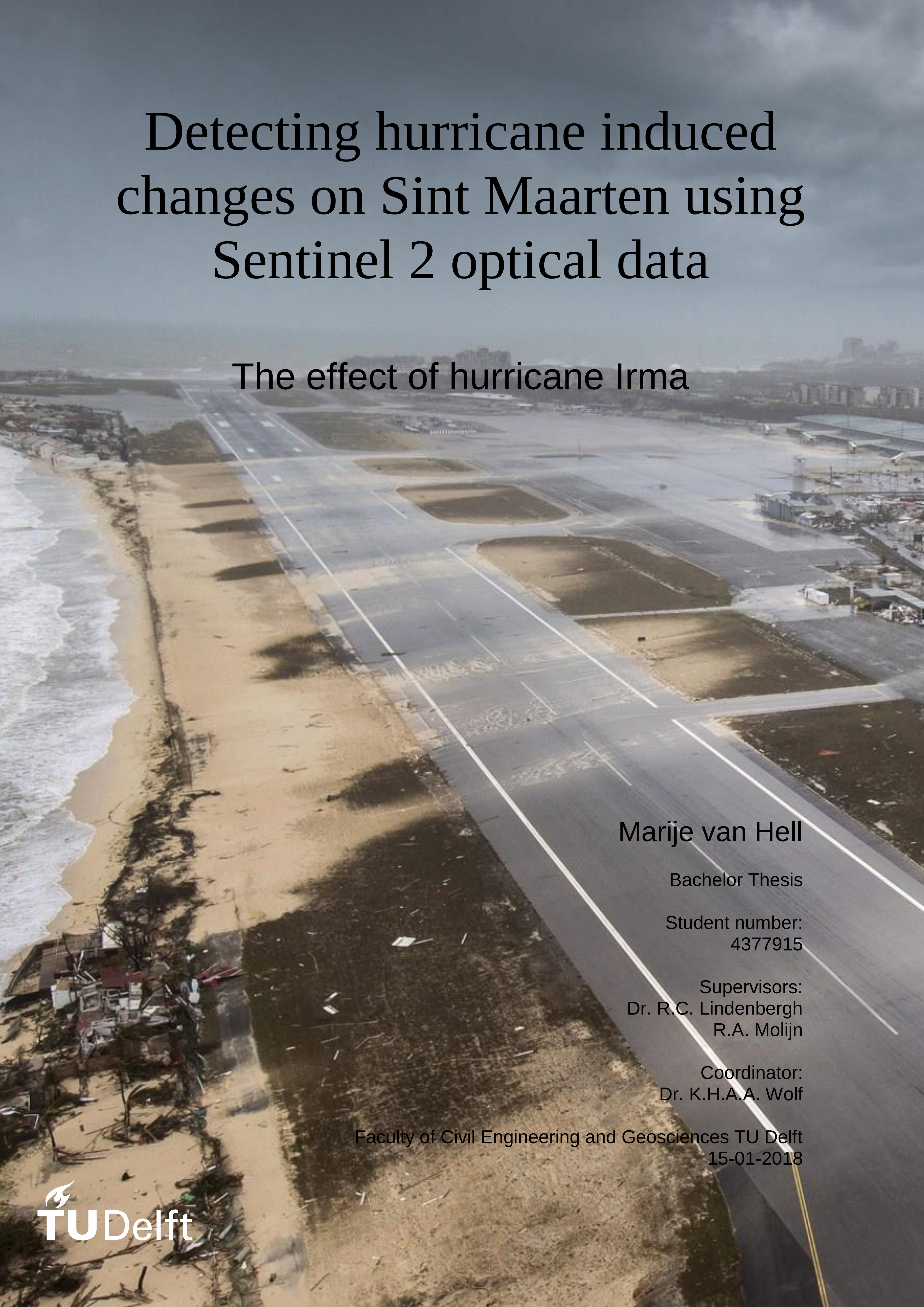

Detecting hurricane induced changes on Sint Maarten using Sentinel 2 optical data

The effect of hurricane Irma

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Bachelor Thesis

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Abstract

In a world of climate change, NASA mentions that the amount of category 4 and 5 hurricanes that form over the North Atlantic Ocean will increase not only in frequency, but also in intensity and duration.

As a result more damage due to hurricanes is expected. Commonly, areas that have been struck by a severe weather event lose power supply and are difficult to reach. Sometimes making any contact at all is impossible. In order for organisations to quickly start with emergency aid at the areas that need it the most, satellite images can be used to distinguish these places. With this method, no prior communication is needed but still help can be offered.

Hurricane Irma struck Sint Maarten on the 6th of September 2017 as a category 5 hurricane on the scale of Saffir-Simpson, leaving an almost completely destroyed island behind. Sentinel 2 optical images are retrieved from before and after the hurricane. The images are analysed using Google Earth Engine which is a free cloud-based platform that can process satellite data online using JavaScript coding and data on the Earth Engine server.

First the Sentinel 2 optical data is retrieved and cloud masked. Training data is retrieved from the before picture and is used to classify both images. Also indices are calculated that highlight vegetation, sand and urban areas in the images. Difference plots are made by subtracting the after image with the before image.

NASA mentions a widespread browning effect of vegetation. Indeed a great decrease in NDVI is seen, indicating a great loss of plants. The NDGI together with classification map show several areas where sand shifting has taken place. Especially at the Prinses Juliana Airport and the North East shoreline of the island this phenomenon is seen. Finally it is discussed that optical imagery is not a good method to indicate changes in urban area. Sentinel 1 radar data should be tried instead.

Contents

Introduction

1.1 Context

On the 6th of September 2017 at 03:00 in the morning, local time, hurricane Irma hit Sint Maarten (Copernicus, 2017). The storm reached maximum sustained winds of 185 mph (295 km/h) with higher gusts. Therefore Irma was a category 5 hurricane on the scale of Saffir-Simpson (NWS National Hurricane Center Miami FL, 2017). Around 06:00 the wind stopped blowing, the eye of the storm was passing the island and then the second part blew over (Ritzen & van Laarhoven, 2017).

Hurricanes commonly form over the Atlantic Ocean between 5° and 20° on the Northern hemisphere at the end of summer. At this time of year water temperatures are high enough to act as a source for the formation of hurricanes. These very strong storms can cause major destruction on Earth surface in several ways. The factors that are discussed for Sint Maarten include: Destruction of vegetation, sand shifting and damage to urban areas.

1.2 Research objective

The main research objective of this Bachelor End Project is to create a general method to quickly detect changes on Earth Surface after a hurricane has blown over the area. This report focusses on Sint Maarten and hurricane Irma.

In order to achieve this goal, several research questions were formulated:

1. In what way will images be processed in Google Earth Engine?
2. How can clouds be masked?
3. What land cover classes can be distinguished for Sint Maarten?
4. How can classification be used to detect changes on Earth surface?
5. How can indices be used to detect changes on Earth surface?
6. How do we validate that the changes that are detected are not false?
7. What issues came up during the research?

This project contains links with the Bachelor Applied Earth Sciences in several ways. Optical data from satellites is also used during the second year fieldwork in Vesc to create classification maps and look for changes over long periods of time in the area. Also the ongoing climate change will increase the weather extremes and thus more natural disasters can be expected. It is therefore important that a quick analysis can be done to assess damage and help an affected area as soon as possible.

In other to create the best possible change method, known changes mentioned by NASA, Copernicus and the newspaper NRC are used for validation. Daniël Kersbergen, a student of TU Delft went to Sint Maarten with the Dutch Red Cross after hurricane Irma. His knowledge of the area is also taken into consideration.

2 Hazard monitoring using satellite data

This chapter discusses geohazards and how they can be monitored using satellite remote sensing. Firstly different types of geohazards will be discussed as well as their impact. Several different studies and a government run organisation are taken into consideration. After that different types of satellite data are discussed. Then the two most common satellite programs, Sentinel and Landsat, will be compared. Finally the programs used for processing will be described.

2.1 Geohazards and their impact

Several geohazards are known, such as earthquakes, tsunamis, floods, droughts and hurricanes. Each can have impact on infrastructure, vegetation and housing. Roads can be blocked by fallen trees or debris that is swept up in the wind, houses can be unroofed and complete forests can be destroyed.

Multiple studies have been carried out to assess the damage after a natural disaster with the use of satellite remote sensing. Four cases are discussed below.
A geohazard can be monitored and the impact can be predicted using remote sensing, but satellite data can also be used after a disaster has taken place. The affected area can be analysed and mapped. Different studies have been carried out in this field. Both studies that cover the monitoring part as well as the change detection part will be discussed.
Firstly David M. Tralli et al consider the monitoring of earthquake, volcano, flood, landslide and coastal inundation hazards. For each hazard the best satellite remote sensing method for monitoring is discussed. Other sources of data that can strengthen the risk analysis, like seismic and precipitation data are also taken into consideration.
W. Wang et al describe in their article how post-hurricane forest damage can be best detected using vegetation indices. The case study is based on hurricane Katrina and the impact it had on The De Soto National Forest located in Southern Mississippi. They used moderate resolution imaging spectroradiometer (MODIS) measurements.
Another study focusses on the post-disaster assessment of landslides in southern Taiwan after Typhoon Morakot in 2009. F. Tsai et al discuss how they detected landslides with the use of NDVI filtering of Formosat-2 satellite data and how they created an accurate landslide map.

There are also government run organisations that help assess geohazards. Copernicus is a program from the EU and has as its goal the development of a European information service that uses Earth Observation satellite data as well as on site information to monitor and forecast changes on land, sea and in the atmosphere. By doing this, they provide information on climate change adaptions and support the efficient management during emergency situations, like after hurricanes, earthquakes and other natural hazards by creating Risk and Recovery Maps. The three main available product are Reference-, Pre-disaster Situation- and Post-disaster Situation maps (European Union, 2017).

2.2 Satellite data types

Different types of satellite data are known: Optical (spectral) and radar. Optical data is retrieved with a multispectral instrument that consists of bands. Each band picks up a different range of wavelengths that is reflected from Earth surface. It includes the visible wavelengths as well as some arbitrary ones like infrared waves. With these an image can be created that is similar to how the human eye sees the world. A radar satellite sends out its own microwave signal and retrieves its backscatter. Therefore clouds and darkness do not pose problems when creating a picture. However the image that is created is difficult to interpret, as the only thing that is seen is the backscatter. Which does not show any resemblance to what the surface really looks like. Therefore it is decided that for this project optical data will be used.

2.3 Sentinel versus Landsat

A lot of different satellites orbit around the earth. Each having their advantages and disadvantages. The two satellites that are discussed on their abilities for this study are Sentinel and Landsat.

Sentinel is a group of satellites launched by ESA (European Space Agency) in the Copernicus program. It consists of several different instruments, each of them carrying a different kind of technology. Sentinel 1 is a radar mission, Sentinel 2 is an optical satellite, Sentinel 3 measures sea-surface topography, temperatures and ocean and land colour and Sentinel 5 provides data on aerosols and trace gasses in the air. Sentinel 1 was launched in 2014, followed by the others from 2015 up till now (ESA, 2017).

The Landsat program started in 1972 when the ERTS-1, later renamed Landsat 1 satellite, was launched by NASA. More satellites followed after, the final one being Landsat 8 that was launched in 2013. Landsat is a group of spectral satellites, that have created a continuous collection of optical data from 1972 and onwards (USGS, 2017).

For this project Sentinel 2 optical data is used instead of Landsat 7 or 8. There are a few reasons for this choice. Firstly, the aim of the project is to create a difference map on the area that is affected as quickly as possible. When comparing the revisit times, a big difference is seen. Landsat 7 and 8 both need 16 days (USGS, 2017), while the Sentinel 2 mission can create images at least every five days when two satellites are used (SUHET, 2013), due to overlap between the swaths, two to three days at the mid latitudes can be achieved (ESA, 2017).

Another parameter that can be compared is the resolution of the images that are created. Table 1 shows the bands that are available, their wavelength and resolution. To correctly compare the two satellites it must be known that for classification the bands that show blue, green, red, NIR (near infrared), SWIR 1 (shortwave infrared) and SWIR 2 are used (see Table 1). For Landsat 8 this means a resolution of 30 meters for all the bands mentioned (USGS, 2017). When looking at Sentinel 2, it can be seen that band B2, B3, B4 and B8 show a resolution of 10 meter and B11 and B12 have a resolution of 20 meters. Because Sentinel 2 shows a higher resolution, it is therefore the preferable satellite data to use.

Table 1: Landsat 8 and Sentinel 2 Band numbers, their wavelength and resolution

Landsat 8			Sentinel 2		
Band	Wavelength (µm)	Resolution (m)	Band	Wavelength (µm)	Resolution (m)
B1 – Ultra Blue	0.435 – 0.451	30	B1 – Aerosols	0.443	60
B2 – Blue	0.452 – 0.512	30	B2 – Blue	0.490	10
B3 – Green	0.533 – 0.590	30	B3 – Green	0.560	10
B4 – Red	0.636 – 0.673	30	B4 – Red	0.665	10
B5 – NIR	0.851 – 0.879	30	B5 – Red Edge 1	0.705	20
B6 – SWIR 1	1.566 – 1.651	30	B6 – Red Edge 2	0.740	20
B7 – SWIR 2	2.107 – 2.294	30	B7 – Red Edge 3	0.783	20
B8 – Panchromatic	0.503 – 0.676	15	B8 – NIR	0.842	10
B9 – Cirrus	1.363 – 1.384	30	B8a – Red Edge 4	0.865	20
B10 – TIRS 1	10.60 – 11.19	100 (30)	B9 – Water vapour	0.940	60
B11 – TIRS 2	11.50 – 12.51	100 (30)	B10 – Cirrus	1.375	60
			B11 – SWIR 1	1.610	20
			B12 – SWIR 2	2.190	20

2.4 Sentinel Hub Playground and Google Earth Engine

There are several programs that can be used to process satellite data. For this project, a combination of two programs is used. The first one that will be discussed is Sentinel Hub Playground. Then Google Earth Engine is taken into consideration.

Sentinel Hub Playground is a web application that can be used for browsing and quick analysis of Sentinel 2 data. The date of acquisition and amount of cloud cover can be selected and different locations can be searched. The app is also capable of creating false colour images that can highlight certain features like trees or urban areas. This program is mainly used to have a quick look at the data before it is processed in Google Earth Engine.

The program that is used to process the satellite data is called Google Earth Engine. It is a free program made available by Google online. The platform being online has as a result that no satellite data has to be downloaded on your computer, it is all available in the cloud. Making the process of retrieving data significantly faster while the speed of your computer stays the same. Satellite data is made available as rasters that can be directly imported into your script. The language used for programming is JavaScript, however in the bachelor, Matlab is taught. There are a few differences between the programming languages. In Matlab signs like plus and minus can be used, while JavaScript expects .subtract() and .add(). Also variables have to be indicated using var, while in Matlab they don’t. The JavaScript language however is not too difficult to learn when you do already have some general knowledge on programming. Also Earth Engine has an extensive user guide as well as a Google GEE Developers Group where a lot of information can be found.

Even if you are not familiar with JavaScript, it is worth learning it. This disadvantage is very small compared to the advantages the program brings in speed and efficiency. As it can create maps, plots and all data can be easily downloaded to CSV. Which makes implementing it in Excel when needed easy as well.

3 Sint Maarten: Climate and land cover

This chapter discusses the climate of Sint Maarten and the hurricane season it experienced in 2017 and before. Also the land cover and geology of the island are taken into consideration.

3.1 Climate

The island of Sint Maarten is located at 18.01°N, 63,03°W, in the North-eastern region of the Caribbean. The average yearly temperature is 27.2°C. When looking at the precipitation chart (Figure 1) a dry season is seen, from January to April and a wet season, from August to December. The normal annual rainfall of the island is 1026 mm, with the driest month receiving just over 50 mm of rain on average (Meteorological Department of St. Maarten, 2016). Therefore when looking at the Köppen climate system, Sint Maarten is classified as Am. A stand for a tropical climate, indicating that the temperature of the coldest month does not fall below 18°C. The m that is added tells that a monsoon season is known (Kottek, M. et al, 2006).

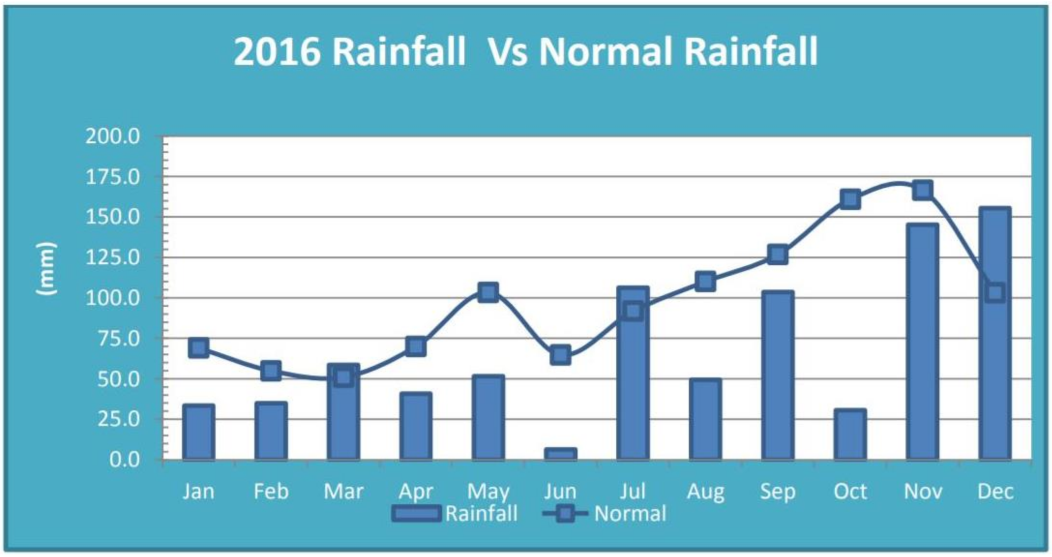
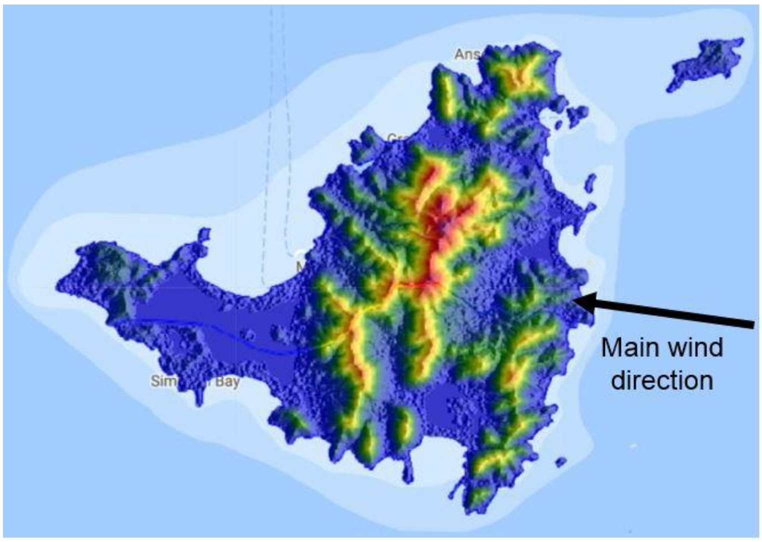


Figure 1: Rainfall chart of Sint Maarten (Meteorological Department of St. Maarten, 2016)

3.2 Warm ocean bodies and orographic lifting

During the whole year the water temperature around Sint Maarten is quite warm, late summer the water temperature of the Atlantic Ocean reaches 27°C and over. As a result water evaporates quickly leading to humid conditions. When this warm air reaches the lifting condensation level, it condenses and forms clouds. In certain circumstances air is forced up to this level. This is what happens above Sint Maarten. Figure 2 shows the SRTM elevation map of Sint Maarten. In the middle of the island a small mountain range can be seen. The wind over the island usually blows from East to West, thus air is forced up over this range to the LCL and condenses. Most clouds form in the middle of the island, over the highest part of the mountain.



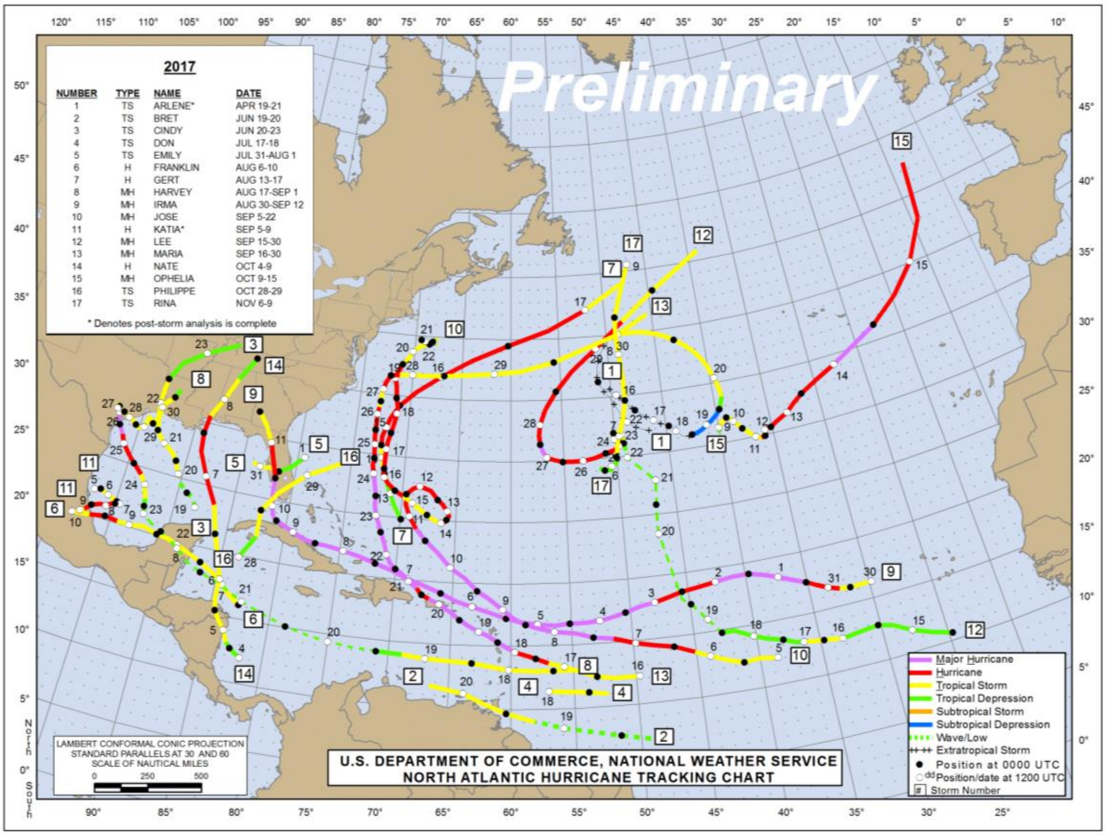
colour	Elevation (m)
🟦	0 – 70
🟩	70 – 140
🟨	140 – 210
🟧	210 – 280
🟥	280 – 350
🟪	350 - 420

Figure 2: SRTM elevation image of Sint Maarten

3.3 Hurricane Season

For Sint Maarten the hurricane season starts at the end of June and ends in November. Figure 3 shows a preliminary map with all the tropical storms, their path, strength and date that were seen from January until November 2017 in the Caribbean area. It can be seen that from August up till now 12 tropical depressions developed, turning into either tropical storms, hurricanes or major hurricanes. In total 2017 counted 17 storms, 10 hurricanes and 6 major hurricanes. Compared to the long term averages of 12 storms, 6 hurricanes and 3 major hurricanes it can be concluded that activity was above average (NWS National Hurricane Center, 2017).

