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Assessing and Analyzing the Spatial Distribution of Green Spaces in Paramaribo using GIS and Remote Sensing

by

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Preface

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Razia Taus

Paramaribo, September 24, 2020

List of figures

Figure 1 Overview of the Study Area Showing the Greater Paramaribo Region and the districts that are in it source: www.gonini.org 13
Figure 2 Overview of Sentinel-2A tiles over the coast of Suriname with the study area in red (European Space Agency (ESA), 2018) 14
Figure 3 Classification Method, source: author 18
Figure 4 Accuracy Assessment Loop, source: author 20
Figure 5 Change Analysis Method Overview, source: author 21
Figure 6 Study Area and Bounding Box above 2 Sentinel-2 Satellite Images 22
Figure 7 NDVI Map of Clipped Satellite Image 23
Figure 8 Overview of Training- and Ground Truthing Polygons within the Bounding Box 24
Figure 9 Classification Map of the Greater Paramaribo Region 2019 25
Figure 10 Map Showing the Classification within the District of Paramaribo relative to the Greater Paramaribo Region 29
Figure 11 The Contrast between 2 Ressorts within the Greater Paramaribo Region regarding the Green Space Distribution 31
Figure 12 Map showing the Spatial Distribution of the Vegetation Classes 32
Figure 13 Land use Land Cover Map 2000 34
Figure 14 Map showing Areas where No Changes have occurred between 2000 and 2019 35
Figure 15 Map Showing Areas that Changed between 2000 and 2019 within the Different Vegetation Classes 36
Figure 16 Areas that Changed between 2000 and 2019 from the Different Vegetation Classes to the Non-vegetation Classes 37
Figure 17 Areas that Changed between 2000 and 2019 from the Different Non-vegetation Classes to the Vegetation Classes 39
Figure 18 Overview of Vegetation Changes on top of the Euclidean Distance Map to Roads of 250 m 40
Figure 19 Map showing the Classification of Ressort Alkmaar 55
Figure 20 Map showing the Classification of Ressort Beekhuizen 55
Figure 21 Map showing the Classification of Ressort Blauwgrond 56
Figure 22 Map showing the Classification of Ressort Centrum 56
Figure 23 Map showing the Classification of Ressort De Nieuwe Grond 57
Figure 24 Map showing the Classification of Ressort Domburg 57
Figure 25 Map showing the Classification of Ressort Flora 58

Figure 26 Map showing the Classification of Ressort Houttuin 58
Figure 27 Map showing the Classification of Ressort Koewarasan 59
Figure 28 Map showing the Classification of Ressort Kwatta 59
Figure 29 Map showing the Classification of Ressort Latour 60
Figure 30 Map showing the Classification of Ressort Lelydorp 60
Figure 31 Map showing the Classification of Ressort Livorno 61
Figure 32 Map showing the Classification of Ressort Meerzorg 61
Figure 33 Map showing the Classification of Ressort Munder 62
Figure 34 Map showing the Classification of Ressort Nieuw Amsterdam................................62
Figure 35 Map showing the Classification of Ressort Pontbuiten...63
Figure 36 Map showing the Classification of Ressort Rainville 63
Figure 37 Map showing the Classification of Ressort Saramacca Polder 64
Figure 38 Map showing the Classification of Ressort Tammenga 64
Figure 39 Map showing the Classification of Ressort Weg Naar Zee.......................................65
Figure 40 Map showing the Classification of Ressort Welgelegen 65

List of Tables

Table 1 The Definitions of Classes used for this Study, source: author 18
Table 2 Overview of Polygons used as Training Data 19
Table 3 NDVI Values and Corresponding Classes (Weier & Herring, 2000)...........................24
Table 4 Overview of Polygons used for Classification and Ground Truthing 25
Table 5 Pixel Based Error Matrix of the Final Classification...26
Table 6 Overview of the Training- and Ground Truthing Data with their Corresponding Producer’s and User’s Accuracy..27
Table 7 The Total Area per Class and Percentages in the Greater Paramaribo Region 28
Table 8 Classification Areas of Paramaribo relative to the Greater Paramaribo Region 30
Table 9 Comparative table showing Paramaribo relative to the Greater Paramaribo Region...30
Table 10 Classification within the Euclidean Distance of 250 m from the Roads 32
Table 11 Changes in Percentages of Vegetation Classes that Changed into other Vegetation Classes...36
Table 12 Classes that Changed into Non-vegetation Classes between 2000 and 2019.............38
Table 13 Changes in Percentages of Non-vegetation Classes that Changed into Vegetation Classes between 2000 and 2019 39
Table 14 Comparison table of google imagery, Sentinel-2 and the NDVI map........................46
Table 15 Pixel count per meter of classification within 250 m 49
Table 16 Area proportions per class of Ressorts Alkmaar, Beekhuizen, Blauwgrond, Centrum and De Nieuwe Grond 66
Table 17 Area proportions per class of the Classification of Ressorts Domburg, Flora, Houttuin, Koewarasan and Kwatta 66
Table 18 Area Proportions per Class of the Classification of Ressorts Latour, Lelydorp, Livorno, Meerzorg and Munder...67
Table 19 Area Proportions per Class of the Classification of Ressorts Nieuw Amsterdam, Pontbuiten, Rainville and Saramacca Polder 67
Table 20 Area Proportions per Class of the Classification of Ressorts Tammenga, Weg Naar Zee and Welgelegen...68

Table of Contents

Preface....2

List of figures....3

List of Tables....5

List of abbreviations....8

Executive Summary....9

1 Introduction....10

1.1 Problem description....11

1.2 Research objectives....11

1.3 Research question....11

2 Literature review....12

2.1 Defining urban green spaces....12

2.2 Study area....12

2.3 Satellite Imagery....13

2.4 Normalized Difference Vegetation Index (NDVI)....14

2.5 Map classification....15

2.5.1 The sampling design....16

2.5.2 The Response Design....16

2.5.3 The Analysis....16

2.6 Analysis of the classified vegetation map....16

2.7 The historical change analysis....17

3. Methodology....17

3.1 NDVI to distinguish green spaces vs non green spaces....17

3.2 Classification method....17

3.3 Analysis of the vegetation map....20

3.4 The historical change analysis....20

4 Results and Discussion....22

4.1 Satellite images....22

4.2 The NDVI map....23

4.3 The classified vegetation map of 2019....24

4.4 Analysis of the classified vegetation map....28

4.5 The historical change analysis....33

Conclusions and Recommendations....41

Bibliography....42

Annex 1 Software....45

SNAP....45

QGIS....45

Annex 2 Training data identifiers....46

Annex 3 Overview of classification data within 250 m....49

Annex 4 Maps showing the classification per ressort....55

Annex 5 Tables showing the classification area per resort....66

List of abbreviations

UGS – Urban Green Spaces

GIS – Geographic Information System

QGIS – Quantum GIS

SBB – Foundation for forest management and production control

SNAP – Sentinel Application Platform

RF – Random Forest

SVM – Support Vector Machine

NDVI – Normalized Difference Vegetation Index

NIR - Near Infra Red

MSI - Multi-spectral imager

SWIR - Short wave infrared spectral range

NASA – National Aeronautics and Space Administration

Ha – hectare

m^2 – square meter

Executive Summary

Urban Green Spaces (UGS) play an important role in the ecosystems of cities and the services they provide. Little research has been done in Suriname regarding urban biodiversity and ecosystem services and this makes it difficult to understand the role that these UGS play within the capital Paramaribo. To do so, it is important to better understand spatial-temporal dynamics and distribution of UGS. Sentinel-2 satellite images from the greater Paramaribo region were downloaded, processed and resampled to 10 m resolution in order to create a classified map of urban vegetation. The following classes were identified: *'Water, built-up areas, trees, mangroves, mixed low vegetation, infrastructure, grass and bare soil'*. The support vector machine (SVM) classifier in QGIS was used to produce a vegetation map of 2019 and analysis of the map showed that 76.11% is still of a vegetation type class, out of which 25.6 % is covered by trees. Further analysis however showed that 1 % of the tree cover is within the capital district of Paramaribo and only 4.78 % of the trees in the region are within a 250 m distance from a road. After comparing the classified map of 2019 with a Land use land cover map created by the Foundation for Forest Management and Production Control (SBB) from the year 2000, the conclusion was drawn that overall changes had occurred in 60.07% of the study area. Further analysis showed that 46% occurred within a distance of 250 meters from the roads network in the greater Paramaribo region. A change map was created showing the different changes within the vegetation and the non-vegetation type classes. The main conclusion is that green spaces within the total study area are not evenly distributed. The capital district has far too little tree cover and the tree cover in the rest of the region is not accessible enough for the people living there. Because the difference between the tree cover that was detected using the NDVI map and the tree cover that was detected using the SVM classifier was only 5.4 %, it is highly recommended that an NDVI map is created on a monthly basis to monitor the tree cover in the area and also that a custom NDVI table is created specifically to identify vegetation in Suriname for the wet and dry periods to increase the accuracy of the classification. The classified map using the SVM classifier can be created every 6 months to get a better view of areas that indicate possible deforestation. The tree cover in Paramaribo needs to be expanded by possibly adding some parks or planting trees on strategic locations. It is also recommended to use this method to analyze the entire coastal area to create a more complete picture of the green spaces distribution for all the urban areas in Suriname and that more research is done on where we can strategically place more of them in order to maximize the benefits for humans, the environment and the ecological functions that they fulfill.

1 Introduction

With the disappearance of forests and an increase in urbanization over the last thirty years, green spaces have become more interesting to researchers and we can see a significant increase in scientific studies being done on the subject, including the urban heat island effect, rainfall and concentration of air pollution (Makhelouf, 2009). Urban green spaces also contribute to recreation and human wellbeing as well as the preservation of historic landscape features (Vatseva, et al., 2016). Studies are also being conducted on the different functions of urban green spaces as well as the impact these spaces can have on their environment. The European Environmental Agency strongly advises that people should have access to an urban green space within fifteen minutes walking distance in order to gain health benefits from the space (Stanners & Bordeau, 1995). A review done in Latin America and the Caribbean shows that one hundred and eighty two articles were published from thirteen countries on trends in urban forestry research. Brazil, Chile, Nicaragua and Mexico published almost 74% of all articles and most of the studies were field based surveys of vegetation diversity (Baronaa, et al., 2020). The amount of green spaces needed in different types of cities has evolved from simply looking at the size of the area relative to the population and the distance from a household to a green space into analyzing and looking at the socio-demographic needs of a city, as well as ecological functions and designing the green spaces based on the results of those needs assessments (Byrne, 2013). There are unfortunately also little to no studies done in the low income tropical areas which also results in a lack of policy when it comes to urban development and planning (Sharma & Bharat, 2009). No studies have been done in Suriname with regards to urban green spaces and the effects they have on their environment. This type of research can help us better understand the benefits of green spaces. Knowing their location and how they develop can give us the advantage of maximizing their effect on society. The existing laws in Suriname regarding urban spatial planning ”Stedenbouwkundige wet (1972)” and “Planwet (1973)” do not provide a framework for monitoring urban green spaces and also don’t prohibit citizens from clearing them. Currently the laws only stipulate the manner in which an area should be designed with regards to allotment plans, destination plans and structure plans. Green spaces are mentioned in the law as an option that should be taken into account and be sold to the government for a fair price (The govt. of Suriname , 1972). Recently the government has been requiring developers to add green spaces in their design plan but they allow them to only leave the bare minimum which is based on the size of the lot that will be developed. The District Commissioner does this case by case. In 2012 a 6.8 ha green patch was clear cut in Paramaribo. In this patch alone one hundred and thirty five sloths were rescued (Pool, et al., 2016). This is one of the few papers that was found related to green spaces in Suriname. Globally the importance of urban green spaces is increasing, because of the positive effect they have on mental health of humans (Hedblom, et al., 2019), and the fact that they can help people live longer. It's not possible to make a statement about green spaces in Suriname because of the lack of research and policy documents. According to Weidum (2014), urban green spaces such as agricultural lands, unique forests and even wetlands are disappearing as a result of urban sprawl in the greater Paramaribo region.

1.1 Problem description

Urban green spaces have not yet been accurately documented in Suriname. There is no quantifiable data on where they are, how big they are and what the possible effects are that they have on their surrounding areas. Research on urban green spaces can be very valuable with regards to urban planning, increasing the wellbeing of the people living in these urban areas as well as the ecosystems. In order to properly research the impact and benefits urban green spaces have on the urban areas in Suriname, it is necessary to make an assessment of the current spatial distribution of these spaces and how they have developed over time.

1.2 Research objectives

The main objective of this study is to develop a baseline of the current extent of green spaces within the urban areas of Suriname and to analyze their spatial distribution over time.

1.3 Research question

What is the spatial distribution of green spaces in the greater Paramaribo region and how have they evolved over the last nineteen years?

The following sub questions were evaluated:

1. What does the spatial distribution of green spaces look like in 2019?
2. How are the trees, shrubs and grass type vegetation distributed within the green spaces in 2019?
3. How has the green space distribution evolved between 2000 and 2019?

2 Literature review

2.1 Defining urban green spaces

According to Taylor & Hochuli (2017) the term green spaces is used many times with a variation in definition by multiple disciplines. Because of the difference in definition in different studies it was deemed not ideal to compare studies with each other and therefore it was recommended that green spaces be properly defined in each paper for future research. In Suriname, the Foundation for forest management and production control (SBB) has worked out the definition on forests for monitoring purposes which states the forest class is defined by 30% crown cover over a 1ha minimum mapping unit and a 5m minimum tree height at maturity (SBB, 2014). There is no definition specifically used in Suriname with regards to urban green spaces. "Urban Green Spaces can be defined as land that is partly or completely covered with grass, trees, shrubs, or other vegetation. Green spaces includes parks, community gardens, and cemeteries." (Environmental Protection Agency, 2017). This definition was ultimately used for this research.

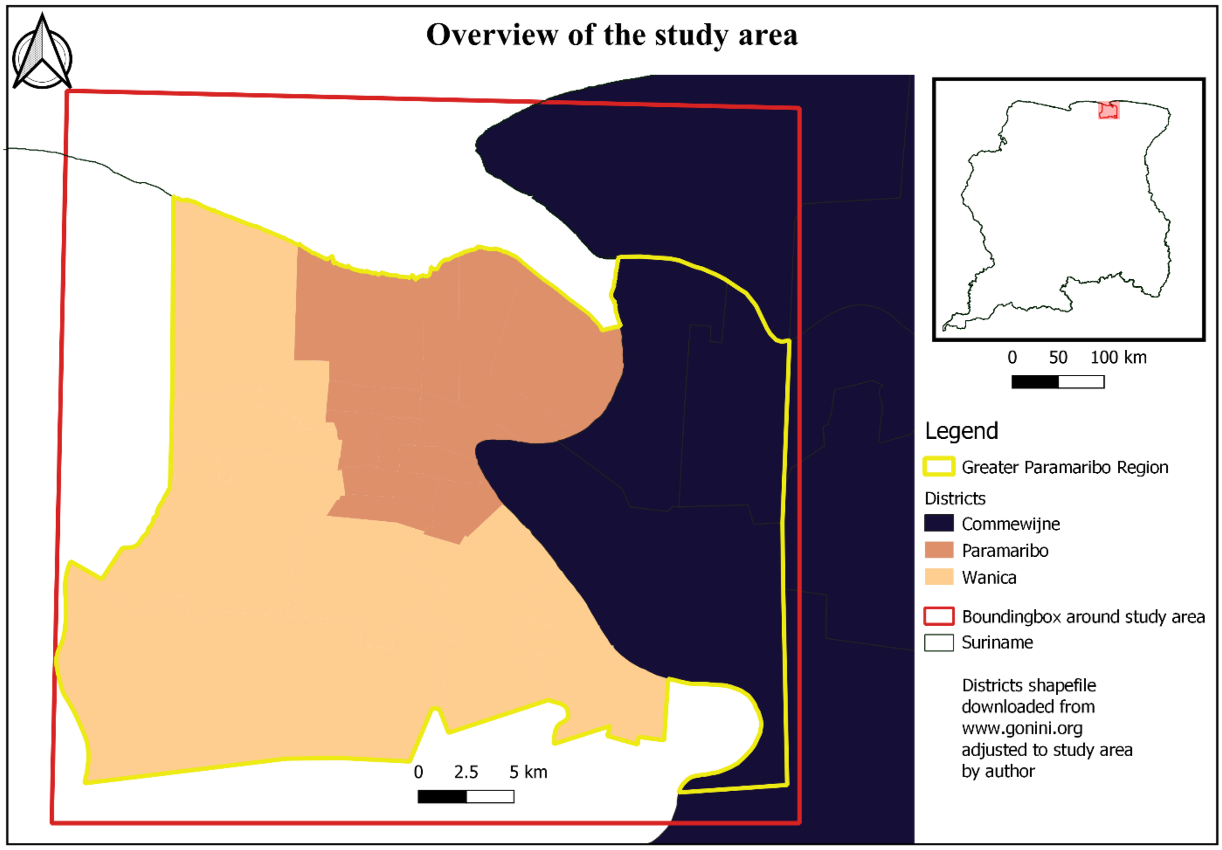
2.2 Study area

According to the planning law of 1972 ("Stedenbouwkundige wet") and the law on land from 1973 ("Planwet") only Paramaribo and Lelydorp can be defined as cities within the greater Paramaribo region, which excludes the expansion of the city to the outer parts of these districts into Commewijne. Although the greater Paramaribo region is not defined on the government of Suriname website or documentations, it is mentioned briefly in their development plan for 2017-2021 (Stichting Planbureau Suriname, 2017). Based on the boundaries described by Fung-Loy et al (2019), the greater Paramaribo region (figure 1) was eventually chosen using those boundaries as the area of interest for this study considering this is the area where presumably the most change has occurred in urban green space distributions.

Figure 1

Overview of the Study Area Showing the Greater Paramaribo Region and the districts that are in it

source: www.gonini.org

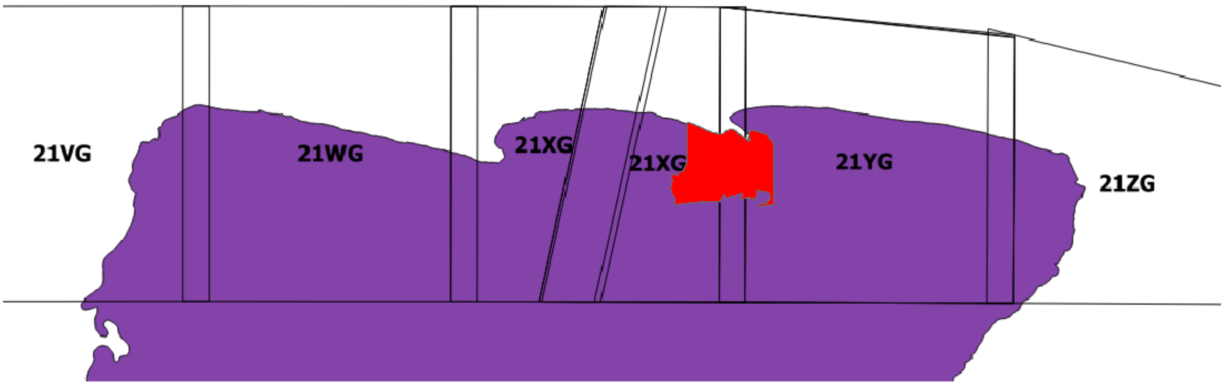


2.3 Satellite Imagery

There are multiple imagery options available to conduct this research. In Kuala Lumpur a combination of SPOT satellite images, field observations and information from the city to classify the different types of urban green spaces (Nor & Abdullah, 2019). In Mexico a normalized difference vegetation index (NDVI) map was created from which the green spaces were extracted, after which they were overlaid with existing municipal land use maps from the Municipal Institute for research and urban planning in order to create the classified map (Peña-Salmón, et al, 2014). A lot of the studies found, show the use of Satellite imagery as a basis for creating a classified map. This is usually combined with either field observations or existing data collected by other official institutions. The most widely used options are the Landsat and Sentinel satellite images. The mission consists of two satellites (Sentinel-2 A and B) carrying a passive multi-spectral imager (MSI) containing thirteen spectral channels (or 'bands') in the visible, near infrared (NIR) and short wave infrared spectral range (SWIR) (European Space Agency (ESA), 2018). One of the main considerations of this study is to create a replicable method that can be used in the future to continue the monitoring and the development of green spaces within the greater Paramaribo region. This means that it must also be financially sustainable i.e. open source software and free imagery. Both Landsat and Sentinel images are freely available to download, however the resolution for Landsat is 30m and for Sentinel-2 can be processed down to 10m. Since urban areas are the focus of this study this means that the green spaces are most likely much smaller than 900m^2. If Landsat were to be used it could result in a loss of valuable green space. With Sentinel-2 images the pixel resolution is 100m^2 which means a lot more information can be extracted from these images compared to the Landsat images. This is the main reason why Sentinel-2 images were chosen for this study (figure 2). The spectral resolution of Sentinel satellites were also designed to improve upon the experience from the SPOT and Landsat missions of the previous decades as well as its accessibility. Sentinel-2 features 13 spectral bands, with a spatial resolution of 10 m, 20 m or 60 m and a radiometric resolution of 12 bit. For urban green space mapping, only the spectral bands with a resolution of 10m were used. The bands at 60m are mainly used for atmospheric corrections. For this study the bands B2, B3, B4, B8 and B11 have been chosen due to their spectral reflectance to enhance vegetation on the images. Figure 2 shows the two tiles covering the study area 21XG and 21YG.

