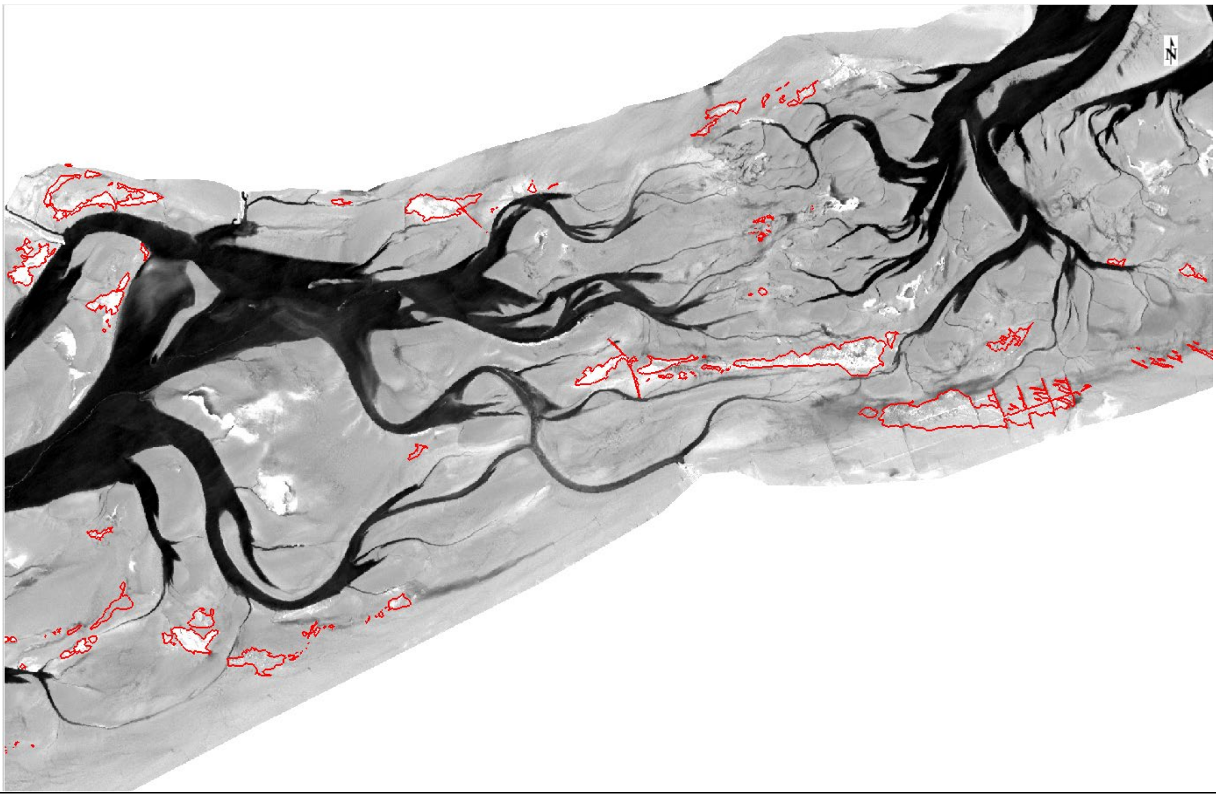
GREEN DIFFERENCE VEGETATION INDEX



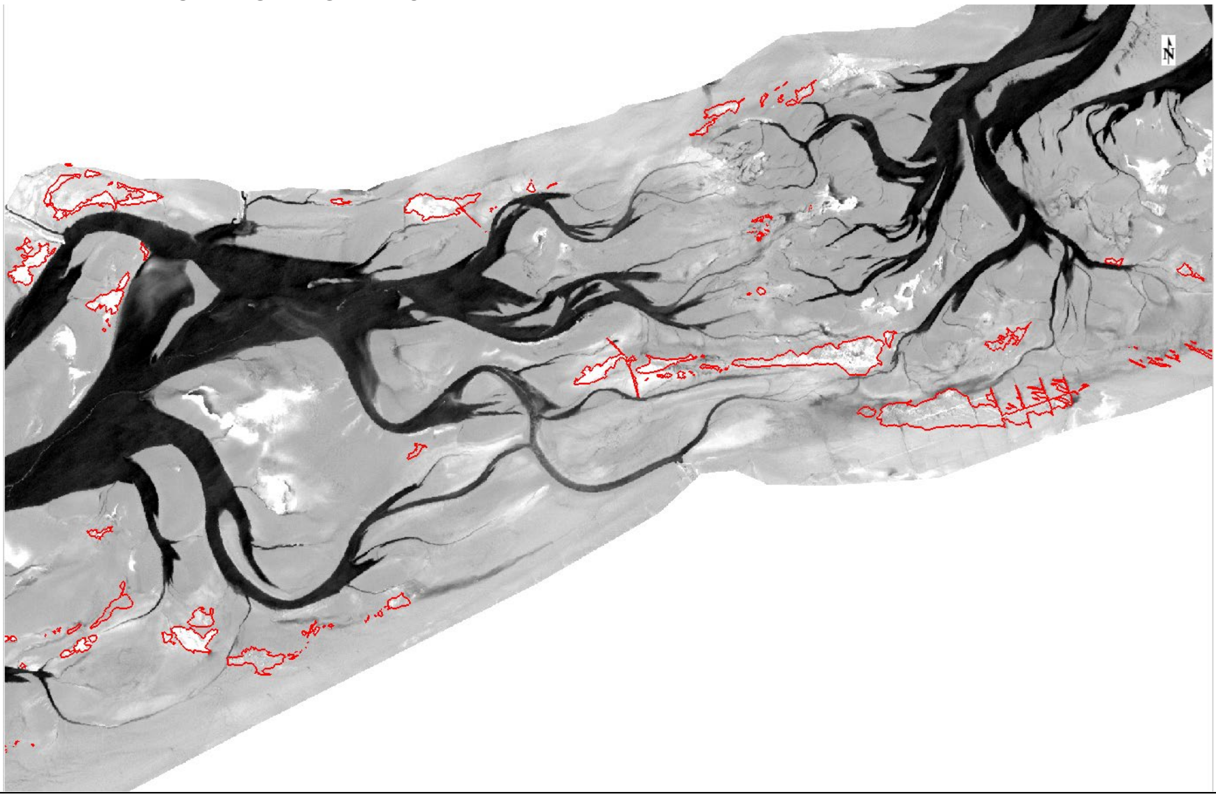
GREEN NORMALIZED DIFFERENCE VEGETATION INDEX