Before a hurricane can develop, the right circumstances are needed. One of the most important is a warm ocean. At the end of summer and early fall sea surface temperatures reach over 27°C. Therefore they are able to provide the heat and moisture that is necessary. Because of this requirement most hurricanes form between 20° and 5° latitude (within 5° of the equator the Coriolis force is too weak to create a rotary motion). Figure 4 shows the sea surface temperature in the Atlantic Ocean and Caribbean Sea on the first of June in 2010.
A hurricane starts as a tropical disturbance far more east to the place where it actually becomes a hurricane. Usually in the Atlantic Ocean the cause of a tropical disturbance is due to ripples in the easterly trade winds. However not all disturbances turn into an actual hurricane. Sometimes the hot air is not able to rise any further due to a temperature inversion higher in the atmosphere or it mixes because of strong winds aloft. But when a storm forms, a low pressure is created in the centre of the storm, as a result a steeper pressure gradient is going outward and thus causing surface wind speeds to increase. On top of the storm a high pressure develops, therefore a flow is created outward from the top to the bottom. This outflow has as a result that at the bottom the low pressure is maintained and even strengthened, making sure that hot moist air keeps on being sucked in the storm. When this supply of warm air is stopped, due to the storm moving over colder water bodies or over land, the hurricane will decrease in strength and eventually disappear completely (Lutgens, F.K. & Tarbuck, E.J., 2013).



2017

NUMBER	TYPE	NAME	DATE
1	TS	ARLENE*	APR 19-21
2	TS	BRET	JUN 19-20
3	TS	CINDY	JUN 20-23
4	TS	DON	JUL 17-18
5	TS	EMILY	JUL 31-AUG 1
6	H	FRANKLIN	AUG 6-10
7	H	GERT	AUG 13-17
8	MH	HARVEY	AUG 17-SEP 1
9	MH	IRMA	AUG 30-SEP 12
10	MH	JOSE	SEP 5-22
11	H	KATIA*	SEP 5-9
12	MH	LEE	SEP 15-30
13	MH	MARIA	SEP 16-30
14	H	NATE	OCT 4-9
15	MH	OPHELIA	OCT 9-15
16	TS	PHILIPPE	OCT 28-29
17	TS	RINA	NOV 6-9

* Denotes post-storm analysis is complete

Figure 3: Map showing the hurricanes of 2017 up till November with their track, power and date (NWS National Hurricane Center, 2017)

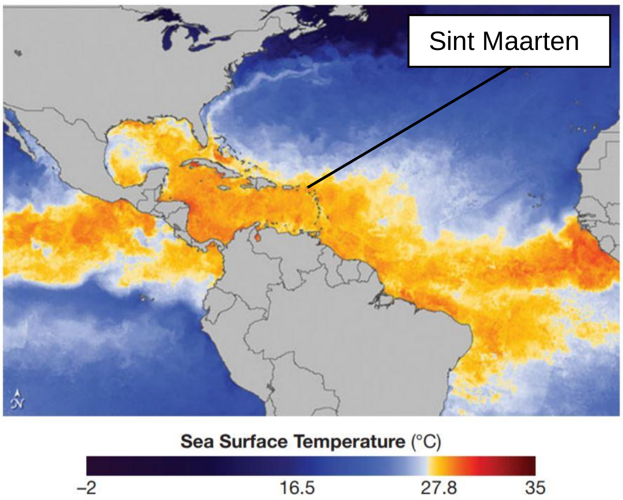


Figure 4: Sea surface temperature on the first of June 2010 (Lutgens, F.K. & Tarbuck, E.J., 2013)

3.4 Geology and Land cover

Figure 5 shows the geology of Sint Maarten. The island is part of the non-volcanic arc of the Lesser Antilles. The oldest formation, called Pointe Blanche consists of tuffs and tuffoid rocks from the Tertiary. A diorite batholith intruded into the Pointe Blanche. Both formations are visible due to the formation being folded and ongoing erosion. During early Miocene a marine transgression took place and as a result marls and limestone were deposited. During the glacial period Sint Maarten and some other small islands surrounding were one landmass. However, after the glacial period part of the big landmass submerged and quaternary limestone was formed at the coast. The youngest formations that are found consist of sand bars and bays (Stoffers, 1956).

The island of Sint Maarten shows, due to its tropical climate, lush vegetation that includes sea grapes, aloe and palm trees in the coastal regions. At higher altitudes ferns and mountain mahogany trees are found. In the salt pond mangrove stands can be seen (SMNHF). Lying South of the salt pond, Philipsburg is found. This is the capital city of the island. Other villages are found as well mainly at the coastal areas. The west of the island consists of a lagoon.

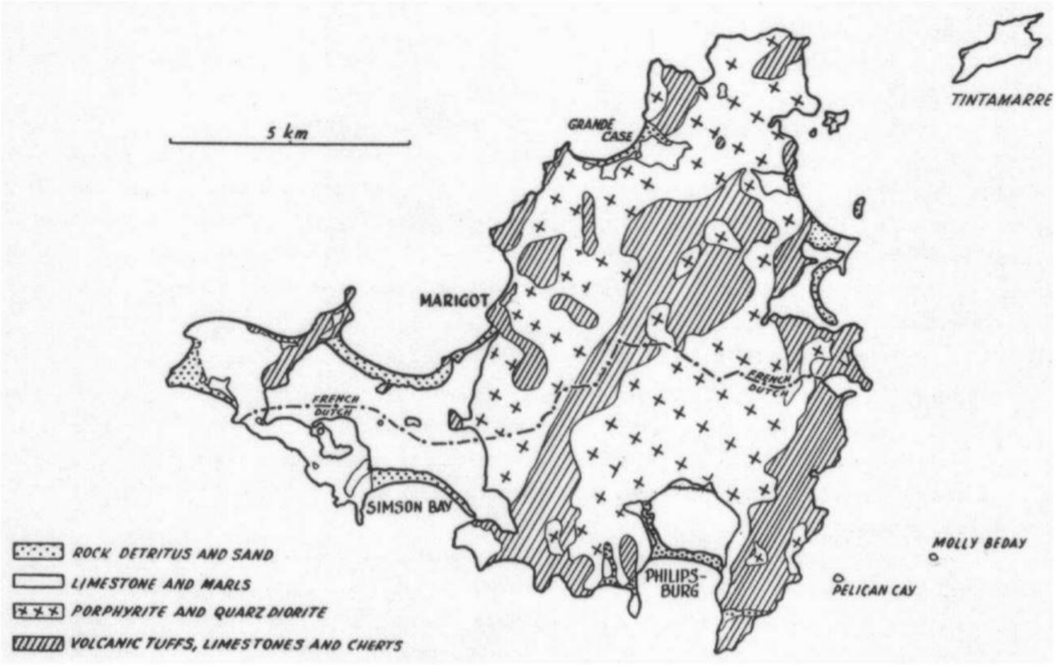


Figure 5: Geologic map of Sint Maarten (Stoffers, 1956)

In conclusion, Sint Maarten has a tropical climate with a drier period from January to April. Most cloud formation will be seen on top of the highest part of the island due to orographic lifting. Hurricanes can form when the sea temperature exceeds 27°C, the hurricane season starts at the end of June and ends in November. In 2017 more tropical storms and hurricanes were seen compared to the long term averages.

4 Method

4.1 Retrieving images

A Sentinel 2 image collection of Sint Maarten is created by filtering the images on boundaries of the island and the dates of retrieving in Google Earth Engine. The island is with its 96 square kilometers quite small and is completely surrounded by ocean (Meteorological Department St. Maarten, 2016). As a result, a cloud free image of Sint Maarten is not very common. Therefore a collection of images is used. The images are taken from the first of January 2017 to the first of September 2017, just before the hurricane blew over.

A different approach is followed for the images after hurricane Irma. This is because the closer the image is to the date of the hurricane, the better the changes can be pictured. As after such an extreme event rebuilding start almost immediately after. Also, just after hurricane Irma another tropical storm hit. Maria passed south of the island on the 20th of September. No further damage was done on the buildings, but debris from Irma was again swept up and placed somewhere else. Therefore, to create a picture of the effect of hurricane Irma alone, a relatively cloud free image of the area in between the 6th and the 20th of September was looked for. The image that is used was retrieved on the 12th of September 2017.

4.2 Cloud removal

To create a cloud free image of the data before the hurricane, a cloud mask is used. This a flag based approach that uses the contents of band QA60, a bit mask band. It contains cloud information on bit 10 and 11. Bit 10 has information on the opaque clouds while bit 11 identifies cirrus clouds. Opaque clouds are thick clouds that form lower in the atmosphere, while cirrus clouds are thin and form at six to seven kilometres height. If both bits are equal to zero for a certain pixel, it is cloud free and can be used for the final image. Some pixels will not be equal to zero and will therefore be masked. The masked area is then filled with cloud free pixels from images retrieved at different days. The pixels that are used in the function are already pre-filtered on CLOUDY_PIXEL_PERCENTAGE, which is a specific metadata field from Sentinel available in Google Earth Engine, of 20%. To create the best possible picture, the median of the pixels of other images that can fill the spot is taken. Taking the median also has another effect. Pixels that are covered by shadows and thus are darker than average will not be selected. Still some spots were found where clouds were not covered completely. These were removed manually. The figure showing the image without manual cloud removal can be found in Appendix B, Figure 39.

In Table 2 the code is shown that is used to filter the satellite data and to perform cloud masking on the image before hurricane Irma. On the left side the code is displayed, on the right the script is explained. The full script can be found in Appendix A.

Table 2: The script that is used to retrieve a cloud free image of Sint Maarten before hurricane Irma

```
var SM_Before = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-01-01', '2017-09-01')
```

A variable is created called SM_Before. It is defined by the Sentinel 2 data which is filtered on the boundaries of a polygon that is placed over Sint Maarten (geometry2). The data is also filtered on their date of retrieval.

```
function maskS2clouds(image) {
  var qa = image.select('QA60');

  // Bits 10 and 11 are clouds and cirrus, respectively.
  var cloudBitMask = Math.pow(2, 10);
  var cirrusBitMask = Math.pow(2, 11);

  // Both flags should be set to zero, indicating clear conditions.
  var mask = qa.bitwiseAnd(cloudBitMask).eq(0).and(
             qa.bitwiseAnd(cirrusBitMask).eq(0));

  // Return the masked and scaled data.
  return image.updateMask(mask).divide(10000);}
```

A function maskS2clouds is stated that selects the QA60 bit mask band from an image.

Descriptions of the script can be added if // is put before

Then two variables are created within the function that can select bit 10 and 11 from the image.

To indicate a cloud free pixel, both the cloudBitMask and the cirrusBitMask should be equal to zero.

The data that is masked and scaled by 10000, is the return of the function.

```
var cloud = /* color: #d63000 */geometry;
```

A polygon is created over the clouds that were not completely covered yet.

```
var geometry_c = geometry2.difference(cloud);
```

A new geometry is created, the final clouds are removed.

```
var Best_Before = SM_Before
// Pre-filter to get less cloudy granules.
.filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))


.map(maskS2clouds)
.median()

.clip(geometry_c)
```

A new variable is created on which more filtering will be done.

The images from 01-01-2017 to 01-09-2017 are filtered on a CLOUDY_PIXEL_PERCENTAGE of 20%. This is a Sentinel-specific metadata field that can be used.
Then the function maskS2clouds is applied.
From the pixels that are still left, the median is chosen.
The image is clipped to the geometry with the extra cloud removal.

```
Map.addLayer(Best_Before,{bands: ['B4', 'B3', 'B2'], min: 0, max: 0.3},'SM_Before');
```

The final image is added as a layer to the map called SM Before. A real colour image is created by selecting B4, B3 and B2. A minimum reflectance of 0 is chosen and a maximum of 3000/10000 = 0.3

In order to create a cloud free image of the data after Irma, the same cloud mask as described above was used. However as a result, the complete island was masked. This was probably due to the cirrus mask being too strict on the single image. Therefore a different approach was tried, rule based masking. Clouds would be selected by their high reflectance values in B2, in this case a value of 3200 was chosen as this was the value that separated the clouds from the other classes. Also a function was added that masked pixels with a value lower than 3200 for B2 that were neighbouring a pixel that was higher. With this feature rims of clouds that show lower coverage could also be masked. However, the result was not completely right yet as some of the light roofs of houses and beaches were also masked. A spectral plot was made for clouds and light roofs and for clouds and sand, to see if another band could distinguish between the two (see Figure 6 and 7).

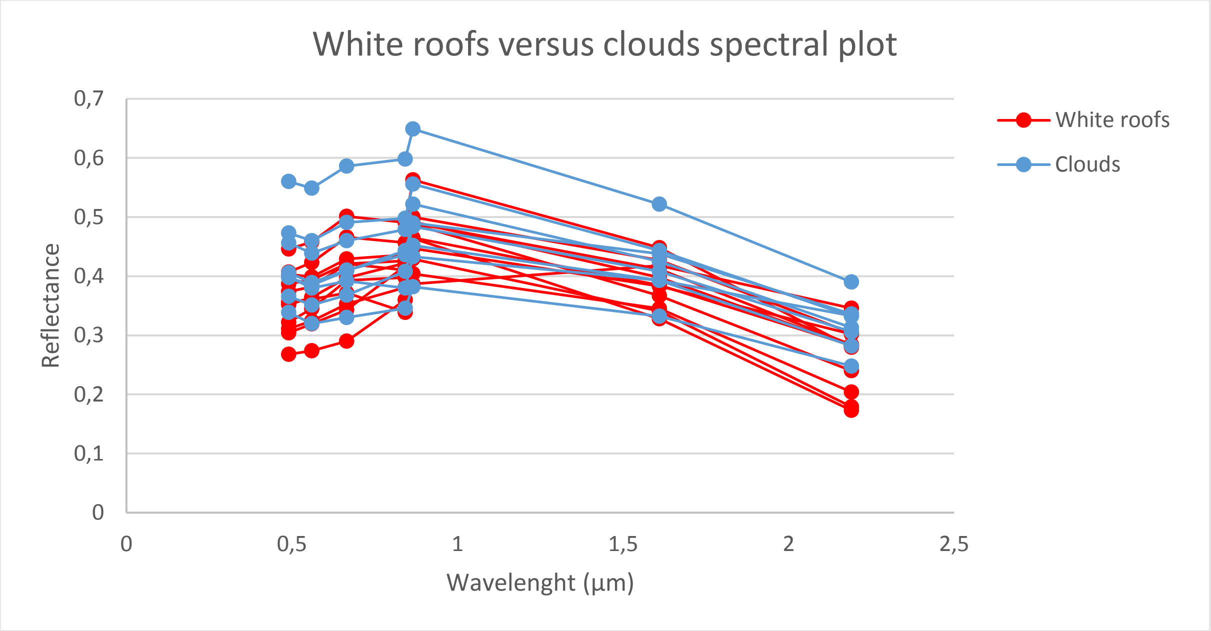


Figure 6: Spectral plot of white roofs and clouds showing their reflectance values at B2, B3, B4, B8, B8A, B11 and B12

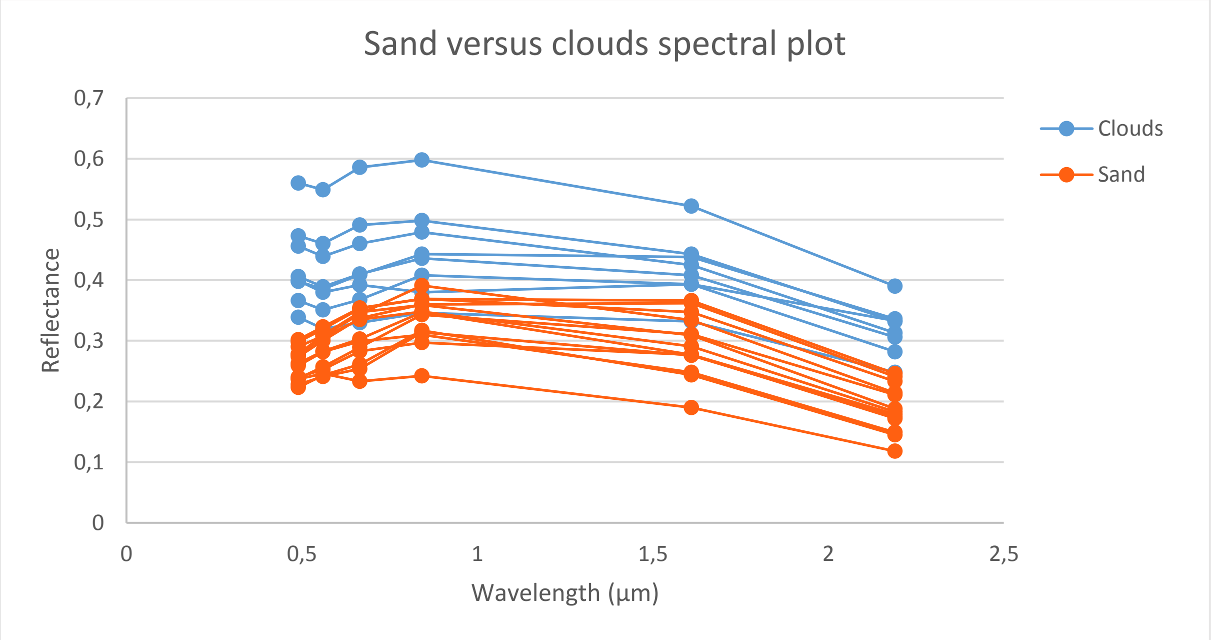


Figure 7: Spectral plot of sand and clouds showing their reflectance values at B2, B3, B4, B8, B11 and B12

When looking at the spectral plot of white roofs versus clouds it can be seen that there is no band value that can distinguish between the two. However when looking at the chart of sand and clouds, it can be seen that the reflectance of clouds is higher for B11 and B12. Therefore the mask is adjusted for high values of B11 and B12. However, this modification had as a result that more white roofs were masked. In the end it was decided that only B2 is used.

The clouds of the image do also create shadows on the image. As a result these areas are a lot darker than other parts. Again the reflectance is checked to obtain an idea on which bands to filter. Initially three criteria are chosen: B2 < 1500, B3 <1250 and B4<1000. Since problems with vegetation were seen. The reflectance for vegetation and shadows were compared. One other aspect was added to the function, B8<1500.

However the mask that was created was not able to cover up everything. Therefore in the end it was decided that clouds and shadows would be removed manually.

4.3 Classification

Classification is a method that extracts information from a raster image that contains multiple bands and sorts it into different classes. It can be used to display different land cover types on an image. This can be done in two ways. The first one is unsupervised classification. The computer uses a technique that determines which pixels should be grouped together in a class without any input data. However afterwards, knowledge of the area is needed to relate classes to actual features. Supervised classification, on the other hand, is based on training data that already contain the common band values for the classes. The classification method then uses this data as a reference when classifying (Google Earth Engine API).

For this project a supervised classification method is used, called minimum distance. It characterizes each class by its mean position on each band that is closest to the training data. Then pixels are placed in the class of the nearest mean (Akgün et al, 2004). Five classes are determined; water, sand, vegetation, asphalt and urban area. For each class shapes are drawn on the applicable area by using Google satellite data and Google street view as reference, the map that shows the polygons can be found in Appendix B, Figure 40. The geometries should have roughly the same size to create an even amount of input data for the classes. For each class a spectral plot is created that shows the reflectance of the different polygons in the class. If one polygon shows a completely different reflectance compared to the rest it can influence the right reflectance for the class. Therefore if such a reflectance is detected, the polygon should be removed from the training data set. These spectral plots can be found in Appendix B, Figure 41 – 45.

After the training data has been created, the bands for classification are chosen. Not all bands can be used for classification as Google Earth Engine has set the maximum amount of training data that it can process on 5000 elements. One element is set as a pixel that contains one band value. Thus if 12 bands are used as training data for one pixel, 12 elements are filled. Also the polygons for the training data should not be drawn too big, otherwise too many pixels are used and less band values can be used for classification. Band numbers B2, B3, B4, B8, B11 and B12 are chosen. The combination of B4, B3 and B2 shows the natural colours. With the band combination B8, B4 and B3 a false colour image can be created to distinguish vegetation from other classes. Finally the urban areas can be separated using band combination B12, B11 and B2 (Sentinel Hub Playground).

Both an image of Sint Maarten before hurricane Irma as well as an image after hurricane Irma has to be classified. To correctly show differences, one set of training data is used for both classifications. The training data is obtained from the image before the hurricane.

4.4 Indices

In order to create the best possible picture of the change that happened at a certain area, indices are calculated for the before and after image of Sint Maarten. Indices can highlight characteristics like healthy vegetation, bare ground, urban area and plenty more.