Figure 2

Overview of Sentinel-2A tiles over the coast of Suriname with the study area in red (European Space Agency (ESA), 2018)



2.4 Normalized Difference Vegetation Index (NDVI)

The most widely used index for classifying vegetation is the Normalized Difference vegetation Index (NDVI), formulated by Jensen (1986). NDVI is calculated from the visible light that hits it, and reflects a large portion of the near Infrared. In this index, vegetation pixels have a value close to one, since the red values are low and the NIR values high. The vegetation index can be used to create an initial vegetation map showing only the vegetation vs non-vegetation pixels. NDVI differencing has been successfully used to detect vegetation change in the south of Italy with a 91.8% accuracy (Mancino, et al, 2014) where 2 NDVI maps from two time periods are compared and the difference between the maps shows the change between the time periods. This method could also be used to detect the changes that occurred in Suriname between 2000 and 2019 with regards to green spaces, however the detailed information on the different vegetation classes would not be taken into account which is why this was only used to get a first indication of where green spaces may be located within the study area using the definition NASA uses. The NDVI values lower or equal to 0.1 define barren areas of rock or sand, while shrub and grassland correspond to values between 0.2 and 0.3, and values between 0.6 and 0.8 indicate temperate and tropical rainforests (Weier & Herring, 2000). These values were created for a global overview of vegetation in the world which means that they can only be used as an indication of the locations and not as identification of absolute locations for the classes.

2.5 Map classification

In order to identify different classes within the vegetation it is necessary to also look at different classifiers. There are different algorithms that can be used to classify satellite images and create a map with multiple classifications. The Random Forest classifier (RF) is a supervised learning algorithm. The Random forest algorithm has now been integrated into QGIS, which can be utilized with a fully cloud free image. The Support Vector Machine classifier (SVM) which is a classifier used to classify satellite images using a set of algorithms and training data. A study comparing RF with SVM suggests SVM classifiers outperform random forest when it comes to cancer classification (Statnikov & Aliferis, 2007). Some studies however show that the RF classifier produces better results than the SVM classifier (Jia, Hu, & Sun, 2013). Both articles state that the subject of classification and the number of data samples that need to be processed play a role in the success of the classifier. In order to determine the accuracy of the classified map and asses the method, the map needs to be validated and compared with higher quality reference data collected through a sample based approach. To do this random samples need to be collected within the different classes (strata).

2.5.1 The sampling design

The sampling design determines how the subset of the map should be selected. The accuracy assessment is based on this selection. Stratification is the process of division of the area of interest into strata which are sub divisions. Each assessment unit is designated to a single stratum. Overall sample size for stratified random sampling is calculated by the *Cochran 1977* equation:

$$n = \left[\left(\frac{\sum w_i s_i}{s(\hat{o})}\right)\right] \qquad (1)$$

The stratified random sampling can then be distributed among the different strata. In the *Cochran 1977* equation, n is the number of units in the area of interest (number of overall pixels if the spatial unit is a pixel, number of polygons if the spatial unit is a polygon), $s(\hat{o})$ is the standard error of the estimated overall accuracy that we would like to achieve, w_i is the mapped proportion of area of class I and s_i is the standard deviation of stratum i. (Food and Agriculture Organization, 2016)

2.5.2 The Response Design

The response design is used to determine if the classified map accurately describes the reference data. The response design consists of four major components. These are: the mapping unit, the sources from which the reference classifications are determined, the protocol for labeling the reference classification and the definition of agreement (Food and Agriculture Organization, 2016).

2.5.3 The Analysis

The error matrix is methodology for relationship analysis between multiple variables and this case the class labels allocated by map and reference data by a q x q matrix with q being the number of classes assessed. (Food and Agriculture Organization, 2016). The accuracy measures including overall accuracy, user's accuracy and producer's accuracy with their respective confidence intervals, are calculated from the error matrix. The overall accuracy is a representation of the probability that a randomly selected location on the map is classified correctly. (Food and Agriculture Organization, 2016). The Semi-Automatic Classification Plugin in QGIS can be used to calculate the accuracy statistics of the classified map.

2.6 Analysis of the classified vegetation map

There are many cities around the world that have researched and implemented their own standards of minimal amount of green space in their city. The city of London for example has a standard of 4ha per 1000 inhabitants which is 40 square meters per person whereas

Pakistan has a minimum standard of 0.52 ha per 1000 inhabitants which comes down to 5.2 m2 per person (Maryanti, et al , 2016). The World Health Organisation (WHO) recommends a minimum of 9 square meters and suggests that an ideal amount considered to be 50 square meters per person (World Health Organization, 2010). The WHO (2010), also recommends minimum distance of 5 min or 300 m from a green space as well as ensuring accessibility and safety of the space for people.

2.7 The historical change analysis

To determine the change within the vegetation another map from the year 2000 is necessary. A study in China on a historical change model used historical data and three satellite images from different years in order to make a historical land use change analysis (Yang, et al, 2017). SBB created a land use land cover map in 2000, which can be used to similarly create the comparison with the final classified map for 2019.

3. Methodology

3.1 NDVI to distinguish green spaces vs non green spaces

The Sentinel-2 satellite images that were downloaded were first processed down to 10m resolution. To help identify sample points between vegetation and non-vegetation, an NDVI map was created. The standard formula for creating the NDVI map is:

$$NDVI = (NIR - RED)/(NIR + RED). \qquad (2)$$

For Sentinel-2 bands this equation would translate to:

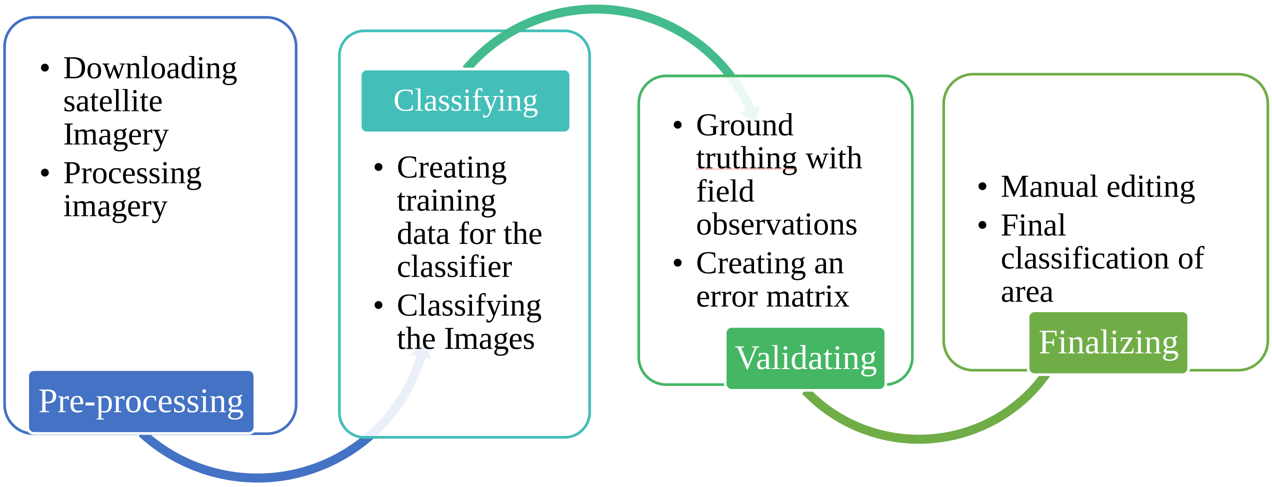
$$NDVI = (B8 - B4)/(B8 + B4) \qquad (3)$$

3.2 Classification method

To determine the spatial distribution of green spaces within the greater Paramaribo area the following classification method was used (figure 3).

Figure 3

Classification Method, source: author



During the pre-processing phase, two Sentinel-2 images were downloaded from the dry period dated September 12th 2019. These images were cloud free images which meant that it was unnecessary to apply a cloud mask or a cloud fill. The images were corrected in SNAP and then resampled down to 10 m. During the classifying phase, a classifier was run on the images and training data was created. Training data is data which tells the algorithm which pixels on the satellite image represent which class. For each class a number of training samples was created. Because of the irregular shape of the area, a bounding box was used to compute both the RF and the SVM classifier. The eight classes defined for this study are: water, built-up area, trees, mangrove, mix low vegetation, infrastructure and bare soil (table 1) and the number of training samples created for each class can be seen in table 2.

Table 1

The Definitions of Classes used for this Study, source: author

Class number	Class	Definition
1	water	More than 50% of 10 x10 m covered by water
2	built-up	More than 50% of 10 x10 m covered by buildings, houses
3	trees	More than 50% of 10 x10 m covered by trees
4	mangrove	More than 50% of 10 x10 m covered by Mangrove
5	mix low vegetation	More than 50% of 10 x10 m covered by a mix of low vegetation
6	infrastructure	More than 50% of 10 x10 m covered by hardened roads
7	grass	More than 50% of 10 x10 m covered by a grass (high and low)

8	bare soil	More than 50% of 10 x10 m covered by bare soil

Table 2

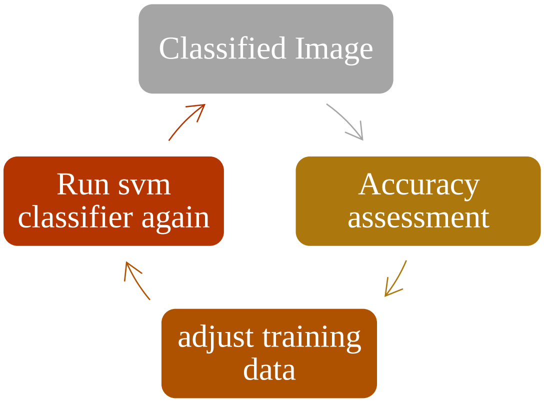
Overview of Polygons used as Training Data

Classes	Number of polygons used for training data
Water	53
Built up	43
Trees	52
Mangrove	34
Mix Low Vegetation	45
Infrastructure	24
Grass	41
Bare Soil	51

Using the training data, two initial maps were created using the two algorithms, namely one classified map using the random forest classifier and one using the support vector machine classifier. This was done to compare the two classifiers using an accuracy assessment and see which one did a better job in order to then further perfect that classifier. An initial accuracy assessment was made during the validation phase on the map produced with the RF classifier as well as on the map produced with the SVM classifier. Ground truthing data was created using high resolution drone images from March 2019 for the center of the city and google earth imagery for 2019. Using this data an error matrix was created for both images. The error matrix showed that the SVM classifier works better on this dataset which is why this method was used to improve the classification. Based on the first SVM classified image, adjustments were made to the training data and a new accuracy assessment was made and tested until the best possible classification was obtained (figure 4). The recent classification of mangroves by SBB was used to create ground truthing data for that class.

Figure 4

Accuracy Assessment Loop, source: author



After the final classified image was created a manual check was done to ensure that green spaces within the area were all properly represented. The reason for this manual check is that there are two significant green spaces in the center of Paramaribo known as the Cultuurtuinlaan and Palmentuin and it was important that these spaces were present on the map. Using drone imagery with a resolution of 10 cm, the existing gaps on the classified map were manually filled in with the right classification. This was only done for these two important green spaces. Once this was complete the classification was categorized as final. The study area was then clipped out of the bounding box.

3.3 Analysis of the vegetation map

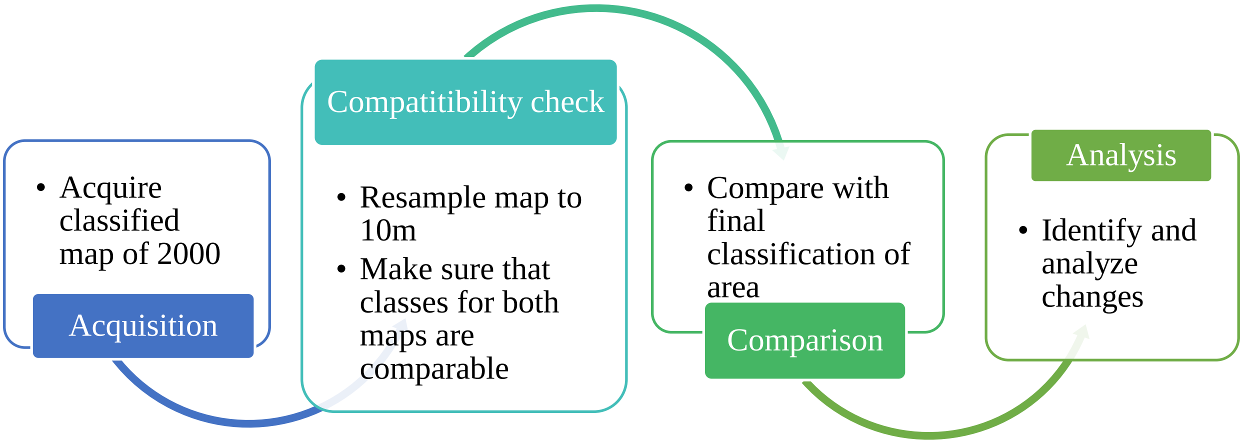
The analysis of the classified vegetation map was done by calculating the number of green spaces available per 1000 inhabitants using census data from 2013 in order to compare it with the standards of the WHO and by creating a Euclidean distance map to analyze the distance to green spaces within 250 m from the roads.

3.4 The historical change analysis

In order to do the historical change analysis a Land use land cover map was obtained from SBB from the year 2000 which was created using Landsat imagery. The classes in the 2000 Land use land cover map were aligned with the classes used to create the vegetation map of 2019. The map was created with a resolution of 30 x 30 m. The map was resampled to 10 x 10 m in order to be compatible with the classified map from 2019 and using raster differencing a change map was created. Figure 5 gives a schematic overview of the method that was followed.

Figure 5

Change Analysis Method Overview, source: author



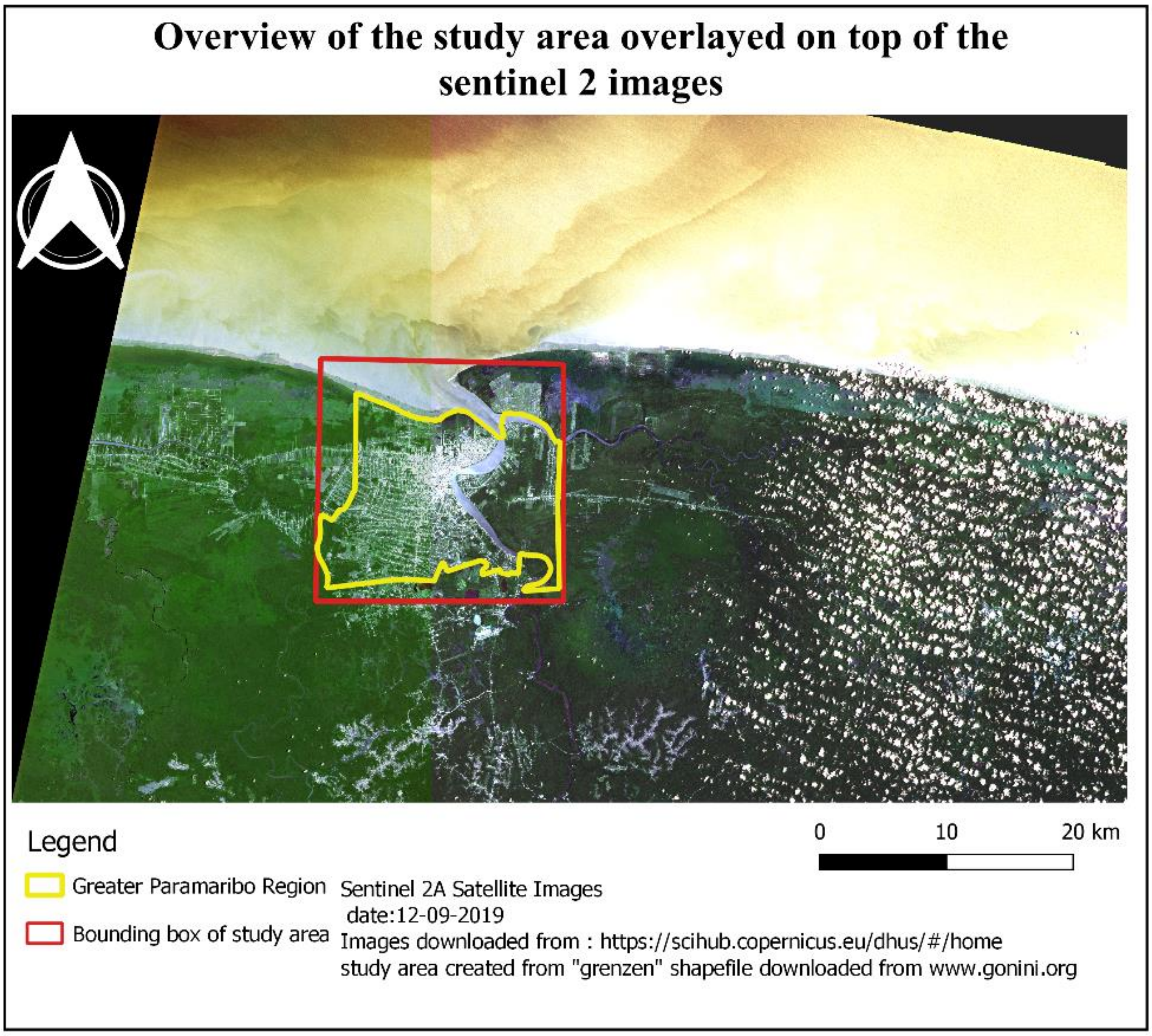
4 Results and Discussion

4.1 Satellite images

The 2 satellite images (21XG and 21YG) both dated September 12, 2019 were downloaded from the Copernicus Open Access Hub (ESA, 2019). The images were unprocessed, containing all bands with no clouds above the study area (figure 6). Using Sentinel Application Platform (SNAP) the images were processed and resampled to 10m resolution after which they were clipped using the bounding box around the study area. The bounding box was used during this phase because the irregular shape of the study area causes the program to make a lot more computations which then caused the computer to freeze.

Figure 6

Study Area and Bounding Box above 2 Sentinel-2 Satellite Images



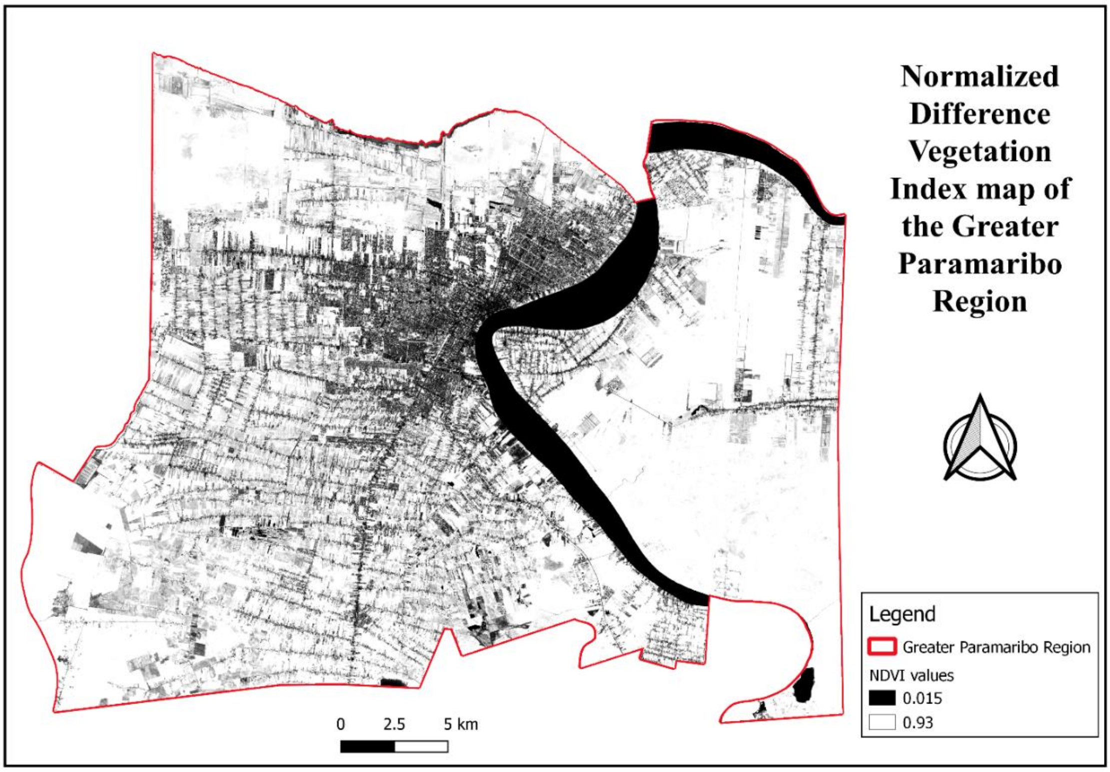
Note. The Sentinel-2 images were downloaded from https://scihub.copernicus.eu/dhus/#/home and the study area was created from the district shapefile downloaded from www.gonini.org

4.2 The NDVI map

The NDVI map was created using the 2 Sentinel-2 satellite images to give a clear image of where the green spaces and the non-green spaces are located. The NDVI map created can be seen as a level one vegetation map for the greater Paramaribo region (figure 7). The NDVI map gives a first indication on where the green spaces are located. The numbers are between zero and one. The NDVI map already gives us an idea about the locations of green spaces and non-green spaces. Even though this is not enough to distinguish the different vegetation types within the green spaces, it was used to assist in identifying the locations and creating a better classified image.

