Master’s Thesis – master Sustainable Development

Collaboratively classifying remote sensing imagery for Land Cover maps of Aruba

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Abstract

Land cover changes are vital in shaping ecosystems, impacting food production, carbon sequestration, and essential services. Human-driven land cover alterations rapidly occur worldwide, leading to significant environmental and socio-economic challenges. This thesis focuses on creating land cover maps for Aruba, a small island nation facing environmental pressures from rapid urbanization. Accurate land cover maps can assist policymakers in addressing these challenges by providing essential data for sustainable land management. This study tackles two main challenges to developing these maps: selecting suitable land cover classes and determining the best machine learning classifiers.

The land cover classes were defined using the WorldCover project as a base, and a hierarchical set of land cover classes was created using input from the Aruban Department of Nature and Environment (DNM) to ensure relevance to local conditions. Multiple machine learning classifiers were tested to determine the most accurate methods for classifying Sentinel-2 imagery into these hierarchical land cover classes. The final land cover maps were then used to fill critical knowledge gaps identified by the DNM. These gaps include the need for data on environmental indicators (SDG 15.1.1: forest cover, SDG: 15.3.1 degraded areas, and BGF: A.2 natural area) and the Build with Nature policy, which integrates conservation with infrastructure planning.

The results of this study showed that K-Nearest Neighbours (KNN) was the best-performing classifier for main land cover classes, achieving an accuracy of 70.49%. These land cover maps with the best-performing classifiers are accessible via a Google Earth Engine application, continually supplying information for future policy development and environmental management on the island. The indicator values for the year 2024 were found to be 2.28% for SDG 15.1.1, 16.24% for SDG 15.3.1, and 70.57% for BGF A.2. Furthermore, the land cover maps provided valuable insights for the Build with Nature policy, offering spatial data that supports sustainable infrastructure planning.

Keywords: Land cover classification, Hierarchical classification, landscape ethnoecology, remote sensing, machine learning classification, Sustainable Development Goals, Kunming-Montreal global biodiversity framework

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Preface

In the context of sustainable development, my thesis explores the innovative integration of governmental knowledge with machine learning methods for vegetation monitoring in Aruba. It addresses the critical need for tailored environmental conservation strategies in response to the unique challenges faced by small island ecosystems. This work is situated at the intersection of advanced remote sensing technologies and locally defined vegetation classifications, aiming to enhance the accuracy and relevance of ecological assessments. Through a collaborative approach with local environmental agencies, this research not only contributes to the scientific community but also supports Aruba's sustainable management and conservation efforts.

Contents

Chapter 1 Introduction

Land Cover Changes

Land cover is crucial in shaping food production, carbon sequestration, and a wide range of ecosystem services. Changes in land cover disrupt ecosystems these ecosystems, potentially amplifying human vulnerabilities to climate change, economic instability, and socio-political challenges. These disruptions can reduce the availability of critical resources like clean water, fertile soil, and other essentials that sustain both natural systems and human well-being (Foley et al., 2005; Kasperson et al., 1995). Human activity is changing the land cover of the earth at a dramatic and unprecedented speed (Ruddiman, 2013; Turner & Meyer, 1994). Critical trends in land cover change include a significant decrease in global forest cover, which declined by a net total of 101 million hectares between 2000 and 2020 (Potapov et al., 2022), and the expansion of urban areas by 30 million hectares between 2000 and 2015 (Our World in Data, 2024). To address uncontrolled land cover change and guide environments toward sustainability, the literature suggests that governments should establish clear targets and policies (Li et al., 2020; Pande, 2022). To provide policymakers with relevant and accessible information, land cover classification is a powerful technique.

Land cover classification

In land cover classification, a map is created showing the distribution of land cover classes in an area. These maps can be analysed to learn patterns or sizes of land cover classes, which can ground policy in knowledge about the state of the environment (Szantoi et al., 2020). Historically, such land cover maps were created using ground survey methods, where researchers needed to physically visit sites to evaluate the land cover class of a given location (Manfreda et al., 2018). The advent of remote sensing technologies such as satellites and machine learning based classification methods have made the creation of a land cover map a lot easier and has facilitated analysis on scales previously impossible (Li et al., 2020). These two techniques can be combined to automatically assign all pixels of a satellite image to the appropriate land cover classes (Latham et al., 2002), creating cost-effective land cover maps for potentially enormous areas. This can be performed using data from a wide range of satellites freely available online and the existing implementation of classification methods in tools like Google Earth Engine (Hermosilla et al., 2022). However, two things are of great importance when utilizing land cover classification: which set of land cover classes to use and which classification method to use.

Challenge 1: Choosing a set of land cover classes

Choosing a set of land cover classes can be solved in two ways. One way to determine the land cover classes of a particular area is for the researcher to pick the classes applicable to the research area themselves. A smart way to go about this would be to start with the set of land cover classes used within a global land cover classification project and then determine which of those classes apply to your area, ensuring that all major land cover classes of a research area are included and achieving consistency with other research (Hermosilla et al., 2022). A good starting point then would be the WorldCover project, which classifies the earth's surface into eleven environmental classes (Zanaga et al., 2022). However, if the goal is to yield information directly relevant to policymakers, the land cover classes used should be chosen collaboratively, which is the other way to choose land cover classes. This can be done using methods from Landscape Ethnoecology, the study of how different peoples recognise and categorize their surrounding landscapes (Johnson & Hunn, 2010). By incorporating local knowledge and cultural perspectives, Landscape Ethnoecology allows for the development of land cover classifications that reflect a given area's specific ecological and social realities. Consequently, land cover data generated through these methods can better support regional environmental management, conservation efforts, and sustainable development planning as they align more closely with the values and practices of local populations. The advantages of both methods to determine the set of land cover classes can be achieved by starting with a global set of land cover classes and then utilising local views to subdivide classes recognised as containing subclasses into a hierarchical set of classes. This has not yet been done, which is the first knowledge gap addressed in this thesis.

Challenge two: choosing land cover classification methods

The second challenge relates to selecting a suitable machine learning classification, also named classifier. Ideally, simply the most accurate classifier would be selected, but an essential result regarding classification is that there exists no universally optimal classification method (Maxwell et al., 2018). Different classifiers perform with the highest accuracy for different imagery and sets of land cover classes. This necessitates that multiple classification methods must be tested for every research area and set of environmental classes to find the one best suited to those specific circumstances. Moreover, for a hierarchical set of classes, the situation becomes even more complex because classification needs to be done both into general and subclasses (Gavish et al., 2018). Therefore, it is necessary to carefully evaluate the performance of different classifiers in the hierarchical classes to ensure optimal land cover maps in each new setting.

Case study: Land cover classification in Aruba

A place that can benefit highly from land cover classification is Aruba. Aruba is a small island nation in the Caribbean that faces unique challenges related to land cover due to its limited land area and rapid economic growth driven by tourism (Jurgens et al., 2024). This growth has led to increased urbanisation and significant pressure on the island's natural environments, making the accurate monitoring and management of land cover crucial for sustainable development. However, the Aruban Department of Nature and Environment (DNM), responsible for guiding the island's land cover policies, has encountered severe knowledge gaps in its attempts to accurately assess past and present land cover.

Knowledge gaps of DNM

Reliable land cover data is essential for the DNM to make informed decisions that protect the island’s ecosystems while accommodating sustainable economic development. Land cover maps can fill these gaps by providing the missing information. Specifically, the classified images fill the knowledge gaps in three major ways.

The first way DNM employees viewed this technology could fill knowledge gaps was through the direct utilisation of the resulting land cover maps for aiding in nature inventories, formulation of new nature reserves, and visual inspection of changes in land cover. Nature inventories are done each time a building permit is issued and involve DNM employees physically visiting a site to collect environmental data. This could be supplemented by the land cover classes present within the building permit area since if these classes are of environmental importance, they could be relevant to whether the permit is issued. Land cover maps can also help DNM plan new nature reserves by highlighting areas where specific land cover types are abundant enough to justify on-site evaluation. Finally, they could potentially identify land cover changes by comparing past and current land cover maps. This could be followed by investigating the causes of these changes, which could then inform new policies to mitigate these causes.

Secondly was through currently missing indicators for global environmental frameworks. These indicators were desired to align their local environmental policy efforts with global targets (Estoque, 2020; Timmermans & Kissling, 2023). Currently, some Sustainable Development Goals indicators are already monitored (DNM, n.d.-b), but the following were perceived as missing and desired. SDG indicator 15.1.1: forest cover, which is currently obtained by deskwork done by FAO using only data from a global inventory of mangroves from 1992. This is incorrect since this only contains a very specific instance of forests on Aruba (using an outdated estimate) and overlooks the ecosystems aligning with the FAO definition of forest (FAO, 2020). Data on SDG indicator 15.3.1: degraded areas is currently missing entirely, but was desired since it could aid by providing a justification for nature restoration of degraded areas. Finally, while the BGF indicators are not currently monitored, there is a desire to begin tracking them, with land cover maps being deemed suitable for monitoring BGF A.2: natural areas.