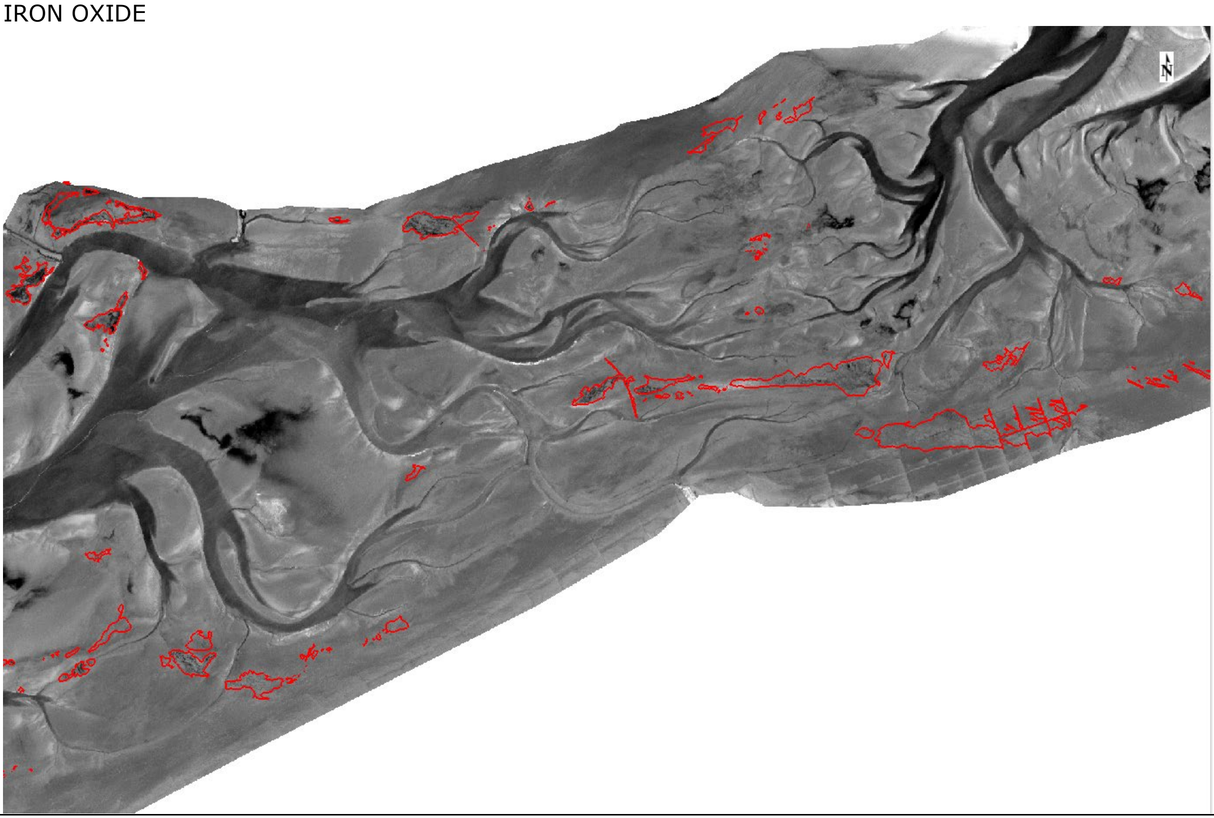
GREEN RATIO VEGETATION INDEX



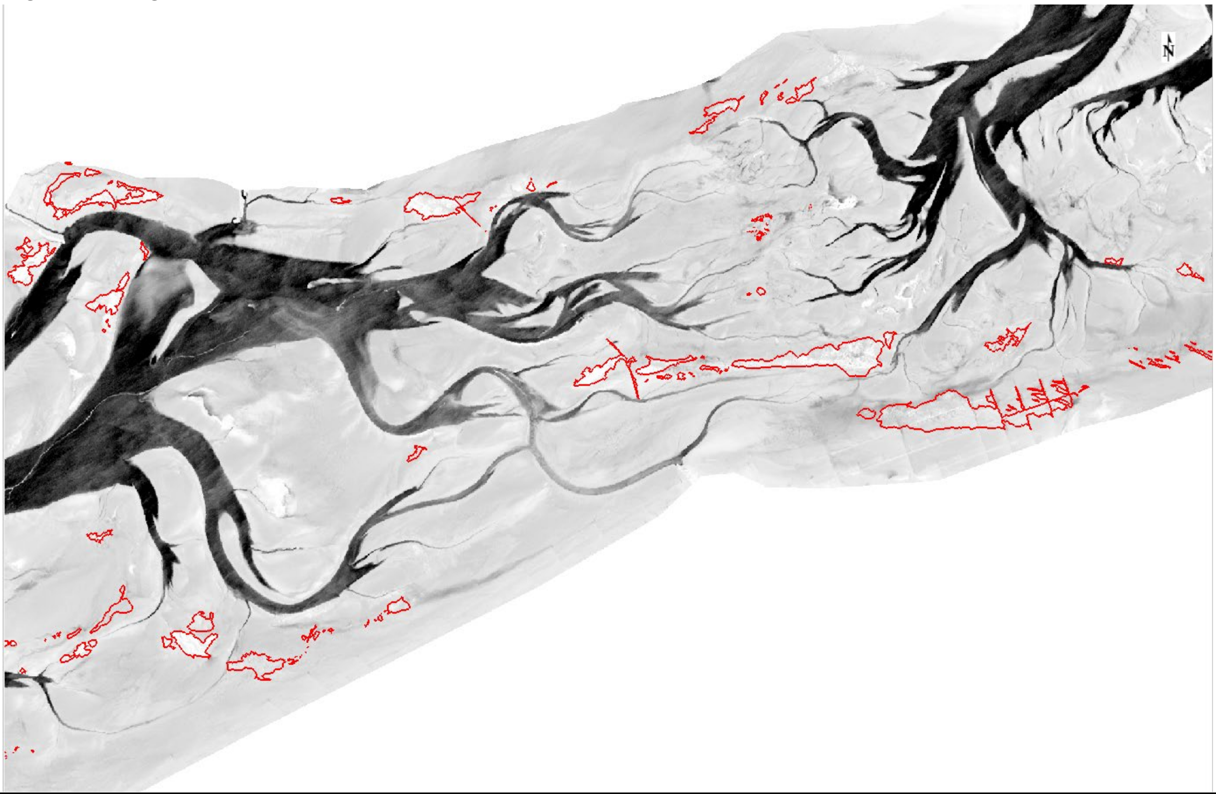