Figure 7

NDVI Map of Clipped Satellite Image



The NDVI results show that 7.18% of the area is classified as water, while 3.9% is classified as grass and shrubs and 30.57% is classified as trees (table 3). These definitions of NDVI values and their corresponding classes were chosen from a study showing these classes on a global scale (Weier & Herring, 2000). This means that the vegetation type classes may be under- or overestimated. To have a more accurate representation of NDVI values and their corresponding classes specifically for Suriname it is necessary to do ground truthing in both the dry and wet season and create standard. This data can then be used to create standard values for Suriname and more accurate NDVI maps can be produced in the future.

Table 3

NDVI Values and Corresponding Classes (Weier & Herring, 2000)

NDVI classes	NDVI values	Pixel count	Area (ha)	%
Water	< 0.1	620,224	6202.24	7.18
Shrubs and grass	0.2 - 0.3	336,504	3365.04	3.90
Trees	0. 6 - 0.8	2,639,538	26395.38	30.57

4.3 The classified vegetation map of 2019

The methods used to create the vegetation map for 2019 can be easily replicated and in the future even be automated for the same area in order to create a sustainable monitoring system. The advantage of the method is that it is straightforward and even-though the literature states that the Random Forest classifier gives better output, in this case the SVM classifier produced a better result. The overall accuracy of RF was 79% and SVM was 84%. The possible reason for this difference may lie in the size of the study area and the number of samples that were used. Random forest works better with larger datasets and SVM works better with smaller datasets. Training polygons were created using field visits and Google Earth imagery. Table 4 shows the number of polygons and pixels used for training the data as well as for ground truthing (figure 8). The shape of the study area created some difficulty for the software during the testing of the classifiers. This is the reason a bounding box was placed around it and used to make the classification. The training and ground truthing samples were also created within this bounding box and not just within the study area.

Figure 8

Overview of Training- and Ground Truthing Polygons within the Bounding Box

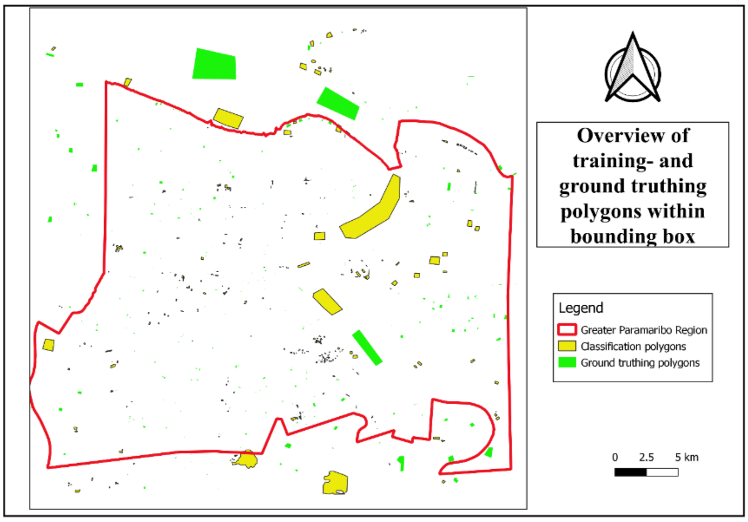


Table 4

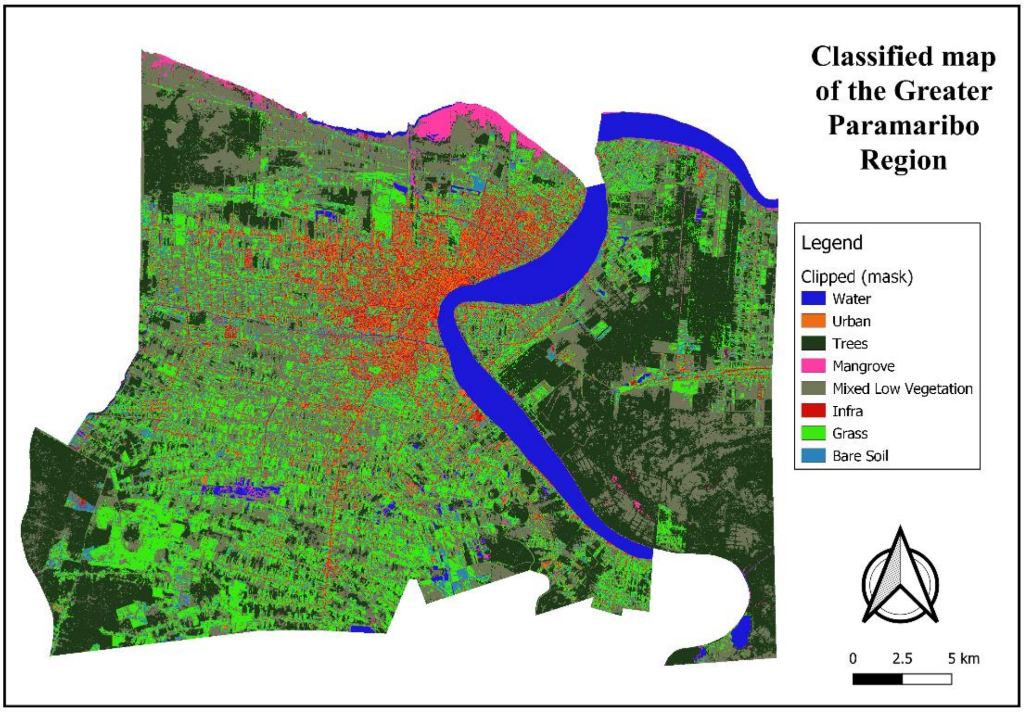
Overview of Polygons used for Classification and Ground Truthing

Classes	Number of polygons used for training data	Number of polygons used for ground truthing	Total number of polygons
Water	53	35	88
Built up	43	32	75
Trees	52	35	87
Mangrove	34	23	57
Mix Low Vegetation	45	30	75
Infrastructure	24	18	42
Grass	41	27	68
Bare Soil	51	30	81

The final classified vegetation map of 2019 shows the forest patches on the outside of the area. The red and orange in the image show the built up areas and the infrastructure. From field observations we know that there are trees within this area, however due to the pixel resolution of 10 m these trees are not visible in this classification. The grey shows mix low vegetation which is covering most of the area along with grass (figure 9).

Figure 9

Classification Map of the Greater Paramaribo Region 2019



The map was validated using the ground truthing data and the error matrix (table 5). The error matrix was produced using the Semi-Automatic Classification Plugin in QGIS. The average producer's accuracy is 88.02 %, the average user's accuracy is 90.31 % and the overall accuracy of the map is 88.36 %. Based on these statistics the conclusion can be drawn that this map is acceptable for use in an analysis.

Table 5

Pixel Based Error Matrix of the Final Classification

REFERENCE

CLASSIFICATION

Classes	**Water**	**Built up**	**Trees**	**Mangrove**	**Mix low vegetation**	**Infra-structure**	**Grass**	**Bare soil**	**Total**
Water	142142	0	0	0	0	6	0	0	142148
Built up	0	457	0	0	0	5	0	81	543
Trees	0	0	16637	114	7	0	0	0	16758
Mangrove	0	0	97	6293	0	0	0	0	6390
Mix low vegetation	0	0	1001	270	2957	0	55	56	4339
Infra-structure	0	13	0	0	0	200	2	18	233
Grass	0	0	92	0	39	0	1441	54	1626
Bare soil	0	0	0	0	4	2	30	1727	1763
Total	142142	470	17827	6677	3007	213	1528	1936	173800

Individually looking at the accuracy assessment it is important to make a distinction between the vegetation type classes and the non-vegetation type classes. This study focusses mainly on the vegetation type classes which is the main reason that the number of pixels used for training data as well as ground truthing data differs between the two main types of classes. Water however is very accurately classified, mainly because it is easy to recognize on the satellite images and also because a very high number of training data as well as ground truthing data was collected (table 6). A large number of pixels was collected to classify and ground truth the trees class and the user's accuracy was very good for this class however the producer's accuracy was 76.1 % which was a little low. Given the large number of pixels used in the training data the choice was made to accept this accuracy, because trying to improve this at this scale would have a big effect on the rest of the classes. A decent amount of pixels was collected to classify and ground truth the mix low vegetation class, resulting in an acceptable producer's accuracy but only having a user's accuracy of 68.1%. This was to be expected given that trees, mangroves and grass can all be found within the mix low vegetation class. The importance of design is clear when looking at the results of trees and mix low vegetation. The large number of tree pixels that was classified as mix low vegetation is effecting the user's accuracy of the mix low vegetation class because it is almost one third of all the pixels collected to ground truth this class. During this phase of the study the decision was made to accept this low user's accuracy for this class mainly because changing the number of ground truthing pixels would mean the number of training data would have to change and that would result in a whole other classified map that would then need to be analyzed. The producer's accuracy for the classes mangroves and bare soil is lower than 80% which can be accounted to the fact that the ground truthing data was harder to collect than expected. Mangrove were difficult to identify and was often seen as trees by the classifier. The accuracy assessment loop (figure 4) was used to try and improve the accuracy of the classes, but improving one class can have a negative effect on the accuracy of another important class which is why the loop was ended with an overall accuracy of 88.36 %. When using this map to identify green spaces for further research it is important to take into account that the mix low vegetation class is poorly represented on this map.

Table 6

Overview of the Training- and Ground Truthing Data with their Corresponding Producer's and User's Accuracy

Classes	Number of pixels for training data	Number of pixels for ground truthing	User's accuracy (%)	Producer's accuracy (%)
Water	185,526	142142	100.0	100.0
Built up	697	470	84.2	92.3
Trees	24,800	17827	99.3	76.1
Mangrove	9,306	6677	98.5	63.3
Mix Low Vegetation	4,313	3007	68.1	98.0
Infrastructure	257	213	85.8	98.9
Grass	2,269	1528	88.6	96.5
Bare Soil	2,607	1936	98.0	79.1

4.4 Analysis of the classified vegetation map

The total area of the greater Paramaribo region is 86 340.53ha. The vegetation type classes such as trees, mangroves, mix low vegetation and grass make up for 65 716.39 ha (76.11%) (table 7). It could be argued that this number is fairly high with regard to green spaces within the area, however the map shows that these green spaces are not evenly distributed across the region. Using the population numbers from census (General Bureau of Statistics, 2013) within the greater Paramaribo region for every 1000 inhabitants there is 57 ha of the trees type class available. However, when looking at Paramaribo alone it shows that there is only 4 ha of the trees type class available per 1000 inhabitants which comes down to 40 square meters per person. Compared to the WHO standard of a minimum of 9 square meters per person this seems to be enough, however the distribution of the population in Paramaribo differs per resort which means that a more detailed vegetation distribution analysis needs to be done using census data on a resort level. When analyzing the spatial distribution of the green spaces it is also clear that only 4.78 % of the trees are within 250 m of the road. The management of green spaces in Suriname is for a big part only done to maintain the side of the roads. The grass is cut and a couple of trees are planted. Trees and mix low vegetation identified in this study are usually not accessible to people. They do provide ecosystem services and are home to many different animals however of the 4.78% of trees within the 250 m of the road, it can be assumed that a big part of this is not accessible to people. These numbers can estimate the quantity of the green spaces, but do not account for the quality or the ecological function of the spaces. Further research needs to be done on the effect these identified green spaces have on the city such as a cooling or air purifying effect in highly populated areas and big roads such as the Martin Luther King weg or the Magentakanaal weg.

Table 7

The Total Area per Class and Percentages in the Greater Paramaribo Region

Class	Area (m²)	Area (ha)	%	Ha / 1000 inhabitants
Water	53 286 300	5328.63	6.17	14
Built up	39 771 000	3977.1	4.61	10
Trees	221 000 100	22 100.01	25.60	57
Mangrove	10 886 800	1088.68	1.26	3
Mix low vegetation	245 244 500	24 524.45	28.40	63
Infrastructure	47 045 200	4704.52	5.45	12
Grass	180 032 500	18 003.25	20.85	46
Bare soil	66 138 900	6613.89	7.66	17
Total classified area	863 405 300	86 340.53	100	

When looking at the non-vegetation type classes the study shows that they make up for 20 624.14ha (23.89%) of the greater Paramaribo region and when examining the capital district of Paramaribo the result shows that the non-vegetation type classes cover a total of 8990.09ha (10.42%) (table 8) concluding that 44% of all the non-vegetation type classes that are within the greater Paramaribo region are located in Paramaribo (figure 10). Further research can also be done in the city of Paramaribo using higher resolution or drone images to map the green spaces that are smaller than 10 x 10m and study the effect of very small green spaces in a resort that has a lot of asphalt and concrete such as Centrum. Analysis of the spatial distribution of the vegetation type classes within the greater Paramaribo region shows that most of the trees are located in the outskirts of the region. A total of 25.6% of the area is covered with trees out of which only 1% is located within Paramaribo. The mix low vegetation and the grass class together cover 49.25% of the region. A possible reason for this is the development that is going on in these districts. It is clear that roads play a vital role when it comes to keeping vegetation, specifically trees intact which can be clearly seen at the edges of the region where there are no roads and where most of the trees are located (figure 10).

Figure 10

Map Showing the Classification within the District of Paramaribo relative to the Greater Paramaribo Region

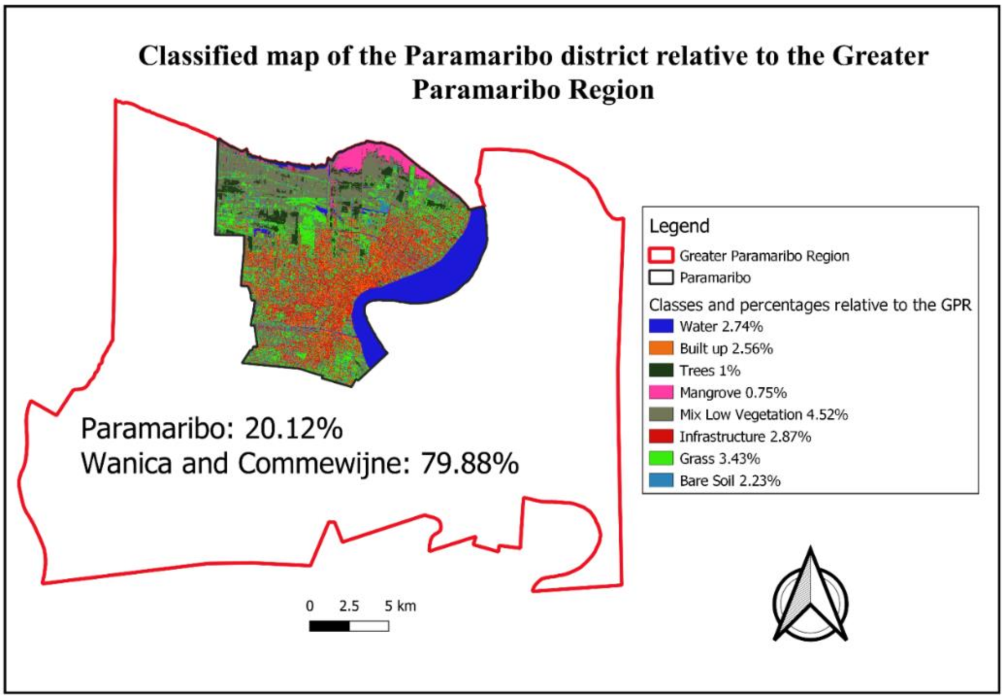


Table 8

Classification Areas of Paramaribo relative to the Greater Paramaribo Region

Class	Pixel count	Area (ha)	%	Ha / 1000 inhabitants
Water	236 800	2368	2.74	10
Built up	221 385	2213.85	2.56	9
Trees	86 110	861.1	1.00	4
Mangrove	65 025	650.25	0.75	3
Mix low vegetation	390 375	3903.75	4.52	16
Infrastructure	247 928	2479.28	2.87	10
Grass	296 247	2962.47	3.43	12
Bare soil	192 896	1928.96	2.23	8
Total area classified relative to the greater Paramaribo region		17367.66	20.12	

Table 9 shows the comparison of the classified areas between the greater Paramaribo region and the district of Paramaribo. Based on this table alone it can be assumed that there is enough green space available per person in this area however a quick comparison of 2 ressorts shows us that the green space distribution within the resorts is not the same and these numbers need to be evaluated on a resort level (figure 11) in a further study.

Table 9

Comparative table showing Paramaribo relative to the Greater Paramaribo Region

	Total classified map		**Paramaribo**	
Class	Area % of total region	Ha / 1000 inhabitants	Area % of total region	Ha / 1000 inhabitants
Water	6.17	14	2.74	10
Built up	4.61	10	2.56	9
Trees	25.60	57	1.00	4
Mangrove	1.26	3	0.75	3
Mix low vegetation	28.40	63	4.52	16
Infrastructure	5.45	12	2.87	10
Grass	20.85	46	3.43	12
Bare soil	7.66	17	2.23	8

Total	100	20.12

Figure 11

The Contrast between 2 Ressorts within the Greater Paramaribo Region regarding the Green Space Distribution

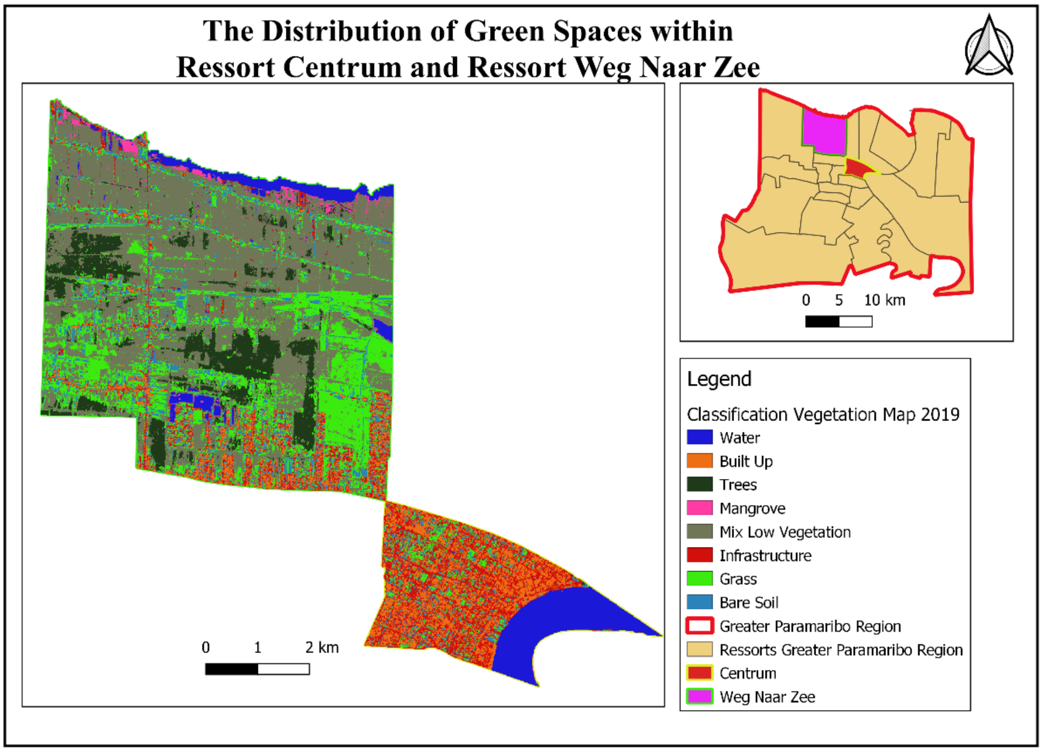
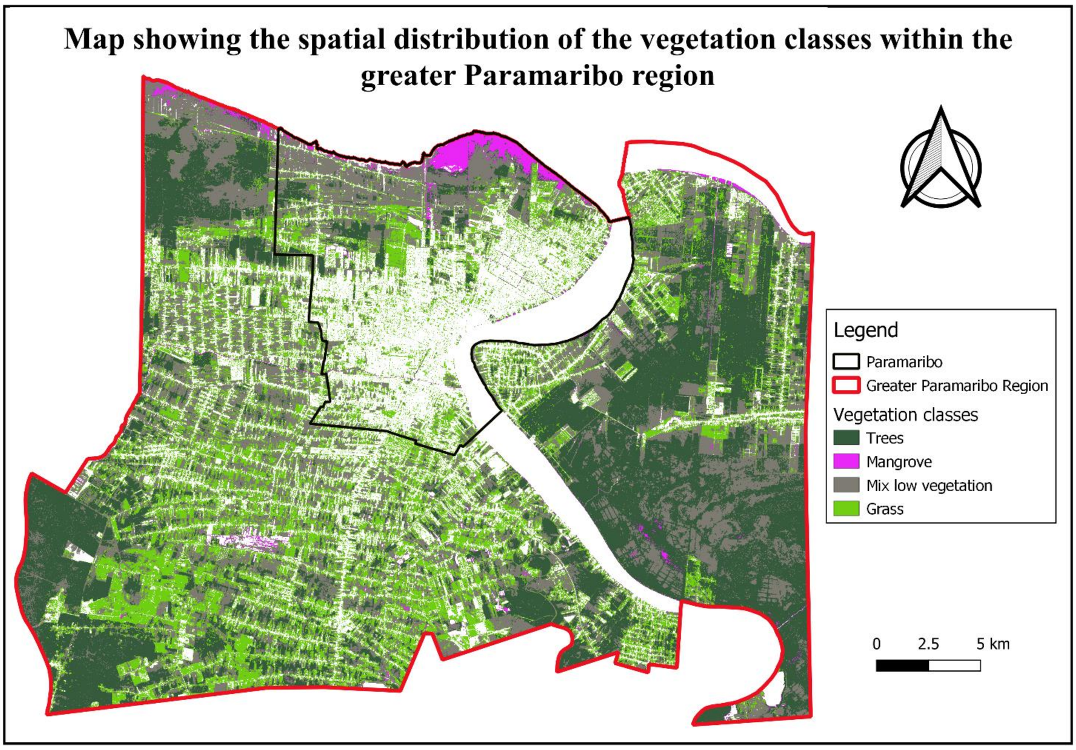


Figure 12

Map showing the Spatial Distribution of the Vegetation Classes



The road map was used to create a Euclidean distance map using a buffer of 250 m. The vegetation map was overlaid on top of the Euclidean distance map showing that 35.29% of all vegetation type classes lay within 250 m of the roads out of which 4.78 % are trees, 30.28% is covered by the grass (15.26 %) and mix low vegetation (15.02 %) classes and 0.23 % account for the mangrove class. Trees are very often removed when they are close to roads due to a number of reasons including houses, electricity poles or even to add underground pipelines which can account for the small percentage of trees that lay within 250 m of the roads. Grass is most often planted on the side of the roads which contributes to the 15.26 % (table 10).