Finally, the land cover maps could aid by providing supporting data for the Build with Nature policy, a domestic policy that focuses on integrating nature conservation into infrastructure development and spatial planning. The policy contains a map that divides the island's area into disjunct categories. Land cover maps could yield information supporting this policy by providing a current estimate for the area of every land cover class within each of these categories. This could then help by setting targets for the land cover classes for the categories, seeing whether these targets are currently met and, if not, taking measures to achieve the targets.

Addressing the identified knowledge gaps

Within this thesis, all of the above challenges will be addressed. This will be done in two parts. The first component consists of finding land cover maps for Aruba. For this, a hierarchical set of classes matching the views of DNM of the environment will be developed starting from the general WorldCover classes. This combines the strength of using a global set of land cover classes and incorporating the needs of policymakers, thus addressing the first knowledge gap outlined above. After this, since there exists no optimal classifier, multiple machine learning methods will be evaluated to classify Sentinel-2 imagery into these land cover classes. The best-performing methods will be used to compute the desired land cover maps. In the second component, these land cover maps will be used to fill the identified knowledge gaps in DNM. In doing so, this research contributes to global research on Landscape ethnoecology and land cover classification and yields information immediately relevant to the DNM, aiding in mitigating land cover change.

In order to gather necessary quantitative data from the island of Aruba, and the qualitative data from the DNM, part of this research was performed on the island and during an internship at the DNM. This internship took place from February 2024 until April 2024 in San Nicolas, Aruba.

Research aims

Matching the two parts outlined above, the aim of this research is also twofold. The first aim is to **develop land cover maps for Aruba incorporating classes recognised by the DNM**. The second aim is to **use the land cover maps to obtain land cover information desired by the DNM.**

Research questions

To structure this analysis, the following research question needs to be answered:

What are current and past land cover maps of the island of Aruba? [RQ1]

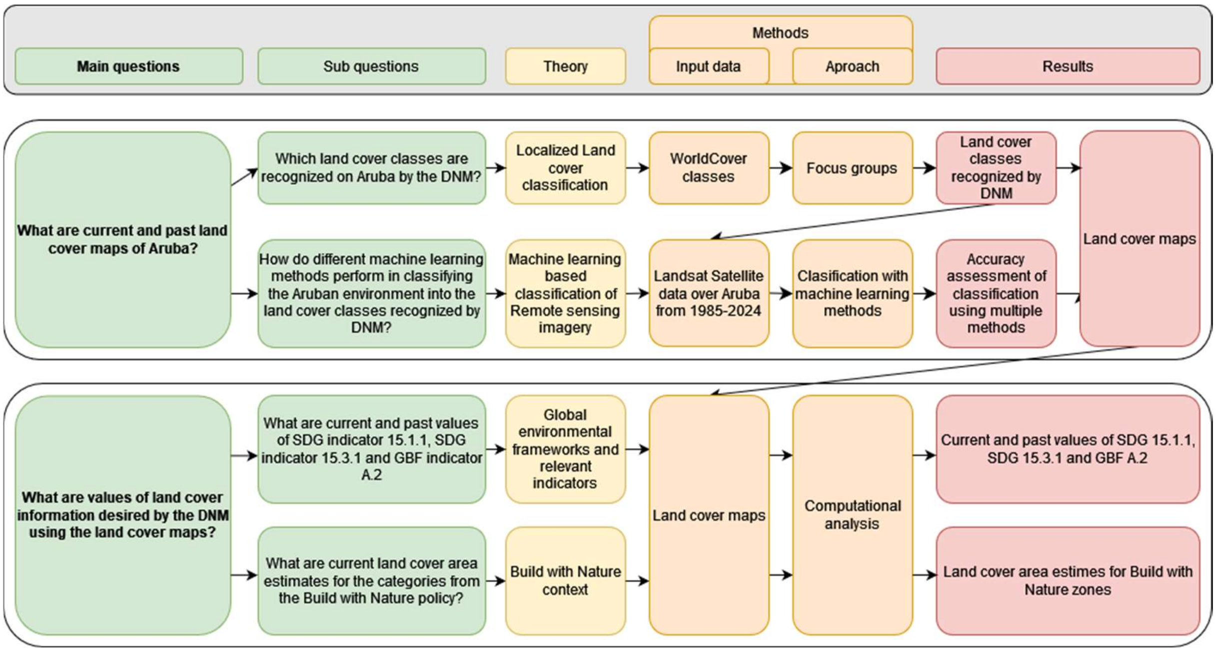
a) **Which land cover classes are recognized as occurring on Aruba by the DNM? [RQ1.1]**

b) **How do different machine learning methods perform in classifying satellite imagery of the current and past Aruban environment into the land cover classes recognised by the DNM? [RQ1.2]**

2) **What are the values of land cover information desired by the DNM using the land cover maps? [RQ2] Specifically, what are …**
   a) **… current and historical indicators for SDG 15.1.1, SDG 15.3.1 and GBF A.2; [RQ2.1]**
   b) **… current land cover area estimates for the categories from the Build with Nature policy? [RQ2.2]**

The rest of this thesis is organised in such a way as to answer the research questions. Given that each of the research questions requires different things, most sections are split into multiple parts, where each part focuses on one of the research questions. Here, within each chapter, section 1 (so 2.1, 3.1 etc.) means that the section relates to RQ1. Similarly, subsection 1 of section 1 (so 2.1.1, 3.1.1 etc.) shows that the subsection refers to RQ1.1, and similarly for all other Research questions. For an overview of this thesis, see **Figure 1**.

Figure 1. Analytical framework of this thesis.



Note: For every research question, a separate theory, methodology, results section and conclusion section are written. There are connections between the components though, the recognized land cover classes are utilised to classify Aruba into the land cover maps, and the land cover maps are utilised to compute desired land cover information.

Chapter 2 starts with the necessary Theoretical Background. In this chapter, the relevant theories of land cover classification, machine learning and the different information desired by DNM are detailed. This section will give the reader the necessary background to understand what is to follow. Chapter 3 is the Method section, this section is again split into multiple components. Each section contains the experimental setup and data used to answer one research question. In Chapter 4 , results of the experiments can be found. In Chapter 5 , a discussion is held regarding the different components of this research, land cover classification, machine learning and obtained land cover information. Finally, my research question will be answered in Chapter 6 , Conclusion, where policy implications of my research will also be given.

Chapter 2 Theoretical Background

This chapter presents the theoretical background and concepts used in this scientific research. The first section explores the underlying theory to find land cover maps. This is split in one subsection focussed on finding a suitable set of land cover classes, and a second subsection which provides a background on machine learning based classification of remote sensing imagery. The second section gives theory regarding the information computed from the land cover maps, specifically SDG and BGF indicators, and the Build with Nature policy.

Section 2.1) Land cover maps

Subsection 2.1.1) Suitable sets of land cover classes

The following concepts are explained to prove a background on sets of land cover classes: land cover class, land cover classification system, hierarchical land cover classification system and landscape ethnoecology.

The core concept underlying this question is that of a **land cover class.** A land cover class is a category used to describe and classify the physical material present on the surface of the Earth. Examples include water bodies, trees and shrubland.

Land cover classes are used in environmental studies, geography, remote sensing, and land management to systematically categorise different types of land surfaces based on their characteristics and usage (Di Gregorio & Jansen, 1998). This categorization into distinct classes enables efficient analysis, monitoring, and management of natural resources and environmental changes (Di Gregorio, 2005).

These land cover classes can be organised in a **set of land cover classes.** This is a structured framework used to categorise and label the various types of land cover found on (part of) the Earth's surface. Such a set organises land cover into predetermined classes based on observable physical characteristics. These land cover classes need to be distinguishable to ensure that each category can be accurately identified and separated from others based on specific, observable criteria (Di Gregorio, 2005). Many different sets of land cover classes exist such as ESA's WorldCover, Google's Dynamic World or ESRI's land cover (Venter et al., 2022). In this study the set of WorldCover classes is used to provide an initial framework. WorldCover is a project initiated in 2017 by the European Space Agency with the aim of classifying the entire surface of the earth into land cover classes. These classes are: Water bodies, Mangroves, Herbaceous wetland, Tree Cover, Shrubland, Grassland, Cropland, Built-up, Bare or sparse vegetation, Snow and Ice, Moss and lichen (Zanaga et al., 2022). As mentioned in the introduction, these general classes are too broad to match the needs of policymakers, therefore more specific land cover classifications are necessary (Gavish et al., 2018).

An **hierarchical set of land cover classes** expands on the notion of a regular set of land cover classes by categorising land cover types into multiple levels. Here, each subsequent level provides a more detailed and specific set of land classes. In such a system, broad land cover classes are broken down into more refined subclasses, allowing for greater specificity in describing the physical characteristics of the land surface (Ojwang et al., 2024). For example, Ojwang et al. (2024) subdivided the broad Woodland class into more specific subclasses such as Closed Grassed Woodland, Closed Shrubbed Woodland, Dense Grassed Woodland, etc. There are different ways to develop such a hierarchical set of land cover classes. To ensure that local views of the environment are included, this thesis employs methods for landscape ethnoecology.