INFRARED PERCENTAGE VEGETATION INDEX



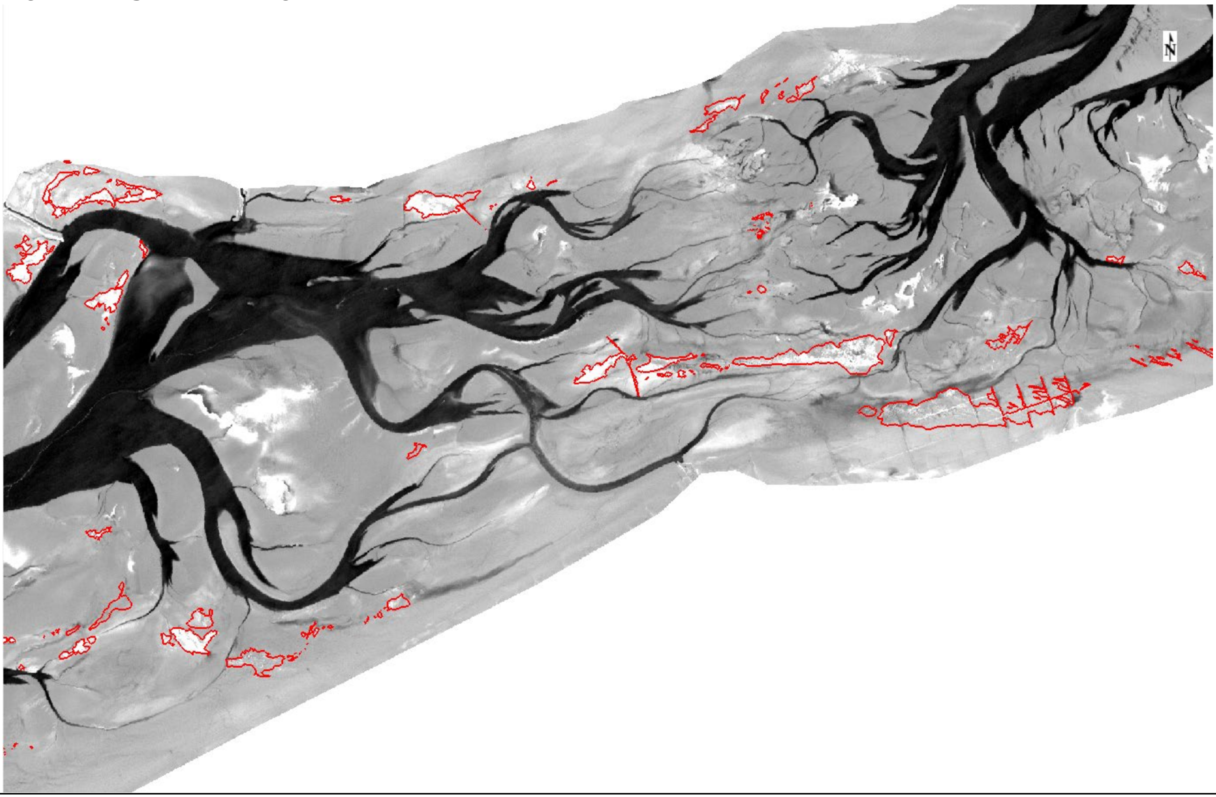
IRON OXIDE