Table 10

Classification within the Euclidean Distance of 250 m from the Roads

	ha	% area of the region
Water	577.42	0.67
Built up	3899.28	4.52
Trees	4125.03	4.78
Mangroves	19804	0.23

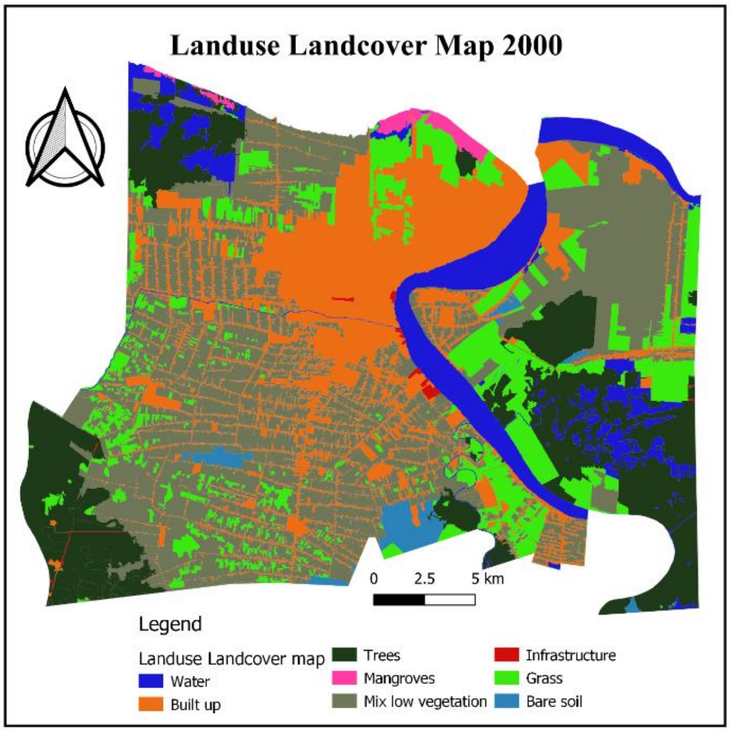
Mix low vegetation	12969.12	15.02
Infrastructure	3723	4.31
Grass	13173.26	15.26
Bare soil	5439.63	6.3

4.5 The historical change analysis

The classified vegetation map of 2019 was compared to the Land use land cover map of 2000 (figure 13).Because of the difference in resolution of the 2000 map and the 2019 vegetation map it is safe to say that not all changes are visible on the change map. The total area change that occurred between 2000 and 2019 is 51 876.48ha (60.07%). A total area of 34 464.05ha (39.93%) did not show changes between 2000 and 2019.

Figure 13

Land use Land Cover Map 2000

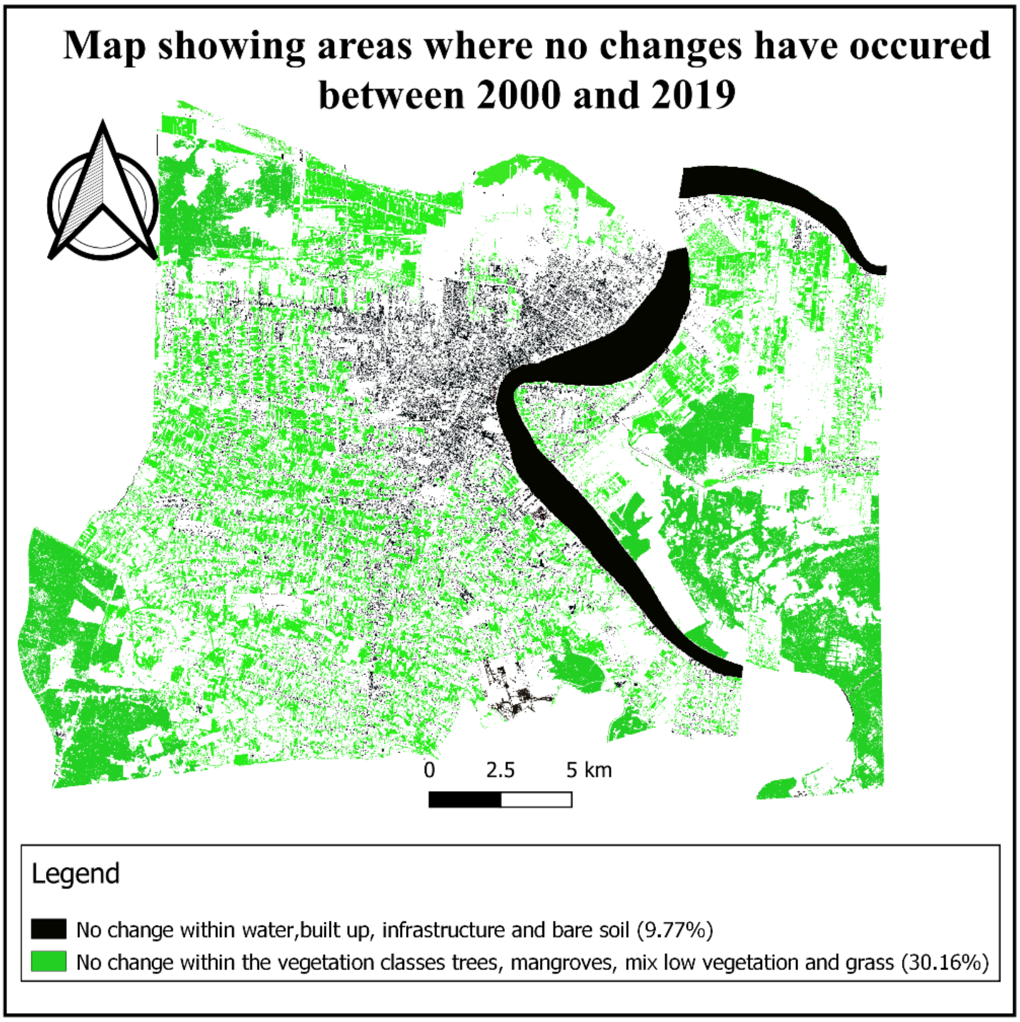


Note. The Land Use Land Cover map was provided by SBB

The classes were sub divided into the vegetation type- and the non-vegetation type classes (figure14). A total of 9.77 % of the area showed no change within the non-vegetation type classes and 30.16 % of the vegetation classes remain the same as they were in 2000. There could still be change within these areas, however the materials used for this analysis do not allow for these changes to be visible in this study.

Figure 14

Map showing Areas where No Changes have occurred between 2000 and 2019



Total change within the vegetation classes was 29 218.73ha (33.86%) (table 10). Figure 15 shows the locations of the changes from one vegetation type class into another one. The changes identified in this study should be viewed with caution because the two maps that were used to do the change analysis were not created using the same methodology or satellite images. They do give a general idea when analyzing between the non-vegetation and the vegetation classes.

Figure 15

Map Showing Areas that Changed between 2000 and 2019 within the Different Vegetation Classes

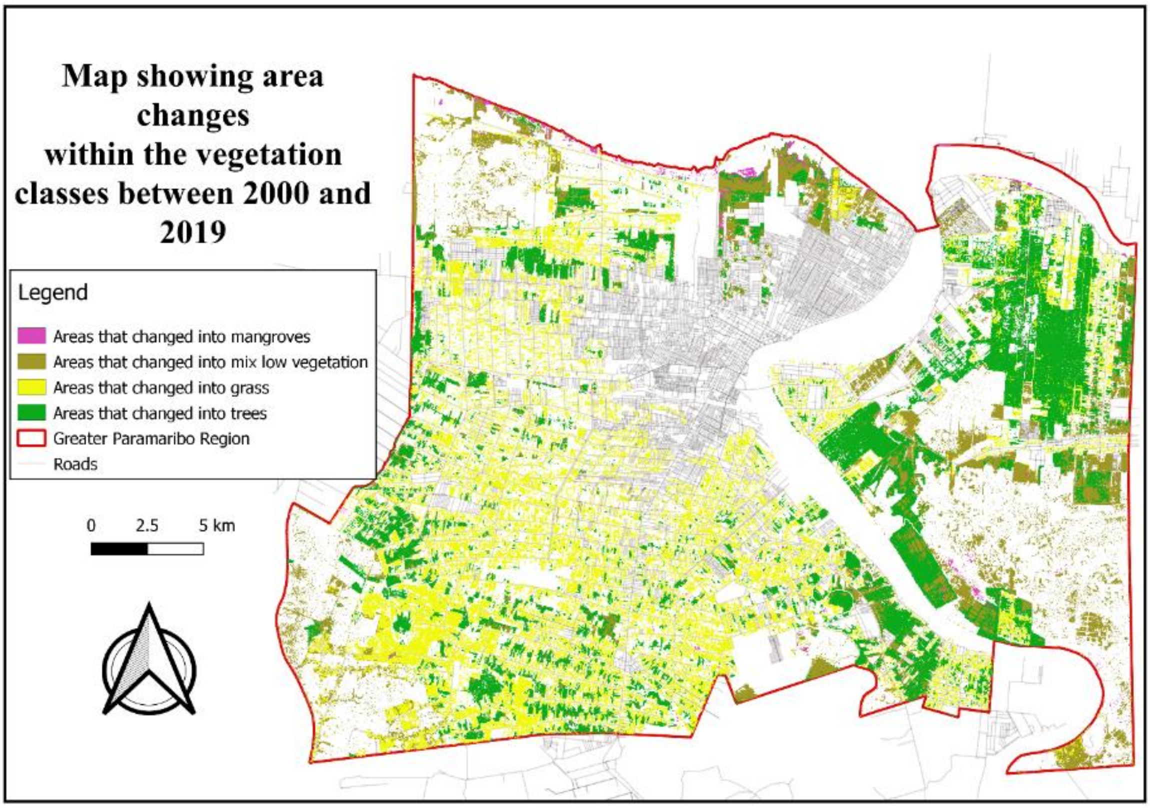


Table 11

Changes in Percentages of Vegetation Classes that Changed into other Vegetation Classes

Class in 2000	**Class in 2019**	**% change**
Trees	Mangroves	0.10
Trees	Mixed Low Vegetation	3.15
Trees	Grass	0.83
Mangroves	Trees	0.04
Mangroves	Mixed Low Vegetation	0.09
Mangroves	Grass	0.03
Mixed Low Vegetation	Trees	5.70
Mixed Low Vegetation	Mangroves	0.16
Mixed Low Vegetation	Grass	13.10
Grass	Trees	6.43
Grass	Mangroves	0.13
Grass	Mixed Low Vegetation	4.08
Total change within the vegetation classes:		**33.86**

Changes that occur from vegetation to non-vegetation can be summarized from the trees, mangroves, mix low vegetation and grass classes to water, built-up, infrastructure and bare soil classes. The total change from vegetation into non-vegetation classes was 3894.51ha (4.51%). (table12). When analyzing these changes it is clear that a lot of the changes occurred alongside the roads network (figure 16). The road network has not substantially expanded into new areas where there is still forest between 2000 and 2019 which could explain the low percentage of change from vegetation type classes to non-vegetation type classes.

Figure 16

Areas that Changed between 2000 and 2019 from the Different Vegetation Classes to the Non-vegetation Classes

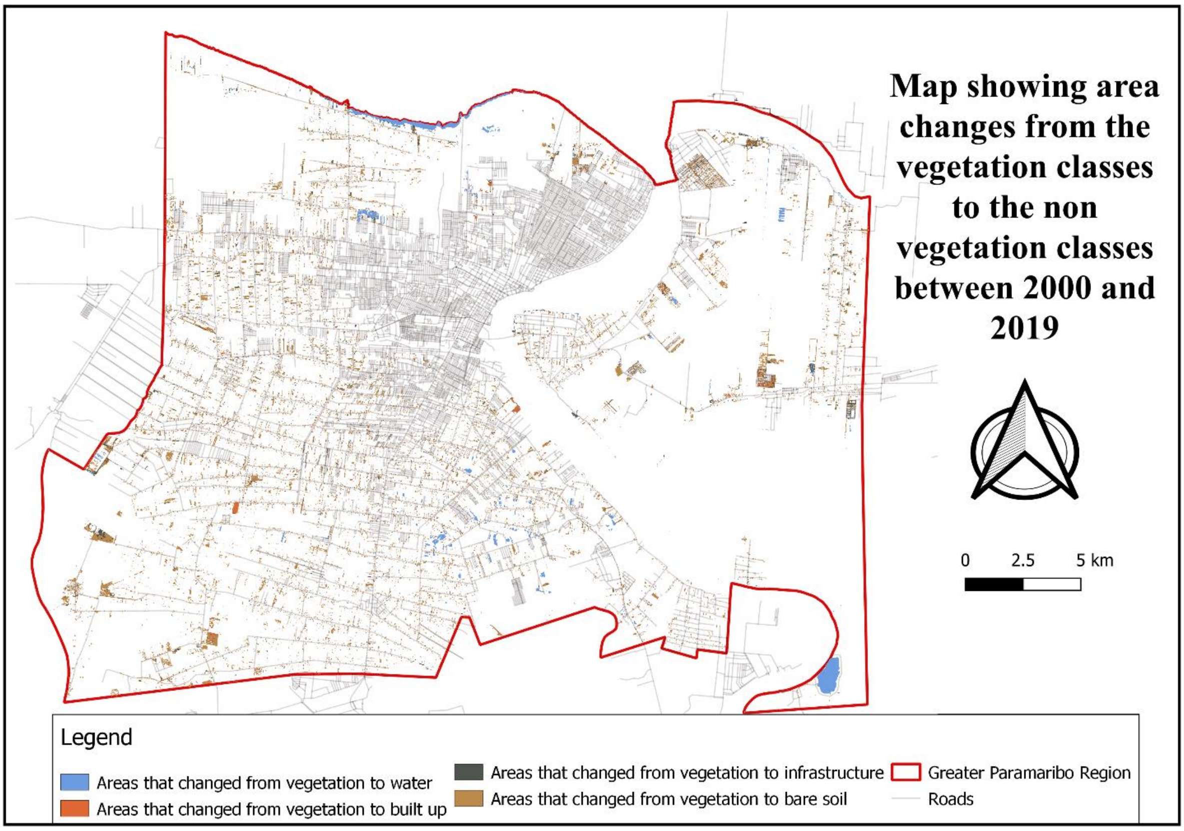


Table 12

Classes that Changed into Non-vegetation Classes between 2000 and 2019

Class in 2000	Class in 2019	% change
Trees	Water	0.15
Trees	Built up	0.01
Trees	Infrastructure	0.05
Trees	Bare soil	0.23
Mangroves	Water	0.02
Mangroves	Built up	0.00
Mangroves	Infrastructure	0.00
Mangroves	Bare soil	0.00
Mixed Low Vegetation	Water	0.30
Mixed Low Vegetation	Built up	0.18
Mixed Low Vegetation	Infrastructure	0.52
Mixed Low Vegetation	Bare soil	2.42
Grass	Water	0.06
Grass	Built up	0.05
Grass	Infrastructure	0.11
Grass	Bare soil	0.39
Total change from the vegetation classes to the non-vegetation classes:		**4.51**

Changes from the non-vegetation type classes to the vegetation type classes cover an area of 10 441.83ha (12.10%) (figure 17). Built up areas that changed into vegetation amount to 7.61% (table 13). One reason can be the economic instability that may have caused people who started building a house, to stop the process due to insufficient funds to complete the project. Once these type of buildings are neglected, grass takes over and grows into mix low vegetation. Changes from the water type class into the non-vegetation type classes between 2000 and 2019 amount to 3.54 % of the change which should not be seen as an exact number because it is highly possible that the waterways are now overgrown with grass and weeds which caused them to be classified as vegetation.