Indices are calculated by computing the normalized difference between two bands. The indices that are used for Sint Maarten include: NDVI (Normalized Difference Vegetation Index), NDGI (Normalized Difference Geology Index), the Water Index, NDUI (Urban Index) and the NDBI (Bareness Index). Their definition is given in Table 2.

To show the amount of chlorophyll in plants the NDVI is used. If vegetation is ripped out, plants will die and the chlorophyll will greatly decrease. This is indicated with B4 and B8. Less chlorophyll has a lower B8 reflectance as a result. Due to vegetation turning brown, B4 (visible red) will increase in reflectance. In general healthy vegetation shows an NDVI of at least 0.3.

The NDGI is used to show the built up of sand and is created by looking at the geology false colour image, that is composed with B12, B4 and B2 in Sentinel Hub Playground. After examining, an index combination with B2 did not produce the sought after result. Therefore an index is created with B4 and B12. Both these bands indicate barer grounds, but B4 will show a great increase in reflectance if sand is detected, while B12 increases a lot less.

However, sometimes water shows the same NDGI as sand, this is probably due to the water being shallower. This does sometimes cause problems distinguishing between the two when just looking at the before and after picture. However two solutions were thought of. Firstly a water index mask is created, that is used as a semi-transparent layer over the NDGI images. This index is created by taking the normalized difference between B3 and B11 (Du, Y et al, 2016). This way it is clear what is land and what not. Secondly, since the difference is of interest, a difference plot is created that does show the built up of sand but ignores the water, as this body does not change.

To look for changes in urban area, two indices can be used. The first one that is tried is the NDUI (Urban Index). It uses B8 and B12 to differentiate between areas with vegetation and built up areas (As-syakur et al, 2012). When the urban index image is plotted however, it is seen that water also comes up as urban area. Therefore the water index is used again as a mask. When the after image is plotted the complete island turns red, indicating an urban area. This probably is because B8 is used in this plot. B8 will show a great decrease because of the vegetation being ripped out. A difference plot is created with the knowledge that big change in vegetation will also be seen. Since the NDUI does not produce the effect that is wanted, the NDBI is tried (Sinergise). This index uses the normalized difference between B11 and B8.

All the before Irma-, after Irma- and difference index images that are made are clipped on the borders of Sint Maarten. This way the main focus is on the land cover of the island and noise of the ocean is not visible. The borders are imported into Google Earth Engine as shapefiles which can be downloaded from the GADM database of Global Administrative Areas.

Table 3: Indices, their calculation and values

Index	Equation	Values from sources	Values for Sint Maarten
NDVI	$\frac{B8-B4}{B8+B4}$	>0.3 healthy vegetation <0.3 unhealthy to no vegetation	
NDGI	$\frac{B4-B12}{B4+B12}$	-	0.15 – 0,35 water 0.15 – 0.25 sand
Water Index	$\frac{B3-B11}{B3+B11}$	Not mentioned	>0.1 water <0.3 other
NDUI	$\frac{B12-B8}{B12+B8}$	> 0 urban area	-
NDBI	$\frac{B11-B8}{B11+B8}$		-

4.5 Validation

Validation is done with the use of a confusion matrix. This is a matrix that outlines the performance of a classification model on a set of validation data for which the true values are known (Data School, 2014). On the horizontal the predicted classes are plotted and on the vertical the actual classes. The diagonal shows the amount of elements for a certain class that has been predicted right.

The validation data is retrieved from the training data set, one for the classification before hurricane Irma and one for the classification after. Only 80% of the training data set is used for the actual training of both the before and after image. Then 20% is left which is used for validation. The validation data for before hurricane Irma is taken from the before data set. The validation data after is taken from 20% of the after training data set.

Not all classes consist of the same amount of elements. Therefore a ratio confusion matrix is made. In this matrix the ratios are calculated as if all classes do have the same amount of elements in them. The user and producer accuracy have been added as well. The user accuracy is the ratio between the correctly identified elements in a given map class over the number that is claimed to be in that map class. The producer accuracy describes how many elements have been labelled correctly by calculating the ratio between the correctly identified elements in the reference plot of a given class over the number that is actually seen in this reference class.

The overall accuracy and the Kappa accuracy of the matrix are also calculated. The Kappa accuracy is described as a measure of how well a classification method would have performed by chance (Data School, 2014).

In conclusion, flag based cloud masking is used to obtain a cloud free image of Sint Maarten before Irma, the few clouds that are still left are removed manually. For the image after Irma only manual masking is carried out. Five different classes are distinguished for Sint Maarten: Water, sand, vegetation, urban area and asphalt. The minimum distance method is used for classification. Classification and indices are used to detect changes on the surface of the island after hurricane Irma. The indices that are used include NDVI, NDGI, the Water Index, NDUI and NDBI. Validation is carried out by creating confusion matrices.

5 Results

In this chapter the results of the project will be displayed. Firstly the final processed image and the figures will be displayed. Then a general change map will be created for Sint Maarten that highlights the areas that show a significant difference in either classification or indices. These areas are chosen by taking into consideration news articles and pictures that were written and taken after hurricane Irma. A more in depth description of each area is done after.

5.1 Final processed images and figures

Figure 8 and 9 show the final obtained satellite images after cloud and shadow removal of Sint Maarten before and after hurricane Irma. In Figure 10 the spectral plot of the training data can be seen. The defined classes all show a significantly different reflectance and it therefore expected that the classification will be mostly carried out correctly. Then Figure 11 shows the classification before Irma, Table 4 and 5 are the corrresponding confusion matrices. 2111 elements are used for the training of both the before and after image and 535 elements are used for validation of the before image. Figure 12 shows the classification after Irma. Table 6 and 7 are the corresponding confusion matrices that are made with validation data of 425 elements. This amount is less due to part of the training data being covered by the cloud mask. The overall accuracy and kappa accuracy are mentioned underneath the ratio confusion matrices.

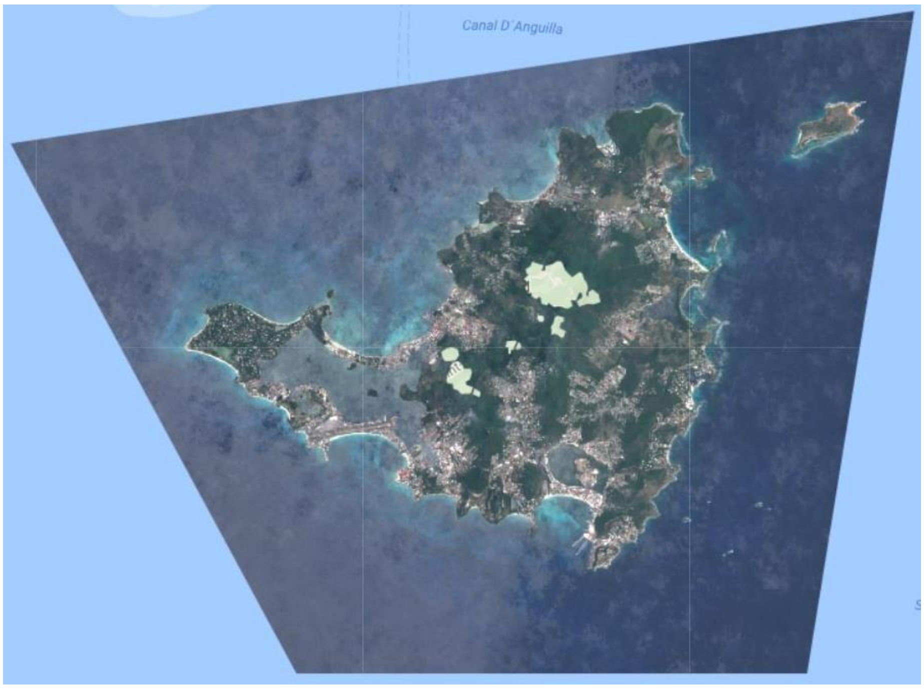


Figure 8: Final retrieved satellite image of Sint Maarten before hurricane Irma

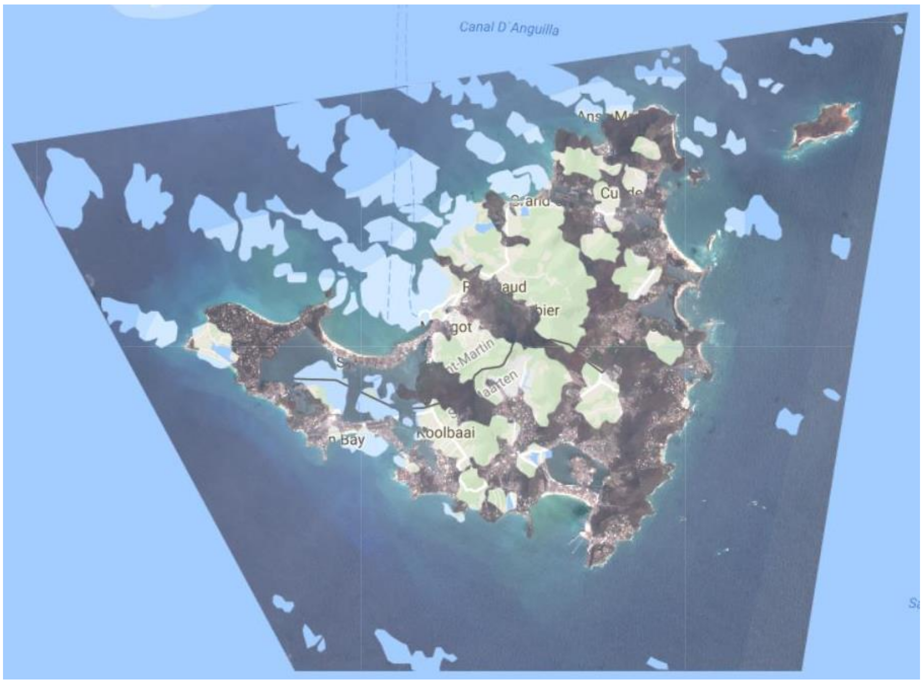


Figure 9: Final retrieved satellite image of Sint Maarten after hurricane Irma

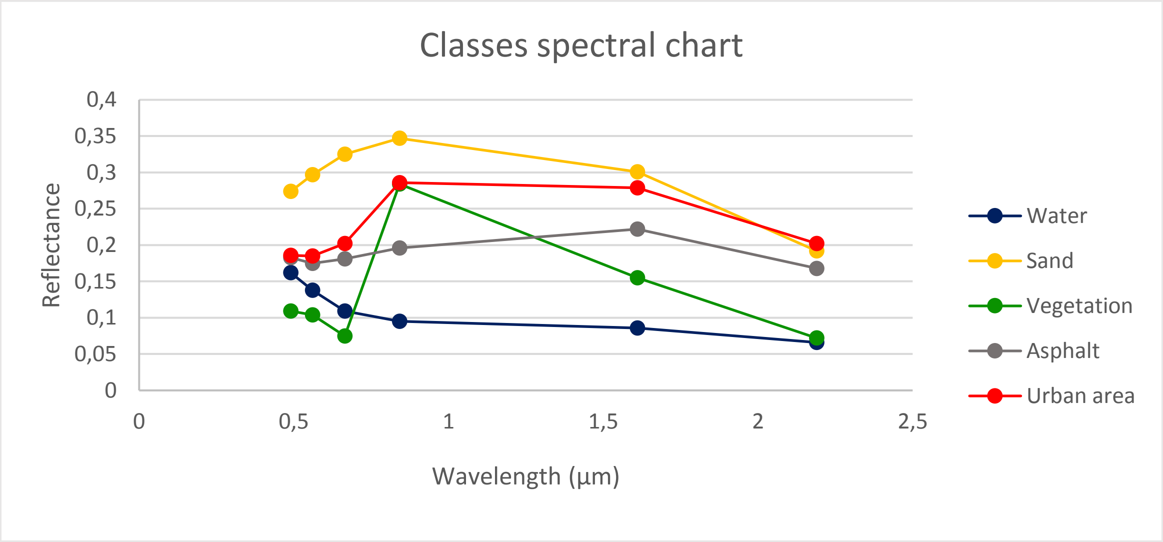
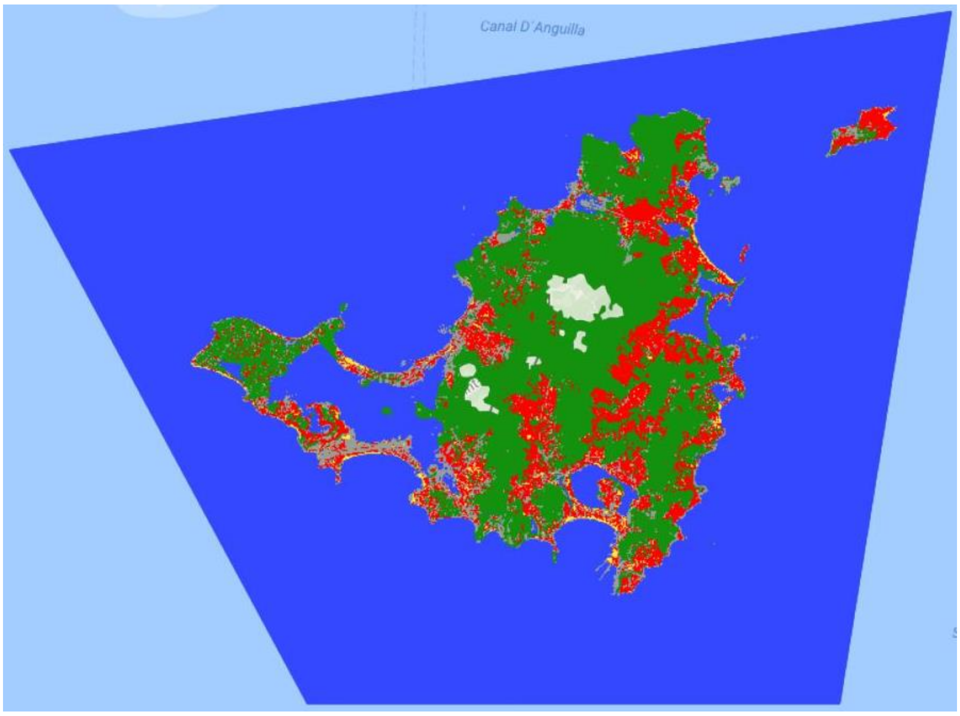


Figure 10: Spectral plot showing the reflectance of different classes



🟦	Water
🟨	Sand
🟩	Vegetation
▨	Asphalt
🟥	Urban area

Figure 11: Classification map of Sint Maarten before hurricane Irma

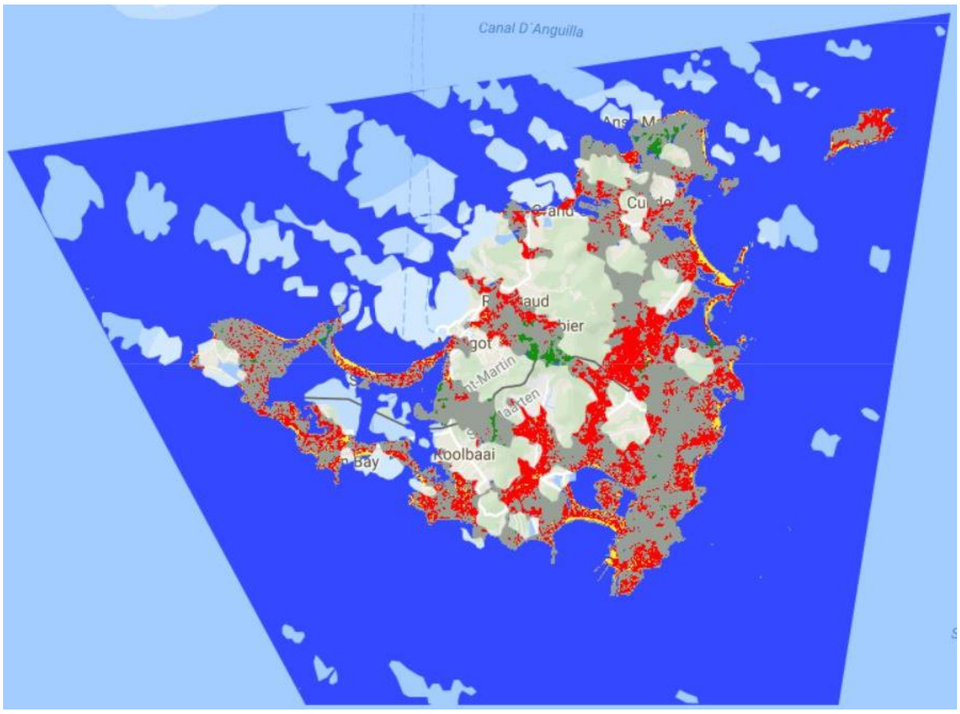


Figure 12: Classification map of Sint Maarten after hurricane Irma

Table 4: Element based confusion matrix before Irma

Predicted Actual	Water	Sand	Vegetation	Asphalt	Urban area	
Water	162	0	0	0	0	162
Sand	0	58	0	3	2	63
Vegetation	0	0	30	0	0	30
Asphalt	11	3	0	113	24	151
Urban area	0	4	0	13	112	129
	173	65	30	129	138	535

Table 5: Ratio based confusion matrix before Irma

Predicted Actual	Water	Sand	Vegetation	Asphalt	Urban area	Producer accuracy
Water	1	0	0	0	0	1
Sand	0	0.92063	0	0.047619	0.031746	0.92063
Vegetation	0	0	1	0	0	1
Asphalt	0.072848	0.019868	0	0.74834	0.15894	0.74834
Urban area	0	0.031008	0	0.10078	0.86822	0.86822
User accuracy	0.9321	0.94763	1	0.83452	0.81992	0

Overall accuracy: 0.9074
Kappa accuracy: 0.8843

Table 6: Element based confusion matrix after Irma

Predicted Actual	Water	Sand	Vegetation	Asphalt	Urban area	
Water	151	0	0	0	0	151
Sand	0	50	0	9	0	59
Vegetation	0	0	18	1	2	21
Asphalt	5	5	19	93	20	142
Urban area	0	4	1	6	41	52
	156	59	38	109	63	425

Table 7: Ratio based confusion matrix after Irma

Predicted Actual	Water	Sand	Vegetation	Asphalt	Urban area	Producer accuracy
Water	1	0	0	0	0	1
Sand	0	0.84746	0	0.15254	0	0.84746
Vegetation	0	0	0.85714	0.047619	0.095238	0.85714
Asphalt	0.035211	0.035211	0.1338	0.65493	0.14085	0.65493
Urban area	0	0.076923	0.019231	0.11538	0.78846	0.78846
User accuracy	0.96599	0.88314	0.84851	0.67485	0.76957	0

Overall accuracy: 0.8296
Kappa accuracy: 0.7870

Sometimes classes mix up. Several houses on the island of Sint Maarten have white roofs. They often get mixed up with the sand class. When taking a closer look at the reflectance (see Figure 13), it is seen that the reflectance of white roofs is closer to that of sand than to urban area. Therefore when using the minimum distance classification technique, white roofs will appear as sand on the map.

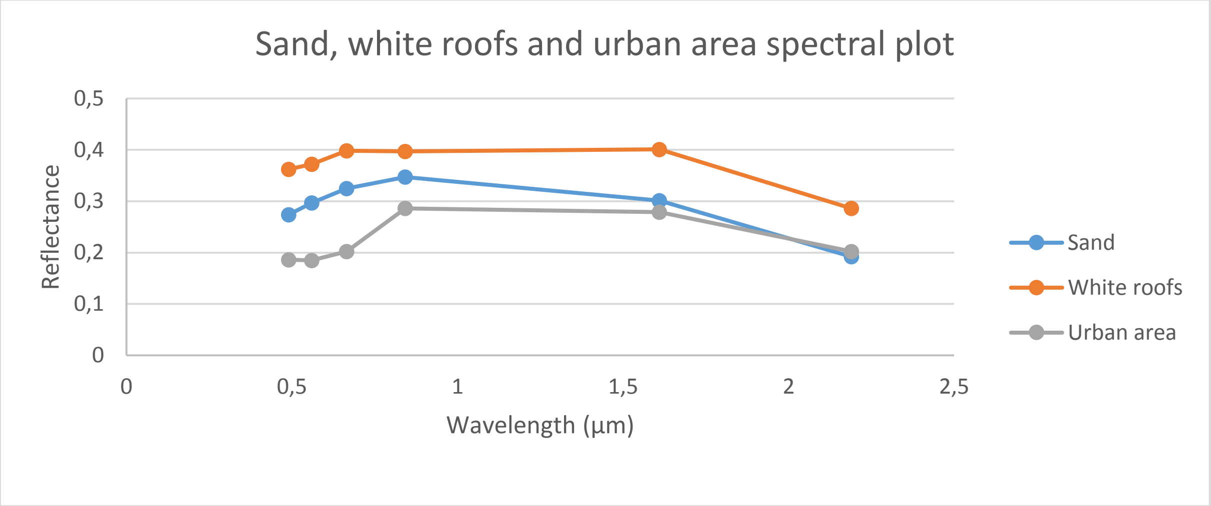


Figure 13: Spectral plot showing the reflectance of sand, white roofs and urban area

5.2 Change map

In Figure 14 an overview of Sint Maarten can be seen. The specific cases that will be discussed are circled and numbered. Three different subcategories are chosen for the change detection. The first one is vegetation, the second goes into sand shifting and the third discusses urban areas. Table 8 outlines the cases further.