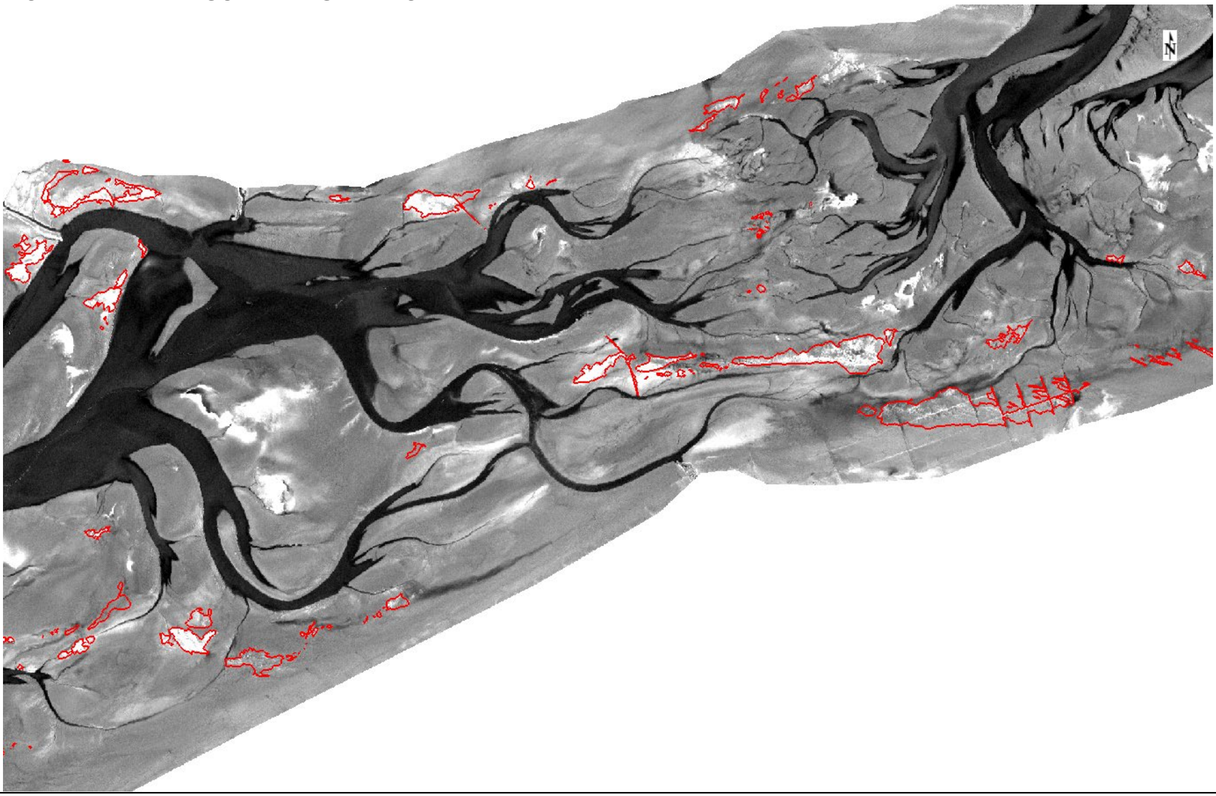
MODIFIED NON-LINEAR INDEX



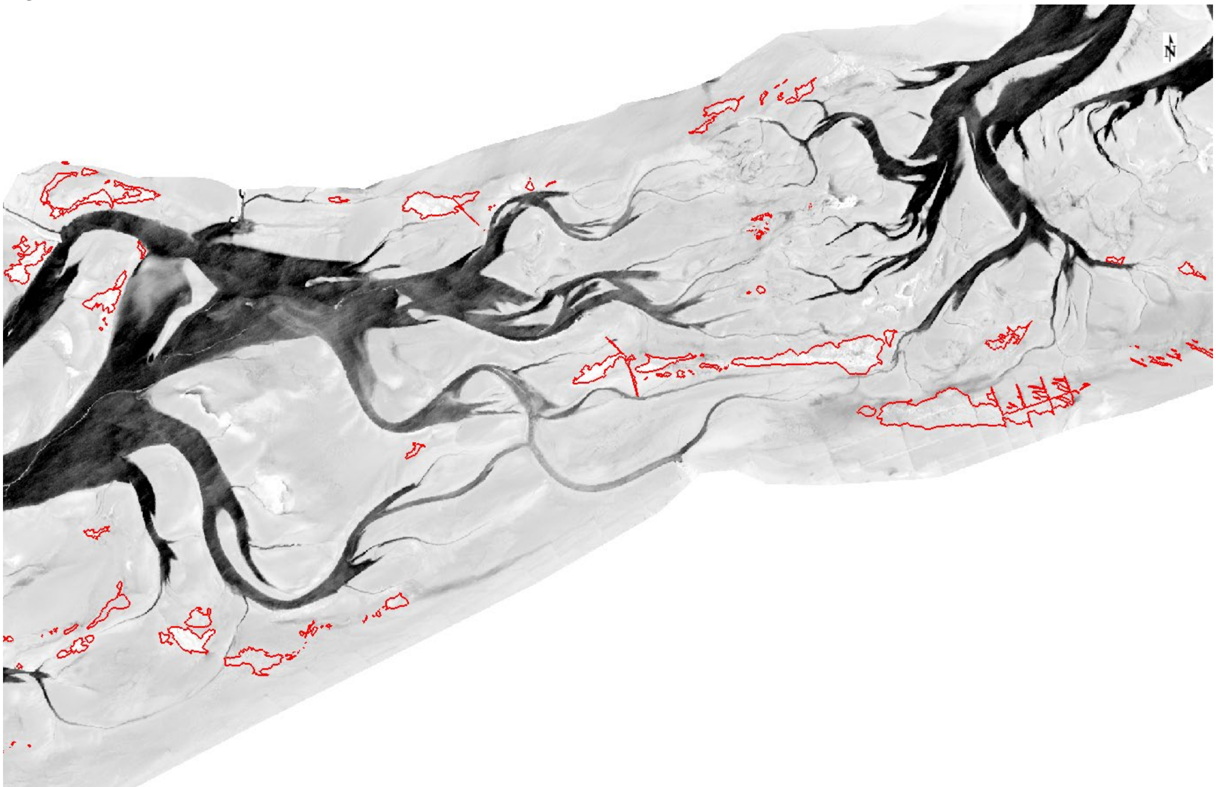