Landscape Ethnoecology

Landscape Ethnoecology is an interdisciplinary field that explores the relationships between human cultures and their surrounding landscapes, focusing on how people recognize, interact with, and manage their environment based on cultural knowledge and practices (Johnson & Hunn, 2010). One of the main aims of this field is to develop **localised sets of land cover classes**: sets of land cover classes incorporating local views of the environment. This is done using multiple methods. For example, in the work of Riu-Bosoms et al. (2015) free listings, a methodology which had the indigenous freely list all classes they recognized to occur within their environment, were used to formulate land cover classes. In addition, Libayakoya and Sertakova (2015) proposed the expert interview method for studying indigenous peoples and De Los Angeles and Islebe (2003) employed interviews and vegetation variable estimation to assess the traditional ecological knowledge of the Maya people in southeastern Mexico.

Creating such localised sets of land cover classes results in context-specific land cover information tailored to the needs of local stakeholders, making it highly suitable for use in policy and planning. In Subsection 3.1.1), the methods in which the above concepts are used to find a localized hierarchical set of land cover classes is explained.

Subsection 2.1.2) Classifying Land cover

The following concepts are explained to provide a theoretical framework for classifying land cover: remote sensing, classification using machine learning, and relevant existing land cover classifiers.

Remote Sensing and satellites

Land cover maps containing any set of land cover classes can now be created using the vast amount of information available through remote sensing.

Remote sensing is the science of acquiring information about the Earth's surface without direct contact. This information is obtained, for example, through the detection and measurement of electromagnetic radiation (NASA, n.d.). There exist multiple technologies capable of acquiring this information (think drones , airborne sensors, etc.) but the particular type of machine utilized in this research is the satellite. One critical aspect of remote sensing is **resolution**, which refers to the level of detail that the sensor can capture.

Spatial resolution refers to the level of detail a satellite can capture in its images. It is defined by the size of each pixel, which is the smallest unit of measurement in a satellite image. A satellite with a spatial resolution of 30 meters means that each pixel covers a 30x30 meter area. Each pixel then contains information on the electromagnetic reflectance of that area on the ground along certain **bands**, i.e. certain wavelength intervals that the satellite is measuring.

Spectral resolution defines the sensor's ability to distinguish between different wavelengths of light. The bands of a regular satellite are all within the wavelength range of visible light. An expansion on these are multispectral satellites, which are equipped with sensors capable of capturing bands including and outside the range of visible light (Hatfield et al., 2008). This additional information can then be used to recognise patterns unnoticeable using visible light alone. For example, this imagery can then be used to distinguish vegetation cover, plant health and even distinguish vegetation types (Bannari et al., 1995; Singh et al., 2022).

Finally, **Temporal resolution** refers to how often a sensor captures data of the same area, which is important for monitoring changes over time (NASA, n.d.).

Two large biases present within remote sensing products are **sub-grid variability** and **sensor drift.** Sub-grid variability refers to the variation of surface characteristics within a single pixel, causing mixed signals that affect the overall accuracy of the data (Crosson & Laymon, 1995).

Sensor drift is the gradual change in a sensor’s performance over time, leading to potential inconsistencies in the captured data if not properly calibrated (Gascon et al., 2017).

Sentinel-2: MSI

The remote sensing data used within this thesis comes from **Sentinel-2**, which is part of the European Space Agency's (ESA) Copernicus program. The Sentinel-2 mission consists of two satellites, Sentinel-2A and Sentinel-2B, launched in 2015 and 2017, respectively, to provide continuous, high-quality data on the Earth's land surfaces. Sentinel-2 is equipped with the **Multispectral Instrument (MSI)**, which captures data in 13 spectral bands ranging from visible to shortwave infrared wavelengths, allowing for detailed observation of various environmental processes, including agriculture, forestry, water quality, and land cover. With a spatial resolution of 10, 20, and 60 meters, depending on the spectral band, Sentinel-2 is well-suited for detailed land classification (ESA, n.d.; Spoto et al., 2012).
Machine learning classification methods can extract data from remote sensing data programmatically, allowing fast amounts of information to be gained from remote sensing imagery.

Machine learning based classification

Machine learning is a branch of artificial intelligence focused on empowering machines to learn and improve from experience without explicit programming, using algorithms that analyse data, recognize patterns, and make decisions (Zhou, 2021). Within this thesis, machine learning methods are used to solve multiple instances of a **classification problem**, the challenge of assigning input data into predefined classes based on learned patterns. Classification algorithms (‘classifiers’) are trained on labelled datasets to distinguish between different categories, and once trained, they can predict the class of new, unseen data. Furthermore, to assess the accuracy of the algorithm, validation data is often used, where the value of a validation point is compared with the algorithm's prediction of the point (Zhou, 2021). This process is critical in a variety of applications, such as spam detection (Guzella & Caminhas, 2009), medical diagnosis (Kononenko, 2001) and particularly relevant for this thesis, land cover classification (Maxwell et al., 2018).

Land cover classification

Now that remote sensing and machine learning-based classification have been explained we can introduce the specific focus of this part of the thesis: **land cover classification**. Land cover classification is the process of assigning land cover into a set of land cover classes. This can be done automatically for large areas using both remote sensing data and machine learning classification. In this case, the training data are the spectral information of selected bands from points where the land cover class is known. If the satellite utilizes is multispectral, bands can be used both within and outside the range of visible light, which can greatly improve the quality of classification (Stević et al., 2016). Furthermore, validation points are taken to be **ground truth points**. These are locations that are manually labelled with the present land cover class. If ground truth points cannot be collected, **synthetic ground truth points** can be made, which are artificially created ground truth points (Mueller-Warrant et al., 2015).

The number of training and ground truth points can vary wildly. Ideally, the sample size can be determined by considering the desired accuracy, the acceptable margin of error, and the anticipated confidence level (Fitzpatrick-Lins, 1981). Although this is the most rigorously designed approach, it is rarely used in practice because it demands large sample sizes and extensive spatial distribution, which are often unfeasible due to resource constraints (Roelfsema

& Phinn, 2013). To get an idea, the GEOBIA dataset (Maxwell et al., 2018) used between 14 to 29 training points per class and between 15 to 97 ground truth points per class.

Hierarchical land cover classification

Since this thesis develops an hierarchical set of landcover classes, it also needs to perform **hierarchical classification**. Here, pixels are not only classified into the main classes, but also into sub classes.

Multiple approaches to achieve this exist. Thoonen et al. (2013) demonstrated that a tree-structured Markov random field approach, which integrates both hierarchical thematic structure and contextual data, outperformed regular (or 'flat') classification methods when applied to heathland areas in Belgium. Similarly, Melgani & Bruzzone (2004) showed that hierarchical models based on support vector machines achieved better results than flat models when classifying land-use classes in northwest Indiana. This hierarchical system has been found to help classification in a number of ways.

First, it may become possible to differentiate land covers that are thematically close to one another but are ecologically/spectrally different. For instance, a desert and a wetland may both be classified under the thematic category of 'natural' land cover, while an urban park might fall under the 'developed' land cover category. However, in terms of both ecological function and spectral characteristics, the urban park might be more similar to the wetland than the desert. A flat classification system overlooks thematic relationships entirely, whereas a hierarchical approach first prioritizes distinguishing between 'natural' and 'developed' land cover (Gavish et al., 2018).

Secondly, when the number of land cover classes is extensive, a flat approach may struggle to handle this complexity. In contrast, a hierarchical approach can simplify the task by dividing the large classification problem into smaller, more manageable classification problems (Gavish et al., 2018).

Finally, incorporating a hierarchical structure into the modelling framework can improve accuracy, as shown by Thoonen et al. (2013) and Silla & Freitas (2011).

Selected classifiers

Land cover classification is performed in this thesis utilizing five often-used classifiers. These are Support Vector Machines, Classification and Random Trees, Random Forests, boosted Decision Trees and k-Nearest Neighbour. An overview of each classifier, including its description, parameters considered within this study, pros, cons, and usage in land cover classification, is provided in **Table 1**.

Table 1. Overview of classifiers used within this thesis

	Description	Considered Parameters	Pros	Cons	Usage in Land cover classification
Support Vector Machines (SVM)	Identifies the optimal hyperplane to separate data points from different classes.	**Kernel**: Defines the type of hyperplane (linear, polynomial, RBF).	Effective in high-dimensional spaces.	Less effective when the data has a lot of noise or overlaps between classes.	(Huang et al., 2002; Shao & Lunetta, 2012)

Classification and Random Trees (CART)	Builds a tree by splitting data based on the feature that provides the maximum information gain	-	Works well on small to medium datasets.	Often less accurate than ensemble methods like Random Forest.	(Shao & Lunetta, 2012)
Random Forests (RF)	Ensemble learning method that builds multiple decision trees and merges them to get a more accurate and stable prediction.	**Number of Trees**: The number of trees in the forest.	Reduces overfitting by averaging results of multiple trees.	Slower to train compared to single decision trees.	(Ghimire et al., 2012; Gislason et al., 2006; Thanh Noi & Kappas, 2017)
boosted Decision Trees (bDT)	Ensemble technique that combines weak learners in a sequential manner, where each tree attempts to correct the errors of the previous ones.	**Number of Trees**: The number of trees in the forest.	Reduces both bias and variance.	Sensitive to noise in the data.	(Ghimire et al., 2012; Pal & Mather, 2003)
k-Nearest Neighbour (kNN)	Classifies a data point based on the majority class among its k-nearest neighbours in the feature space.	**k:** The number of neighbours to consider for classification. Should be odd to avoid ties (Peterson, 2009)	Highly accurate with smaller datasets. Handles multiple classes naturally by simply counting the majority among the nearest neighbours	Poor performance with large datasets and high-dimensional data.	(Lefulebe et al., 2023; Thanh Noi & Kappas, 2017; Upadhyay et al., 2016)

Performance assessment

The ground truth points can be used to assess the performance of land cover classification in multiple ways.