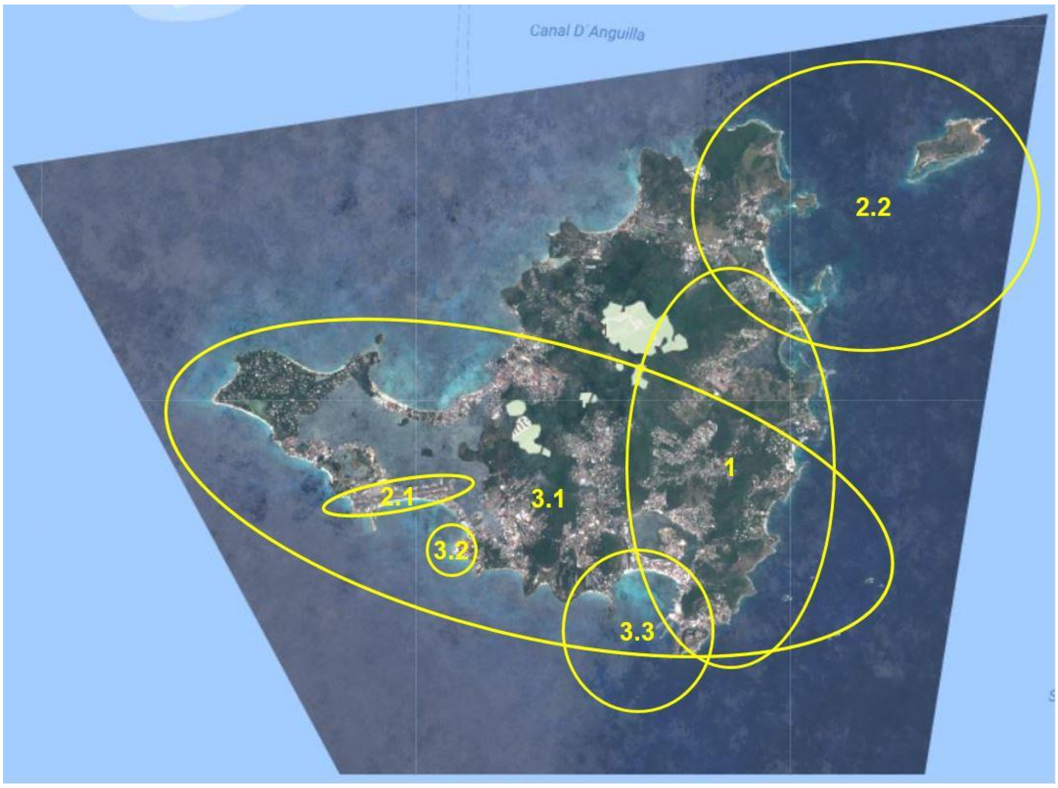


Figure 14: Overview map of Sint Maarten

Table 8: Description of the three subcategories

	Vegetation
1	Looks into an area where thick vegetation is seen. NDVI is considered as well as the classification images.
	Sand
2.1	Sand has been blown on top of the landing strip of the Prinses Juliana Airport from both Simpson Bay and Maho Beach.
2.2	Area on the French side of the island where sand shifting has also been detected
	Urban area
3.1	The damage map from the NRC newspaper will be compared to several index images.
3.2	A row of red houses on Billy Folly Road have been destroyed. The classification before and after will be discussed.
3.3	The damage of Philipsburg and the container harbour are tried to be distinguished with help of the classification maps

5.3 Vegetation: Browning effect

After hurricane Irma had passed over the Caribbean, NASA mentioned a widespread browning effect on the landscape of the islands (NASA Earth Observatory, 2017). The usually green tropical vegetation had been ripped out by the strong winds. Therefore the satellite showed more bare ground. Also salt that was swept up by the hurricane could dry out leaves that are still attached to trees. The browning effect should be visible with NDVI. Before the hurricane higher values for NDVI are expected than after.

Figure 15 shows the NDVI values of Sint Maarten before Irma, while Figure 17 shows the after image. It can clearly be seen that in the red circled areas a decrease in NDVI is seen and thus have become drier. For these areas a difference plot is created to take a closer look. Indeed in the difference plot it is seen that areas that showed a NDVI of 0.6 to 0.8 have decreased by at least 0.3 indicating that the vegetation has been harmed quite much (the full NDVI difference plot can be found in Appendix B Figure 41). It probably can be assumed that underneath the cloud masked areas the same pattern is seen.

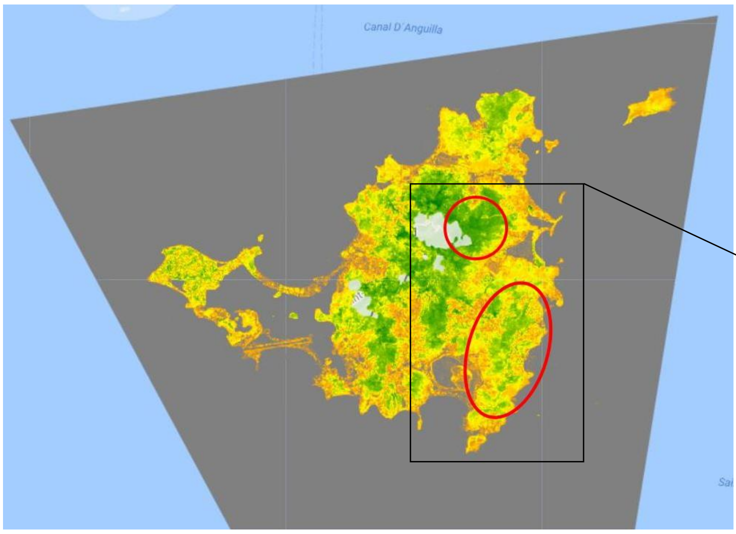


Figure 15: NDVI image of Sint Maarten before hurricane Irma

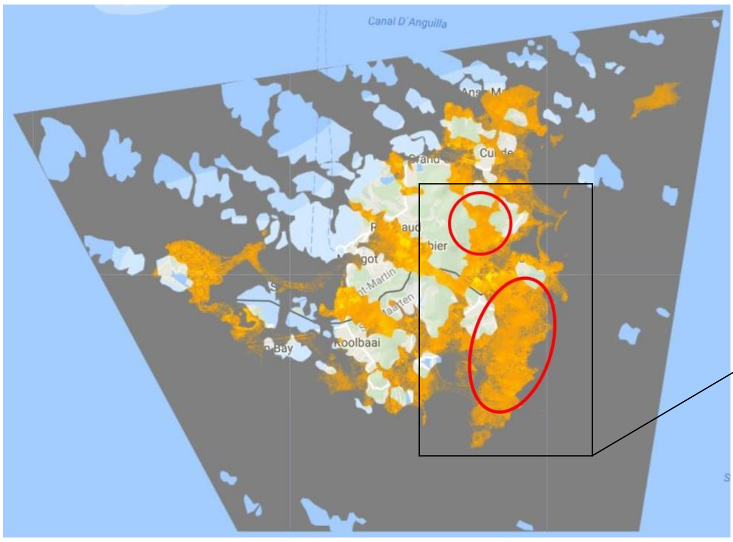
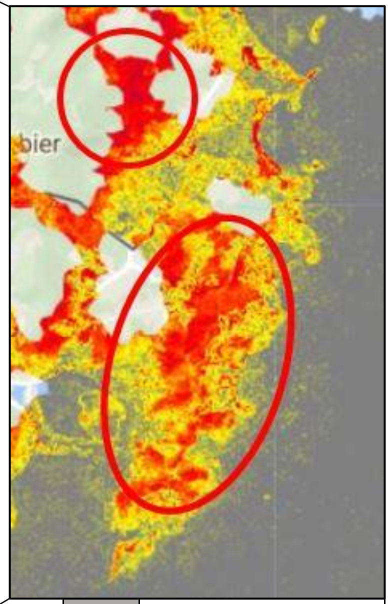


Figure 17: NDVI image of Sint Maarten after hurricane Irma

Table 9: legend: NDVI values

▨	0 – 0.2
🟧	0.2 – 0.4
🟨	0.4 – 0.6
🟩	0.6 – 0.8
🟦	0.8 – 1.0



▨	0 – 0.15
🟨	0.15 – 0.3
🟥	0.3 – 0.45
🟪	0.45 – 0.6

Figure 16: Zoomed in NDVI difference image

Figure 18 shows that the browning effect is also visible on the RGB image. In Figure 19 the classification map, zoomed in on the area with the most change, can be seen. It can be seen that the classification has mostly changed from vegetation to asphalt. Therefore it can safely be said that the bareness of the land has also been picked up by the classification. To take a closer look, a spectral plot is created (see Figure 20) that shows the reflectance of the training data for the vegetation and asphalt class. Also the reflectance of the vegetation polygons from the after image are added. The change in class can mainly be pinned to the change in B8 and B11. B8 is used to indicate the health of vegetation while B11 shows higher reflectance in more bare areas. The decrease in B8 and increase in B11 have as a result that the former vegetation does now show more similarity to the asphalt reflectance and is thus classified this way. This does make a lot of sense knowing that most of the vegetation on the island has been ripped out by hurricane Irma.

Figure 18: The zoomed in RGB image before (left) and after (right) hurricane Irma showing the browning effect

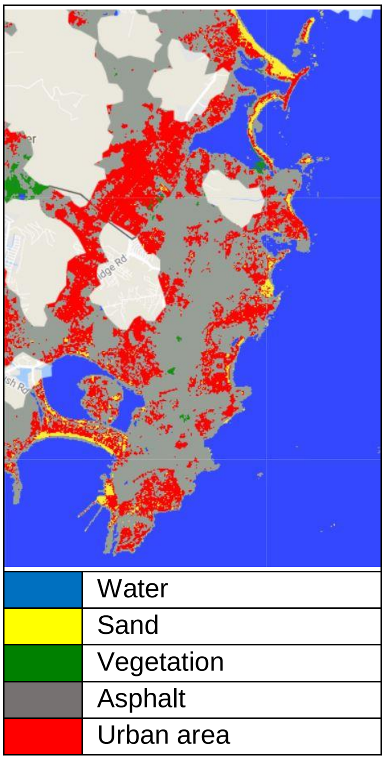


Figure 20: Classification after of the zoomed in the area with the most change

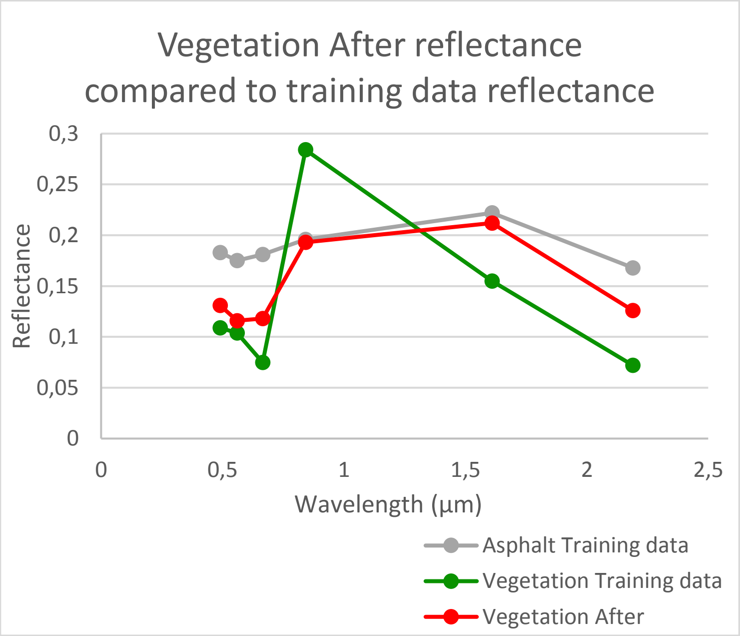


Figure 19: Spectral plot of the training data and the vegetation class reflectance after

5.4 Sand shifting

The second effect of the hurricane that will be discussed is de sand shifting at Simpson Bay. In an article of NRC several aerial photograph can be seen. Two of them showing the beaches of Simpson Bay close to the Princess Juliana International Airport (see Figure 21 and 22). Both cases will be discussed separately below.

Figure 22: Beach at Simpson Bay where most of the sand has shifted on the landing strip (NRC, 2017)

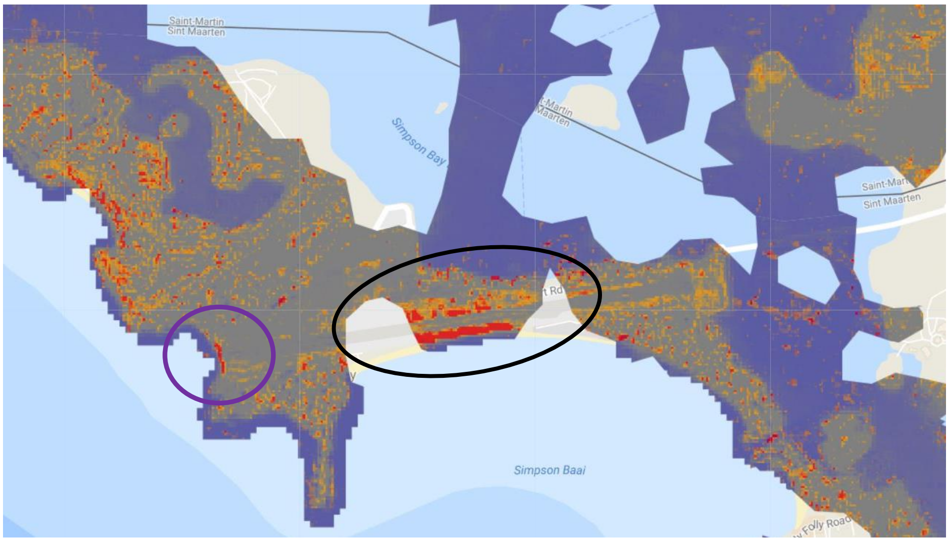
Figure 21: Maho Beach completely washed away and moved up the beginning of the runway (NRC, 2017)

5.4.1 Sand on runway at Simpson Bay

The first case that is discussed is the sand that has shifted from the Simpson Bay on the runway. It is know that just after the hurricane had passed over, the sand was already shoved off. Therefore first a look is taken at an image of the 7th of September. Even though it is quite cloudy, the landing strip can clearly be distinguished (see Figure 22). The sand that has shifted from the beach on the strip is circled red. When taking a look at the image of the 12th of September, the sand has already been removed from the runway. However, due to the sand also covering the grass, still an image can be created that shows this shifting.

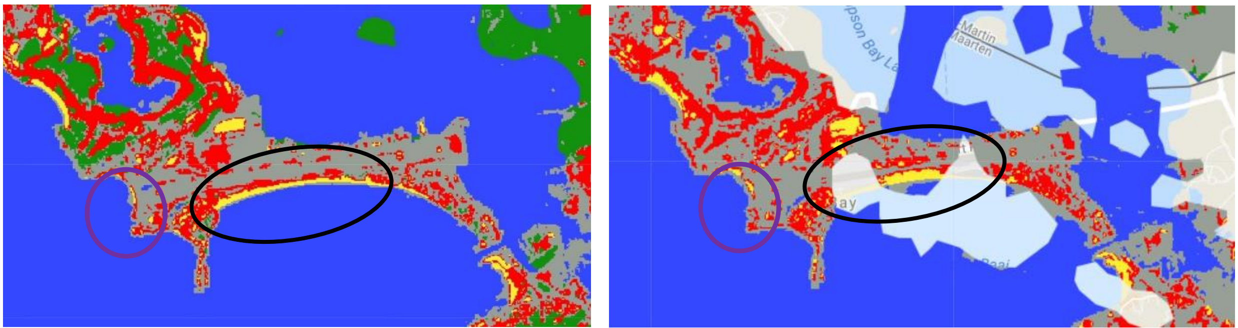
Figure 23: Sand shifting, on the left an image of the 7th of September, on the right from the 12th of September

Figure 24 shows the difference map of the NDGI, with an overlay of the Water Index image. The biggest changes that are seen are coloured red, here the difference between before and after is bigger than 0.2. As expected the shifted sand has coloured red (circled black). When looking at the exact same spot on the classification maps before and after (see Figure 25), the spreading of sand is also visible (circled black).



⬜	0 – 0,15
🟨	0,15 – 0,2
🟥	> 0,2
🟪	Water

Figure 24: NDGI difference plot with Water Index overlay

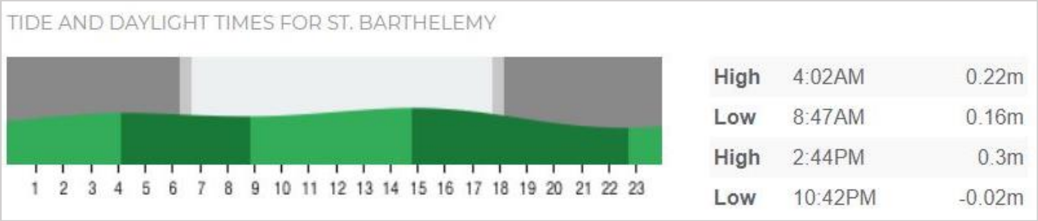


🟦	Water
🟨	Sand
🟩	Vegetation
⬛	Asphalt
🟥	Urban area

Figure 25: Zoomed in classification map of the landing strip, before (left) and after (right)

5.4.2 Washed away Maho beach

The second case that is known is the washing away of Maho beach. Part of the sand can be spotted at the beginning of the runway (see Figure 21 at the beginning of the paragraph). Part of it has probably been removed by a heavy ocean current during the storm. In order to spot this pushed away coastline the water index is used. First the tides for Sint Maarten are looked up, to make sure that only real change will be highlighted. Figure 26 shows the tides. It can be seen that the maximum difference between high and low tide at St. Barthelemy is 0.24 meter at the 27th of December 2017. Since the image has a tile size of 20 by 20 meters, it will not be of influence.



TIDE AND DAYLIGHT TIMES FOR ST. BARTHELEMY

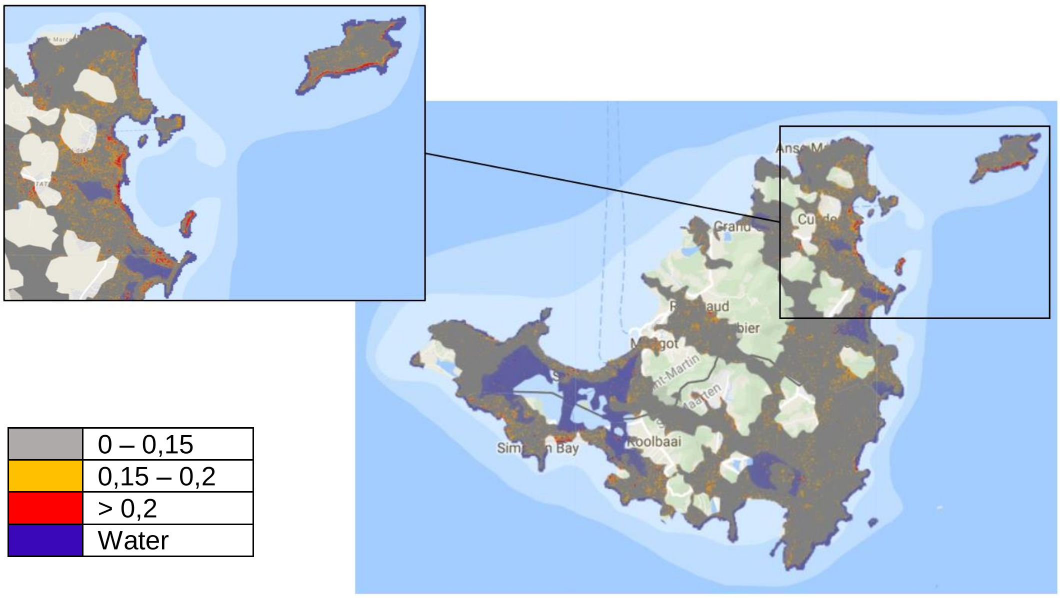
High	4:02AM	0.22m
Low	8:47AM	0.16m
High	2:44PM	0.3m
Low	10:42PM	-0.02m

Figure 26: Tide information for St. Barthelemy for the 27th of December 2017 (location: South-West of the island) (Magic Seaweed, 2017)

Since the shoreline is only pushed back a little bit, it is almost impossible to spot. This is probably also due to the pixel size being bigger than the change that has taken place. However the sand being pushed on the landing strip is visible in the NDGI index, it is circled purple in Figure 24. However due to the smaller scale of the sand shift, it is not very clearly visible on the classification map (circled purple on Figure 25).

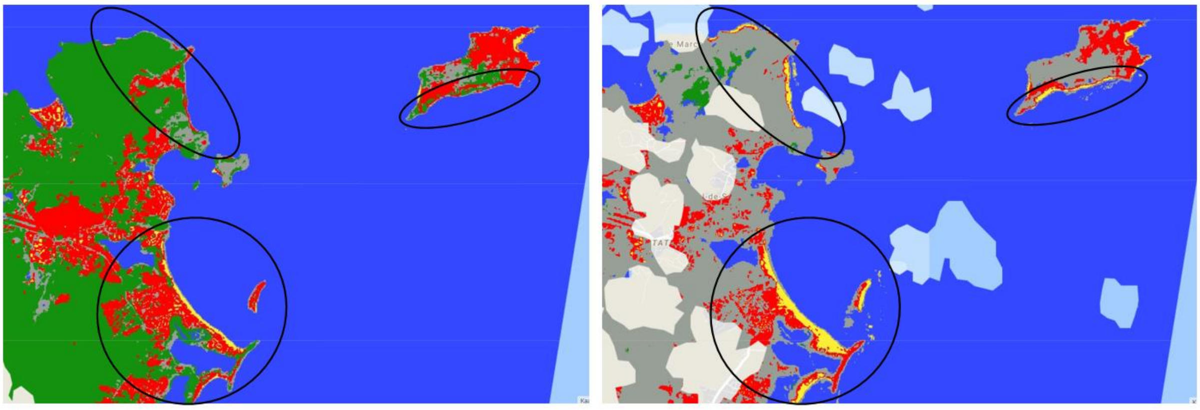
5.4.3 The bigger picture

In the paragraphs before only known changes, from news articles and pictures, have been discussed. Since these changes are found in the NDGI difference and classification images, it can be tried to find more places where sand shifting has taken place. First a look is taken at the full NDGI difference image, to quickly find the biggest changes (see Figure 28). Especially in the North East of the island red areas are seen. This area is enlarged and classifications are plotted in Figure 27. The areas that show change in the amount of sand have been circled black. These areas do coincide with the red areas on the NDGI difference plot. Therefore it can probably be concluded that in these areas, sand shifting has taken place as well.