MODIFIED SIMPLE RATIO



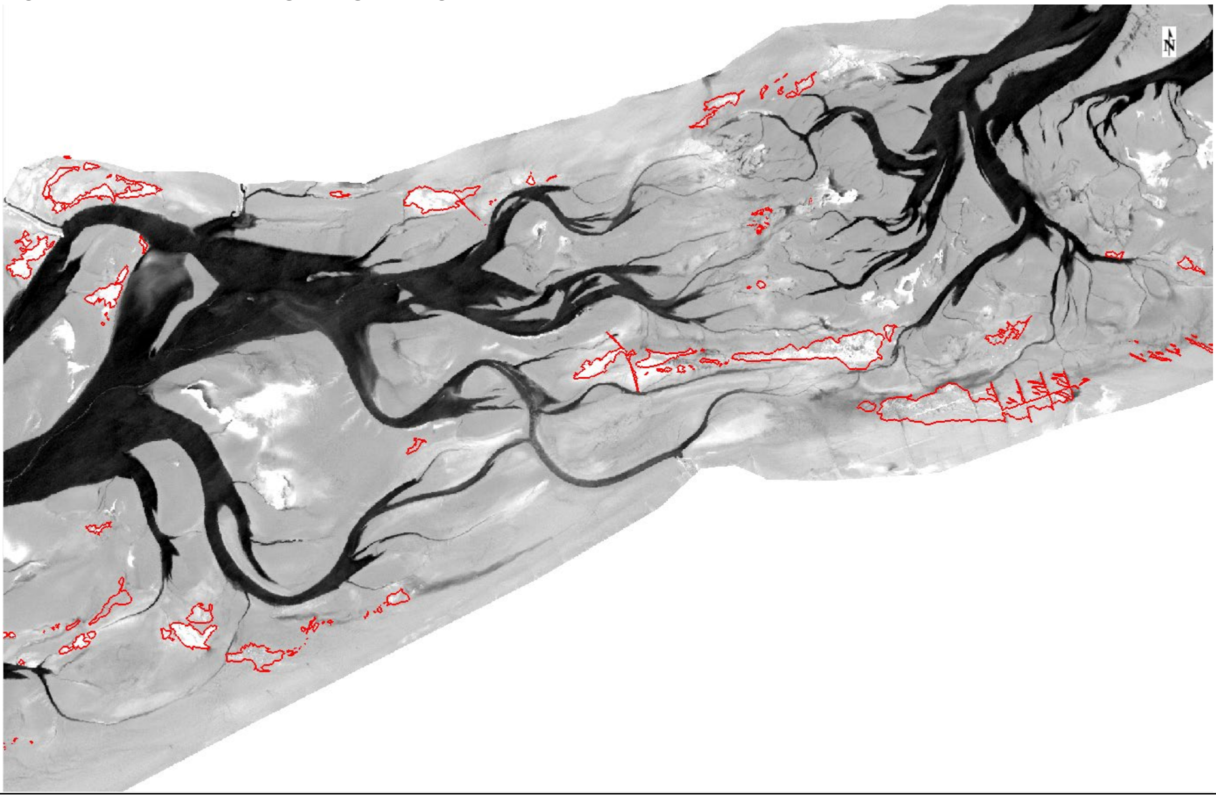
MODIFIED TRIANGULAR VEGETATION INDEX