A key tool to assess the performance of a classification algorithm is the confusion matrix. A confusion matrix is a table that compares the true class labels (obtained from ground truthing) with the class labels predicted by the classification algorithm. The diagonal elements show the number of correct classifications (true positives and true negatives), whereas the off-diagonal elements reflect misclassifications (false positives and false negatives) (Foody, 2002).

In addition to inspecting the confusion matrix itself, various performance metrics can be calculated from it, such as user accuracy and producer accuracy. **User accuracy** represents the proportion of instances predicted to belong to a certain class that actually do (i.e., the reliability of the predicted class). On the other hand, **producer accuracy** measures the proportion of actual instances of a class that were correctly identified (i.e., the classifier's ability to detect instances of a particular class) (Foody, 2002).

These metrics provide deeper insight into the classification's performance for specific classes and complement the overall **accuracy**, which gives an overview of how well the algorithm performed across all classes. Together, user and consumer accuracy, along with other metrics, offer a detailed view of the model's effectiveness in different contexts (Beauxis-Aussalet & Hardman, 2014). An example of a confusion matrix with the metrics explained above can be seen in **Table 2.**

Table 2. Example of a confusion matrix, furthermore illustrating accuracy, user accuracy and producer accuracy from a confusion matrix

	Predicted Class A	Predicted Class B	Predicted Class C	Producer Accuracy
Actual Class A	40	10	5	40/55 (73%)
Actual Class B	5	50	5	50/60 (83%)
Actual Class C	5	5	40	40/50 (80%)
User Accuracy	40/50 (80%)	50/65 (77%)	40/50 (80%)	Total Accuracy: 130/165 (79%)

The regular confusion matrix and corresponding metrics were all created for non-hierarchical classification problems. However, to evaluate the overall performance of a hierarchical problem, evaluation measures need to take this hierarchical structure into account. One such measure is **hierarchical accuracy**. This is the total number of correctly classified points for all classes divided by the total number of ground truth points for all classes. This number then represents the overall accuracy of the hierarchical classification. Since misclassification into a wrong subclass belonging to the same general class can be seen as less severe than misclassification into a wrong main classes, misclassifications can be weighted by their position in the hierarchy (Kiritchenko et al., 2005).

Together, the information above should provide a clear background to understand the land cover classification performed within this thesis.
Next, a background is given on the identified information that will be computed using the land cover maps.

Section 2.2) Context for the usage of land cover maps

The third component of this research is the utilisation of land cover maps for various land cover information sources desired by DNM. To understand better what they wanted and what existing things they connected with, some theory is required. Specifically, they wanted to calculate some SDG indicators and one GBF indicator, where a background is given on these frameworks in general and the specific indicators calculated. Furthermore, background information for the Build with Nature, the policy for which the DNM desired information, will be given.

Subsection 2.2.1) Indicators for global environmental frameworks

The **Sustainable Development Goals (SDGs)** and the **Global Biodiversity Framework (GBF)** are both overarching frameworks focused on the balance between development and conservation, emphasizing sustainability as a guiding principle for global progress (Joly, 2023; Sachs et al., 2024).

Sustainable Development Goals

The United Nations established the Sustainable Development Goals (SDG) framework to address various social, economic, and environmental challenges. Within this framework, each goal is measured through dedicated indicators (Sachs et al., 2024). The UN offers metadata standards and specific methodologies for capturing specific SDG indicator data (UN, 2024). One particular difficulty with the SDGs is that methodologies for the indicators are defined globally and not always immediately applicable to every local situation, which increasingly calls for localized SDG indicators (Kulonen et al., 2019). Furthermore, a big point of contention is that the indicators are required to be reported as single numbers. This overlooks the spatial distribution of the indicators, which could aim in devising policies aimed at areas where the indicators are present (Kraak et al., 2018).

Two indicators are relevant for this study, namely SDG indicators 15.1.1: Proportion of land covered by forests and 15.3.1: Proportion of land that is degraded over the total land area, which are both part of SDG 15) Life on Land (Sayer et al., 2019, p. 15). SDG 15 is about 'Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss' (Sayer et al., 2019), and is one of the SDGs for which remote sensing data can be most useful (Estoque, 2020).

SDG indicator 15.1.1

The data reporter for this indicator is the Food and Agriculture Organization of the United Nations (FAO). SDG indicator 15.1.1 is defined as '**Forest area as a proportion of total land area'**. Here, forest is defined as follows: "Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds *in situ*. It does not include land that is predominantly under agricultural or urban land use". Land area is defined as: "The country area excluding area under inland waters and coastal waters" (UN, n.d.-a).

Data for this indicator is provided in two ways. The first way is through officially nominated national correspondents, who have to submit a country report through the online Forest Resources Information Management System, a web platform developed by the FAO. The second method is when no such correspondent exists, the FAO conducts a combination of literature search and remote sensing, calculating a value of this indicator themselves. In 2020, 47 countries and territories, including Aruba, did not submit information, necessitating FAO's use of the latter methodology (UN, n.d.-a).

Land cover classification is often utilised for this indicator since forest area can be quantified well using this technique (UN, n.d.-a).

SDG indicator 15.3.1

The data reporter for this indicator is the United Nations Convention to Combat Desertification (UNCCD). SDG indicator 15.3.1 is defined as '**Proportion of land that is degraded over total land area'**. Land degradation is defined as the reduction or loss of the biological or economic productivity and complexity of rain-fed cropland, irrigated cropland, or range, pasture, forest, and woodlands resulting from a combination of pressures, including land use and management practices" (UN, n.d.-b).

Data for this indicator is again collected in two main ways. The primary method involves national authorities submitting their data to the UNCCD following a standard format. This includes quantitative data for the indicator and sub-indicators, as well as a qualitative assessment of trends. The indicator is derived from three sub-indicators: Trends in Land Cover, Land Productivity, and Carbon Stocks. These sub-indicators are evaluated using the "One Out, All Out" principle, where land is classified as degraded if any one of the sub-indicators shows a negative trend, subject to validation by national authorities (UN, n.d.-b). The sub-indicator utilized within this research is Trends in Land Cover, which marks areas as degrading if the area was previously natural and is now deteriorating (i.e. natural land cover is replaced with degraded land cover).

In the absence of national data submissions, the UNCCD and its partners provide estimates using regional or global data sources, which are then validated by national authorities.

Land cover classification is highly effective in monitoring this indicator as well (Bentekhici et al., 2023; UN, n.d.-b).

Kunming-Montreal Global Biodiversity Framework

The Kunming-Montreal Global Biodiversity Framework (GBF), established in December 2022, is another significant framework. Similar to the SDGs, it targets global challenges but places a stronger emphasis on biodiversity and environmental issues. The GBF succeeds the Convention on Biological Diversity (CBD), a key international treaty from 1992 aimed at conserving biodiversity and sustainable resource use. It provides 23 targets to reach by the year 2030, along with four goals guiding development until 2050 (Kraak et al., 2018).

This thesis aims to find the value of one particular indicator for the island of Aruba, namely indicator A.2. This is defined as '**the extent of natural ecosystems'**, which designate areas with minimal human impact, such as forests, grasslands, and wetlands. The data reporter for this indicator is the United Nations Statistics Division (UNSD). This indicator addresses Goal A and Target 1 of the Global Biodiversity Framework (GBF), aiming to increase the area of natural ecosystems by 2050 and minimize biodiversity loss by 2030 through effective management and spatial planning (UNEP, n.d.).