⬜	0 – 0,15
🟧	0,15 – 0,2
🟥	> 0,2
🟦	Water

Figure 28: NDGI difference map, zoomed in on area showing change



🟦	Water
🟨	Sand
🟩	Vegetation
⬛	Asphalt
🟥	Urban area

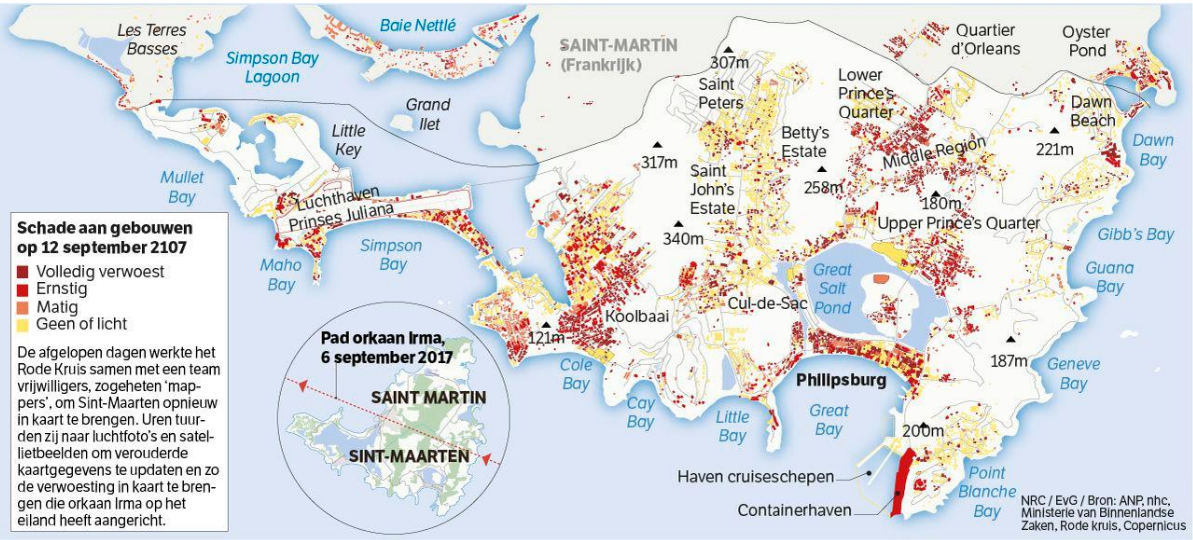
Figure 27: Classification before (left) and after (right) of the zoomed in area

5.5 Destroyed urban areas

The third and for the population of Sint Maarten the most devastating loss are the houses that have mostly been unroofed or are completely blown away. The first paragraph shows a comparison of an existing damage map of Sint Maarten and two index images. The second part will have a look at specific buildings (Billy Folly Road, Philipsburg and the container harbour) and their classification before and after the hurricane.

5.5.1 The Dutch side of Sint Maarten

First a look is taken at the NDUI difference map (Figure 30). Figure 29 shows the damaged areas map of the NRC newspaper, which is used as a reference. Red indicates a completely destroyed building while yellow shows areas that only have minor damage. The areas with most damage are of interest. In the NDUI difference map, it can be seen that the water is classified as having changed as much as the urban areas. This is not actually expected as the water class has actually not changed. Also the changes seen in built up areas are quite small. Therefore the NDUI is not a good method to indicate damage in urban regions.



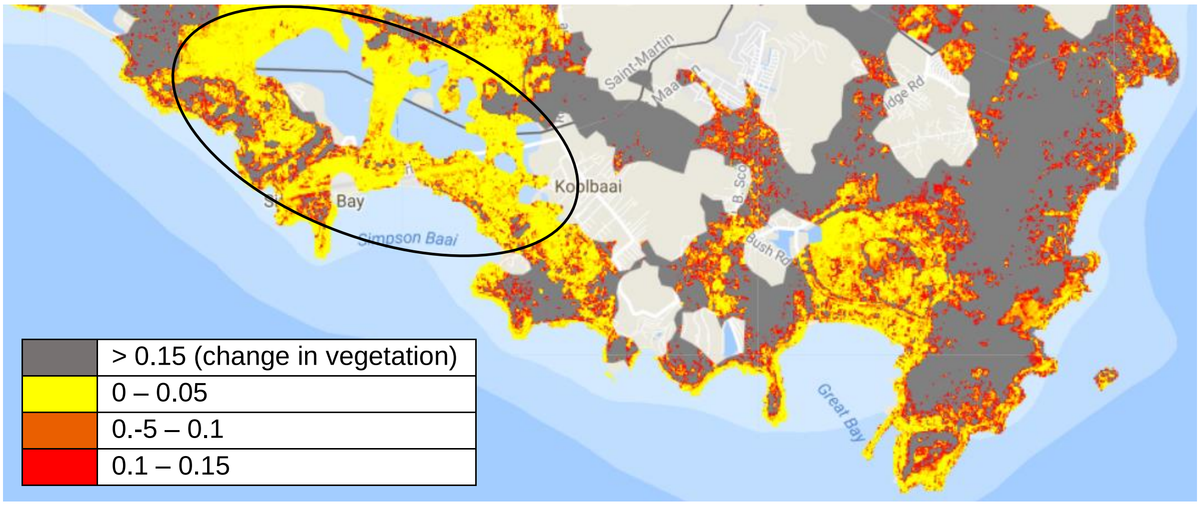
Schade aan gebouwen op 12 september 2107

- ■ Volledig verwoest
- ■ Ernstig
- ■ Matig
- ■ Geen of licht

De afgelopen dagen werkte het Rode Kruis samen met een team vrijwilligers, zogeheten 'mappers', om Sint-Maarten opnieuw in kaart te brengen. Uren tuurden zij naar luchtfoto's en satellietbeelden om verouderde kaartgegevens te updaten en zo de verwoesting in kaart te brengen die orkaan Irma op het eiland heeft aangericht.

NRC / EvG / Bron: ANP, nhc, Ministerie van Binnenlandse Zaken, Rode kruis, Copernicus

Figure 29: Damage map of Sint Maarten (NRC, 2017)



⬛	> 0.15 (change in vegetation)
🟨	0 – 0.05
🟧	0.-5 – 0.1
🟥	0.1 – 0.15

Figure 30: NDUI difference map of the Dutch part of Sint Maarten

The second index that can be looked at is the bareness index. The bareness is expected to increase over the urban areas. However the bareness will also increase at regions where vegetation grows, this increase will probably be bigger than the increase that is seen at urban areas. In Figure 31 the NDBI difference image can be seen. The high difference values due to change in vegetation have been coloured grey. However when looking at Philipsburg and the container harbour (circled red) where most has been destroyed no real change is seen. This is probably has to do with the debris of the buildings and houses still being in the same area. Since Sentinel 2 retrieves optical data, no information is known about the height of the houses. However, radar data could be used to look at the difference in phase of the signal, this will probably be picked up, as a signal will be reflected differently from a roof than from debris at ground level. The full before and after Irma and difference images considering NDUI and NDBI can be found in Appendix B, Figure 46 – 50.

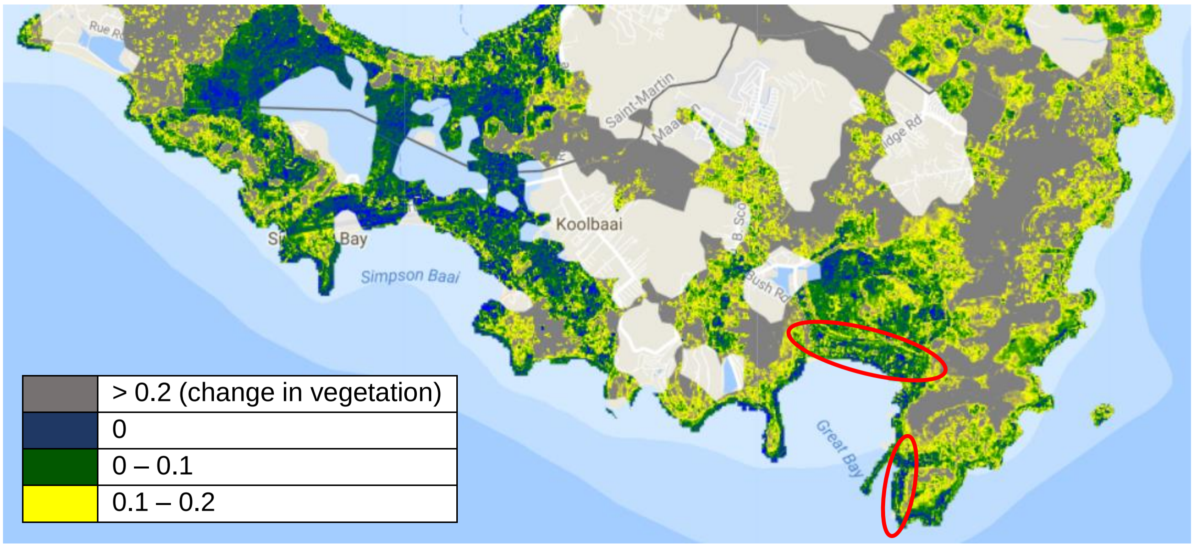


Figure 31: NDBI difference image of the Dutch part of Sint Maarten

5.5.2 Billy Folly road

Billy Folly Road is situated on the East side of Simpson Bay. A significant set of houses with red roofs been destroyed can be seen in Figure 32. These houses show a significant change in colour due to their red roof being gone. Therefore a change in classification is expected from urban area to asphalt. The outline of the houses is marked in black in both the before and after picture.

Figure 32: Aerial photograph of the Billy Folly Road (NRC, 2017)

When looking at Figure 33 a change in class from urban area to asphalt can indeed be seen. Since it is working for one single building, it is tried to look at a bigger area. To see if this effect is also visible in a bigger picture.

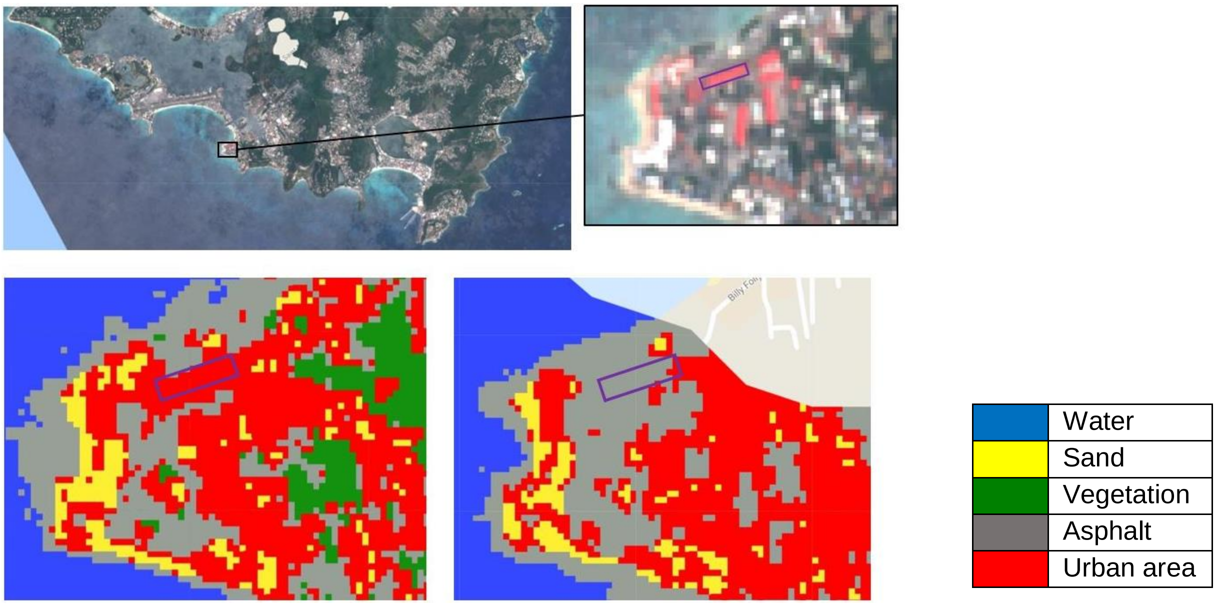


Figure 33: Destroyed red roofs on Billy Folly Road, left: classification map before Irma, right: after Irma

5.5.3 Philipsburg and the container harbour

Figure 34 shows the classification before and after Irma of Philipsburg. When comparing the images, big changes are not really seen. You even have to look very close to see any change at all in the urban area region. When taking a closer look at the container harbour, the same is seen (see Figure 35). Therefore it can be said that when looking at bigger urban regions, classification is not the right tool to look for change.

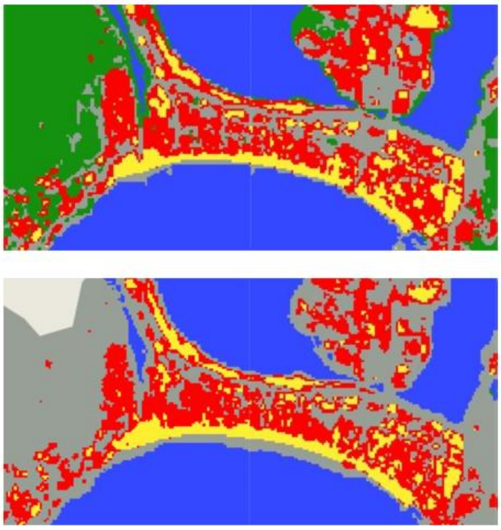


Figure 34: Classification of Philipsburg before (top) and after (bottom)

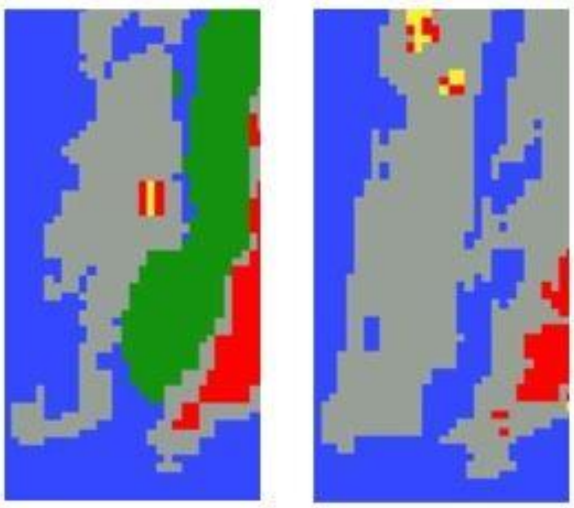


Figure 35: Classification of the container harbour before (left) and after (right)

In conclusion change in vegetation can be spotted in both the NDVI difference image and the classification map. The shifting of sand can be seen in both the NDGI difference image and the classification map as well. Change in urban area is difficult to determine with classification maps and NDUI and NDBI index images.

6 Discussion

The discussion is divided into separate themes. Firstly clouds will be discussed. The problems with cloud masking will be taken into consideration as well as the comparison in data. Secondly problems during classification will be outlined. This includes problems during acquisition of training data, mix ups of classes and the classification method. After that some difficulties with creating the indices will be discussed. Finally Google Earth Engine as a program is taken into consideration.

6.1 Clouds

6.1.1 Cloud masking

Sentinel 2 consists of a cloud bit mask band. This band is used for the before picture to create a cloud free image in a flag based approach. However this band is not completely able to mask everything. It does have trouble distinguishing thin clouds, even when the data has already been pre-filtered on images with less than 20% cloud cover. This malfunction was discovered when a closer look was taken at the classification before hurricane Irma. In the middle of the island an urban area is seen, however, when looking at the satellite, this does not appear. Therefore three different images were compared: Sentinel, Google satellite and the classification. Figure 36 shows a zoom in of the area that has been wrongly classified. Figure 37 shows the corresponding zoomed in images of the classification and the google satellite. When comparing the areas that have been circled yellow, especially looking at the Sentinel and Google satellite image, it can be concluded that the cloud mask is not able to completely filter out everything.

Figure 37: Zoom in of the area in Sentinel 2 that causes trouble in the classification

Figure 36: Zoom in of the classification and Google satellite image in the same area

The same flag based method of cloud masking is tried for the image after hurricane Irma first. However the cirrus mask is too strict on this image. However the fact that the cirrus mask, masks practically everything, does mean there is a lot of humidity six to seven kilometre up in the atmosphere. This could have an effect on the index images and on the reflectance values of the bands that are used for classification.

The second problem concerning cloud masking in the after picture came up during the rule based approach. Figure 38 shows the retrieved image after masking. The main problem that is seen is that thin clouds and rims of clouds are not detected by the threshold. This can later cause problems when classifying and calculating indices. Therefore it was decided that the clouds and shadows would be removed manually by drawing polygons on top of them. Sint Maarten is a small island, therefore manually removing clouds is not very time consuming. However, this will not be a good solution if bigger areas have to be masked.

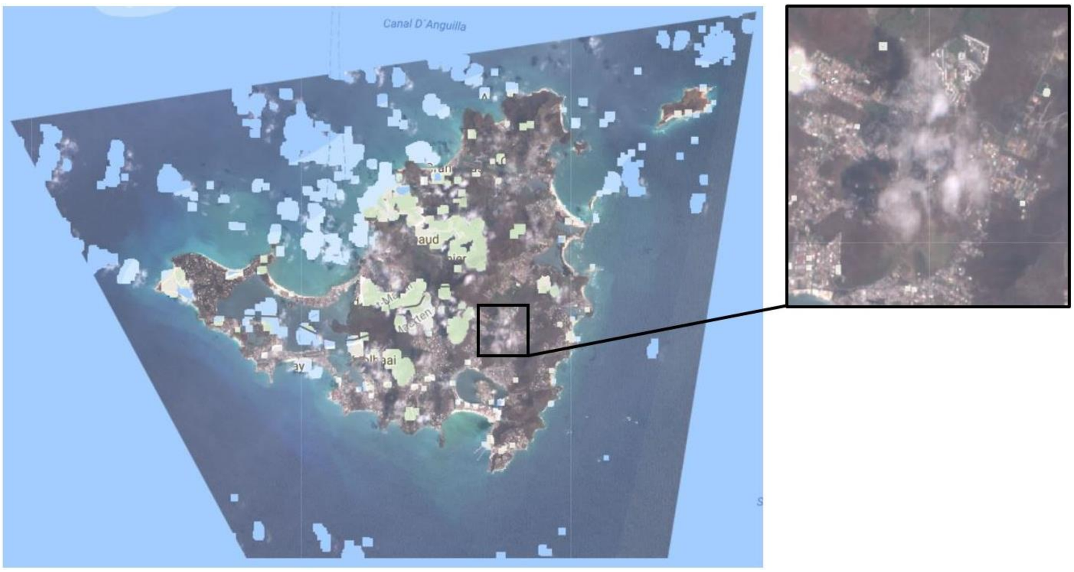


Figure 38: Image of Sint Maarten after cloud and shadow masking, zoomed in an area that shows thin clouds that have not been masked

The rule based approach posed a second problem. It had a problem with also masking bright surfaces together with clouds. Since Sint Maarten consists of both beaches and lots of white roofs, this caused a gaps on the image that were not supposed to be there. Due to the lack of a thermal infrared sensor on Sentinel 2 this problem is very difficult to solve. TIR chasers are able to distinguish between bright surfaces and clouds. This problem could be solved by removing isolated masked pixels from the cloud mask, this way beaches and roofs that were masked before will be unmasked.

6.1.2 Comparison of data

The data that is compared has two significantly different ways in which it has been processed, due to the problems that came up concerning cloud masking.

The before image is a mosaic created with data that was taken between the first of January until the first of September. Each of these images can have a different solar angle and thus have a slightly different colour. This could lead to a patchy mosaic image. However, part of this problem has been solved by taking the median value when more images were available for a pixel. This way, shadows are usually filtered out as well. As pixels that contain shadow are a lot darker than regular pixels. Some areas still pose problems. Due to the mountain range in the middle of the island, same areas are covered by clouds more often than others. This creates less input data for certain pixels, increasing the chance of a less accurate pixel. Also, each pixel could have been retrieved from an image with a different date. As a result, some parts of the image will be taken during drier months and others during wetter months. This could pose problems in both classification and index images.

The data that is used after consists of a single image. Therefore no median can be taken for the solar angle which means that the pixels could be darker or lighter than the pixels in the before image. Therefore the changes that are seen between the two could possibly be false.

6.2 Classification

6.2.1 Distinguishing classes

Some difficulty came up between distinguishing trees and grass when collecting the polynomials for the training data. The satellite images of Google that were used to retrieve the polynomials did not have a big enough resolution. Google Earth street view was also taken into consideration. However due to the small amount of street view pictures, differences between grass and trees were still difficult to see. Therefore a general vegetation class was chosen.

6.2.2 Confusion in classification

Three main mix ups where seen in the classification. The first one being that bright areas and white roofs (most houses on Sint Maarten have a white roof) were classified as sand instead of urban area. It could be tried to increase the accuracy of the classification by creating a separate class for white roofs.

The second mix up that can be seen has to do with drier areas, asphalt and urban area. Part of the areas that are wrongly classified are probably grasslands. This problem can be fixed by taking the NDVI values into consideration, as described in the paragraph above. After this has been done, some areas might still be false. These areas could then be classified as dry or bare land, when the google satellite does agree.

Sometimes the shoreline is also classified as asphalt. This is probably due to the water being very shallow. To fix this problem it is advisable to first create a spectral plot of the asphalt, water and shoreline. Then it could be tried to add some training data of the shoreline to the water class or a separate class could be created.

In the after classification most of the vegetation class has turned into asphalt. This indicates that the area has become bare. When a separate class for bare land is created, these areas will probably by classified right.

6.3 Indices

6.3.1 Index values of water

When creating the index images for the urban areas and sand shifting detection, some problems came up with values of water. In both these plots the values were the same as the values of the areas that needed to be highlighted by the index. Since the change was of interest, the difference map could possibly solve this problem. For the NDGI this worked, as the NDGI for water stayed the same, and the NDGI for areas where sand had shifted went up. However the NDUI difference plot still showed problems with water. This was partly due to the change in NDUI being very small, just like that of water.

6.3.2 The NDUI and NDBI

The NDUI difference was probably very small because of the small scale urban areas of Sint Maarten. No big cities are found on the island. But mostly smaller houses with relatively big gardens. This probably increases the difficulty of detecting change. In order to solve this problem radar data from Sentinel 1 could be used. As this satellite can more easily detect unroofed houses and differences in height of buildings. Another advantage of Sentinel 1 is that clouds do not pose a problem, as the signal goes through them.

6.4 Google Earth Engine

The process level of the Sentinel data available in Google Earth Engine is 1C. This indicates that only TOA (top of atmosphere) images are available. Meaning that the influence of the atmosphere has not yet been corrected. This could lead to differences in the data when looking at bio- and geophysical parameters (DLR).