Figure 17

Areas that Changed between 2000 and 2019 from the Different Non-vegetation Classes to the Vegetation Classes

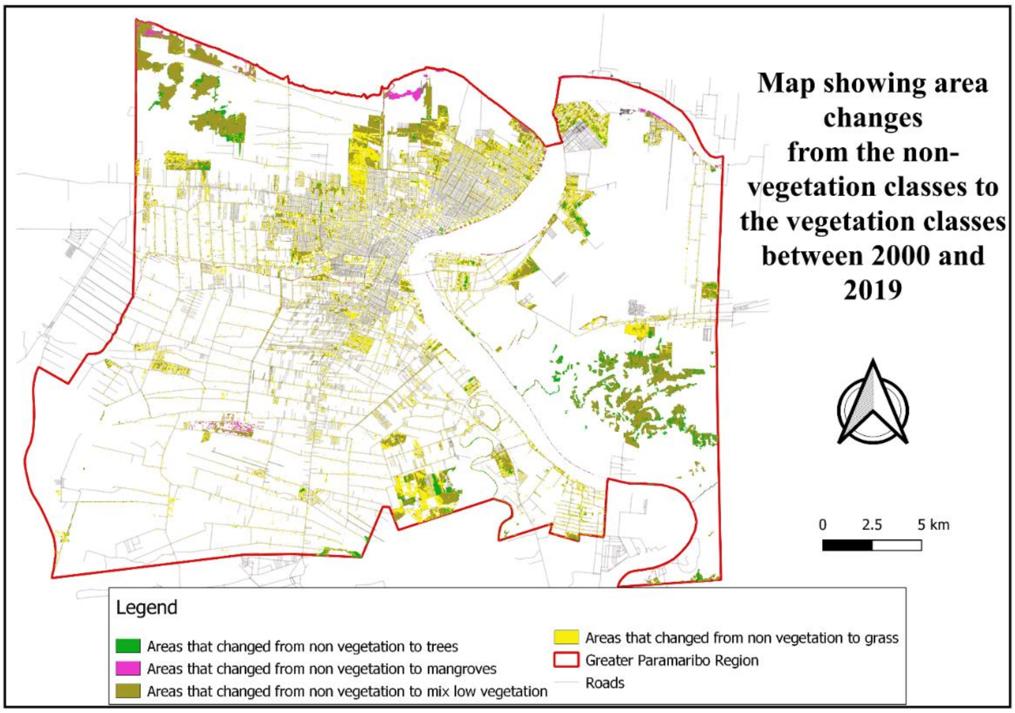


Table 13

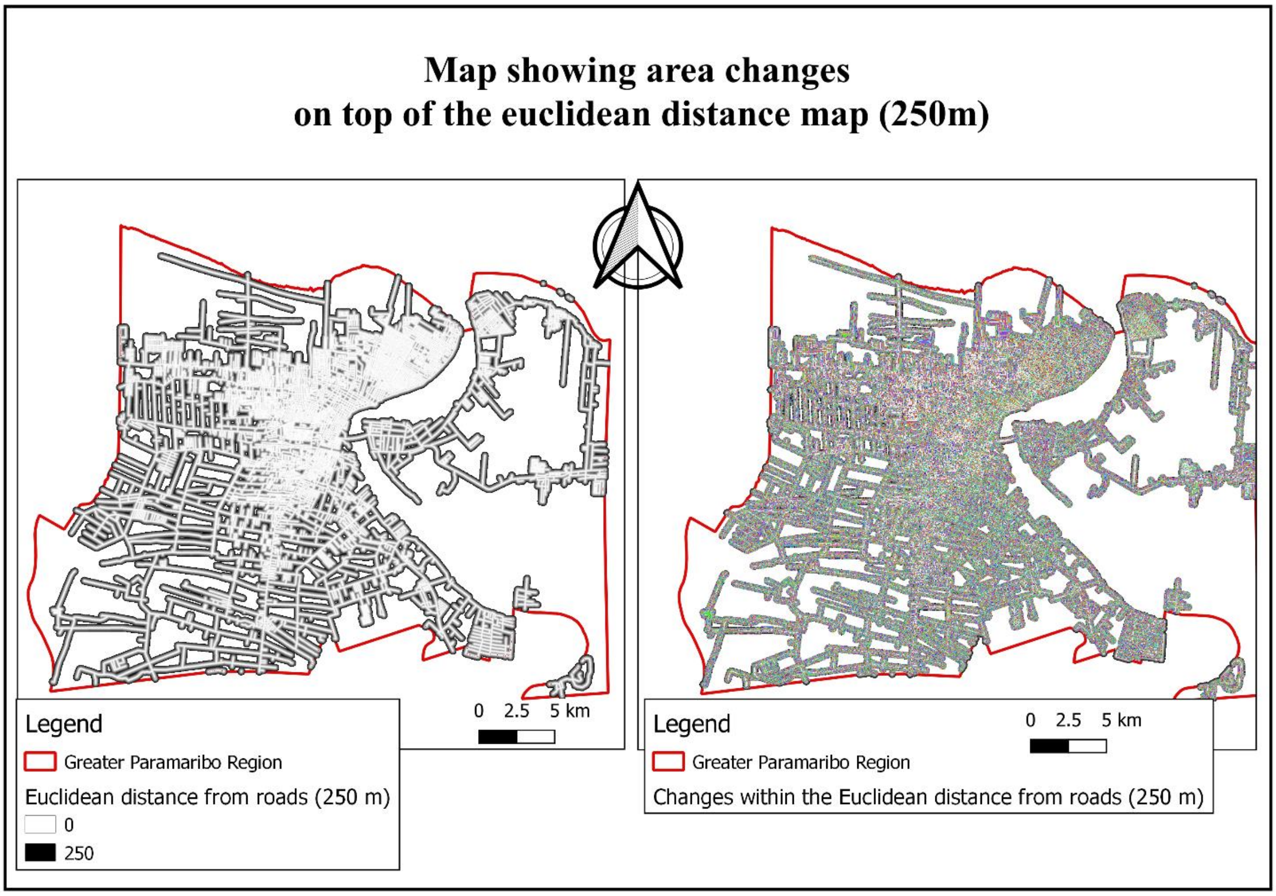
Changes in Percentages of Non-vegetation Classes that Changed into Vegetation Classes between 2000 and 2019

class in 2000	class in 2019	% change
Water	Trees	0.63
Water	Mangroves	0.23
Water	Mix Low Vegetation	2.51
Water	Grass	0.17
Built up	Trees	0.20
Built up	Mangroves	0.05
Built up	Mix Low Vegetation	2.50
Built up	Grass	4.69
Infrastructure	Trees	0.01
Infrastructure	Mangroves	0.00
Infrastructure	Mix Low Vegetation	0.03
Infrastructure	Grass	0.04
Bare Soil	Trees	0.12
Bare Soil	Mangroves	0.05
Bare Soil	Mix Low Vegetation	0.51
Bare Soil	Grass	0.37
Total change from the non-vegetation classes to the vegetation classes:		**12.10**

The Euclidean distance map covers 63 710.74 ha (73.79%) and all changes occurring within the 250 m distance are 40 385.81ha (47%) which is a big part of the total area change of 60.07% (figure 18). A total of only 4.78 % of the trees in the region are within a 250 m distance from a road. Roads are a determining factor in the location of change within the region.

Figure 18

Overview of Vegetation Changes on top of the Euclidean Distance Map to Roads of 250 m



Conclusions and Recommendations

The classified vegetation map for 2019 provides a baseline for the spatial distribution of green spaces within the greater Paramaribo region of which 76.11% is classified as a vegetation type and 23.89% as a non-vegetation type class. Approximately 10.41% can be found in the district of Paramaribo. Which means that 44% of all non-vegetation type classes are located in Paramaribo which consists of only 20.11% of the greater Paramaribo region. This is an indication that the distribution of green spaces within the greater Paramaribo region is uneven and that the capital where the population density is also higher per square meter needs a policy that allows green spaces to be maintained and created instead of removed.

The study also showed that 47% of all changes occurred within 250 m of the roads which indicates that the roads should be monitored on a regular basis in order to identify changes more quickly. The methods used to create the vegetation map can be a valuable tool to monitor urban green spaces in the future considering they are very cost effective. The resolution of 10 m is high enough to see the changes even within the smaller area of Paramaribo. The map that was produced can be used in combination with development maps in order to monitor and regulate the locations of green spaces.

This study can now also be used as a basis for studying the impact that green spaces have on the environment, the people and the different ecosystems in and around the greater Paramaribo region. It is highly recommended to add this to an automatic workflow and create a yearly vegetation map in order to do further and regular monitoring. The resulting percentages on trees from the NDVI map (31%) and the classified vegetation map (25.6%) gives a quick overview on where the trees are and does not require going through the long process of creating training data and ground truthing data. Even though the NDVI map is less accurate, the frequency at which these maps can be created can help the government to monitor the tree type vegetation much better and if there is an indication of deforestation in an area, the SVM classifier can be used to create a more accurate map or new technology such as drone mapping or field observations can be used to evaluate the situation better.

The resulting vegetation map from this study can now also be used to study the effects and impact urban green spaces have on their environment. It is important that the Ministry of Spatial Planning adds the monitoring and development of green spaces to their list of duties in order to create a more balanced environment for people to live in. The map clearly shows an incoherence between green spaces and the center of Paramaribo. Since the government has no funds it would be the perfect open source method to monitor these spaces and link their policies to these maps.

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Annex 1 Software

SNAP

SNAP (Sentinel Application Platform) is the common architecture for all Sentinel Toolboxes. Sentinel-2 data for Suriname is currently only available as Level1C product, which has Top-Of-Atmosphere (TOA) reflectance. To perform an additional atmospheric- , terrain and cirrus correction of these TOA-images towards Bottom-Of-Atmosphere images (Level 2A products), the Sen2Cor tool available in SNAP is used. This processor also generates additional Aerosol Optical Thickness-, Water Vapor-, Scene Classification Maps and Quality indicators for cloud and snow probabilities. As output the format is equivalent to the input: JPEG 2000 images with bands of three different resolutions (60, 20 and 10 m). Within SNAP the generated images of resolution 20m are also resampled to a resolution of 10m, for later operations. SNAP contains also a library of tools for the measurement of vegetation indices, specially adapted to the Sentinel2 images.

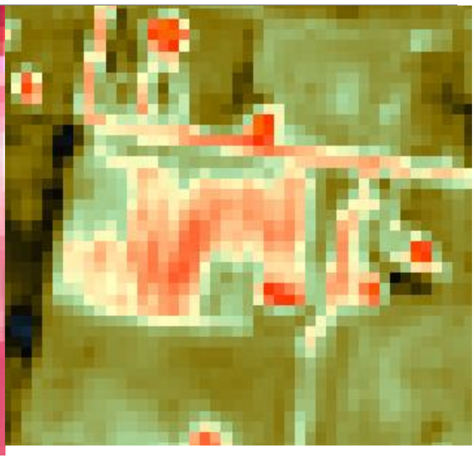
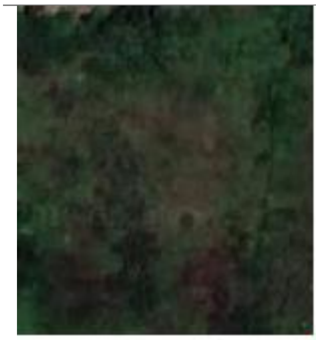
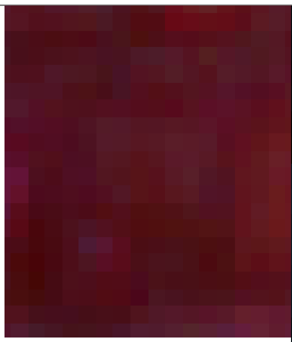
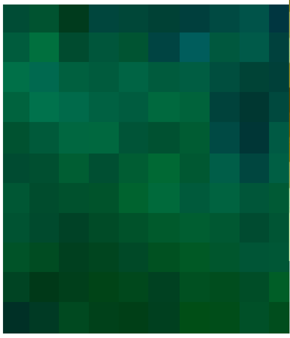
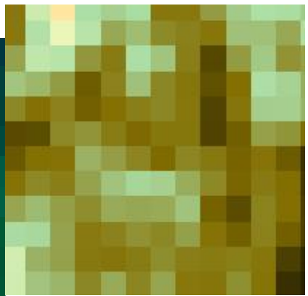
QGIS

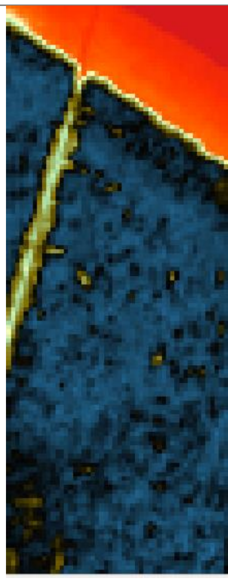
QGIS is an open source Geographical Information System (GIS) application to view, edit and analyse geospatial data, supporting both raster and vector layers. QGIS offers the integration of other open-sources GIS packages such as PostGIS, GDAL, GRASS GIS, Orfeo Toolbox, SAGA GIS and the integration of a python geocode API. Two versions of Qgis are available: QGIS 3.4 (latest and most rich on features) and QGIS 2.8 (Long term release, most stable). Qgis 2.8 is used in the course of this project.

Annex 2 Training data identifiers

Table 14

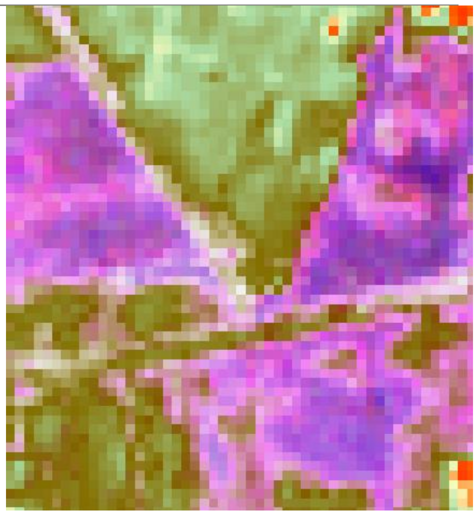
Comparison table of google imagery, Sentinel-2 and the NDVI map

Google	**Sentinel-2**	**NDVI**
 Bare Soil/cropland		
  Mix Low Veg	 Stretched to image  Stretched to local area	 

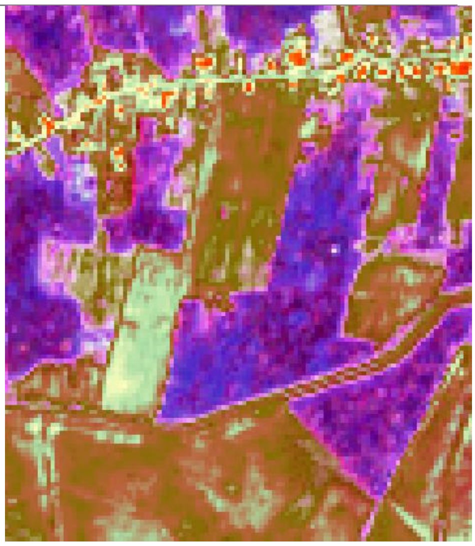


Mangrove

Grass



Different vegetation types overview



Different vegetation types overview

Annex 3 Overview of classification data within 250 m

Table 15

Pixel count per meter of classification within 250 m

Meter	Water	Built up	Trees	Mangrove	Mix low veg	Infrastructure	Grass	Bare soil
10	1564	78302	4391	633	52155	112486	114833	110606
20	1593	60510	5620	592	43362	51163	84821	51829
30	1136	29345	5560	445	33217	26563	55219	30348
	625	26237	1606	216	16628	24806	36514	23640
	651	24169	2577	233	17727	19800	34710	19066
	510	18666	2753	213	15932	15852	29802	15758
	453	10818	2402	222	13304	10094	21998	11153
	601	10871	3528	279	17762	10498	27040	12370
40	1130	14088	6381	519	33054	14624	48984	20866
	510	5583	2751	231	13258	5644	18860	7476
	526	4647	2915	227	13170	4539	18056	6709
	251	1858	1335	81	5483	1885	6965	2618
50	1644	11340	9872	732	44736	11947	57839	19895
	371	1638	1826	185	8445	1753	10963	3308
	543	3146	3165	235	12974	2987	16256	5094
	360	1081	1616	78	5025	1048	5498	1850
	569	2634	3247	244	12959	2568	15691	4700
60	815	4036	5995	437	27554	4712	31463	9583
	373	1173	2008	176	8381	1227	9761	2644
	557	2271	3409	222	12810	2073	14529	4112
	478	930	1994	109	5729	874	5723	1741
	581	1964	3468	224	12638	1962	14021	3843
70	822	2924	6435	466	27069	3483	28393	7972
	802	1563	3809	261	12667	1663	13132	3481
	354	900	2097	96	6279	924	5871	1688
	368	841	2115	181	8126	902	8610	1986
	575	1442	3569	227	12309	1510	12657	3217
	509	660	2170	96	5448	631	4676	1363
80	830	2279	6807	404	26158	2710	25486	6754
	723	1324	4246	272	13666	1417	13058	3305

	372	650	2166	169	7857	669	7789	1786
	438	553	1771	58	4287	455	3674	1026
	493	903	3149	203	10701	1028	10406	2441
	234	253	1174	62	2775	259	2275	557
	595	941	3682	200	11757	1084	11053	2552
90	711	1440	5906	355	21198	1734	19190	4769
	297	333	1605	115	5196	420	4924	1127
	884	991	4337	259	12373	1027	11031	2575
	344	417	2039	87	5338	503	4425	1081
	381	497	2253	190	7260	526	7055	1410
	605	739	3722	227	11072	842	10148	2250
	336	261	1259	61	2857	274	2184	569
100	981	1204	7342	431	22474	1631	19113	4578
	315	266	1590	113	4765	327	4493	973
	395	404	2257	176	6880	461	6450	1376
	366	305	2020	83	4946	406	4034	959
	397	370	2280	186	6726	466	6303	1298
	539	377	2171	90	4461	389	3352	838
	538	452	3153	201	9183	629	8219	1795
	255	134	1184	47	2351	186	1675	449
110	749	812	6082	378	18839	1132	15558	3513
	347	200	1584	93	4471	287	4067	825
	807	575	4254	242	11186	734	9479	2045
	375	229	1288	59	2590	240	1845	452
	662	442	3431	240	8470	564	7357	1547
	406	216	2070	68	4559	317	3546	789
	423	324	2203	168	6305	343	5660	1088
120	799	680	6113	385	17823	966	14360	3162
	905	510	3690	181	8344	575	6542	1405
	361	216	2135	130	5250	284	4162	842
	316	202	1558	102	4365	218	3782	742
	278	106	1169	33	2057	143	1394	353
	396	261	2199	181	6066	323	5355	1001
	411	186	2127	68	4358	262	3194	712
	412	266	2200	168	6038	280	5210	1004
	387	182	1291	65	2381	198	1535	380

	287	105	1211	41	2020	126	1322	332
130	1235	807	8692	547	22778	1108	17681	3860
	540	210	2381	108	5266	262	4096	838
	324	171	1458	101	3989	184	3410	660
	404	236	2187	171	5828	277	4933	927
	429	165	2172	64	4119	236	2922	602
	482	159	1569	80	2764	194	1731	441
	690	312	3333	201	7684	384	6001	1204
	436	164	2186	64	4051	200	2850	601
	415	208	2180	164	5819	242	4698	872
140	681	428	5340	324	13882	642	10266	2331
	261	110	1126	63	2928	121	2458	453
	741	258	2700	177	5972	356	4465	915
	301	87	1219	35	1829	95	1189	279
	708	279	3673	205	8718	392	6631	1259
	278	86	1155	37	1789	104	1097	240
	413	181	2152	149	5610	220	4458	849
	455	122	2209	53	3838	191	2636	525
	959	301	3758	247	8015	389	5933	1173
150	967	445	6379	334	14883	622	10710	2327
	263	91	1125	55	2766	123	2271	377
	321	125	1424	115	3668	152	2934	510
	401	114	2057	94	4190	173	2972	545
	303	84	1328	50	2150	103	1387	297
	303	115	1409	124	3609	145	2920	499
	404	142	2144	170	5335	227	4208	765
	485	111	1222	76	1934	135	1108	288
	307	67	1176	45	1648	90	1035	245
	322	75	1589	41	2845	99	1876	344
	710	224	3303	214	6824	299	5125	945
160	654	311	5099	293	12549	483	9043	1837
	262	69	1111	57	2613	99	2143	357
	764	202	3592	158	6813	249	5007	888
	262	73	1232	79	2648	103	1846	332
	927	208	2930	200	5605	277	4046	759
170	288	68	1154	51	1475	96	919	222

	408	111	2102	173	5088	200	3936	679
	318	64	1565	36	2750	101	1705	322
	285	61	1120	39	1466	77	904	224
180	415	126	2152	159	5009	197	3915	640
	0	328	1413	0	3274	0	2414	391
	0	439	2160	0	3026	0	1893	395
	0	749	2321	0	3746	0	2385	437
	0	683	2270	0	4266	0	3329	0
	0	349	1123	0	1346	0	900	0
	0	422	2146	0	4818	0	3485	561
	0	314	1578	0	2397	0	1551	301
	0	285	1100	0	1306	0	783	162
	0	445	2121	0	4738	0	3494	524
190	0	633	137	0	14029	0	284	7376
	0	265	997	0	1974	0	1684	0
	0	1043	2572	0	4311	0	3109	0
	0	305	1106	0	1244	0	760	162
	0	637	2846	0	5372	0	3684	631
	0	259	1175	0	2282	0	1536	219
	0	718	2431	0	4271	0	3328	0
	0	436	2092	0	4627	0	3230	492
	0	323	1515	0	2296	0	1425	255
	0	286	1046	0	1194	0	716	149
	0	533	933	0	1234	0	0	725
	0	272	805	0	905	0	517	128
	0	516	2117	0	4544	0	3578	0
200	0	662	100	0	12851	0	195	6416
	0	637	2343	0	3801	0	2969	0
	0	613	1988	0	3137	0	2384	0
	0	379		0	1501	0	2703	1882
	0	742	1938	0	3024	0	2098	333
	0		300	0	738	0	786	530
	0	329	1269	0	2732	0	1920	269
210	0		322	0	949	0	1033	685
	0	341	1415	0	1897	0	1193	234
	0	298	1197	0	2033	0	1308	0