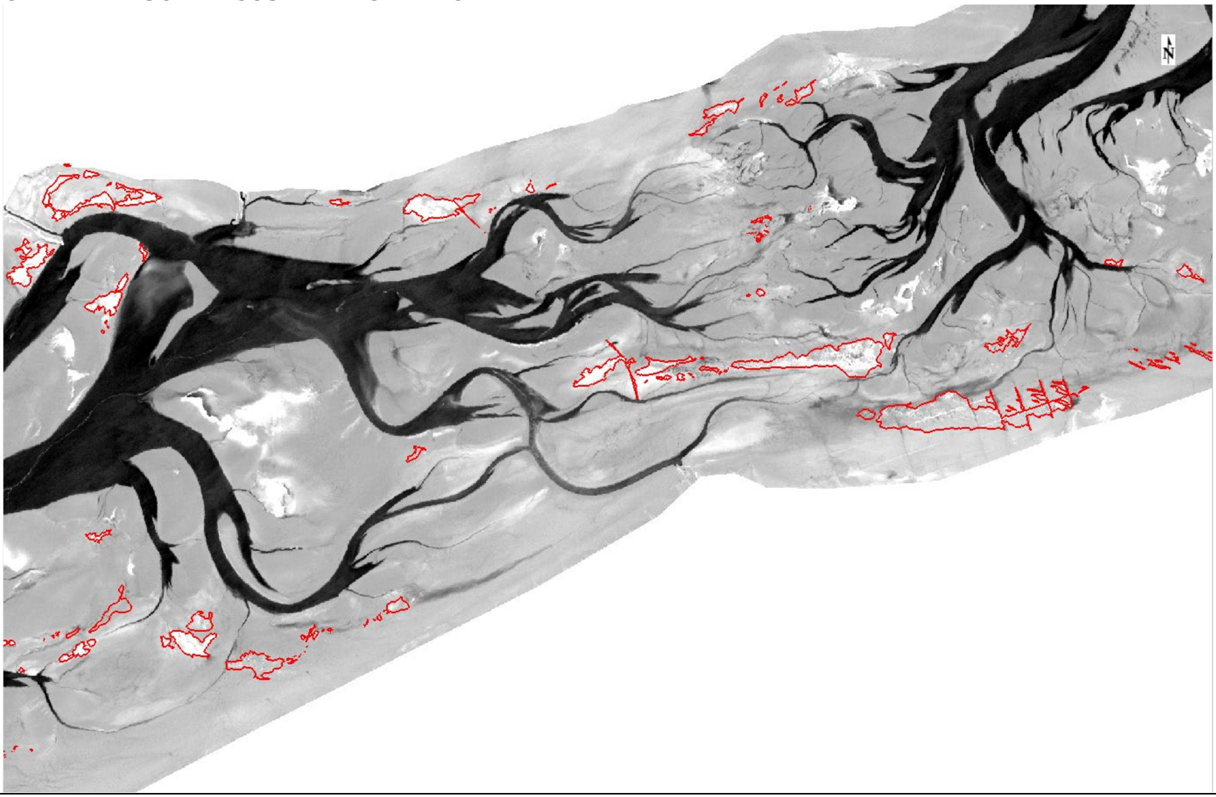
NON-LINEAR INDEX



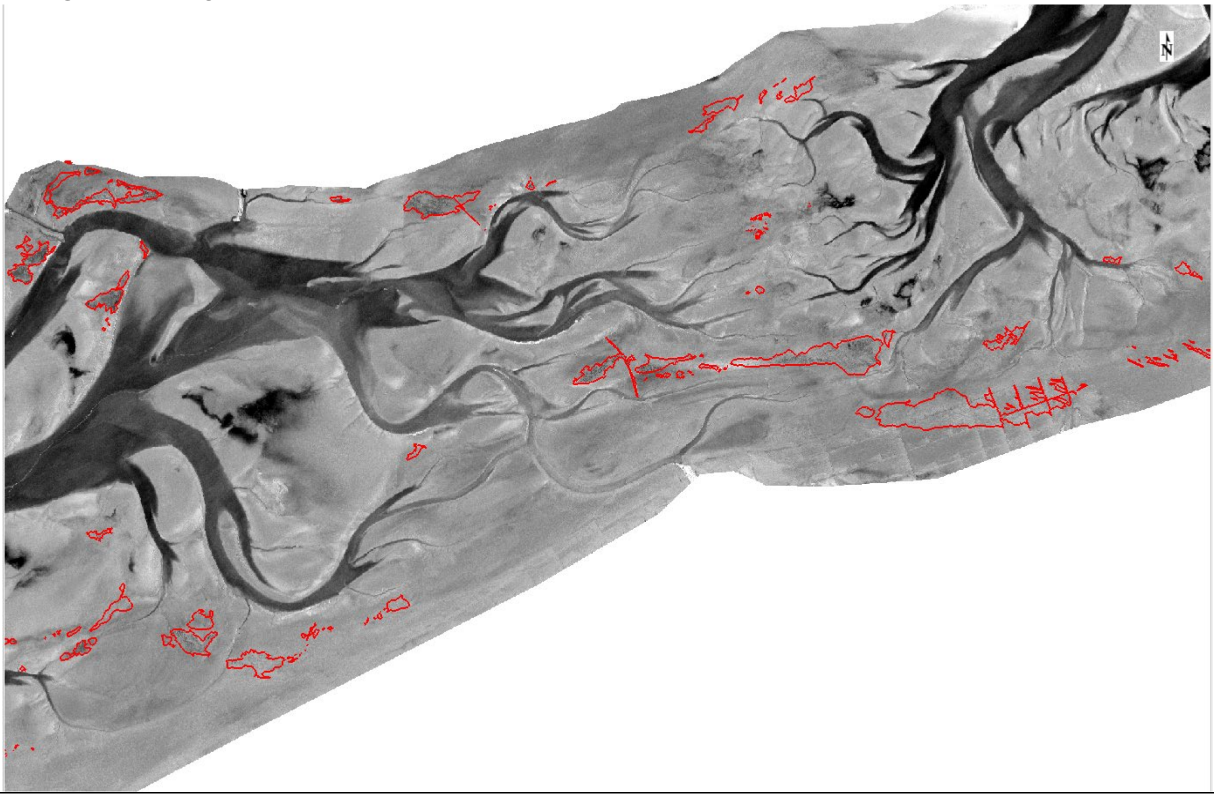
NORMALIZED DIFFERENCE