To create a level 2 image, the sen2cor Prototype Processor is needed. This software contains intellectual property rights of the DLR (German Space Centre). This part of the software is not open source (GITHub). A work around for Google Earth Engine has been created, however this work around takes plenty of time when processing and is too difficult to understand during the time that stands for the BEP.

7 Conclusion

It can be concluded that Sentinel 2 optical data can be used for change detection after a natural disaster using Google Earth Engine. This program greatly increases the accessibility of satellite data. Before, satellite data had to be downloaded on a computer. Opening the data was already a challenge. Since in GEE all data is already available online, this does not pose a problem anymore. Emphasis can now be put on application of satellite data.

Changes in vegetation can clearly be distinguished. In a subtropical climate the thick vegetation shows an NDVI between 0.6 and 0.8, if this vegetation is ripped out by a storm an NDVI of 0.2 to 0.4 is seen after. Thus when a difference of around 0.4 is seen on an NDVI change map, it can be concluded that vegetation has been severely damaged. The change in vegetation can also be distinguished by looking at the RGB image. The image after hurricane Irma shows vegetation that has completely turned brown. On the classification maps the vegetation class has turned to asphalt in the image after.

Sand shifting can also be distinguished, both on the NDGI index image and the classification maps. On the NDGI image a value between 0.12 and 0.23 indicates sand. Everything lower is something else. Water usually shows a value higher than 0.23. Therefore in the difference picture, a change of around 0.2 is expected when sand has shifted over an area that was something else before. The sand shift is also detected on the classification image, the area that has been classified as sand has widened in the after image.

Changes in urban area are difficult to detect using only indices and classification methods.

8 Recommendations

Cloud masking is done manually. However an automatic way of detecting clouds is needed when bigger areas have to be masked.

There is a lack of data for Sint Maarten concerning land cover. The accessibility of a land cover map can greatly increase the accuracy of the training data used for classification of the island.

To further improve the classification, the NDVI image can be used to differentiate between vegetation types like grass, bushes and trees. The classification method is also expected to perform better when NDVI is added as a band value.

The NDGI method that is created to show the shifting of sand should also be validated by for different islands in the Caribbean.

Changes in urban area are very difficult to detect with indices and classification. Therefore it should be tried to use radar data from the Sentinel 1 satellite to detect these changes. In general the change maps can be further improved by combining Landsat 8, Sentinel 2 and Sentinel 1 data.

A different method for classification can be used, like RandomForest. If this will actually solve the problem of light roofs being classified as sand is still questionable.

A different way of displaying change can be tried. Instead of using indices, the difference in reflectance for each band can be calculated by subtracting the after value from the before value. These newly retrieved difference pixels can be plotted in an image.

References

Akgün, A, Eronat, AH, Türk, N. (2004). *Comparing different satellite image classification methods: an application in ayvalik district, western Turkey.* Research Project at Dokuz Eylul University. Retrieved from: http://cartesia.org/geodoc/isprs2004/comm4/papers/505.pdf [Last visited: 14 January 2018]

As-syakur, AR, Adnyana, WS, Arthana, IW, Nuarsa, IW. (2012). *Enhanced Built-Up and Bareness Index (EBBI) for Mapping Built-Up and Bare Land in an Urban Area.* Remote Sensing, No 4, p2957-2970

Copernicus (2017). *EMSR234: Hurricane Irma in Sint Maarten.* Retrieved from: http://emergency.copernicus.eu/mapping/list-of-components/EMSR234 [Last visited: 20 December 2017]

Data School (2014). *Simple guide to confusion matrix terminology.* Retrieved from: http://www.dataschool.io/simple-guide-to-confusion-matrix-terminology/ [Last visited: 15 January 2018]

DLR. *Atmospheric Correction.* Retrieved from: http://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-5450/10028_read-20715/ [Last visited: 3 January 2018]

Du, Y, Zhang, Y, Ling, F, Wang, G, Li, W, Li, X (2016). *Water Bodies' Mapping from Sentinel-2 Imagery with Modified Normalized Difference Water Index at 10-m Spatial Resolution Produced by Sharpening the SWIR Band.* Remote Sensing, No 8.

ESA (2017). *Copernicus overview.* Retrieved from: http://m.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Overview4 [Last visited: 12 January 2018]

ESA (2017). *SENTINEL-2.* Retrieved from: https://sentinel.esa.int/web/sentinel/missions/sentinel-2 [Last visited: 4 January 2018]

GADM database of Global Administrative Areas. Retrieved from: http://gadm.org/ [Last visited: 15 January 2018]

European Union (2017). *What is Copernicus.* Retrieved from: http://emergency.copernicus.eu/mapping/ems/what-copernicus [Last visited: 4 January 2018]

GITHub. *Sen2cor: Sentinel 2 Level 2A Prototype Processor.* Retrieved from: https://github.com/umwilm/SEN2COR) [Last visited: 3 January 2018]

Google Earth Engine API. Retrieved from: https://developers.google.com/earth-engine/ [Last visited: 15 January 2018]

Kottek, M, Grieser, J, Beck, C, Rudolf, B & Rubel, F. (2006). *World Map of the Köppen-Geiger climate classification updated.* Meteorologische Zeitschrift, Vol 15, No 3, p259 -263.

Lutgens, F.K. & Tarbuck, E.J. (2013). *The atmosphere: An introduction to meteorology.* Pearson 12th edition.

Magic Seaweed (2017). *Tide figure.* Retrieved from: https://magicseaweed.com/St-Martin-and-St-Barthelemy-Surfing/290/ [Last visited: 3 January 2018]

Meteorological Department St. Maarten (2016). *Climatological Summary 2016 & Hurricane Season Review.* Retrieved from: http://www.meteosxm.com/wp-content/uploads/Climatological-Summary-2016.pdf [Last visited: 14 January 2018]

NASA Earth Observatory (2017). *Browning Effect*. Retrieved from: https://earthobservatory.nasa.gov/NaturalHazards/view.php?id=90952 [Last visited: 14 January 2018]

NWS National Hurricane Center (2017). *Hurricane Irma Intermediate Advisory Number 30A.* Retrieved from: http://www.nhc.noaa.gov/archive/2017/al11/al112017.public_a.030.shtml [Last visited: 20 December 2017]

NWS National Hurricane Center (2017). *Monthly Atlantic Tropical Weather Summary.* Retrieved from: http://www.nhc.noaa.gov/text/MIATWSAT.shtml [Last visited: 20 December 2017]

Ritzen, G. & van Laarhoven, K. (2017). *'De mensen zijn hier wanhopig'.* NRC. Retrieved from: https://www.nrc.nl/nieuws/2017/09/07/spullen-knalden-tegen-ons-hotel-12871450-a1572499 [Last visited: 29 December 2017]
Sentinel Hub Playground (app). Available from: http://apps.sentinel-hub.com/sentinel-playground [Last visited: 13 January 2018]

Sinergise. *Indices.* Retrieved from: http://www.sentinel-hub.com/eotaxonomy/indices?page=1 [Last visited: 2 January 2018]

Stoffers, A.L. (1956). *The vegetation of the Netherlands Antilles.* Botanisch Museum en Herbarium, Utrecht.

St. Maarten National Heritage Foundation (SMNHF). *Flora and Fauna.* Retrieved from: http://www.museumsintmaarten.org/index.php?option=com_content&view=article&id=104&Itemid=141 [Last visited: 3 January 2018]

SUHET (2013). *Sentinel -2 User Handbook.* ESA Standard Document Issue 1 Revision 2.

Tralli, DM, Blom, RG, Zlotnicki, V, Donnellan, A, Evans, DL (2005). *Satellite remote sensing of earthquake, volcano, flood and landslide and coastal inundation hazards.* ISPRS Journal of Photogrammetry & Remote Sensing No 59, p185-198.

Tsai, F, Hwang JH, Chen, LC, Lin, TH (2010). *Post-disaster assessment of landslides in southern Taiwan after the 2009 Typhoon Morakot using remote sensing and spatial analysis.* Natural Hazards and Earth System Science No 10, p2179-2190.

USGS (2017). *What are the acquisition schedules for the Landsat satellites?* Retrieved from: https://landsat.usgs.gov/what-acquisition-schedule-landsat [Last visited: 4 January 2018]

USGS (2017). *What are the band designations for the Landsat satellites?* Retrieved from: https://landsat.usgs.gov/what-are-band-designations-landsat-satellites [Last visited: 4 January 2018]

USGS (2017). *What is Landsat and when did it begin?* Retrieved from: https://landsat.usgs.gov/what-landsat-and-when-did-it-begin [Last visited: 12 January 2018]

Wang, W, Qu, JJ, Hao, X, Liu, Y, Stanturf, JA (2010). *Post-hurricane forest damage assessment using satellite remote sensing*. Agricultural and Forest Meteorology No 150, p122-132.