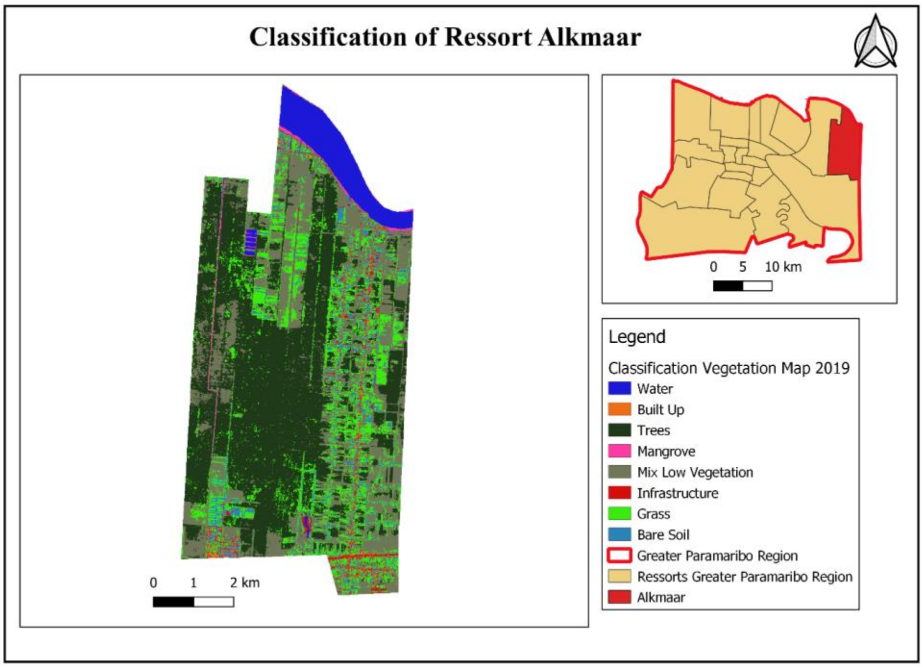
	0	363	1302	0	2666	0	2109	0
	0	325		0	920	0	994	668
	0	528	2072	0	4083	0	2983	0
	0	1025	2724	0	3372	0	2072	427
	0	201		0	697	0	741	495
	0	654	83	0	12299	0	166	5870
	0	545	1579	0	2395	0	1859	0
	0	654	83	0	12299	0	166	5870
	0	545	1579	0	2395	0	1859	0
	0	261	991	0	1907	0	1413	193
220	0	388	1454	0	2612	0	1710	0
	0	558	1907	0	2823	0	1901	345
	0	661	2601	0	4447	0	2895	465
	0	602	2058	0	2837	0	1873	0
	0	328	1250	0	2545	0	1779	248
	0	503	779	0	912	0	623	0
	0	281	665	0	691	0	426	92
	0	860	2929	0	4779	0	3376	0
	0	308	1113	0	1395	0	898	0
	0	193	690	0	974	0	625	0
230	0	651	67	0	11798	0	148	5516
	0	562	1766	0	2412	0	1822	0
	0	626	2372	0	4274	0	2704	398
	0	289	999	0	1750	0	1426	0
	0	330	1352	0	1761	0	1031	206
	0	315	840	0	845	0	583	0
	0	919	2159	0	3405	0	2265	373
	0	286	1101	0	1820	0	1025	170
	0	273	615	0	631	0	381	90
	0	359	1252	0	2354	0	1812	0
	0	303	804	0	827	0	450	130
	0	333	1290	0	1650	0	975	211
	0	630	2325	0	4094	0	2619	394
	0	299	812	0	789	0	453	113
240	0	650	60	0	11321	0	151	4957
	0	240	852	0	1410	0	1176	0

	0	892	2140	0	3339	0	1977	351
	0	518	1468	0	1974	0	1361	251
	0	341	1224	0	1646	0	944	188
	0	441	1499	0	2170	0	1498	259
	0	263	571	0	611	0	330	91
	0	377	1204	0	2228	0	1631	0
	0	289	1091	0	1666	0	971	145
	0	316	754	0	747	0	516	0
	0	375	1220	0	2216	0	1674	0
	0	362	1213	0	1608	0	1020	0
	0	590	1858	0	2389	0	1347	275
	0	378	1217	0	2205	0	1651	0
	0	611	908	0	920	0	634	0
	0	274	602	0	559	0	314	81
250	0	1400	98	0	16231	0	240	6827
Total	57742	389928	412503	19804	1296912	372300	1317326	543963
% of region	0.67	4.52	4.78	0.23	15.02	4.31	15.26	6.3

Annex 4 Maps showing the classification per ressort

Figure 19

Map showing the Classification of Ressort Alkmaar



Note. The Boundaries of Ressort Alkmaar were adjusted to fit within the study area and lies in reality a little further to the east.