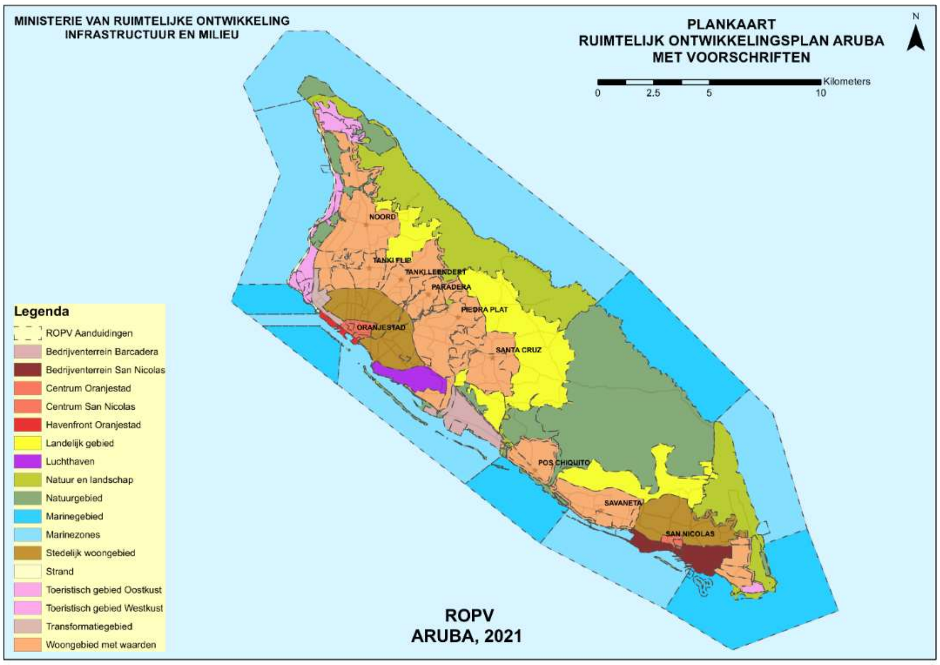
A key advantage of this approach is its flexibility in defining natural areas. Remote sensing plays a crucial role in assessing the extent of these areas, as demonstrated in this thesis. Countries can then report the extent of each ecosystem online through the SEEA Ecosystem Accounting framework, with the indicator automatically calculated through the framework (UNEP, n.d.).

Subsection 2.2.2) Informing Build with Nature policy

Land cover maps were also beneficial for the Build with Nature policy. The overlying idea, to 'Build with Nature', emphasises the importance of sustainable development in harmony with Aruba's natural environment (DNM, 2021).

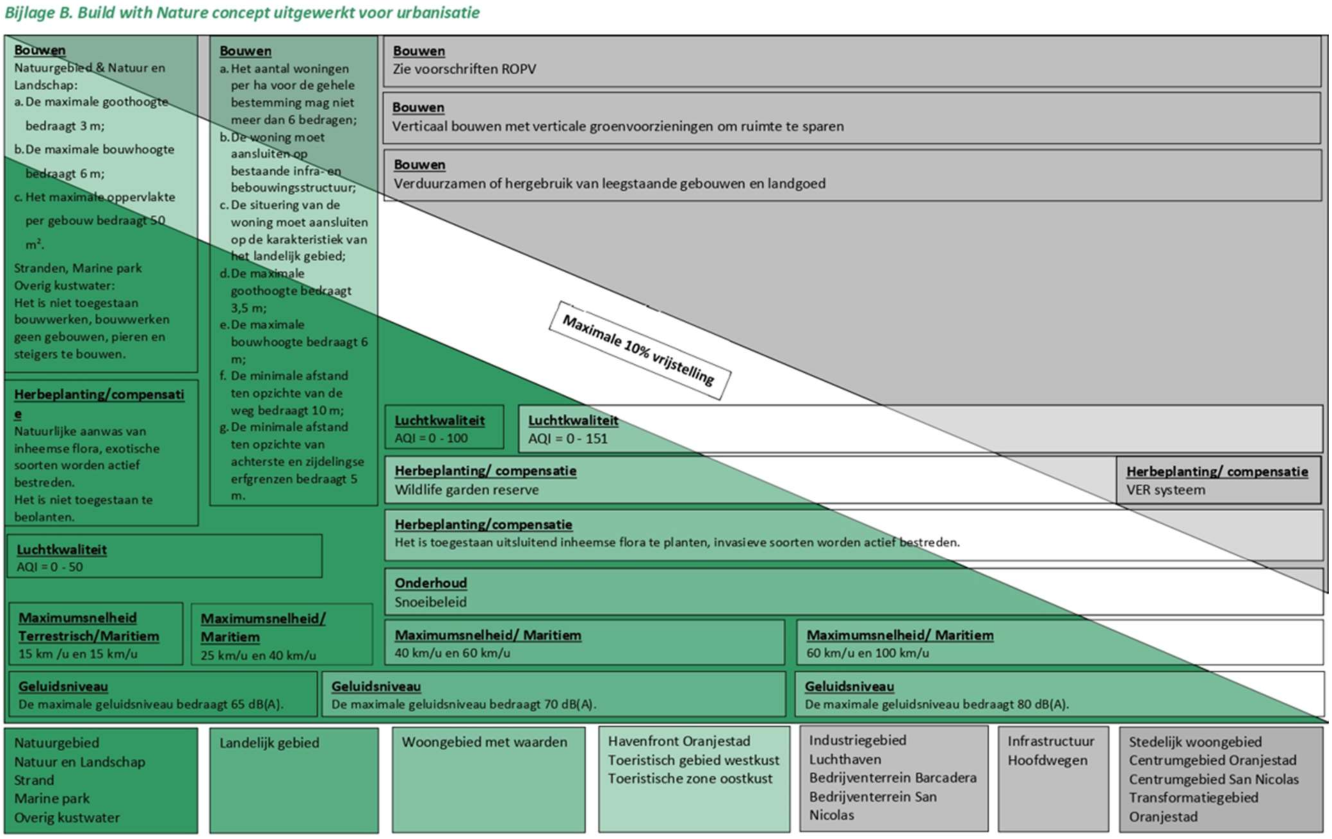
The Build with Nature policy contains a map that divides the islands area into distinct zones as can be observed in **Figure 2.**

Figure 2. Zoning of the Aruban environment (DNM, 2021).



These categories come back in **Figure 3** which is a central figure from the Build with Nature policy. Here, for seven collections of zones different regulations are specified for building, air quality, maximum speed and maximum sound volume. Also, for each collection of zones, an aimed maximum percentage of natural area versus build area is specified. Here, as collections of zones are seen as more natural fewer build environment the aimed maximum percentage becomes lower.

Figure 3. Seven broad categories of the Aruban environment from Build with Nature policy.



Note: For each category, policy and an aim for the extent of build environment is stated (source: (DNM, 2021)).

Chapter 3 Methods

This section outlines the methodology implemented to address the research questions. A visual summary of the methodological approach and the corresponding results can be found in **Figure 4**. In this study, a mixed-methods approach is employed to leverage both qualitative and quantitative data for comprehensive land cover classification (Ivankova & Creswell, 2009).

The first part of this research focussed on finding land cover maps. This first required land cover classes. To obtained these, focus groups consisting of DNM employees were held. These groups began by selecting preexisting WorldCover classes relevant to the land cover of Aruba, considered the **main classes** from that point forward. The next round of focus groups had DNM employees subdividing the main classes they viewed as too broad into more specific subclasses.

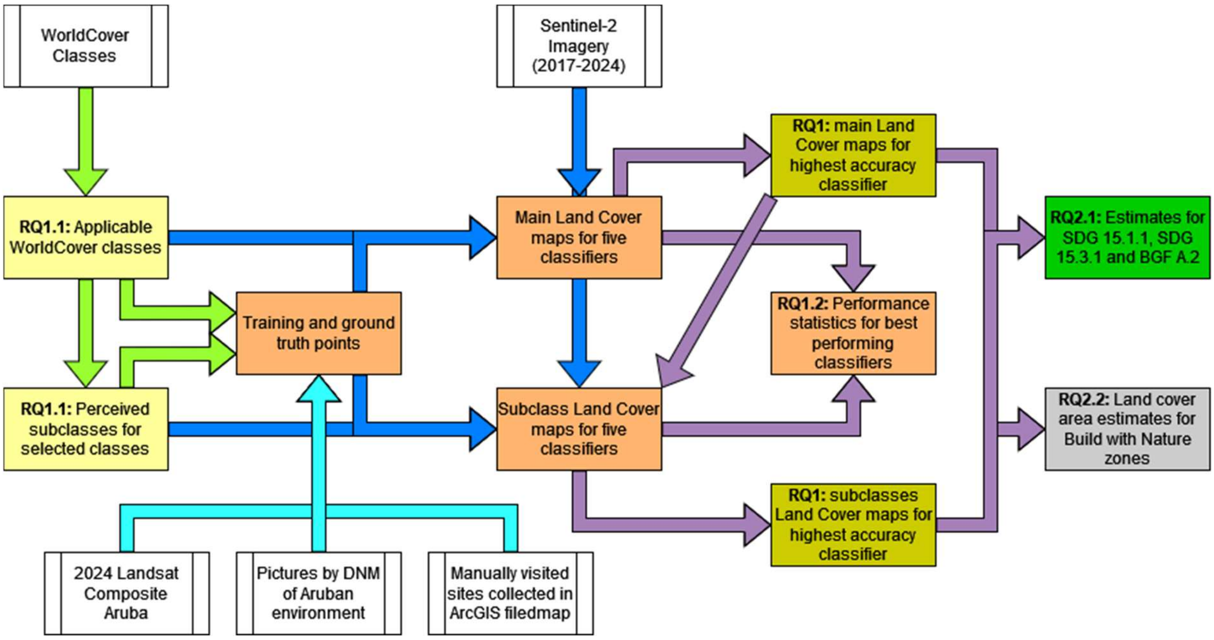
Secondly, the land cover maps needed to be created using the identified land cover classes. To achieve this, the performance of multiple classifiers in classifying biannual Sentinel imagery of the Aruban environment from 2017 until 2024 into the main classes. The accuracy of each method was then calculated, and the land cover maps from the highest accuracy classifier were stored. Then, the same classifiers were used to classify the subclasses. Here, again, the accuracy of each method was calculated, and the land cover maps of the best-performing classifiers were stored. The land cover maps were visualised using a GEE application, and an in-depth analysis was conducted on the performance of the best-performing classifiers for both the main and the subclass classifications.