Appendix A: Script

```
//Creating an image of Sint Maarten before hurricane Irma using Sentinel 2
data and filtering on date
var SM_Before = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-01-01', '2017-09-01')
//.filterMetadata('CLOUDY_PIXEL_PERCENTAGE',"less_than",10)
//.filterMetadata('CLOUD_COVERAGE_ASSESSMENT','less_than',2)

// Function to mask clouds using the Sentinel-2 QA band.
function maskS2clouds(image) {
  var qa = image.select('QA60');

  // Bits 10 and 11 are clouds and cirrus, respectively.
  var cloudBitMask = Math.pow(2, 10);
  var cirrusBitMask = Math.pow(2, 11);

  // Both flags should be set to zero, indicating clear conditions.
  var mask = qa.bitwiseAnd(cloudBitMask).eq(0).and(
             qa.bitwiseAnd(cirrusBitMask).eq(0));

  // Return the masked and scaled data.
  return image.updateMask(mask).divide(10000);
}

var geometry_c = geometry2.difference(cloud);

// Map the function
var Best_Before = SM_Before
                  // Pre-filter to get less cloudy granules.
                  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
                  .map(maskS2clouds)
                  .median()
                  .clip(geometry_c); //.clip(geometry2)


//Display the results
Map.centerObject(geometry2);
Map.addLayer(Best_Before,{bands: ['B4', 'B3', 'B2'], min: 0, max:
0.3},'SM_Before');
//Map.addLayer(Best_Before,{bands: ['B8', 'B4', 'B3'], min: 0, max:
0.3},'SM_Before_IR');
//Map.addLayer(Best_Before,{bands: ['B12', 'B11', 'B4'], min: 0, max:
0.3},'SM_Before_Urban');

// Get the number of images
var count_before = SM_Before.size();
print('size of collection SM_Before',count_before);

//CLASSIFICATION MAP 1
var Features =[
ee.Feature(water,{name: 0}),
ee.Feature(sand,{name: 1}),
ee.Feature(trees,{name: 2}),
ee.Feature(asphalt,{name: 3}),
ee.Feature(urbanarea,{name: 4})];

var Class = ee.FeatureCollection(Features);
print(Class);
```

```
var Trainingdata = Best_Before.sampleRegions({collection:Class,properties:
['name'],scale:50,tileScale:2});
//print(Trainingdata);

var ran = Trainingdata.randomColumn();
var train = ran.filter(ee.Filter.gte('random',0.2));// for classification
var valid = ran.filter(ee.Filter.lt('random',0.2));// for accuracy '
var trained = ee.Classifier.minimumDistance().train(train,'name',
['B2','B3','B4','B8','B11','B12']);
  //var trainaccuracy = valid.classify(train)//.errorMatrix('name',
'classification')
var classification =  Best_Before.classify(trained);

var Colours = ['3348FF','FFEF33','14910F','979F97','FF0101'];
print(classification,'classification');
Map.addLayer(classification, {min:0, max:4, palette:Colours},
'Classification');

//CLASSIFICATION MAP 2
var Features2 =[
ee.Feature(water2,{name: 0}),
ee.Feature(sand,{name: 1}),
ee.Feature(trees2,{name: 2}),
ee.Feature(asphalt,{name: 3}),
ee.Feature(urbanarea2,{name: 4})];

var Class2 = ee.FeatureCollection(Features2);

var Trainingdata2 =
Best_Before.sampleRegions({collection:Class2,properties:
['name'],scale:20,tileScale:2});
print(Trainingdata2,'Trainingdata2');

var ran2 = Trainingdata2.randomColumn();
var train2 = ran2.filter(ee.Filter.gte('random',0.2));// for classification
var valid2 = ran2.filter(ee.Filter.lt('random',0.2));// for accuracy '
var trained2 = ee.Classifier.minimumDistance().train(train2,'name',
['B2','B3','B4','B8','B11','B12']);
var validated_before = ee.Classifier.minimumDistance().train(valid2,'name',
['B2','B3','B4','B8','B11','B12']);
var classification2 =  Best_Before.classify(trained2);

print(classification2, 'classification2');
Map.addLayer(classification2, {min:0, max:4, palette:Colours},
'Classification2');

//CONFUSION MATRIX
var TrainAccuracy_before = validated_before.confusionMatrix();
print('confusion matrix before', TrainAccuracy_before);
print('confusion matrix before overall accuracy',
TrainAccuracy_before.accuracy());

//Best_Before image now also filtered on bands, as the classifications are
made on B1-5
var Best_Before2 = SM_Before
                  // Pre-filter to get less cloudy granules.
                  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
                  .map(maskS2clouds)
                  .median()
                  .clip(geometry2)
                  .select(['B2','B3','B4','B8','B11','B12']);
```

```
var Features2_1 =[
ee.Feature(water2,{'label':'water2'}),
ee.Feature(sand,{'label':'sand'}),
ee.Feature(trees2,{'label':'trees2'}),
ee.Feature(asphalt,{'label':'asphalt'}),
ee.Feature(urbanarea2,{'label':'urbanarea2'})];

var Best_Before3 = SM_Before
                  // Pre-filter to get less cloudy granules.
                  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
                  .map(maskS2clouds)
                  .median()
                  .clip(geometry2)
                  .select(['B2','B3','B4','B8','B8A','B11','B12']);

var wavelengths2 = [0.49, 0.56, 0.665, 0.842, 0.865, 1.610, 2.19];

//creating a chart of the spectral data to look at differences/similarities
of the signal
// Define customization options.
var options = {
  title: 'Sentinel 2 Reflectance of Classes Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: '3348FF'}, // water2
    1: {color: 'FFEF33'}, // sand
    2: {color: '14910F'}, // trees2
    3: {color: '979F97'}, // aphalt
    4: {color: 'FF0101'}, // urbanarea2
}};

// Define a list of Sentinel 2 wavelengths for X-axis labels.
var wavelengths = [0.49, 0.56, 0.665, 0.842, 1.610, 2.19];

// Create the chart and set options.
var spectraChart = ui.Chart.image.regions(
    Best_Before2, Features2_1, ee.Reducer.mean(), 30, 'label', wavelengths)
        .setChartType('LineChart')
        .setOptions(options);

print(spectraChart);

//CHART OF WATER POLYGONS REFLECTANCE
var water_2 = ee.FeatureCollection(water2);
print(water_2,'water_2');

var water_poly_feature = new Array(9)

for(var i = 0; i < 9; i++) {
  var water_poly = ee.Geometry.Polygon({
  coords: water_2.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  water_poly_feature[i]=ee.Feature(water_poly, {'label': +i})
}

  var options_water = {
  title: 'Sentinel 2 Reflectance of Water Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
```

```
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
    8: {color: '75006D'}, //purple
}};
  // Create the chart and set options.
var spectraChart_water = ui.Chart.image.regions(
    Best_Before3, water_poly_feature, ee.Reducer.mean(), 30, 'label',
wavelengths2)
        .setChartType('LineChart')
        .setOptions(options_water);

print(spectraChart_water);
print(water_poly_feature,'water_poly_feature');

//CHART OF TREES2 POLYGONS REFLECTANCE
var trees_2 = ee.FeatureCollection(trees2);
print(trees_2,'trees_2');

var trees_poly_feature = new Array(9)

for(var i = 0; i < 9; i++) {
  var trees_poly = ee.Geometry.Polygon({
  coords: trees_2.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  trees_poly_feature[i]=ee.Feature(trees_poly, {'label': +i})
}

  var options_trees = {
  title: 'Sentinel 2 Reflectance of Tree Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
    8: {color: '75006D'}, //purple
}};
  // Create the chart and set options.
var spectraChart_trees = ui.Chart.image.regions(
    Best_Before2, trees_poly_feature, ee.Reducer.mean(), 30, 'label',
wavelengths)
        .setChartType('LineChart')
        .setOptions(options_trees);
```

```
print(spectraChart_trees);
print(trees_poly_feature,'trees_poly_feature');

//CHART OF URBANAREA2 POLYGONS REFLECTANCE
var urbanarea_2 = ee.FeatureCollection(urbanarea2);
print(urbanarea_2,'urbanarea_2');

var urbanarea_poly_feature = new Array(8)

for(var i = 0; i < 8; i++) {
  var urbanarea_poly = ee.Geometry.Polygon({
  coords: urbanarea_2.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  urbanarea_poly_feature[i]=ee.Feature(urbanarea_poly, {'label': +i})
}

  var options_urbanarea = {
  title: 'Sentinel 2 Reflectance of Urban area Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
}};
  // Create the chart and set options.
var spectraChart_urbanarea = ui.Chart.image.regions(
    Best_Before3, urbanarea_poly_feature, ee.Reducer.mean(), 30, 'label',
wavelengths2)
        .setChartType('LineChart')
        .setOptions(options_urbanarea);

print(spectraChart_urbanarea);
print(urbanarea_poly_feature,'urbanarea_poly_feature');

//CHART OF ASPHALT POLYGONS REFLECTANCE
var asphalt_2 = ee.FeatureCollection(asphalt);
print(asphalt_2,'asphalt_2');

var asphalt_poly_feature = new Array(8)

for(var i = 0; i < 8; i++) {
  var asphalt_poly = ee.Geometry.Polygon({
  coords: asphalt_2.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  asphalt_poly_feature[i]=ee.Feature(asphalt_poly, {'label': +i})
}

  var options_asphalt = {
  title: 'Sentinel 2 Reflectance of Asphalt Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
```

```
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
}};
  // Create the chart and set options.
var spectraChart_asphalt = ui.Chart.image.regions(
    Best_Before2, asphalt_poly_feature, ee.Reducer.mean(), 30, 'label',
wavelengths)
        .setChartType('LineChart')
        .setOptions(options_asphalt);

print(spectraChart_asphalt);
print(asphalt_poly_feature,'asphalt_poly_feature');

//CHART OF SAND POLYGONS REFLECTANCE

var sand_2 = ee.FeatureCollection(sand);
print(sand_2,'sand_2');

var sand_poly_feature = new Array(13)

for(var i = 0; i < 13; i++) {
  var sand_poly = ee.Geometry.Polygon({
  coords: sand_2.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  sand_poly_feature[i]=ee.Feature(sand_poly, {'label': +i})
}

  var options_sand = {
  title: 'Sentinel 2 Reflectance of Sand Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
    8: {color: '75006D'}, //purple
    9: {color: '000000'}, //black
    10:{color: '888888'}, //grey
    11:{color: 'FFA0E9'}, //light pink
    12:{color: 'B2BDFF'}, //light light blue
}};
  // Create the chart and set options.
var spectraChart_sand = ui.Chart.image.regions(
    Best_Before3, sand_poly_feature, ee.Reducer.mean(), 30, 'label',
wavelengths2)
        .setChartType('LineChart')
```

```
        .setOptions(options_sand);

print(spectraChart_sand);
print(sand_poly_feature,'sand_poly_feature');


//SPECTRAL PLOT OF WRONG CLASSIFIED AREA
var wrong_class = ee.FeatureCollection(wrong_classification);
print(wrong_class,'wrong_class');

var wrong_class_poly_feature = new Array (2);

for(var i = 0; i < 2; i++) {
  var wrong_class_poly = ee.Geometry.Polygon({
    coords:wrong_class.geometry().coordinates().get(i).getInfo(),
    geodesic:true});

wrong_class_poly_feature[i]=ee.Feature(wrong_class_poly,{'label':+i});
}

  var options_wrong = {
  title: 'Sentinel 2 Reflectance of Wrong Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: '01FFAF'}, //light blue
    1: {color: '0120FF'}, //dark blue

}};
  // Create the chart and set options.
var spectraChart_wrong = ui.Chart.image.regions(
    Best_Before2, wrong_class_poly_feature, ee.Reducer.mean(), 30, 'label',
wavelengths)
        .setChartType('LineChart')
        .setOptions(options_wrong);

print(spectraChart_wrong);
print(wrong_class_poly_feature,'wrong_class_poly_feature');

//SPECTRAL PLOT OF WHITE ROOFS
var whiteroofs1 = ee.FeatureCollection(whiteroofs);
print(whiteroofs1,'whiteroofs');

var whiteroofs_poly_feature = new Array(11)

for(var i = 0; i < 11; i++) {
  var whiteroofs_poly = ee.Geometry.Polygon({
  coords: whiteroofs1.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  whiteroofs_poly_feature[i]=ee.Feature(whiteroofs_poly, {'label': +i})
}

  var options_whiteroofs = {
  title: 'Sentinel 2 Reflectance of White Roof Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
```

```
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
    8: {color: '75006D'}, //purple
    9: {color: '000000'}, //black
    10:{color: '888888'}, //grey
}};
  // Create the chart and set options.
var spectraChart_whiteroofs = ui.Chart.image.regions(
    Best_Before3, whiteroofs_poly_feature, ee.Reducer.mean(), 30, 'label', 
wavelengths2)
        .setChartType('LineChart')
        .setOptions(options_whiteroofs);

print(spectraChart_whiteroofs);
print(whiteroofs_poly_feature,'whiteroofs_poly_feature');

//WHITE ROOFS, SAND AND URBAN AREAS
var FeaturesRSU=[
ee.Feature(sand,{'label':'sand'}),
ee.Feature(whiteroofs,{'label':'whiteroofs'}),
ee.Feature(urbanarea2,{'label':'urbanarea2'})];

//creating a chart of the spectral data to look at differences/similarities 
of the signal
// Define customization options.
var optionsRSU = {
  title: 'Sand, white roofs and urban area spectral plot',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 3,
  pointSize: 5,
  series: {
    0: {color: 'orange'}, // sand
    1: {color: 'grey'}, // white roofs
    2: {color: 'red'}, // urban area
}};

// Define a list of Sentinel 2 wavelengths for X-axis labels.
var wavelengths = [0.49, 0.56, 0.665, 0.842, 1.610, 2.19];

// Create the chart and set options.
var spectraChartRSU = ui.Chart.image.regions(
    Best_Before2, FeaturesRSU, ee.Reducer.mean(), 30, 'label', wavelengths)
        .setChartType('LineChart')
        .setOptions(optionsRSU);

print(spectraChartRSU);

//Satellite image of Sint Maarten just after Irma hit, quite cloudy
var SM_Quick = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-07','2017-09-08')
.median()
.clip(geometry2);

print('SM_Quick',SM_Quick);
```

```
//Map.addLayer(SM_Quick,{bands: ['B4', 'B3', 'B2'], min: 0, max:
3000},'SM_Quick');

//Satellite image of Sint Maarten on the 12th of September (less cloudy)
//5 days after the hurricane hit

var SM_Quick2 = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-12','2017-09-13')
//.select(['B2','B11','B12'])
.median()
.clip(geometry2);

Map.addLayer(SM_Quick2, {bands:['B4','B3','B2'], min: 0, max:
3000},'SM_Quick2')

var SM_Quick3 = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-12','2017-09-13')

// Function to mask clouds using the Sentinel-2 QA band.
function maskS2cloudsonly(image) {
  var qa = image.select('QA60');

  // Bits 10 and 11 are clouds and cirrus, respectively.
  var cloudBitMask = Math.pow(2, 10);
  var cirrusBitMask = Math.pow(2, 11); //only the cloud mask is used,
otherwise the whole picture is gone

  // Both flags should be set to zero, indicating clear conditions.
  var maskcloud = qa.bitwiseAnd(cloudBitMask).eq(0);//.and(
            //qa.bitwiseAnd(cirrusBitMask).eq(0));


  // Return the masked and scaled data.
  return image.updateMask(maskcloud).divide(10000);
}

var SM_Quick3_Cloudless = SM_Quick3
.map(maskS2cloudsonly)
.median()
.clip(geometry2);

print('SM_Quick3_Cloudless',SM_Quick3_Cloudless);

Map.addLayer(SM_Quick3_Cloudless,{bands: ['B4', 'B3', 'B2'], min: 0, max:
0.3},'SM_Quick3_Cloudless');

//CHECKING CLOUD POLYNOMIALS
var SM_Quick2_clouds = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-12','2017-09-13')
.select(['B2','B3','B4','B8','B8A','B11','B12'])
.median()
.clip(geometry2);

var clouds_bandvalues = ee.FeatureCollection(clouds);
print(clouds_bandvalues,'clouds_bandvalues')

var clouds_poly_feature = new Array (8)
// Define a list of Sentinel 2 wavelengths for X-axis labels.
```

```
var wavelengths = [0.49, 0.56, 0.665, 0.842, 0.865, 1.610, 2.19];

for(var i = 0; i < 8; i++) {
  var clouds_poly = ee.Geometry.Polygon({
  coords: clouds_bandvalues.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  clouds_poly_feature[i]=ee.Feature(clouds_poly, {'label': +i})
}

  var options_clouds = {
  title: 'Sentinel 2 Reflectance of Cloud Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
}};

  // Create the chart and set options.
var spectraChart_clouds = ui.Chart.image.regions(
    SM_Quick2_clouds.divide(10000), clouds_poly_feature, ee.Reducer.mean(),
30, 'label', wavelengths)
        .setChartType('LineChart')
        .setOptions(options_clouds);

print(spectraChart_clouds);

function maskCloud(img) { // function to mask pixels in every image in
collection wrt the threshold
  var mask =
img.select('B2').gt(3200)//.and(img.select('B11').gt(3000));//.and(img.sele
ct('B12').gt(3000);
  mask = mask.eq(0).focal_min({kernel: ee.Kernel.square({radius: 2})});
//to mask rims of clouds
  return img.updateMask(mask);
}

var SM_Quick3 = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-12','2017-09-13')
.map(maskCloud)
.median()
.clip(geometry2);

Map.addLayer(SM_Quick3,{bands:['B4','B3','B2'], min: 0, max:
3000},'SM_Quick cloudmasked');

//SHADOWS
//FIRST CHECKING BAND VALUES TO LATER CREATE A MASK
var shadow = ee.FeatureCollection(shadows);
print(shadow,'shadow')

var shadows_poly_feature = new Array (8)
```

```
// Define a list of Sentinel 2 wavelengths for X-axis labels.
var wavelengths = [0.49, 0.56, 0.665, 0.842, 0.865, 1.610, 2.19];

for(var i = 0; i < 8; i++) {
  var shadows_poly = ee.Geometry.Polygon({
  coords: shadow.geometry().coordinates().get(i).getInfo(),
  geodesic:true});

  shadows_poly_feature[i]=ee.Feature(shadows_poly, {'label': +i})
}

  var options_shadows = {
  title: 'Sentinel 2 Reflectance of Shadow Polygons Sint Maarten',
  hAxis: {title: 'Wavelength (micrometers)'},
  vAxis: {title: 'Reflectance'},
  lineWidth: 1,
  pointSize: 4,
  series: {
    0: {color: 'FF0101'}, //red
    1: {color: 'FF6D01'}, //orange
    2: {color: 'FFFC01'}, //yellow
    3: {color: '52FF01'}, //green
    4: {color: '01FFAF'}, //light blue
    5: {color: '0120FF'}, //dark blue
    6: {color: 'FF01EC'}, //pink
    7: {color: '076200'}, //dark green
}};

  // Create the chart and set options.
var spectraChart_shadows = ui.Chart.image.regions(
    SM_Quick2_clouds.divide(10000), shadows_poly_feature,
ee.Reducer.mean(), 30, 'label', wavelengths)
        .setChartType('LineChart')
        .setOptions(options_shadows);

print(spectraChart_shadows);

function maskShadow(img) { // function to mask pixels in every image in
collection wrt the threshold
  var mask =
img.select('B2').lt(1500).and(img.select('B3').lt(1250)).and(img.select('B4
').lt(1000)).and(img.select('B8').lt(1500));//.and(img.select('B4').lt(1000
);
  mask = mask.eq(0).focal_min({kernel: ee.Kernel.square({radius: 3})});
//to mask rims of clouds
  return img.updateMask(mask);
}

var SM_Quick4 = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-12','2017-09-13')
.map(maskShadow)
.median()
.clip(geometry2);

Map.addLayer(SM_Quick4,{bands:['B4','B3','B2'], min: 0, max:
3000},'SM_Quick shadowmasked');

var SM_Quick5 = Sentinel2
.filterBounds(geometry2)
.filterDate('2017-09-12','2017-09-13')
.map(maskShadow)
```

```
.map(maskCloud)
.median()
.clip(geometry2);

Map.addLayer(SM_Quick5,{bands:['B4','B3','B2'], min: 0, max:
3000},'SM_Quick C + S mask');

//MASKING CLOUDS AND SHADOWS BY POLYNOMIALS MANUALLY TO FIX PROBLEMS FROM
BEFORE
var mask_cs = ee.Feature(mask,'mask')

var cloud_geo = geometry2.difference(mask);

print(cloud_geo,'cloud_geo')

var SM_Quick_masked = SM_Quick2.clip(cloud_geo);

Map.addLayer(SM_Quick_masked,{min :0, max :3000, bands:
['B4','B3','B2']},'SM_Quick_masked');

var Best_Before_B1 = Best_Before.clip(border1);
var Best_Before_B2 = Best_Before.clip(border2);

//INDICES TO CREATE DIFFERENCE MAPS OF DIFFERENT CLASSES
//NDVI
var addNDVI = function(image) {
  var ndvi = image.normalizedDifference(['B8', 'B4']).rename('NDVI');
  return image.addBands(ndvi);
};
var NDVI_before = addNDVI(Best_Before).select('NDVI');
var ndviParams = {min: 0, max: 1, palette: ['grey','orange','yellow',
'green','blue']};

Map.addLayer(NDVI_before, ndviParams, 'NDVI before image');

//Bareness
var addNDBaI = function(image) {
  var ndbai = image.normalizedDifference(['B8', 'B11']).rename('NDBaI');
  return image.addBands(ndbai);
};

var NDBaI_before = addNDBaI(Best_Before).select('NDBaI');

var NDBaI_before_B1 = NDBaI_before.clip(border1);
var NDBaI_before_B2 = NDBaI_before.clip(border2);

var NDBaI_before_B = ee.ImageCollection([NDBaI_before_B1,
NDBaI_before_B2]);
var ndbaiParams = {min: -0.2, max: 0.6, palette: ['red', 'red','blue',
'grey','grey','grey']};

Map.addLayer(NDBaI_before_B, ndbaiParams, 'NDBaI before image');

// // WATER INDEX
var addH2O = function(image) {
  var ndh2o = image.normalizedDifference(['B3', 'B11']).rename('NDH2O');
  return image.addBands(ndh2o);
};

var NDH2O_before = addH2O(Best_Before).select('NDH2O');

var NDH2O_before_B1 = NDH2O_before.clip(border1);
```

```
var NDH2O_before_B2 = NDH2O_before.clip(border2);

var NDH2O_before_B = ee.ImageCollection([NDH2O_before_B1,
NDH2O_before_B2]);
var ndh2oParams = {min: -0.3, max: 0.3, palette: ['grey','grey','blue']};

Map.addLayer(NDH2O_before, ndh2oParams, 'NDH2O before image');
Map.addLayer(NDH2O_before_B, ndh2oParams, 'NDH2O before image');

//"Geology" index
var addGEO = function(image) {
  var ndgeo = image.normalizedDifference(['B4', 'B12']).rename('NDgeo');
  return image.addBands(ndgeo);
};

var NDgeo_before = addGEO(Best_Before).select('NDgeo');

var NDgeo_before_B1 = NDgeo_before.clip(border1);
var NDgeo_before_B2 = NDgeo_before.clip(border2);

var NDgeo_before_B = ee.ImageCollection([NDgeo_before_B1,
NDgeo_before_B2]);
var ndgeoParams = {min: 0, max: 0.3, palette:
['grey','grey','grey','red','red','red','blue','blue']};

Map.addLayer(NDgeo_before_B, ndgeoParams, 'NDgeo before image');

//URBAN INDEX
var addUI = function(image) {
  var ndui = image.normalizedDifference(['B12','B8']).rename('NDUI');
  return image.addBands(ndui);
};

var NDUI_before = addUI(Best_Before).select('NDUI');

var NDUI_before_B1 = NDUI_before.clip(border1);
var NDUI_before_B2 = NDUI_before.clip(border2);

var NDUI_before_B = ee.ImageCollection([NDUI_before_B1, NDUI_before_B2]);
var NDUIParams = {min:-0.6, max: 0, palette:
['grey','grey','red','red','red']};

Map.addLayer(NDUI_before_B, NDUIParams, 'NDUI before image')

///////////////////////////////////////////////////////
//AFTER
var SM_Quick_masked_B1 = SM_Quick_masked.clip(border1);
var SM_Quick_masked_B2 = SM_Quick_masked.clip(border2);

Map.addLayer(SM_Quick_masked.divide(10000),{min :0, max :0.3, bands:
['B4','B3','B2']},'SM_Quick_masked');

var Colours_After = ['3348FF','FFEF33','14910F','979F97','FF0101'];

var SM_Quick_masked2 = SM_Quick_masked.divide(10000);
var classification_after2 = SM_Quick_masked2.classify(trained2);
print(classification_after2, 'classification_after2')

Map.addLayer(classification_after2,{min:0, max:4, palette:Colours_After},
'Classification After 2');

//CONFUSION MATRIX AFTER
```

```
var Trainingdata_after =
SM_Quick_masked2.sampleRegions({collection:Class2,properties:
['name'],scale:20,tileScale:2});

var ran_after = Trainingdata_after.randomColumn();
var valid_after = ran_after.filter(ee.Filter.lt('random',0.2));// for
accuracy
var validated_after =
ee.Classifier.minimumDistance().train(valid_after,'name',
['B2','B3','B4','B8','B11','B12']);

var TrainAccuracy_after = validated_after.confusionMatrix();
print('confusion matrix after', TrainAccuracy_after);
print('confusion matrix after overall accuracy',
TrainAccuracy_after.accuracy());

//NDVI AFTER
var NDVI_after = addNDVI(SM_Quick_masked).select('NDVI');
var ndviParams = {min: 0, max: 1, palette: ['grey','orange','yellow',
'green', 'blue']};

Map.addLayer(NDVI_after, ndviParams, 'NDVI after image');

//Bareness
var NDBaI_after = addNDBaI(SM_Quick_masked).select('NDBaI');

var NDBaI_after_B1 = NDBaI_after.clip(border1);
var NDBaI_after_B2 = NDBaI_after.clip(border2);

var NDBaI_after_B = ee.ImageCollection([NDBaI_after_B1, NDBaI_after_B2]);

Map.addLayer(NDBaI_after_B, ndbaiParams, 'NDBaI after image');

//"Geology" index
var NDgeo_after = addGEO(SM_Quick_masked).select('NDgeo');

var NDgeo_after_B1 = NDgeo_after.clip(border1);
var NDgeo_after_B2 = NDgeo_after.clip(border2);

var NDgeo_after_B = ee.ImageCollection([NDgeo_after_B1, NDgeo_after_B2]);

Map.addLayer(NDgeo_after_B, ndgeoParams, 'NDgeo after image');


//URBAN INDEX AFTER
var NDUI_after = addUI(SM_Quick_masked).select('NDUI');
var NDUI_after_B1 = NDUI_after.clip(border1);
var NDUI_after_B2 = NDUI_after.clip(border2);

var NDUI_after_B = ee.ImageCollection([NDUI_after_B1, NDUI_after_B2]);

Map.addLayer(NDUI_after_B, NDUIParams, 'NDUI after image');

//WATER INDEX

var NDH2O_after = addH2O(SM_Quick_masked).select('NDH2O');

Map.addLayer(NDH2O_after, ndh2oParams, 'NDH2O after image');

//DIFFERENCE NDVI
var difference_NDVI = NDVI_before.subtract(NDVI_after); //subtract begin -
end
```

```
Map.addLayer(difference_NDVI, {min: 0, max:0.6, palette:
['grey','yellow','red','purple']},  'difference NDVI');

//DIFFERENCE NDBaI
var difference_NDBaI_B1 = NDBaI_before_B1.subtract(NDBaI_after_B1);
//subtract begin - end
var difference_NDBaI_B2 = NDBaI_before_B2.subtract(NDBaI_after_B2);

var difference_NDBaI_B = ee.ImageCollection([difference_NDBaI_B1,
difference_NDBaI_B2]);

Map.addLayer(difference_NDBaI_B, {min: -0.1, max: 0.5, palette:
['blue','green','yellow','grey','grey','grey']},  'difference NDBaI');

//DIFFERENCE GEOLOGY
var difference_NDgeo_B1 = NDgeo_before_B1.subtract(NDgeo_after_B1);
var difference_NDgeo_B2 = NDgeo_before_B2.subtract(NDgeo_after_B2);

var difference_NDgeo_B = ee.ImageCollection([difference_NDgeo_B1,
difference_NDgeo_B2]);

Map.addLayer(difference_NDgeo_B,{min: -0.2, max: 0, palette:
['red','orange','grey','grey']}, 'difference NDgeo');

//DIFFERENCE URBAN INDEX
var difference_NDUI_B1 = NDUI_before_B1.subtract(NDUI_after_B1);
var difference_NDUI_B2 = NDUI_before_B2.subtract(NDUI_after_B2);

var difference_NDUI_B = ee.ImageCollection([difference_NDUI_B1,
difference_NDUI_B2]);

Map.addLayer(difference_NDUI_B,{min: -0.4, max: 0, palette:
['grey','grey','grey','grey','grey','red','orange','yellow']}, 'difference
NDUI');

// WATER INDEX (MASKING LAYER)
var NDH2O_after = addH2O(SM_Quick_masked).select('NDH2O');

var NDH2O_after_B1 = NDH2O_after.clip(border1);
var NDH2O_after_B2 = NDH2O_after.clip(border2);

var NDH2O_after_B = ee.ImageCollection([NDH2O_after_B1, NDH2O_after_B2]);
var ndh2oParams = {min: -0.3, max: 0.2, palette: ['grey','grey','blue']};

//Map.addLayer(NDH2O_after, ndh2oParams, 'NDH2O after')
Map.addLayer(NDH2O_before_B, ndh2oParams, 'NDH2O before image');
Map.addLayer(NDH2O_after_B, ndh2oParams, 'NDH2O after image');

//WATER INDEX DIFFERENCE
var difference_water = NDH2O_before.subtract(NDH2O_after);

Map.addLayer(difference_water, {min: -0.1, max: 0.3, palette:
['red','grey','grey','grey','grey']}, 'difference water');

var SRTM_SM = SRTM.clip(geometry);

//CHECKING THE DATA OF THE SHAPE FILE
print(SM_border1,'SM_border1');
print(SM_border2,'SM_border2');

//TWO ELEVATION MAPS WITH BORDERS OF SINT MAARTEN AND SAINT MARTIN
```

```
var elevation_SM1 = SRTM.clip(SM_border1);
var elevation_SM2 = SRTM.clip(SM_border2);

//ADDING THE TWO IMAGES TO CREATE A PICTURE OF THE WHOLE ISLAND


var elevation_SM = ee.ImageCollection([elevation_SM1, elevation_SM2]);
print(elevation_SM,'elevation_SM');

//CREATING A LAYER ON THE MAP
var colours = ['blue','green','yellow','orange','red','purple'];

//Map.addLayer(SRTM_SM, {min: 0, max: 500, palette:colours}, 'SRTM Sint
Maarten');
//Map.addLayer(elevation_SM1, {min: 0, max: 500, palette: colours},
'elevation Sint Maarten 1');
//Map.addLayer(elevation_SM2, {min: 0, max: 500, palette: colours},
'elevation Sint Maarten 2');

Map.centerObject(geometry)
Map.addLayer(elevation_SM, {min: 0, max: 420, palette: colours}, 'elevation
Sint Maarten');

//CREATING A SLOPE MAP OF SINT MAARTEN
var slope1 = ee.Terrain.slope(elevation_SM1);
var slope2 = ee.Terrain.slope(elevation_SM2);

var slope = ee.ImageCollection([slope1, slope2]);

Map.addLayer(slope, {min: 0, max: 60}, 'slope Sint Maarten');

//CREATING AN ASPECT OF SINT MAARTEN
// Get the aspect (in degrees).
var aspect1 = ee.Terrain.aspect(elevation_SM1);
var aspect2 = ee.Terrain.aspect(elevation_SM2);

var aspect = ee.Terrain.aspect(SRTM_SM)

var sinImage1 = aspect1.divide(180).multiply(Math.PI).sin();
var sinImage2 = aspect2.divide(180).multiply(Math.PI).sin();

var sinImage = ee.ImageCollection([sinImage1, sinImage2])

Map.addLayer(sinImage, {min: -1, max: 1}, 'terrain Sint Maarten');

var scale = SRTM.projection().nominalScale();
print('SRTM scale in meters', scale)
```

Appendix B: Figures

Figure 39: A flag based cloud masked image of Sint Maarten before hurricane Irma with images retrieved between 01-01-2017 and 01-09-2017