VEGETATION INDEX



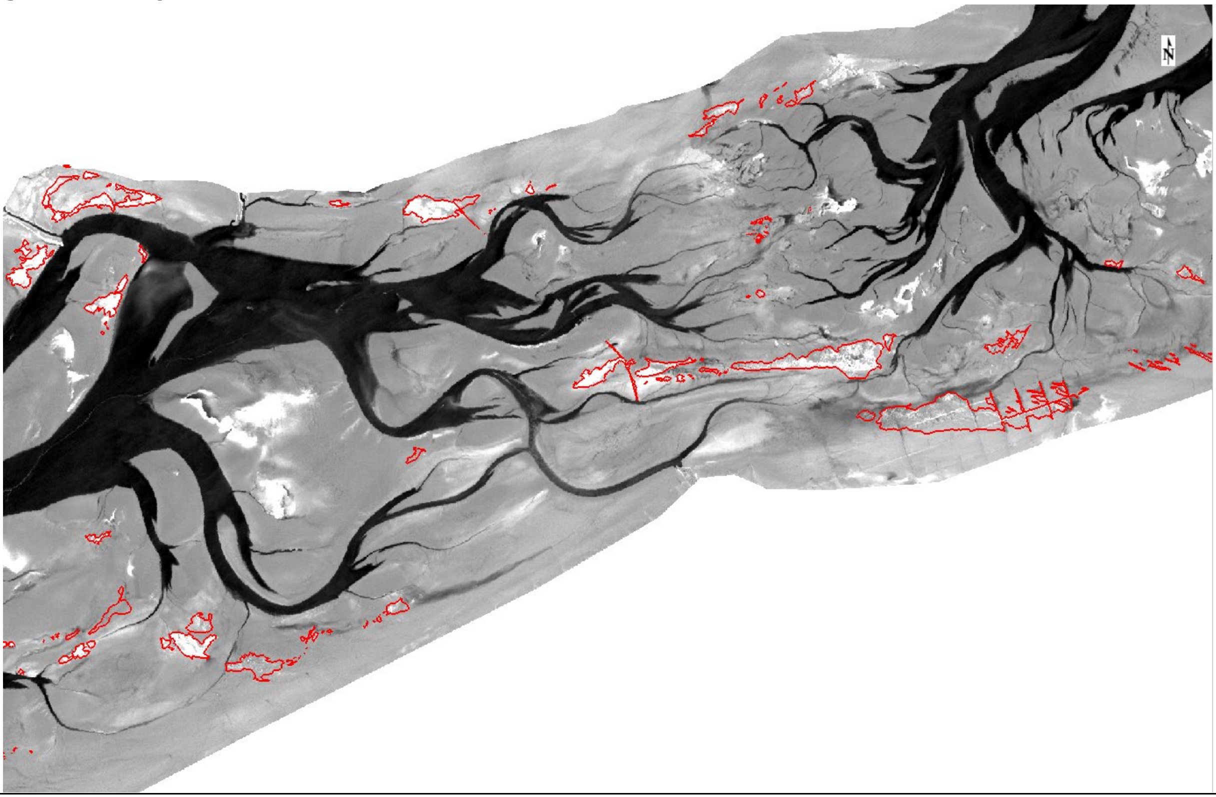
OPTIMIZED SOIL ADJUSTED VEGETATION INDEX