The second part of this research, focussed on the creation of land cover information desired by the DNM using the land cover maps.

Specifically, current and historic indicators were calculated for SDG indicators 15.1.1 (Forest cover), SDG 15.3.1 (Degraded land area), and the GBF indicator A.2 (Natural Areas). This was done by first determining the land cover classes making up the indicators through focus groups, after which the area of these classes were added to determine the indicator values.

Furthermore, land cover area estimates were computed for the different 'Build with Nature' categories. This was done by creating masks of the different categories and overlapping these with the land cover maps to determine the class size per category.

Figure 4. Overview of the methodology and results



Note: The white boxes with double vertical borders indicate external data. The coloured boxes indicate results, with yellow boxes relating to RQ1.1, orange to RQ1.2, dark yellow to RQ1, green to RQ2.1 and grey to RQ2.2. If the RQ is explicitly stated, this result will answer the research question. The arrows indicate methods to achieve the results, where green indicates focus groups, cyan manual selection of suitable points, blue machine learning classification in Google Earth Engine and purple computational analysis in Google Earth Engine.

All code written for this methodology can be found in the accompanying GitHub repository.

Research area

Aruba is a small island located in the southern Caribbean Sea **Figure 5**. The island lies 27 km north of the Venezuelan coast and 80 west of the island Curacao. The area of the island is about 179.9 square kilometres, and has an elongated shape from the northwest to the southeast. Aruba is characterised by a semiarid hot climate, with an annual temperature of 28.4°C (1991-2020) and an annual rainfall of 451.1 mm (1991-2020). On the island, northeasterly trade winds are dominant, averaging speeds of 7.4 m/s (1991-2020). The island has a wet season starting from September until January, with a mean rainfall of 65mm per month, and the rest of the year (February until June) is the dry season, with a mean rainfall of 18mm per month (Metereologische Dienst Aruba, 2021).

Figure 5. Location of the island Aruba within the Caribbean

Note: Source: Google Maps

Aruba's distinct climate and geographical features have contributed to the development of a unique and diverse plant life, which plays a vital role in the island's ecological balance (Oduber et al., 2015). This diverse vegetation, encompassing everything from coastal mangroves to inland cacti, forms the cornerstone of the island's ecosystem (Stoffers, 1956). The flora of Aruba is not only pivotal for maintaining the island's biodiversity but also plays a crucial role in defining its landscape and supporting various ecosystem services. Examples range from climate regulation and nutrient cycling to recreation, tourism, and cultural heritage (Nelson et al., 2020).

While Aruba's unique vegetation plays a key role in sustaining its ecosystem, the island's rapid economic development, particularly driven by tourism, has brought significant environmental challenges. The island is considered to be a developing country by the International Monetary Fund (WorldData, n.d.), with the main economic activity currently being tourism. Tourism on the island made up 88.1% of the total GDP in 2019 and is expected to reach 97.4% in 2027 (Sanders et al., 2019). These developments have had positive impacts on the wealth of the country, as GPD per capita rose from 16.5k in 1995 to 38.02k in 2024, but this has also resulted in stark environmental changes in Aruba. The spatial development of Aruba is characterised by significant urban sprawl and tourism-driven urbanisation. Build environment increased from 29 km^2 in 1985 to 60 km^2 in 2023, which was largely built in previously natural areas (Jurgens et al., 2024).

Although Aruba's rapid urbanisation and tourism have brought environmental challenges, the Department of Nature and Environment (DNM), established in 2012, plays a crucial role in shaping policies aimed at protecting the island's natural and environmental qualities. The Department of Nature and Environment (DNM) is a governmental department of Aruba part of the Ministry of Transport, Integrity, Nature and Elderly Affairs. It is tasked with "Preparing, shaping, implementing and evaluating policy that leads to a sustainable healthy environment for people and the environment in Aruba whereby the central focus is the preservation, protection and improvement of natural and environmental qualities." (DNM, n.d.-a). There are twelve full-time employees at DNM.

Ensuring ethical handling of qualitative and quantitative data

Three measures were taken to ensure that no ethical boundaries were crossed. The first two relate to the handling of qualitative data gathered throughout the focus groups and internship. First, the expectations of the internship were outlined in a signed agreement which can be found in Appendix 1). Second, prior to conducting the interviews, informed consent was organised by verbally going over the Informed Consent form and then asking consent, which can be found in Appendix 2). Finally, regarding quantitative data I signed a non-disclosure agreement which states that the data I gained access to would only be used for this thesis, which can be found in Appendix 3).

Section 3.1) Finding land cover maps for Aruba

Subsection 3.1.1) Selecting classification systems

In this section, focus groups, consisting of DNM employees, are used to find the relevant land classes of Aruba.

The WorldCover classes were taken as a starting point for determining Aruban land cover classes. To format the information necessary for this, **Table 3** was used as a template and filled out during the focus groups.

Table 3. Template for data gathering during focus groups

Selected World-Cover class	Subclass	Justifying comments	Locations or defining species

Note: Table used to gather information on land cover classes in a consistent way. Column one was filled with WorldCover classes that are deemed applicable. In column two subclasses for which DNM employees could state representative locations are placed. Column three has reasons why a particular class or subclass was desired to be included in the land cover classification. Finally column four contains comments by DNM employees on how/where representative locations for the class are identified.

Two focus groups were held to determine which of the eleven WorldCover classes (see Subsection 2.1.1)) applied to Aruba. This was done with DNM employees Robert and Yahaira on the 14th and 21st of February 2024, from 15:00 until 16:00. During the first of these, for each of the WorldCover classes, it was explored if they were present in Aruba, and if the class was of interest to the DNM employees. Here, I presented each class in turn, and both of them would comment whether and why this class was or was not suitable for the island of Aruba, where the final decision was reached by consensus among the two focus group attendants. This yielded data for the first column of **Table 3**. In the second focus group, each of the selected classes was revisited, and they had to list a way to obtain representative locations for each selected class, yielding data for column four. This column will also contain information for representative locations of the subclasses, which is why it is last in the table. They were asked to list where representative locations were present for each class. For classes defined by the domination of certain types of vegetation, the defining plant species for that class were noted. This yielded the main set of classes for the Aruban environment.

To expand this classification system to include land cover classes recognised to be relevant by the DNM, the land cover classification system was expanded into a hierarchical system. Here, some of the recognised WorldCover classes (from now on called ‘main classes’) will now obtain subclasses. This was done by conducting two more focus groups with Robert and Yahaira from DNM. These were held on March 20th and 27th 2024 from 15:00 until 16:00. Here, a free listing approach (as described in section 2.1) was used. Within the third focus group, the employees were encouraged to list land cover classes for each class as freely as they wanted, yielding a large number of possible subclasses. Here, they were also asked to explain why they wanted this subclass to be contained in the classification system (yielding information for column three). In the fourth focus group, only subclasses with sufficient distinguishing representative locations in Aruba were selected. Participants were asked to verify if 40 representative locations could be identified for each subclass. If they could, the subclass was included in the hierarchical system and noted in column two of **Table 3**, along with representative locations or defining plant species in column four. Subclasses without sufficient locations were excluded from the system.

This yielded a land cover classification system for the island of Aruba containing land cover classes recognised by DNM employees.

Subsection 3.1.2) Performing classification of Aruba using machine learning methods

In the section it is described how the Aruban environment was classified into the hierarchical set of land cover classes found using the previous methodology. If readers want to see this set before continuing with this section, these can be found in Subsection 4.1.1).

Selecting and preprocessing satellite imagery

An initial step before classification can be performed is obtaining and saving suitable. The code written for this can be found in the repository at '/code/ 3.2.1) selectingImagery'. The data used is from the Sentinel-2 Multispectral Instrument, for the entire period data has been available for the island of Aruba. First, the data of the first Sentinel-2 image over Aruba was calculated to determine when the analysis could start. Next, from the starting date onwards, for every year, two composites were created, one using all images from February until July and another using all images from August to January, corresponding to the Aruban dry and wet season. These composites were created using all pictures of each period. For all these pictures, clouds were masked using the S2 cloud probability dataset (Google Earth Engine, n.d.-b). After this, the median function was used to obtain a composite image (Ramoino et al., 2017). The median function calculates the median pixel for every image pixel, and since clouds were previously masked this creates a composite where clouds are disregarded. Each of these composites obtained the name 'dry/wet_year' (so for example dry_2024) to able to refer to them consistently.

After this, the bands utilised in the subsequent analysis were selected. The selected bands for analysis were Blue, Green, Red, Near-Infrared (NIR), Short-Wave Infrared 1 (SWIR1), Short-Wave Infrared 2 (SWIR2)

These pictures were then clipped to the island of Aruba and stored in Google cloud to be used in later analysis.