Figure 20

Map showing the Classification of Ressort Beekhuizen

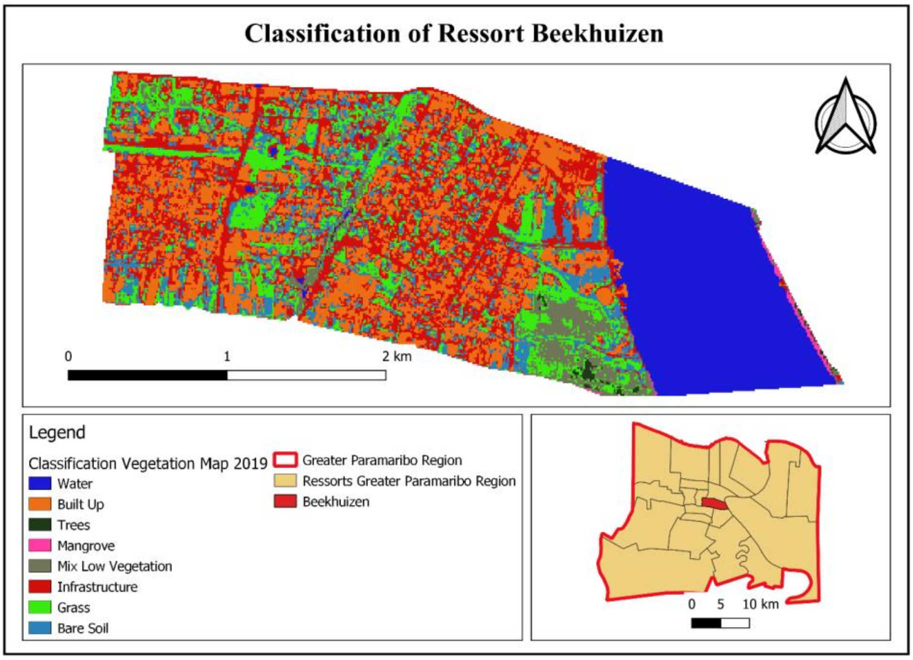


Figure 21

Map showing the Classification of Ressort Blauwgrond

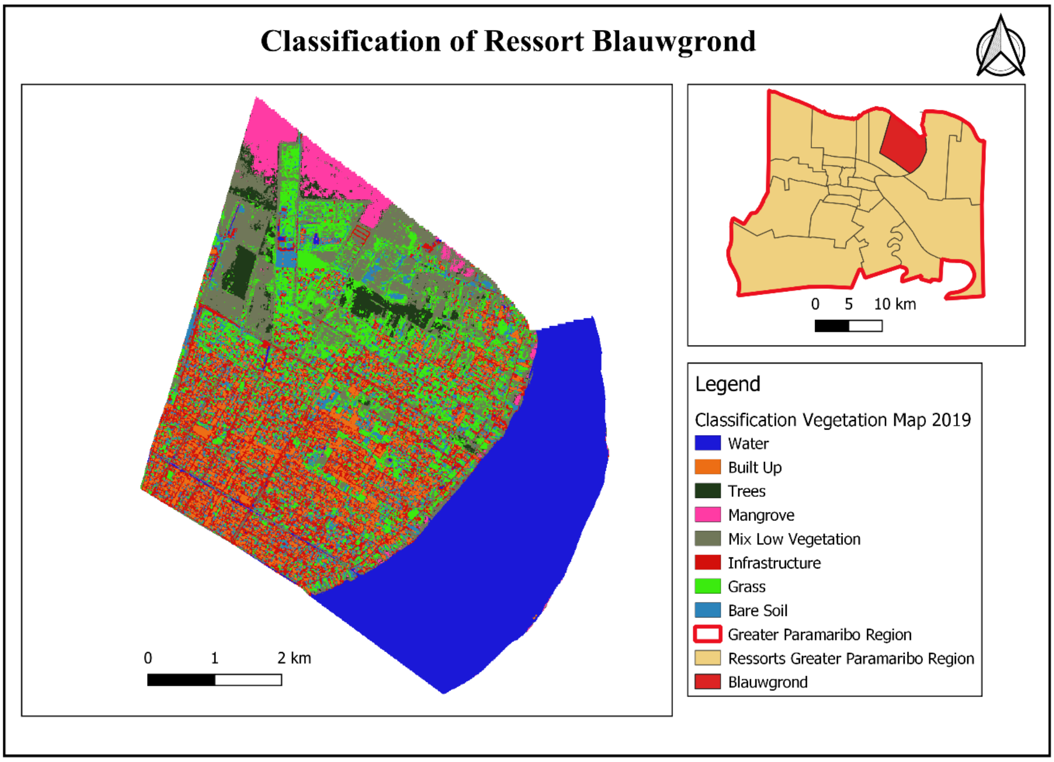


Figure 22

Map showing the Classification of Ressort Centrum

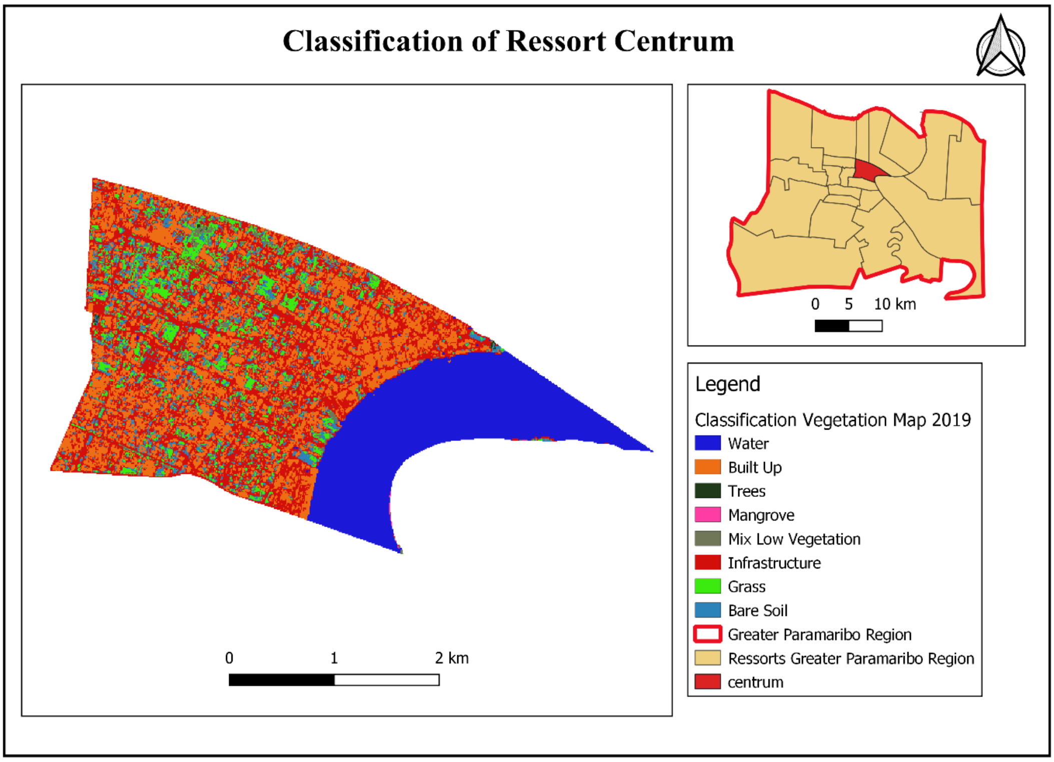


Figure 23

Map showing the Classification of Ressort De Nieuwe Grond

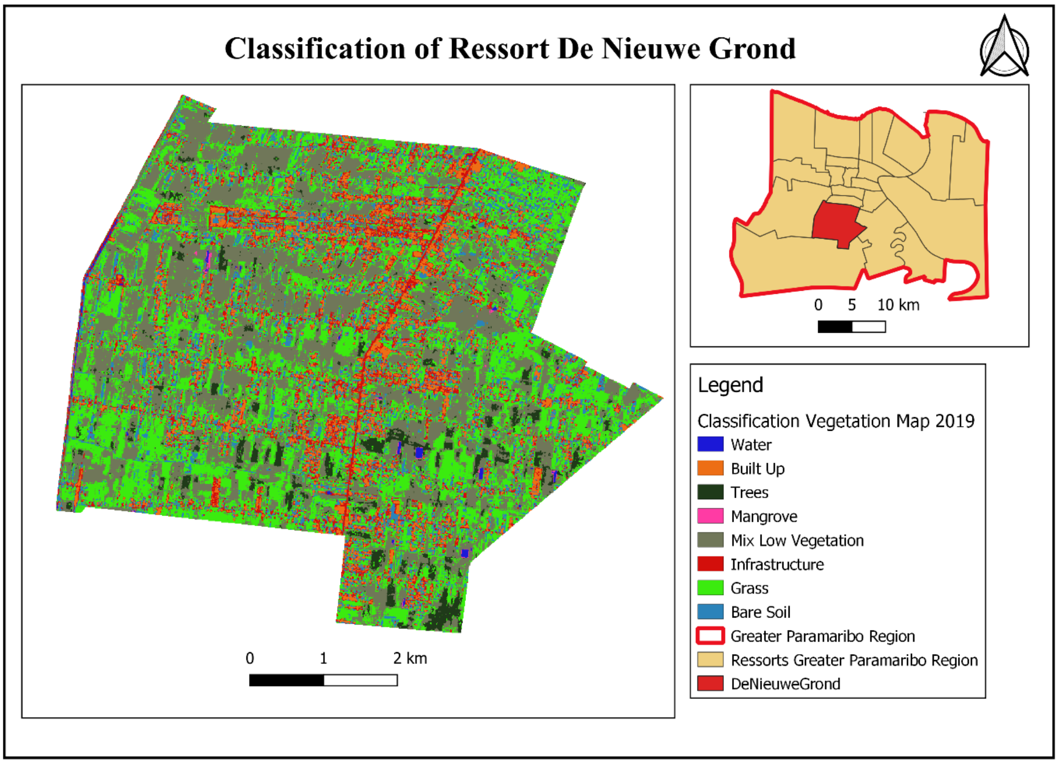


Figure 24

Map showing the Classification of Ressort Domburg

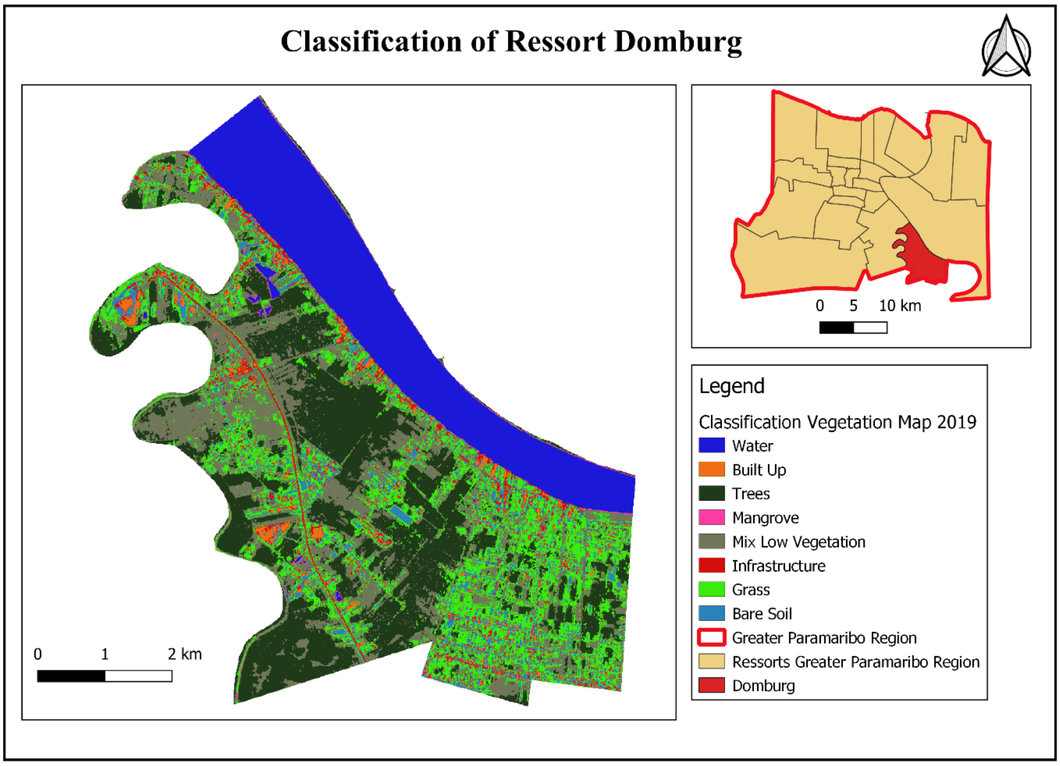


Figure 25

Map showing the Classification of Ressort Flora

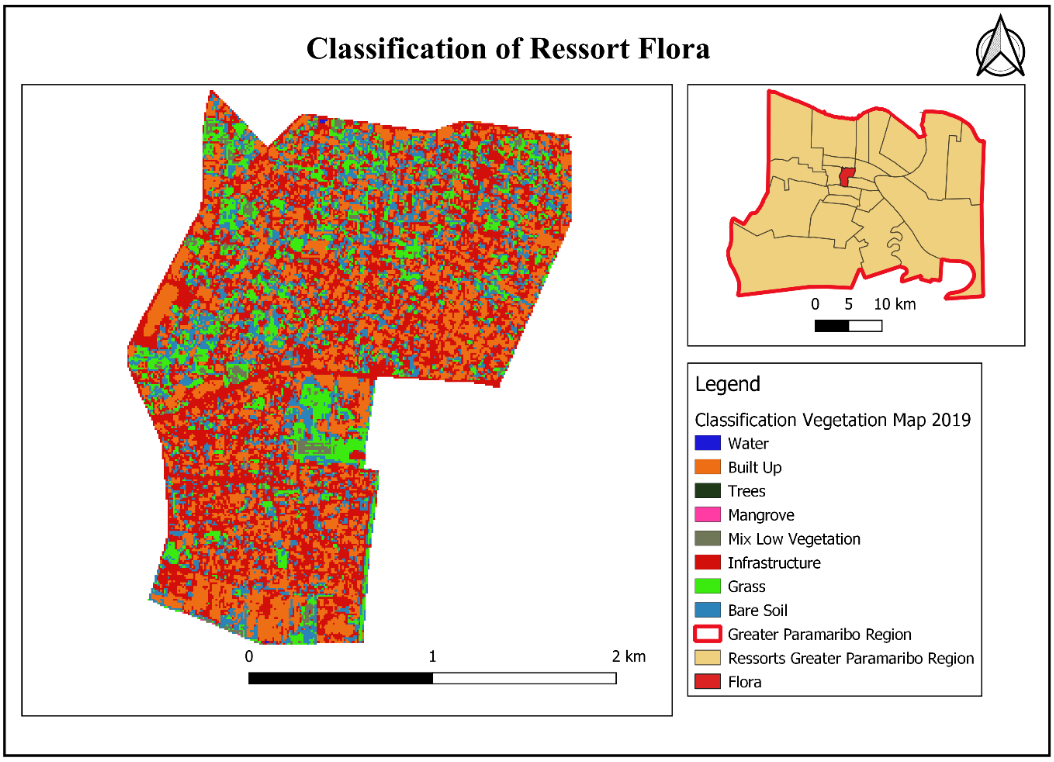


Figure 26

Map showing the Classification of Ressort Houttuin

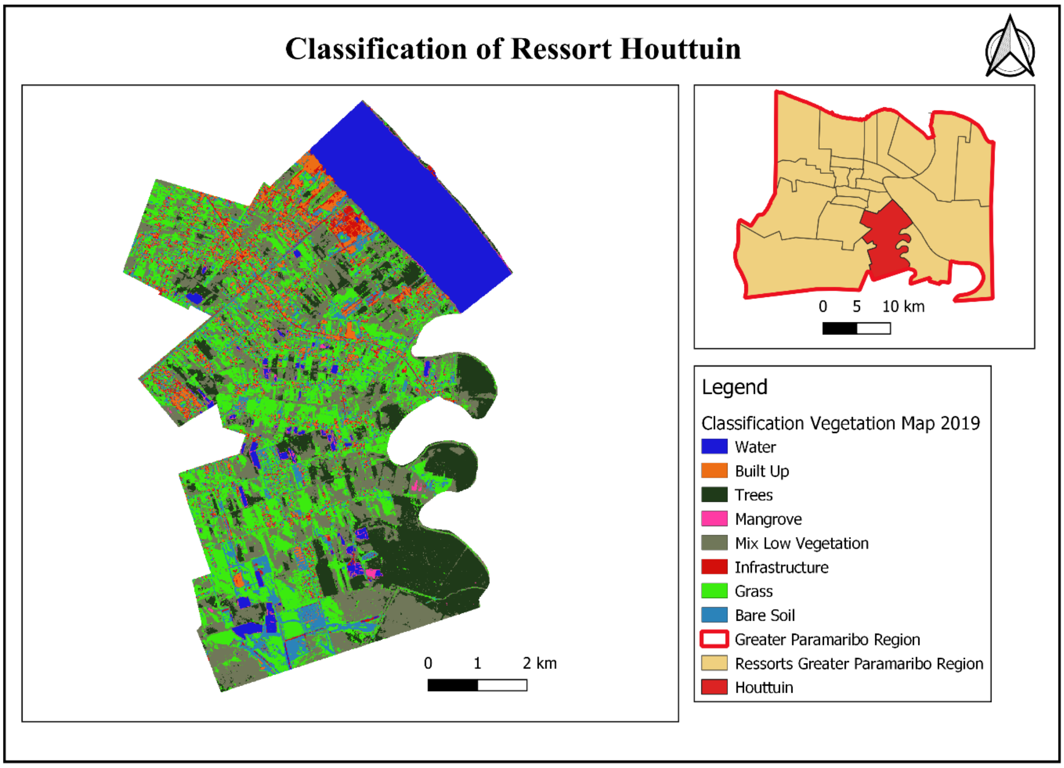


Figure 27

Map showing the Classification of Ressort Koewarasan

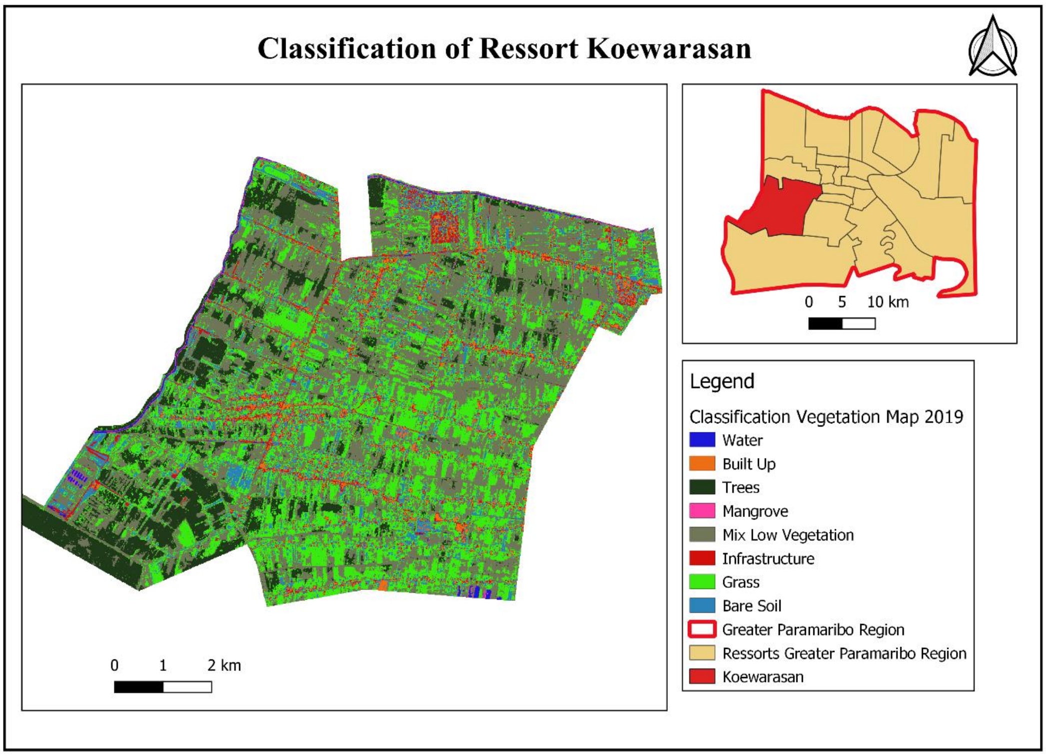


Figure 28

Map showing the Classification of Ressort Kwatta

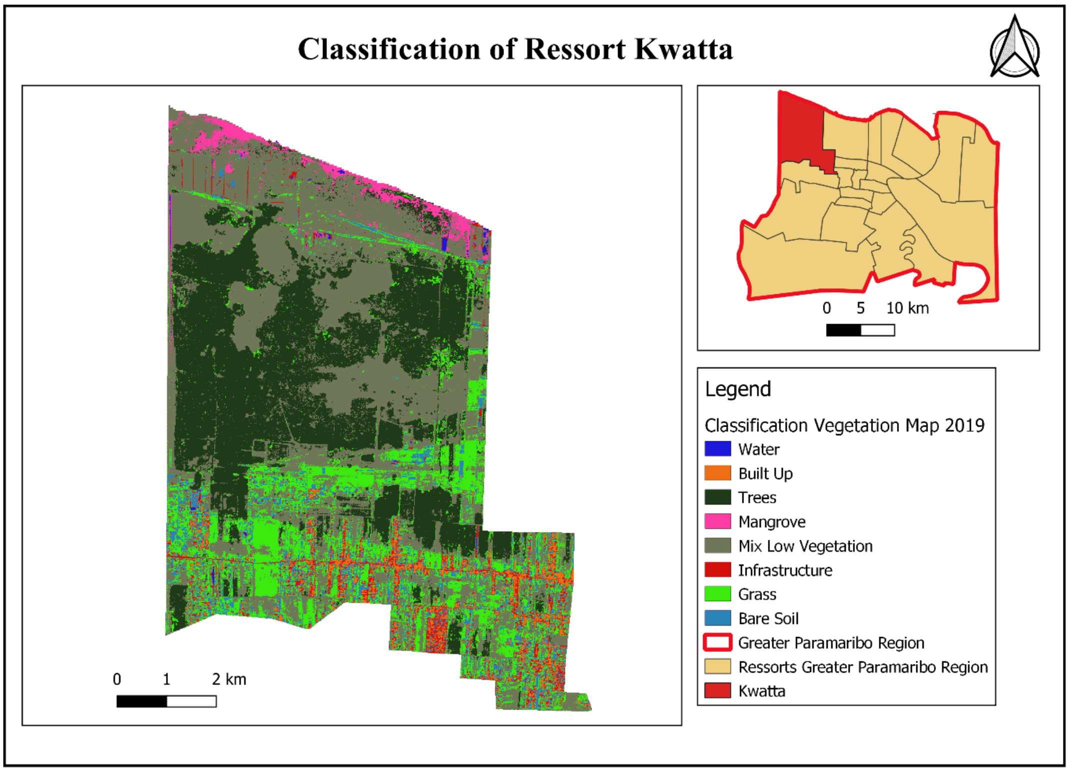


Figure 29

Map showing the Classification of Ressort Latour

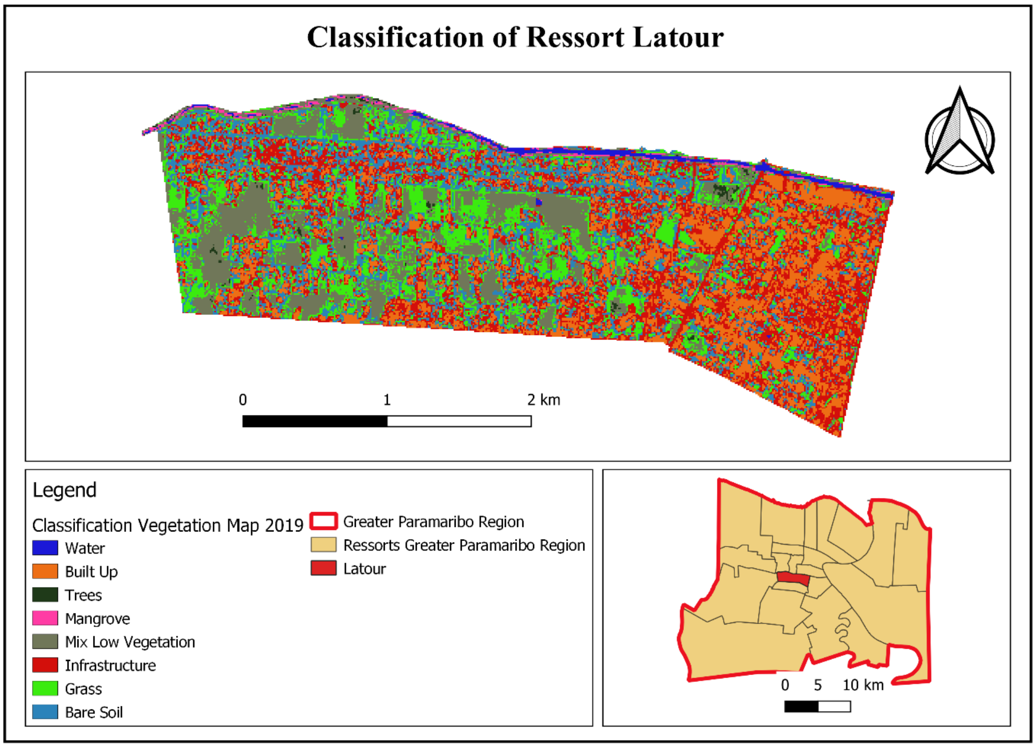


Figure 30

Map showing the Classification of Ressort Lelydorp

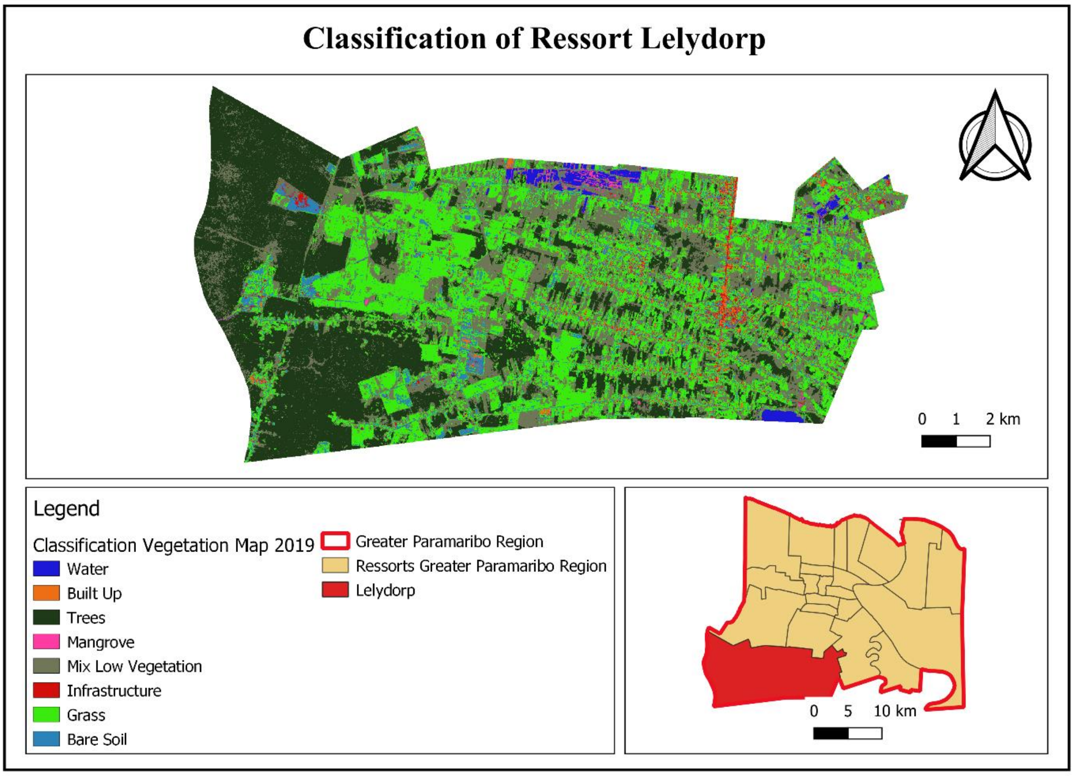


Figure 31

Map showing the Classification of Ressort Livorno

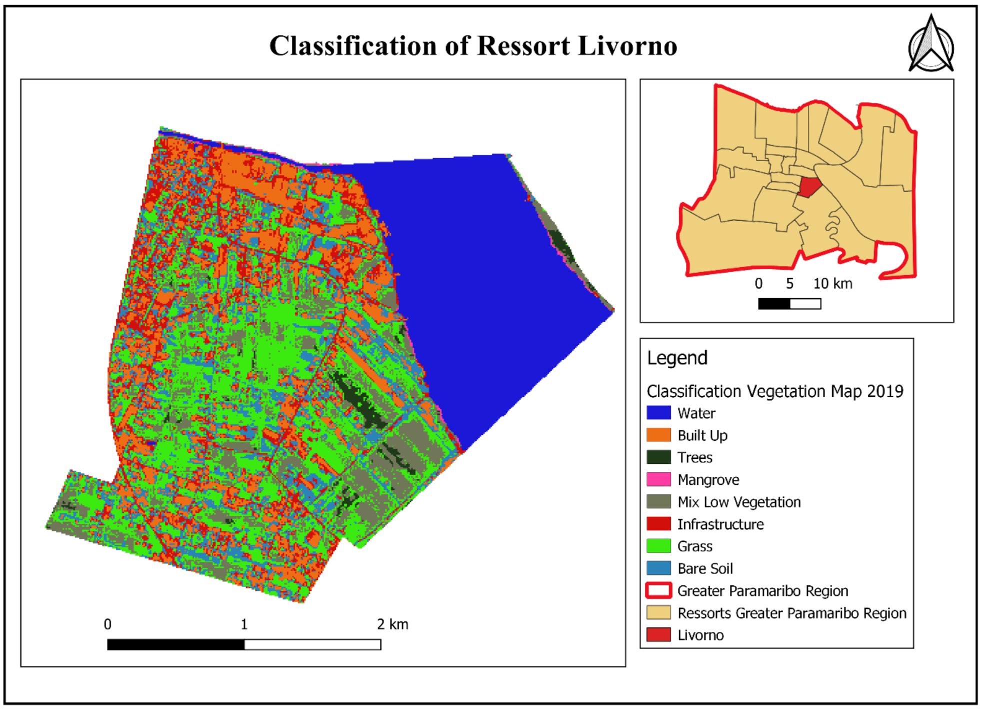
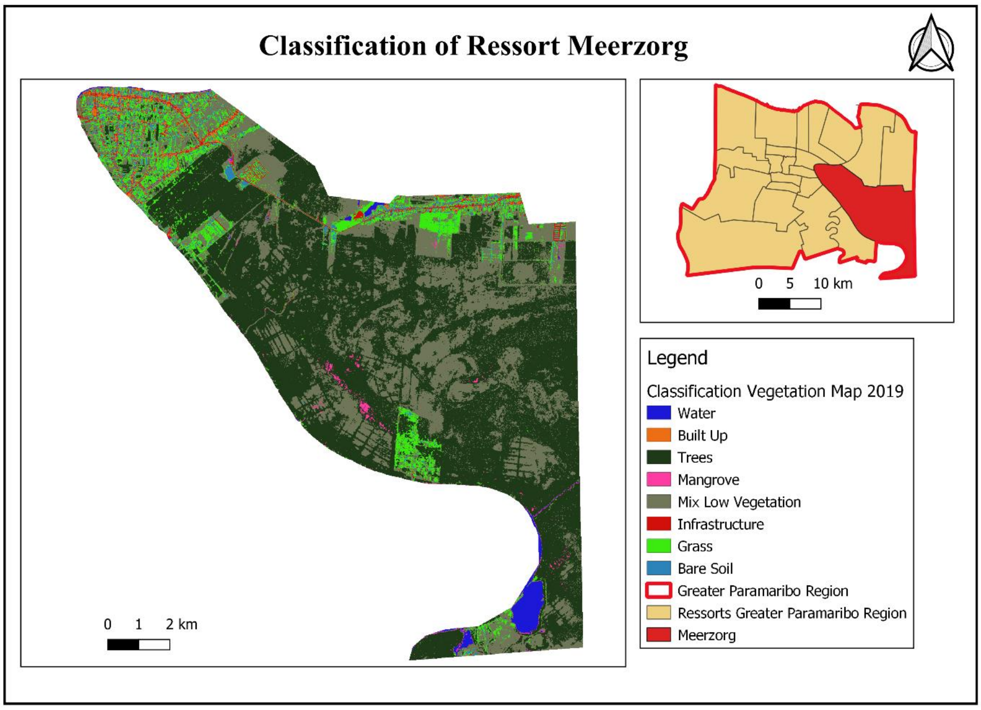


Figure 32

Map showing the Classification of Ressort Meerzorg



Note. The Boundaries of Ressort Meerzorg were adjusted to fit within the study area and lies in reality a little further to the east.