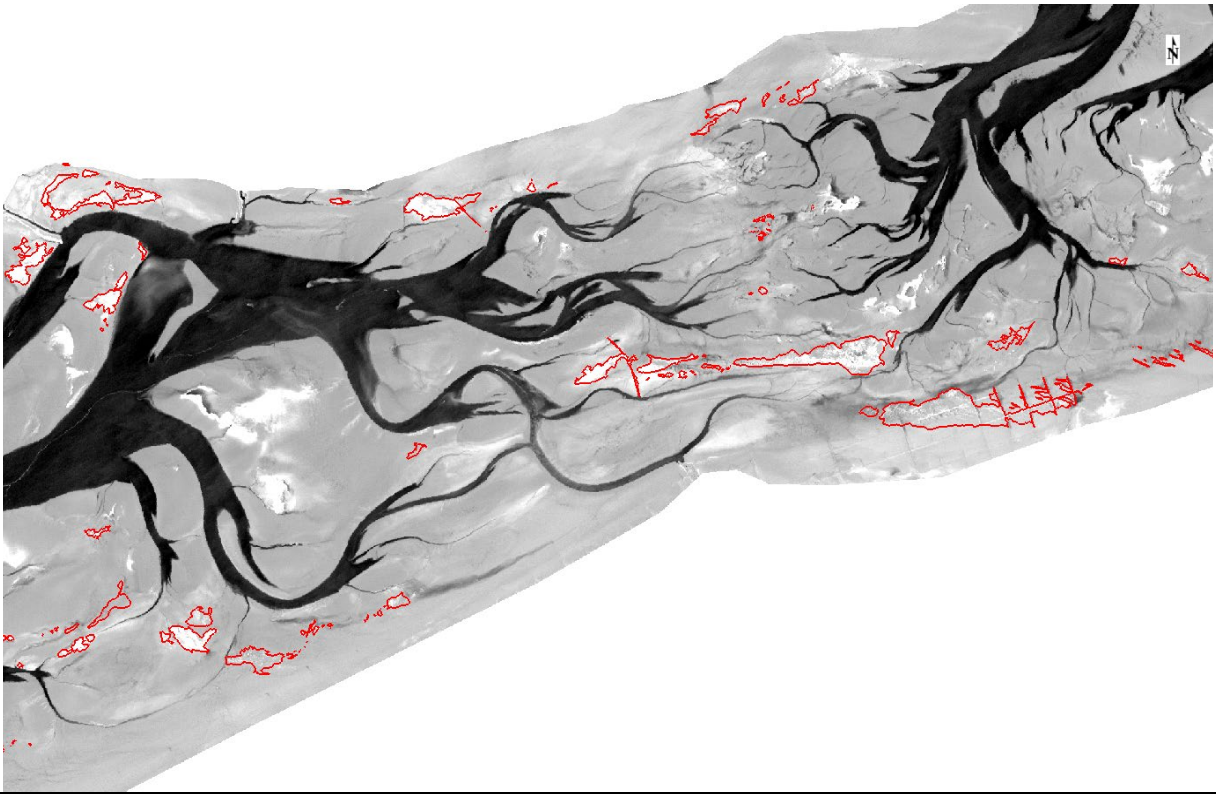
RED GREEN RATIO INDEX



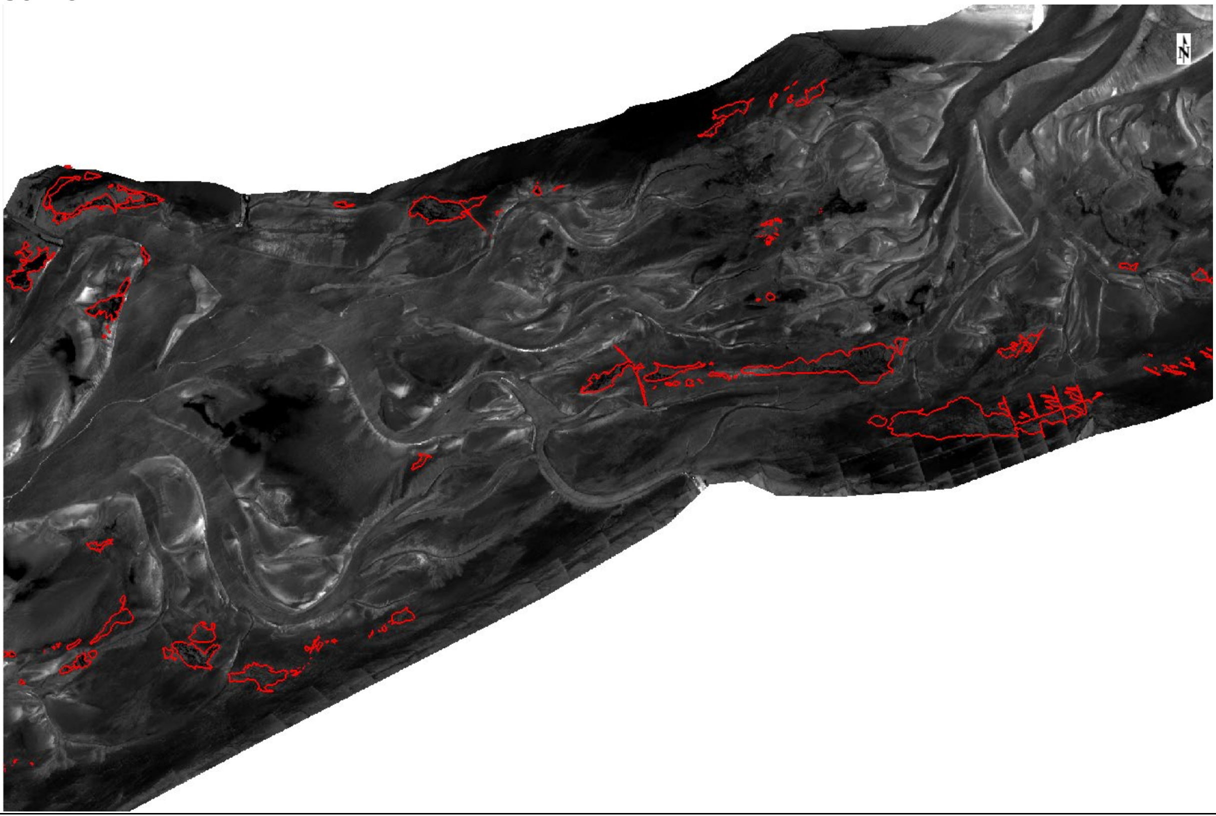
SIMPLE RATIO



SOIL ADJUSTED VEGETATION INDEX



SUM GREEN INDEX



TRANSFORMED DIFFERENCE VEGETATION INDEX