Training and ground truth points

The step needed was selecting training and ground truth points. While general locations were identified earlier, specific coordinates were gathered for this research in the summer of 2024. To obtain a manageable dataset, 20 training points and 20 ground truth points were collected for each class and subclass.

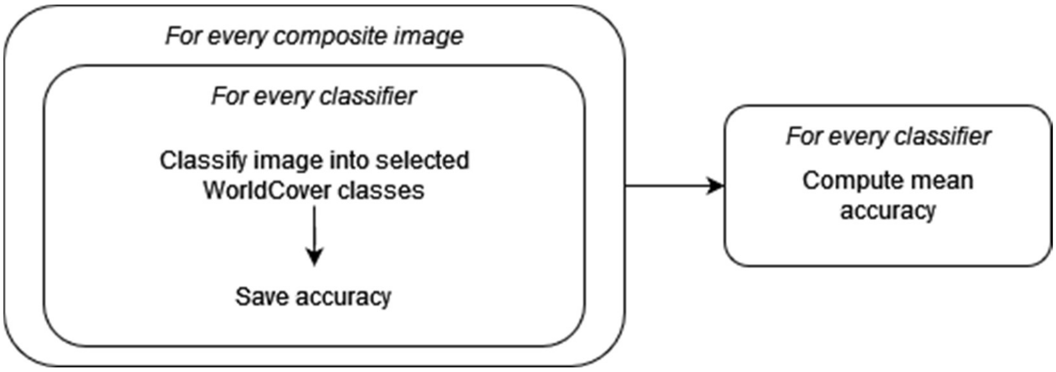
Data was sourced from ground images collected by DNM, field observations, and satellite imagery. For the ground images, I accessed DNMs OneDrive, reviewing photos from 2019 onward and selecting those from sites where the environment remained unchanged. Pictures with GPS coordinates were sorted by land cover class, and their locations were extracted and saved as CSV files. When images were insufficient, I conducted field visits, using ArcGIS Fieldmaps to collect coordinates of representative points. These points were also saved as CSV files categorised by class. Additionally, satellite imagery, particularly the dry 2024 image computed within the last step (since this was the latest image), was used to identify points for classes easily seen from space, like Permanent Water.

The data from these sources was consolidated into a Python dictionary, with classes and subclasses as keys and feature collections as values. Each class had 40 points, which were evenly split into training and ground truth datasets. For classes with subclasses, no points for the class themselves were gathered. Instead, points from the subclasses were also used for the main class, ensuring balance by limiting the number of points to 20 for each class. This prevented the model from being biased towards classes with more data. The final training and ground truth points were saved for later use in the classification.
All of these training and ground truth points were gathered to ensure correspondence with the land cover present in 2024. These points were used in the creation and validation of all land cover maps, but since they were not gathered using past data, for past maps, these points became synthetic training and ground truth points.

Classification of the Aruban environment
Now that land cover classes, satellite imagery of the research area and training and ground truth points have been computed, the classification methods could be utilised. In order to consistently refer to things with the same name, some terms that will be used will no be defined.
First, the **main classification problem** refers to the classification of a single composite picture into all the selected WorldCover classes. Similarly, each **subclassification problem** refers to assigning all of the pixels of a class into the selected subclasses for a single composite picture. The final necessary term is that of the **main/sub temporal classification problem**. This is taken to mean the task of assigning all earlier obtained composite images of Aruba into the main set of land cover classes/all pixels of a main class of all images into the set of subclasses of that class.
An overview of the classifiers used can be found in **Table 1**. For some of the classifiers, multiple parameters were used to find not only the optimal classifier but also the parameter for which this classifier performed optimally. Namely, for the Support Vector Machine, a linear and radial basis function kernel was tested. For the Random Forests and boosted Decision Trees, 10, 20, 30, 40 and 50 trees were chosen. For k-Nearest Neighbour, a k (or the number of neighbours) of 1, 3, 5 and 7 were chosen. This means that in total, 17 classifier-parameter pairs were tested in each classification problem.

Performing the main temporal classification problem
First, each of the composite images was classified using all classifiers, an illustration of this process can be found in **Figure 6**.

Figure 6. An overview showing how the classification of all composite images into main classes was done using all classifiers, to determine the mean accuracy of every classifier.



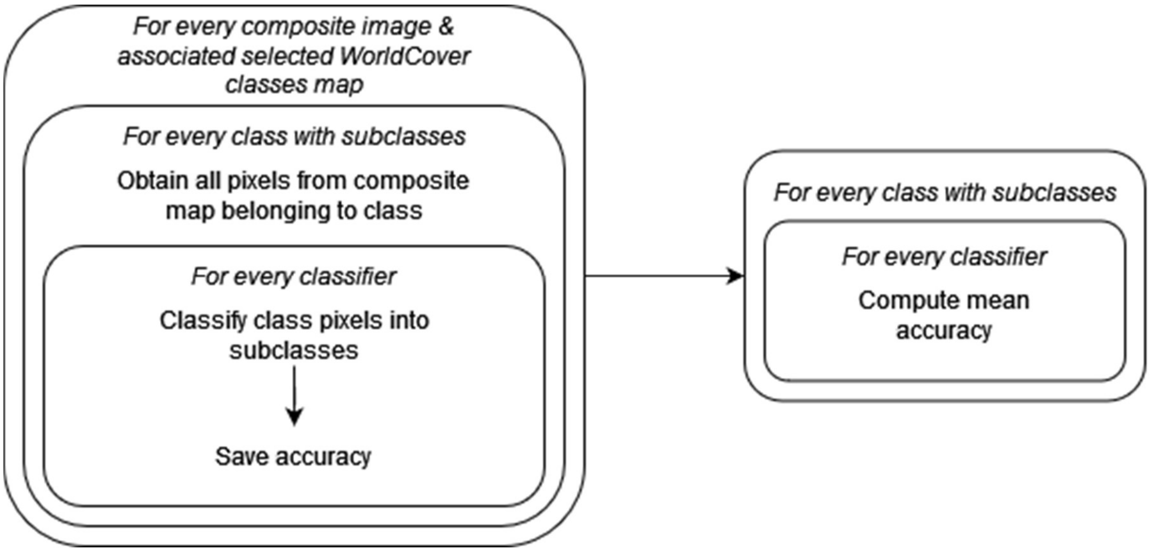
This was done by doing the following for every composite image and every classifier. The classifier was trained by giving them the pixel values (i.e. information on earlier specified bands) present at the 20 training locations. After this, the trained classifier classified every pixel of the island of Aruba into one of the main classes. Finally, the ground truth points were used to assess the mean accuracy of the classification, which was stored for comparison.

After this was done for every image and classifier, the performance of each of the classifiers could be learned. This was done by computing the average accuracy of each classifier over all the images. Finally, for them to be used later, all land cover maps created with the classifier with the highest mean accuracy (hereafter '**main land cover maps**') were stored in Google Cloud.

Performing the sub temporal classification problems

Next, pixels belonging to a class with subclasses were assigned to a subclass, for an illustration of this process see **Figure 7**.

Figure 7. An overview showing how the classification of all classes with subclasses into these subclasses, for composite images and using all classifiers, to determine the mean accuracy of every classifier for each subclassification problem.



First, a mask is created of the pixels belonging to the class. Then, this mask is applied to the original composite images, to get a composite image showing only the pixels belonging to the main class. After this, these pixels are classified using all of the evaluated machine learning methods into the subclasses in the exact same way as this was done in the previous section. The main difference is that more than one class has subclasses, so for every image, pixels belonging to a main class are selected and classified multiple times. This was done to investigate which classifier performed best for each subclassification problem. The accuracy of the different classifications was calculated and stored in a separate file.

Lastly, the performance of the different classification methods was investigated. To find the most accurate one, the mean accuracy of every classifier for every sub temporal classification problem was calculated. This allowed the classifier with the highest mean accuracy for each problem to be learned. Finally, to have usable land cover maps available, the land cover maps of the different subclasses classified by the best-performing classifiers were stored (hereafter **'sub land cover maps'** or **'(name of a subclass) land cover maps'**).

Creating Google Earth Engine application to visualize resulting maps.

A Google Earth Engine application was developed to view the maps created using the preceding methodology. Dropdown menus allowing users to select the composite images of Aruba, the main land cover maps, and the sub land cover maps were each created. This was made possible by leveraging the existing Google Earth Engine API (Google Earth Engine, n.d.-a), and the code for the application can be found in '/code/application.js' in the GitHub repository. This code was executed in the GEE Javascript terminal, which yielded the application, and this application was saved and shared using the 'Get Link' functionality from that terminal.

Performance analysis of optimal classifiers

To estimate the quality of the classifications beyond the overall mean accuracy, further statistics were calculated for each of the classifiers with the highest mean accuracy in the different temporal classification problems. First, to see accuracy in all years, for the main, sub and hierarchical classification problems the accuracy was calculated in every year and plotted over time. To assess whether accuracy worsened significantly for earlier composite images, a regression line and corresponding p-value were generated for each accuracy plot. This was done to assess the quality of the synthetic training points from earlier years.