Figure 33

Map showing the Classification of Ressort Munder

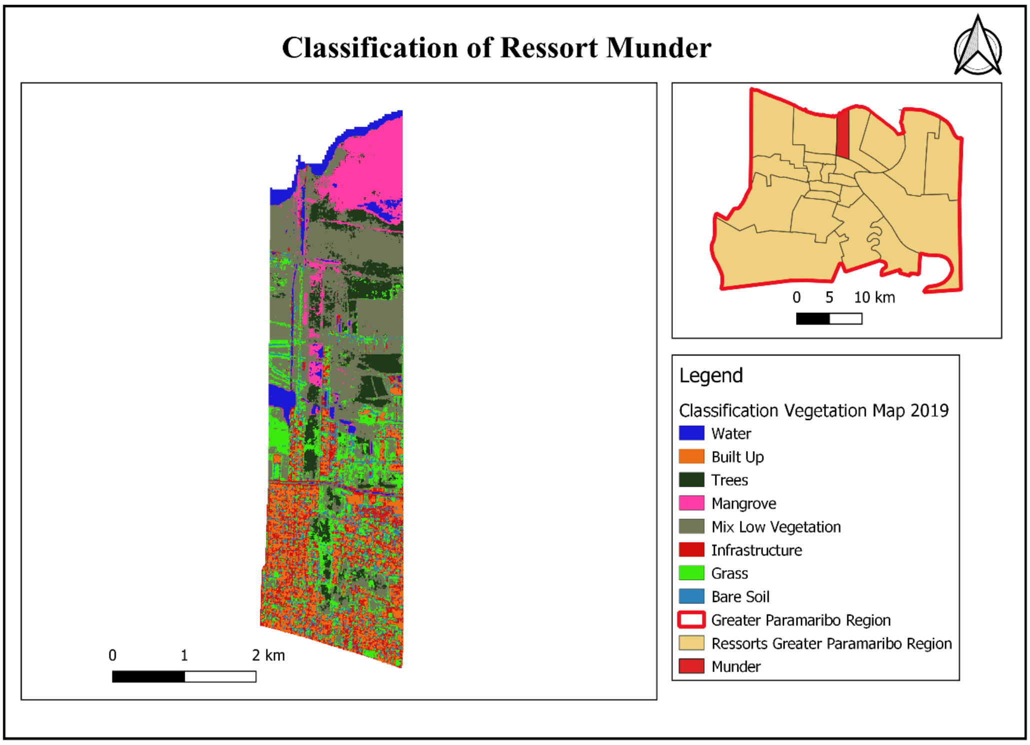


Figure 34

Map showing the Classification of Ressort Nieuw Amsterdam

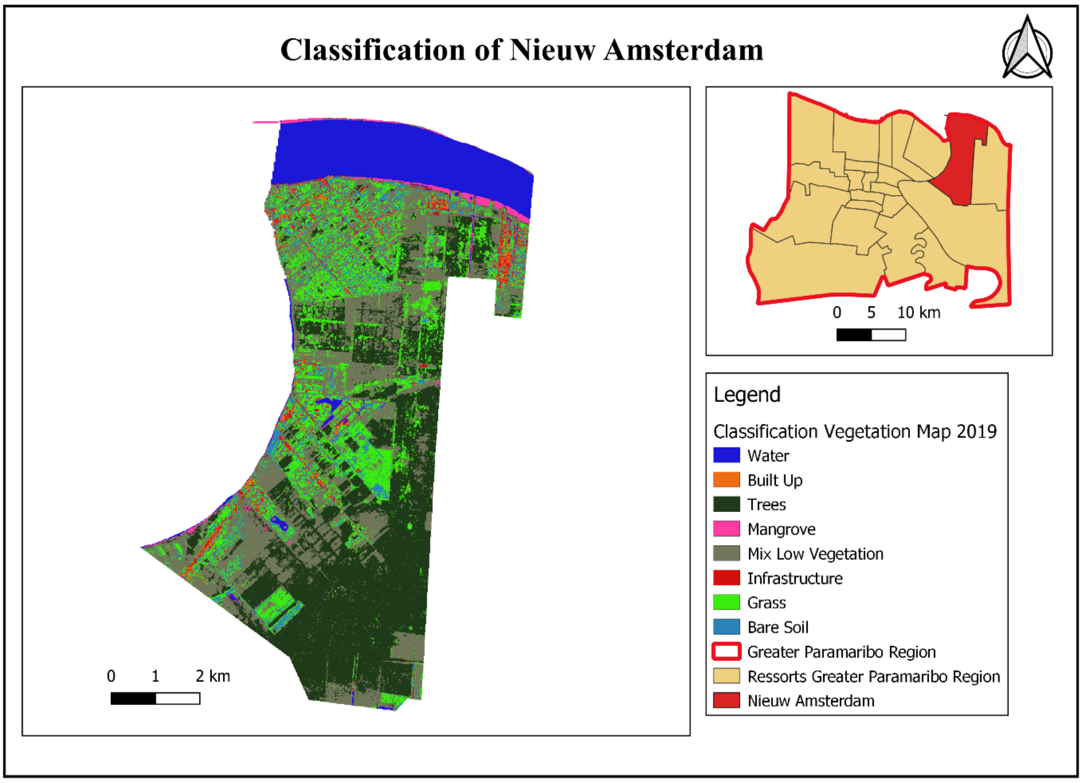


Figure 35

Map showing the Classification of Ressort Pontbuiten

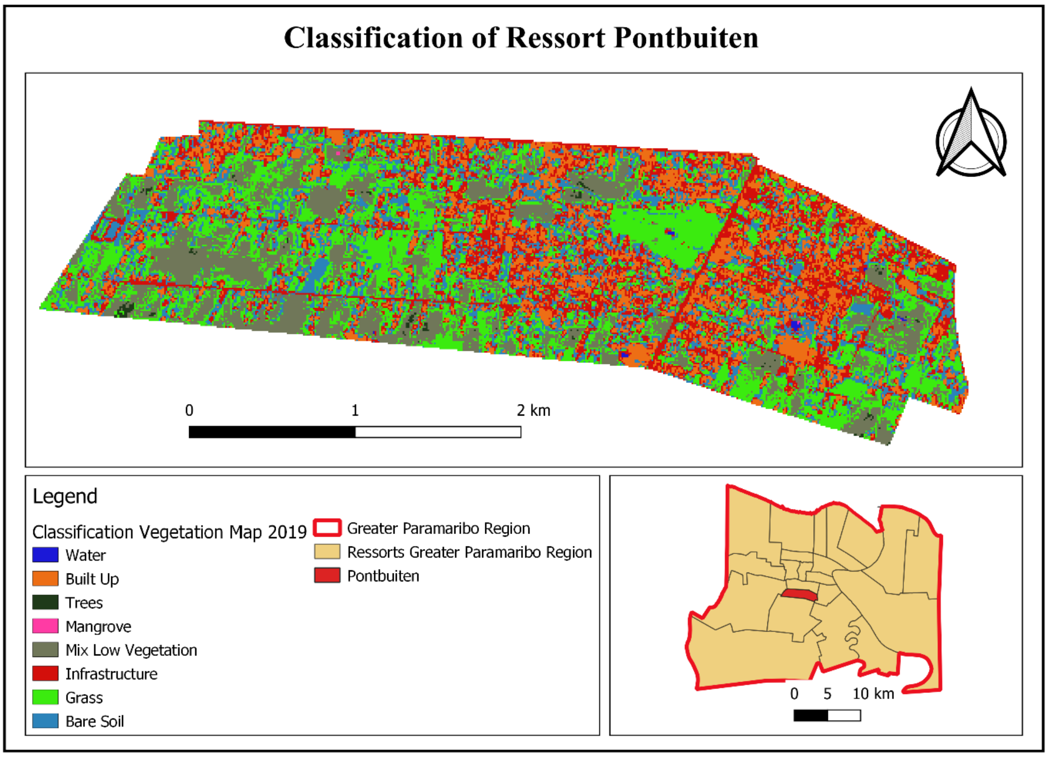


Figure 36

Map showing the Classification of Ressort Rainville

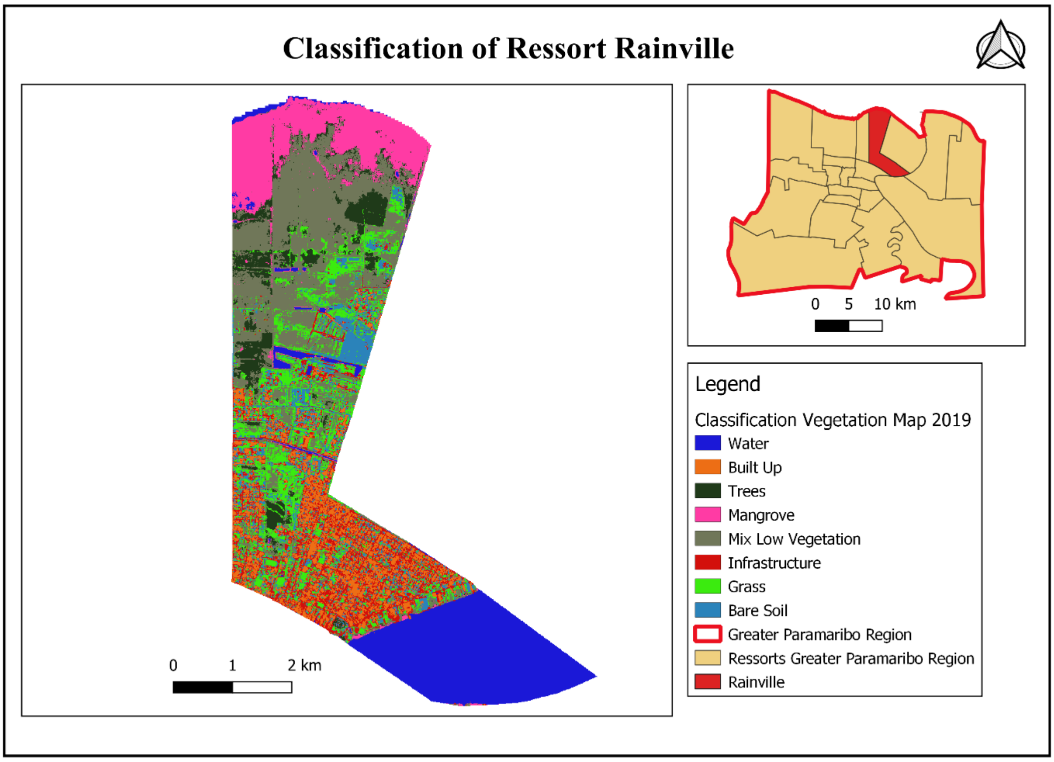


Figure 37

Map showing the Classification of Ressort Saramacca Polder

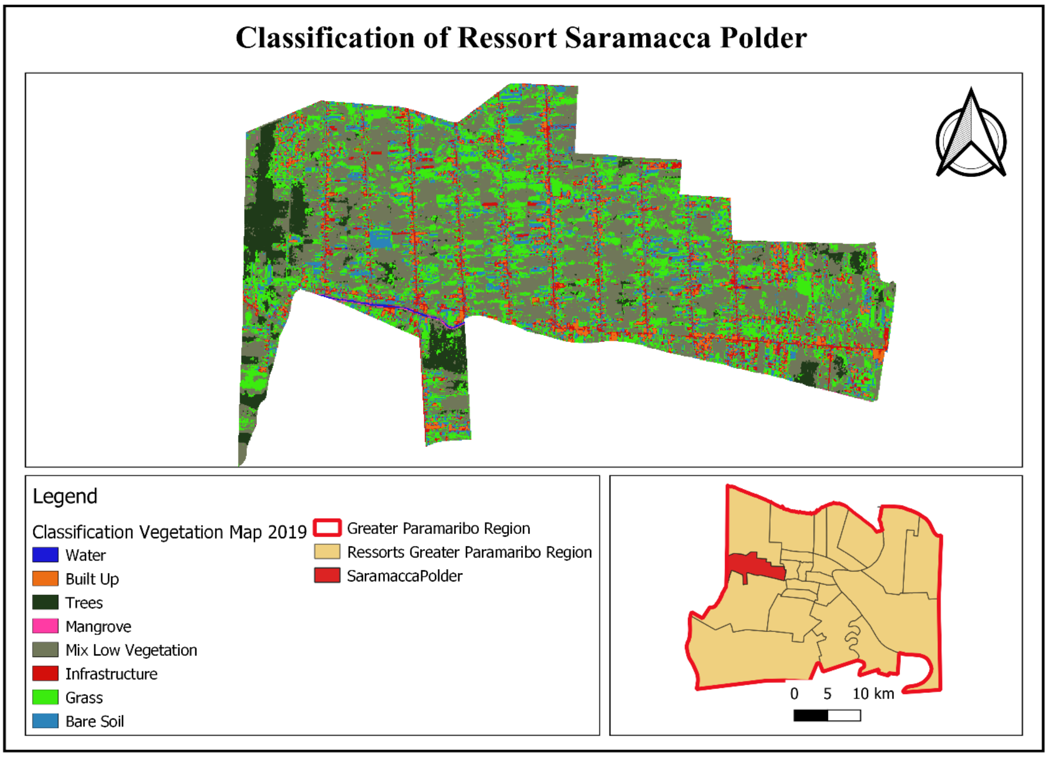


Figure 38

Map showing the Classification of Ressort Tammenga

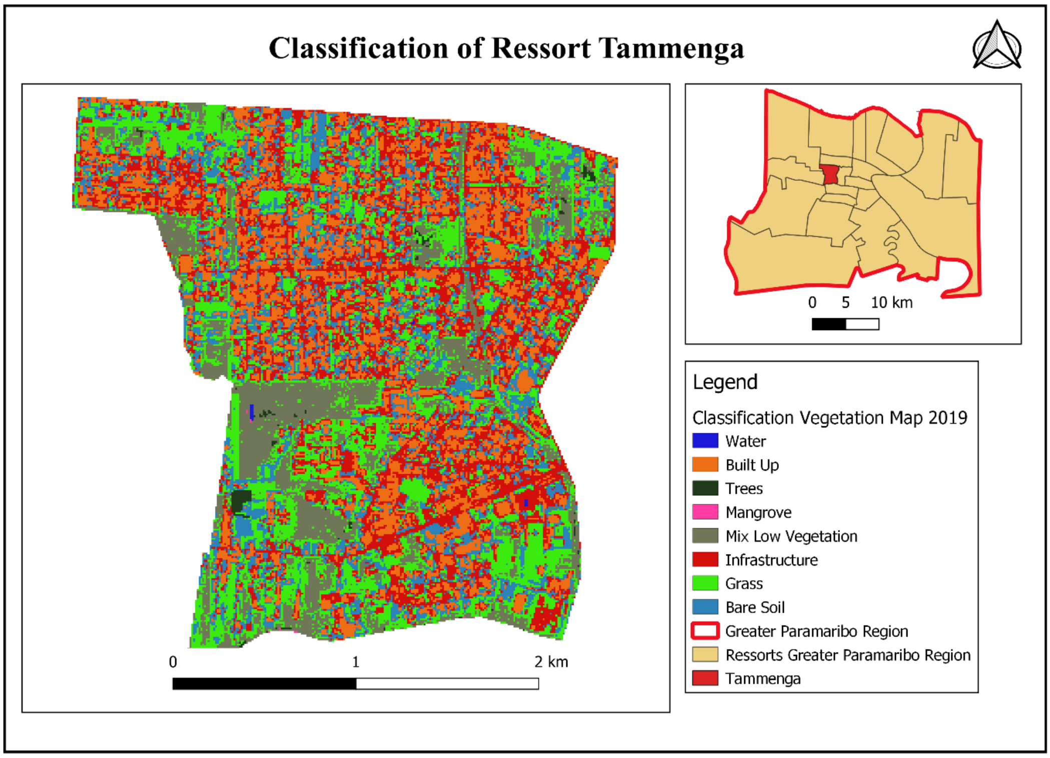


Figure 39

Map showing the Classification of Ressort Weg Naar Zee

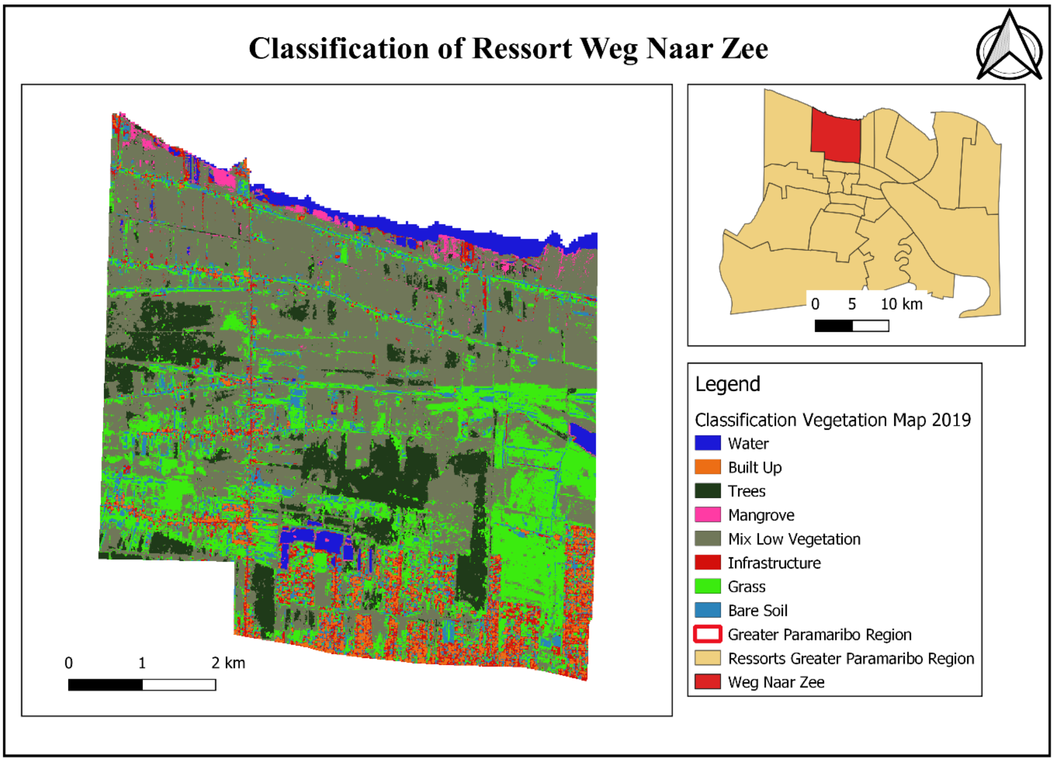
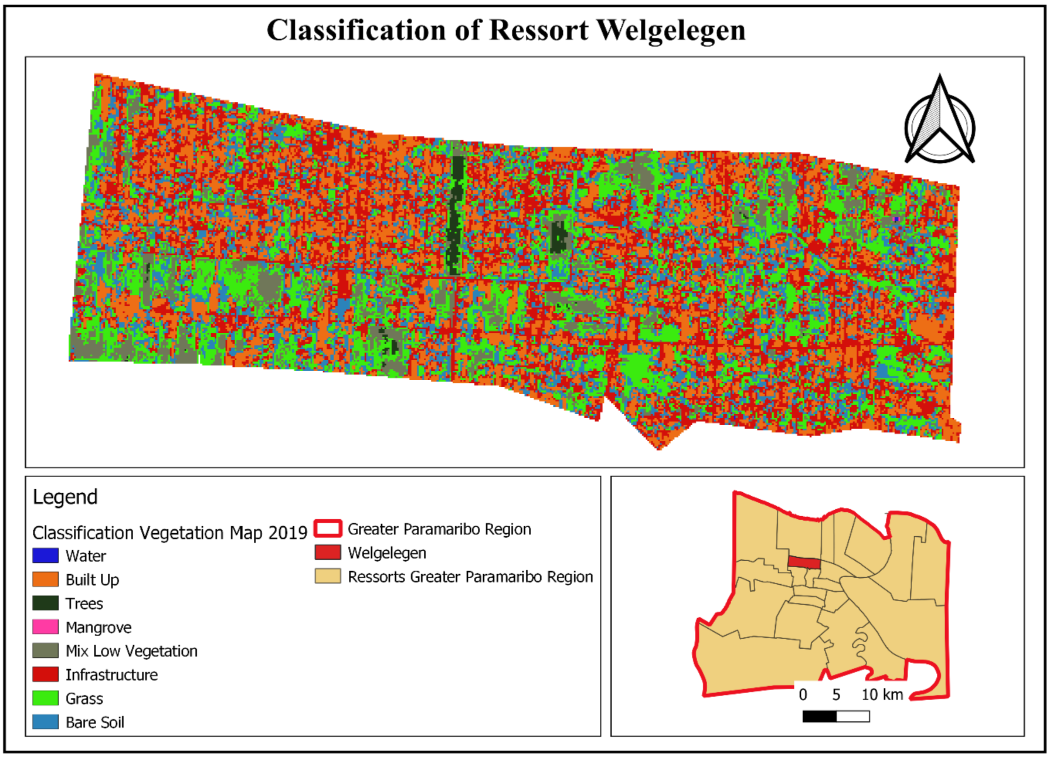


Figure 40

Map showing the Classification of Ressort Welgelegen



Annex 5 Tables showing the classification area per resort

Table 16

Area proportions per class of Ressorts Alkmaar, Beekhuizen, Blauwgrond, Centrum and De Nieuwe Grond

	Alkmaar	**Beekhuizen**	**Blauwgrond**	**Centrum**	**De Nieuwe Grond**
Classes	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**
Water	308.42	135.97	1067.22	233.64	10.66
Built up	55.35	145.41	387.9	272.21	312.14
Trees	2295.89	2.5	108.79	0.65	125.64
Mangrove	33.05	2.4	135.89	0.38	4.13
Mix Low Vegetation	1449.36	34.51	500.28	16.61	1143.54
Infrastructure	109.37	152.04	516.15	300.72	329.8
Grass	849.96	78.46	554.28	70.09	1277.15
Bare Soil	267.96	79.83	390.67	79.12	502.84

Note. These numbers may only serve as estimated area proportions due to the fact that the image was clipped alongside an irregular shaped file (boundaries) and the error is unaccounted for.

Table 17

Area proportions per class of the Classification of Ressorts Domburg, Flora, Houttuin, Koewarasan and Kwatta

	Domburg	**Flora**	**Houttuin**	**Koewarasan**	**Kwatta**
Classes	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**
Water	730.69	0.09	755.4	39.16	14.43
Built up	94.19	130.79	275.14	237.14	191.98
Trees	963.76	0	815.14	992.99	2089.18
Mangrove	13.75	0.04	30.45	25.61	144.2
Mix Low Vegetation	830.47	9.12	1422.69	2700.96	2564.63
Infrastructure	120.92	166.91	250.66	347.83	217.55
Grass	674.97	56.24	1573.32	2213.41	1047.47
Bare Soil	215.98	84.49	579.78	731.01	389.57

Note. These numbers may only serve as estimated area proportions due to the fact that the image was clipped alongside an irregular shaped file (boundaries) and the error is unaccounted for.

Table 18

Area Proportions per Class of the Classification of Ressorts Latour, Lelydorp, Livorno, Meerzorg and Munder

	Latour	**Lelydorp**	**Livorno**	**Meerzorg**	**Munder**
Classes	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**
Water	9.52	189.76	228.62	178.54	60.3
Built up	148.62	246.64	121.85	144.42	144.8
Trees	2.65	4767.54	11.49	7138.17	135.07
Mangrove	5.59	53.72	2.66	70.82	139.4
Mix Low Vegetation	107.58	3886.3	93.9	4025.47	426.78
Infrastructure	171.65	298.83	102.26	217.55	135.35
Grass	127.64	4819.3	210.49	959.04	178.34
Bare Soil	142.99	979.01	116.06	342.91	95.31

Note. These numbers may only serve as estimated area proportions due to the fact that the image was clipped alongside an irregular shaped file (boundaries) and the error is unaccounted for.

Table 19

Area Proportions per Class of the Classification of Ressorts Nieuw Amsterdam, Pontbuiten, Rainville and Saramacca Polder

	Nieuw Amsterdam	**Pontbuiten**	**Rainville**	**Saramacca Polder**
Classes	**area (ha)**	**area (ha)**	**area (ha)**	**area (ha)**
Water	742.09	0.55	503.54	4.52
Built up	88.84	111.81	273.26	117.16
Trees	1869.54	2.1	174.22	169.82
Mangrove	64.9	0.08	321.28	2.78
Mix Low Vegetation	1622.23	116.26	652.32	957.33
Infrastructure	139.79	129.43	264.81	192.75
Grass	946.56	181.53	341.98	676.04
Bare Soil	348.79	119.51	241.44	326.12

Note. These numbers may only serve as estimated area proportions due to the fact that the image was clipped alongside an irregular shaped file (boundaries) and the error is unaccounted for.

Table 20

Area Proportions per Class of the Classification of Ressorts Tammenga, Weg Naar Zee and Welgelegen

	Tammenga	**Weg Naar Zee**	**Welgelegen**
Classes	**area (ha)**	**area (ha)**	**area (ha)**
Water	0.31	127.84	0.13
Built up	133.45	161.51	177.9
Trees	2.81	415.21	5.61
Mangrove	0.13	42.25	0.04
Mix Low Vegetation	83.61	1810.49	51.65
Infrastructure	148.09	192.75	191.68
Grass	146.47	870.51	144.88
Bare Soil	116.6	323.54	137.47

Note. These numbers may only serve as estimated area proportions due to the fact that the image was clipped alongside an irregular shaped file (boundaries) and the error is unaccounted for.