🟦	Water
🟨	Sand
🟩	Vegetation
⬛	Asphalt
🟧	Urban area

Figure 40: The training data of the classes on top of a Google satellite image

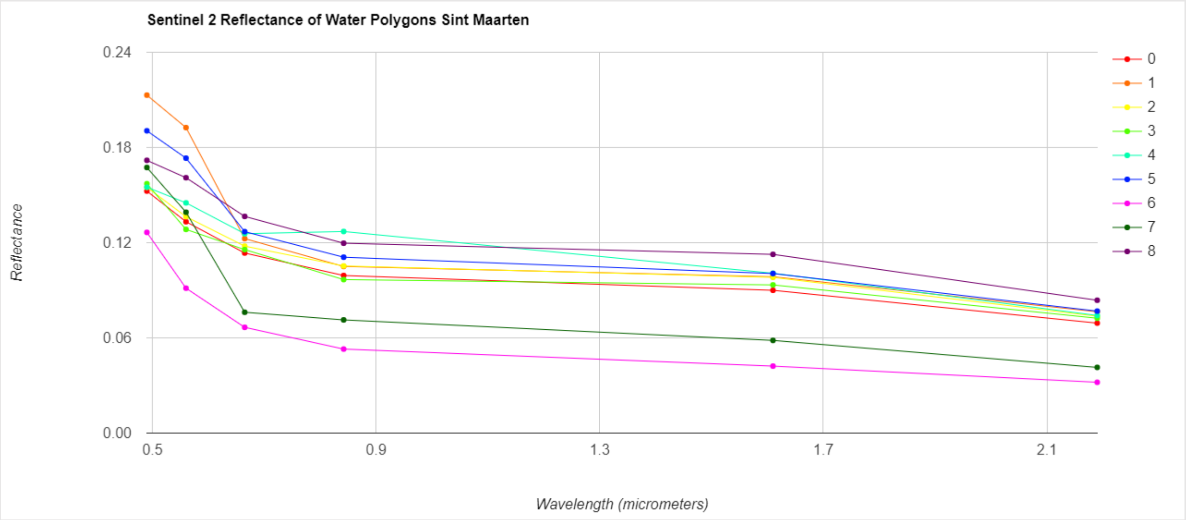


Figure 43: Water polygons spectral plot

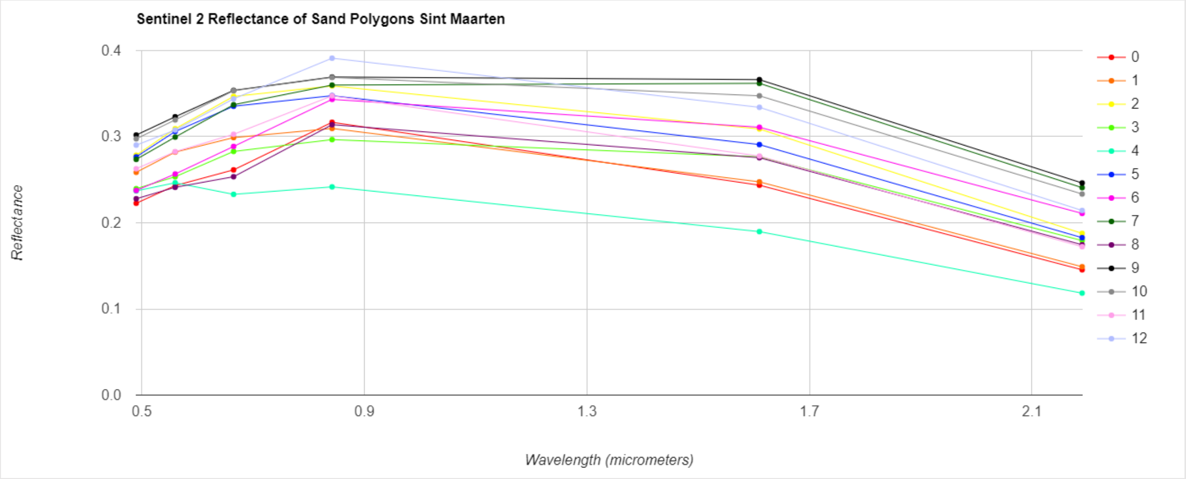


Figure 42: Sand polygons spectral plot

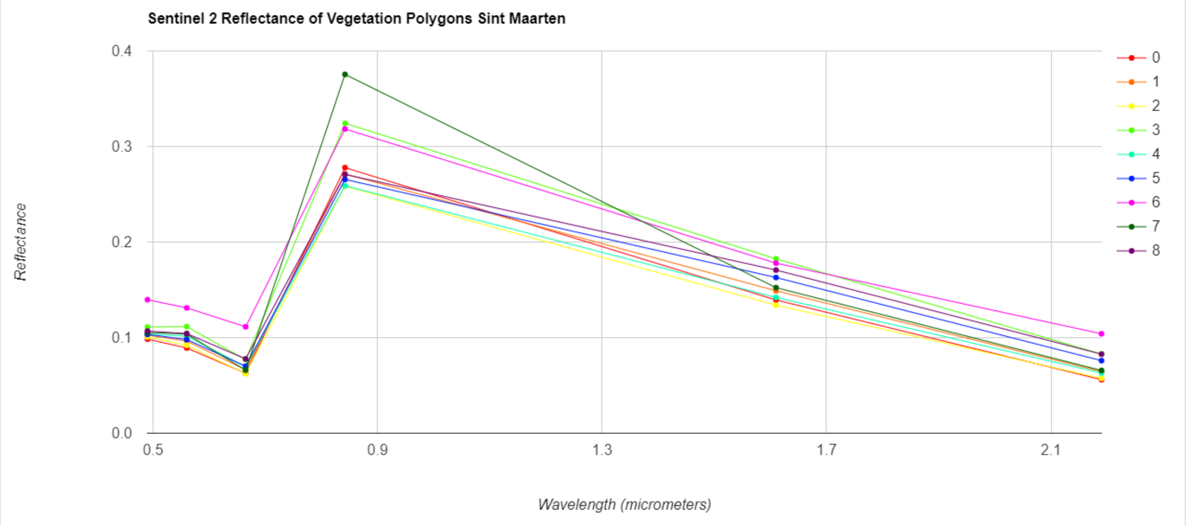


Figure 41: Vegetation polygons spectral plot

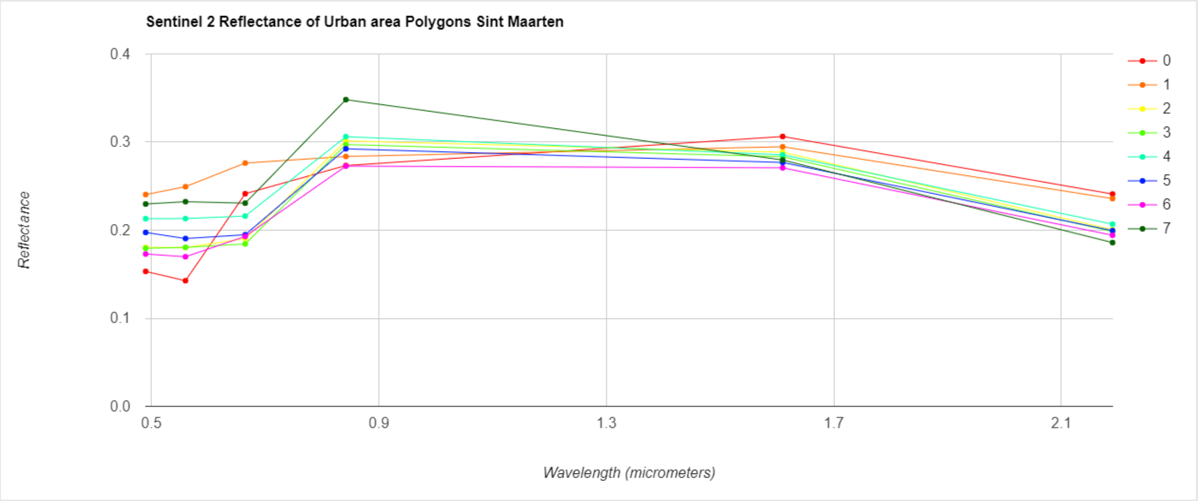


Figure 45: Urban area polygons spectral plot

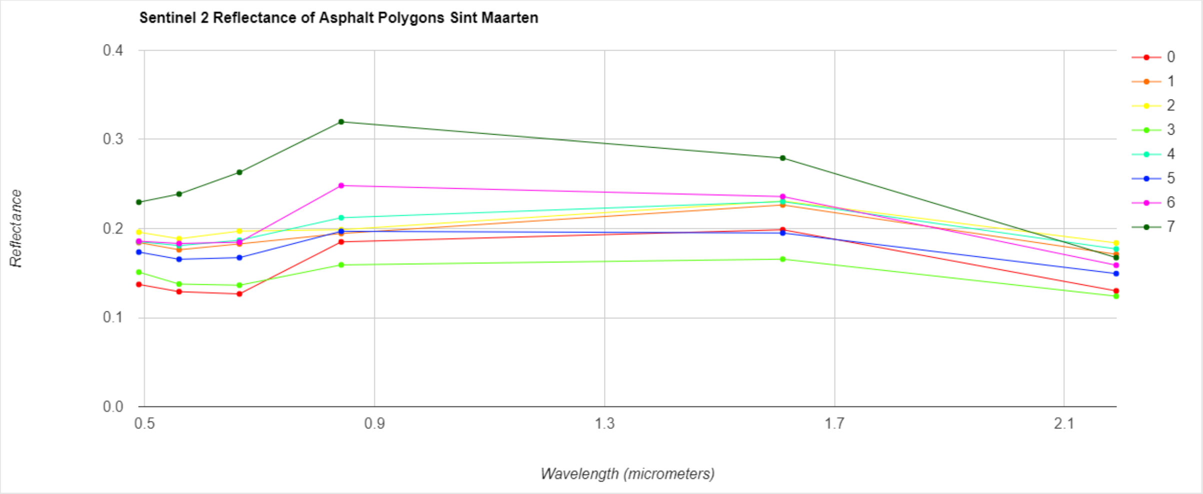


Figure 44: Asphalt polygons spectral plot

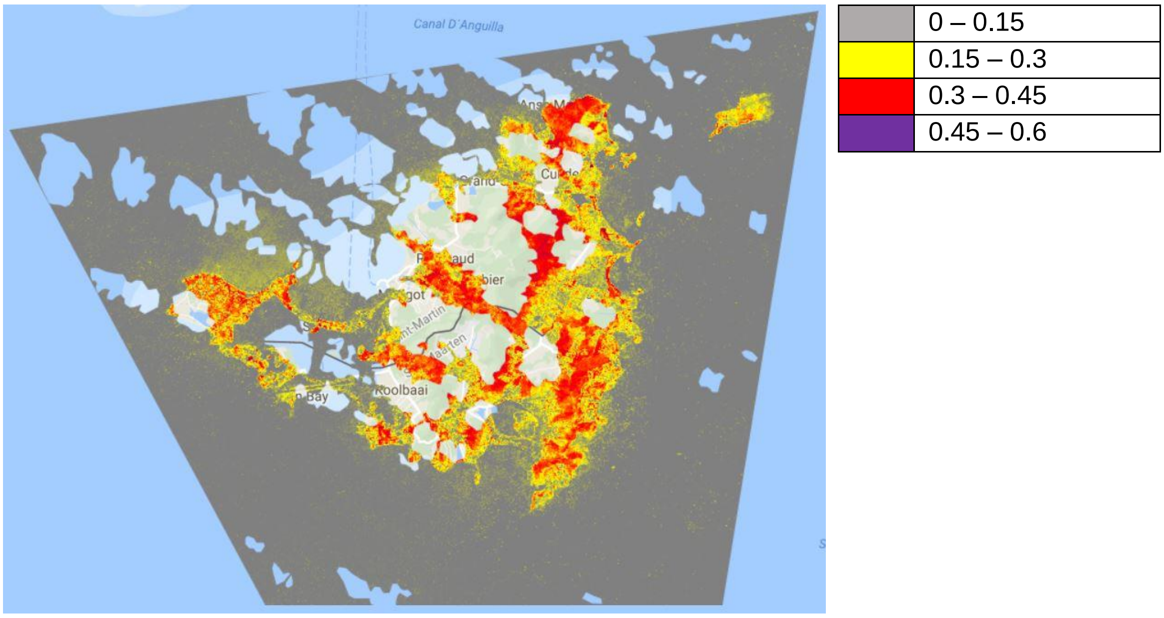


Figure 46: NDVI difference image

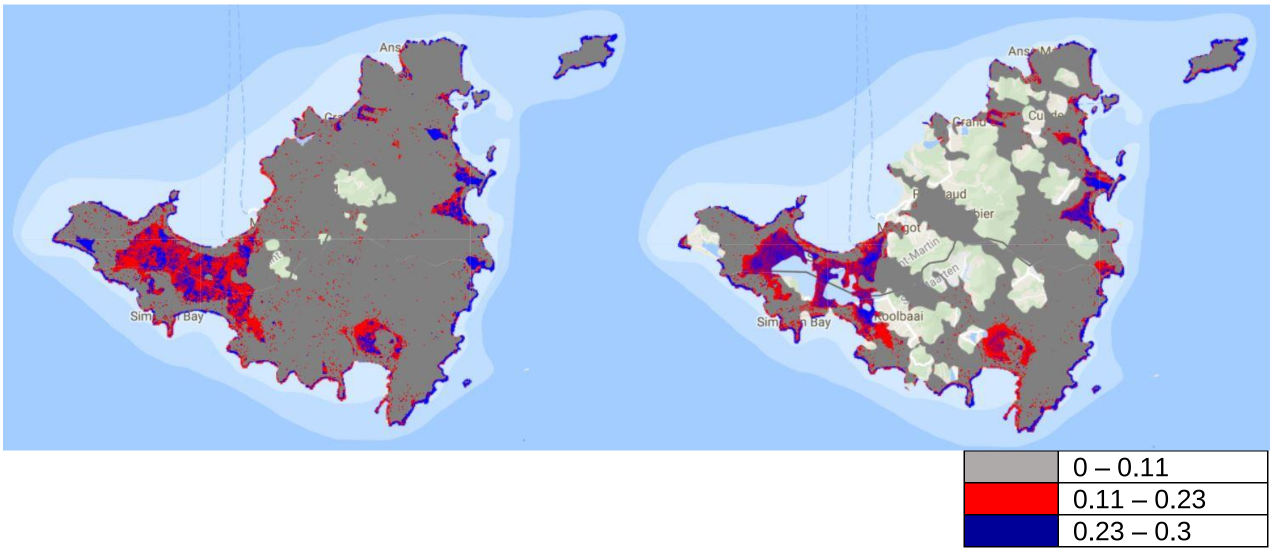


Figure 47: Before (left) and after (right) NDGI image

Figure 48: NDGI difference image

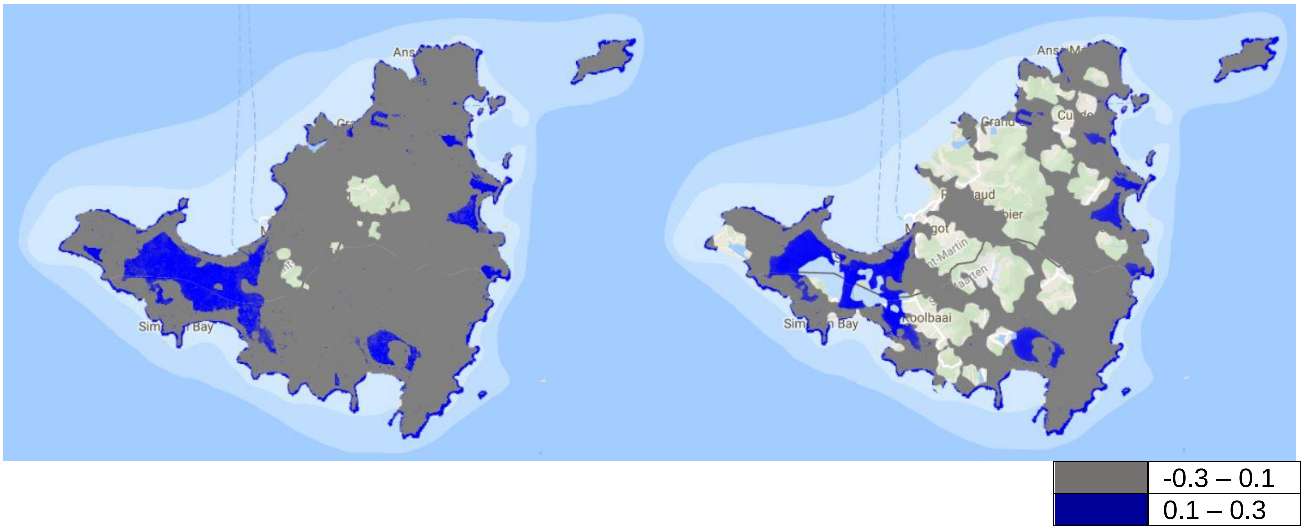


Figure 49: Before (left) and after (right) water index image

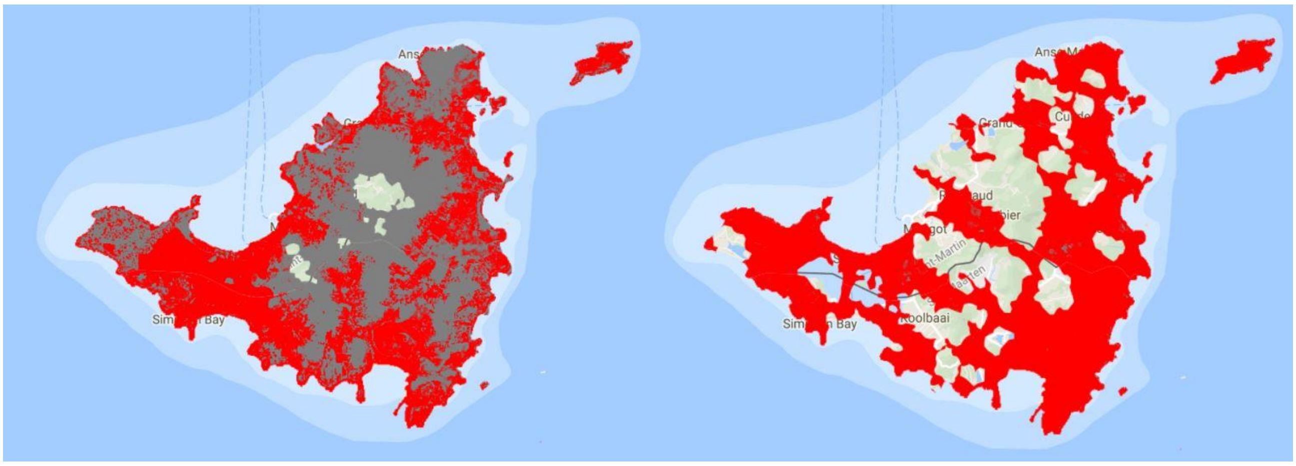


Figure 50: Before (left) and after (right) NDUI image

⬛	-0.6 - -0.35
🟥	-0.35 - 0

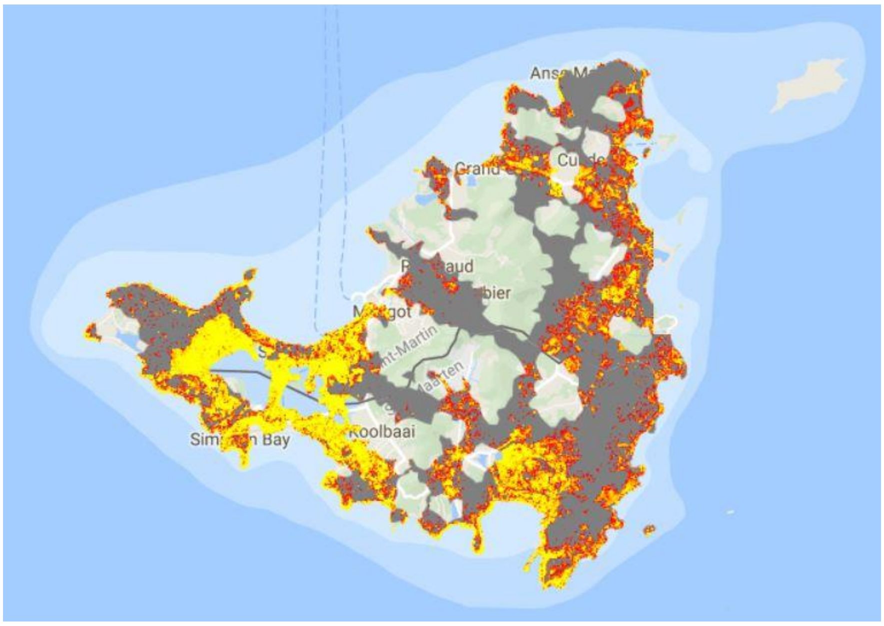


Figure 51: NDUI difference image

⬛	> 0.15 (change in vegetation)
🟨	0 – 0.05
🟧	0.-5 – 0.1
🟥	0.1 – 0.15

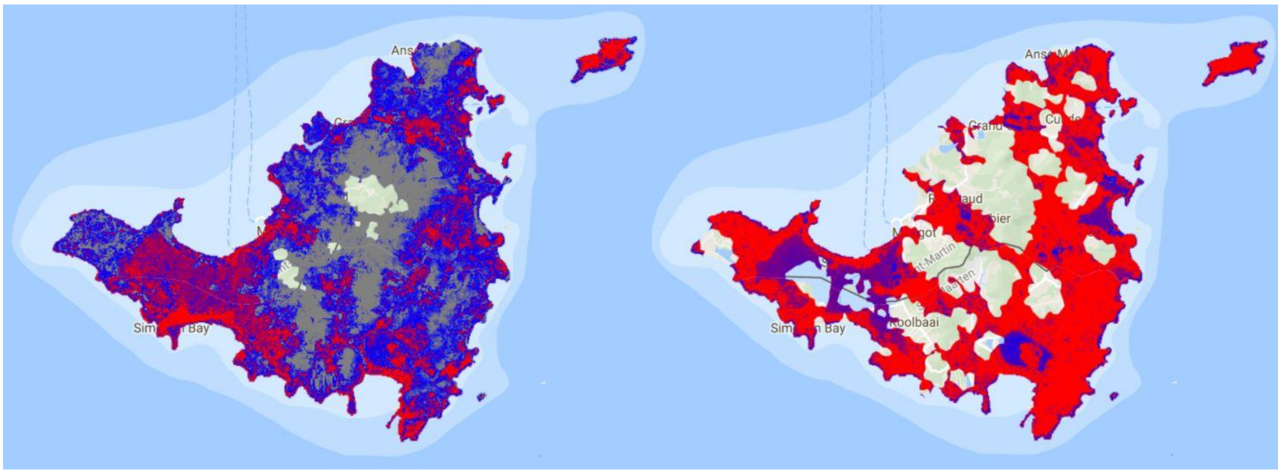
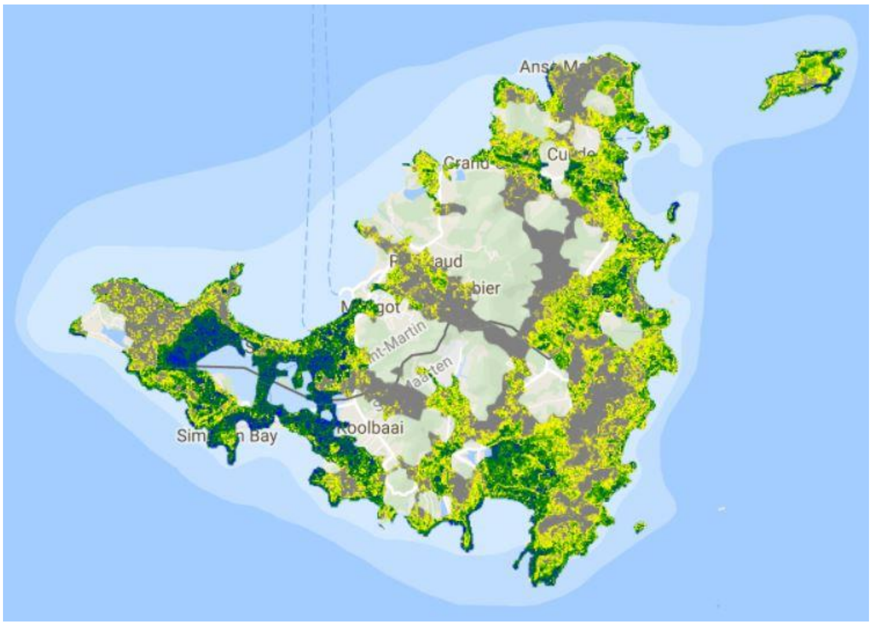


Figure 52: Before (left) and after (right) NDBI image

🟥	-0.2 – 0.06
🟦	0.06 – 0.2
▩	0.2 – 0.6



▩	> 0.2 (change in vegetation)
🟦	0
🟩	0 – 0.1
🟨	0.1 – 0.2

Figure 53: NDBI difference image