To investigate classification into each of the classes the confusion matrix was calculated for the land cover maps from the dry_2024 composite (the latest at time of research). Furthermore, for every confusion matrix the user and producer accuracy of every class was calculated.

Beyond this accuracy assessment, the resulting land cover maps were inspected. Here, it was checked whether classes occurred at locations where I knew they should occur, and general patterns of classes were noted.

Section 3.2) Computing land cover information

Now that the land cover maps are known, these can be used to calculate information desired by the DNM. Readers who would like to see these land cover maps before progressing can follow this link.

The information desired can be split in two categories: environmental indicators for global environmental frameworks (the SDGs and the GBF), and land cover area estimates to support the Build with Nature policy. In this section the methodology employed to provide information for each of these purposes is given.

Subsection 3.2.1) Monitoring SDG 15.1.1, SDG 15.3.1 and BGF A.2

Since some indicators required environmental knowledge about which land cover classes counted for which indicator, a single focus group was held to obtain this knowledge. On the

10th of April, from 15.00-16.00, Yahaira and Robert were asked which of the land cover classes and subclasses fit the indicator definitions. Specifically, for 15.3.1, classes are picked which were perceived to fall under sub-indicator 1) Trends in Landcover (as explained in section SDG indicator 15.3.1), which meant that they thought the land cover class occurred solely in places where the was previously natural land.
Similarly, GBF A.2 measured 'natural areas', where 'natural areas' are purposefully left as vague as possible to be filled in by local knowledge. Therefore, the general definition of 'natural area' from the indicator (UNEP, n.d.), which was 'areas with minimal human impact', was relayed to the focus group attendees and they were asked to list which classes they thought fit this definition.
Since SDG 15.1.1 has a very strict definition of what a tree is, which was already specifically captured within the land cover classes, no classes were asked to be listed regarding this class.

Indicator 15.3.1 and GBF A.2 were directly derived from the areas of the classes in the land cover maps. Since the researcher found the area estimates of all classes and subclasses potentially useful, these were calculated by summing the pixels for each (sub)class on each land cover map. This total represented the land cover area of the (sub)class on Aruba when the composite image underlying the land cover map was created.

However, since SDG 15.1.1 only counted areas as forests if the total connected area was greater than 5000 m^2 (as described in the Subsection 2.2.1)), to calculate these values additional steps needed to be taken. Specifically, the land cover maps were converted to vector maps, where connected pixels belonging to a particular (sub)class were patched together into a polygon for that class. This yielded maps of polygons, where each polygon belongs to a class but with multiple polygons per class. The value of SDG 15.1.1 could now be calculated by adding the sizes of all polygons that are larger than 5000 m^2.

Subsection 3.2.2) Support Build with Nature policy

The land cover maps were also used to provide data for the domestic Build with Nature policy by providing current values of the areas of the main classes within the different categories. First, a function was made from all of the zones used within the map (**Figure 2**) to the seven categories of the policy (**Figure 3**), as each category consists of one or multiple zones. Then, maps containing the zones were obtained from the DNM. These could be used to create a mask for every category by creating masks of the constituent zones and merging these. These masks were then combined with the main land cover map of the dry season of 2024. Specifically, the land cover map was partitioned into the different categories using the masks. This gave a land cover map for each of the category areas. Now, for each of these category land cover maps, the total size of the map was calculated, and the size of each land cover class within the map. This yielded class estimates within each category. Finally, to be able to display the size of the classes in a single comprehensive figure matching the format from **Figure 3** the proportion of each class's size relative to each category's size was calculated and plotted in a single summarizing figure.

Chapter 4 Results

In this section the results achieved with the methodology discussed in the previous section will be documented. The utilized code can be found through a dedicated GitHub Repository.

Section 4.1) Land cover maps Aruba

This first section contains the developed set of land cover classes, and the performance of different classifiers in classifying the Aruban environment into these classes. Next, the

application where the land cover maps can be viewed and investigated is explained. Finally, the resulting performance analysis of the best performing classifiers is given.
All of the resulting maps are available through a Google Earth Engine application.

Subsection 4.1.1) Hierarchical set of land cover classes of Aruba as recognised by the DNM

The first goal was to identify which land cover classes are recognised by the Department of Nature and Environment. Results from the focus groups related to this are presented in **Table 4**, where the applicable WorldCover classes and selected subclasses are listed, along with justifying comments on their presence and representative locations. Classes and subclasses belonging to the same overarching category are highlighted using the same colour. A more extensive description of the selected classes and subclasses, including pictures and more justification, can be found in Appendix 4).

Table 4. The resulting classes and subclasses.

World-Cover class	Subclass	Justifying comments	Locations or defining species of representative points
Permanent water	-		Sea
Mangrove	-		Locations: Savaneta, Spanish lagoon. Species: Green, Red and Black Mangrove
Herbaceous wetland	Dam & tanki	Unique landscape on the island of Aruba, cultural significance	Rooi Afo and Dam di Moko.
	Salina	Different category since a lot dryer, surrounded by more flora and present at coastal areas.	Coastal shallow rainwater catchment containing lots of salt. Examples are tourist south coast and near Savaneta
	Wetland other	Only true historic Wetland left on Aruba	Bubali
Tree cover	Cactus dominated	Cacti on Aruba can be considered trees due to their significant size, long lifespan, and crucial ecological role in providing shade, habitat, and structural stability in the island's arid environment.	Breba, Breba di Pushi, Cadushi
	Deciduous tree dominated		Watapana, Pal'i siya blanco, Kwihi

Shrub-land	-		Aloe, Basora preto, Bringamosa, Flor di Sanger, Hubada, Seida, Taya, Tuna, Walishali
Bare or sparse vegetation	Quarry	Different since exposed rock and soil is visible, desired since this can quantify effects of quarries on the natural environment over time.	Excavations. Afgraving Budui, Maria Maai, Picaron. Butucu & Fontein excavation.
	Degraded land	Sandy roads heavily affected by vehicles. Desired to quantify and effects of UTV on natural environments.	UTV Roads at north Coast.
	Sand coast	Naturally occurring harsh conditions and minimal plant cover.	Beaches & dunes. Westcoast, Arikok & sasarawichi
	Rock coast	Harsh, rocky environment, which supports minimal plant life. Composed of limestone.	Mostly on northcoast
	Rock formation	Inland areas displaying exposed rock surfaces and minimal plant growth. Composed primarily of igneous rocks like diorite and quartz diorite.	Ayo, casibari & other polygons provided by DNM.
	Dead mangrove	Degradation of a previous mangrove ecosystem, resulting in barren landscapes with little to no plant life.	Savaneta & mangel halto
Build environment	Road	Man-made, replacing natural vegetation with paved surfaces for transportation.	Asphalt road
	Building	Man-made, replacing natural landscapes with developed structures.	Divide over Oranjestad and San Nicolaas
	Sport field	Man-made, replacing natural landscapes with barren or synthetic surfaces.	Once natural land turned into sport fields

Note. Completed table using within the focus groups, containing the resulting main and subclasses present and relevant on the island of Aruba as recognised by the DNM. Furthermore, comments justifying the selection of particular subclasses and information on representative locations can be found in the table.

Subsection 4.1.2) Classification of Aruban environment

The next section will give the results of the classification and subclassification of the entire island of Aruba into the hierarchical set of classes. First, the results of the selection and preprocessing of satellite imagery are given. Next, the resulting training and ground truth points are referenced. Then, the mean accuracies of classifying into the main and subclasses with all machine learning methods are given.

Selection of satellite imagery

The first thing gathered necessary for classification was relevant imagery from the Sentinel-2: MSI satellites. The first month for which data was available of the island of Aruba is March

2016, meaning that composite images were created from that date onwards. The first image was dry_2016, and the last was dry_2024. All images can be viewed through the application.

Training and ground truth points

The second thing needed for classification was training and ground truth points. These can be found in the GitHub repository, specifically:

- The points selected using GEE can be found under code/input/geeCsv
- The points selected from the available pictures can be found under code/input/picturesCsv
- The points selected from the fieldmap application can be found under code/input/arcGisCsv
- The training and ground truth points for the classes can be found in /output/classDict, and the training and ground truth points for the subclasses in code/output/subClassDict

Classification into main and subclasses

With the imagery and training and ground truth points gathered, the classification of all imagery into both the main and subclasses was done. The best-performing classifiers for each of these temporal classification problems, along with the associated mean accuracy, can be seen in **Table 5**. The mean error for all temporal classification problems can be found in Appendix 6)**.**

Table 5. Best performing classifiers for each temporal classification problem

	Main	Herbaceous wetland	Tree cover	Bare or sparse vegetation	Build environment
Best-performing classifier (Accuracy)	**K-Nearest Neighbours (1 neighbour) (70.49%)**	**K-Nearest Neighbours (1 neighbour) (98.82%)**	**Random Forests (20 trees) (71.03%)**	**K-Nearest Neighbours (3 neighbours) (85.32%)**	**Random Forests (20 trees) (78.30%)**
Second best-performing classifier (Accuracy)	Random Forests (40 trees) (68.51%)	Support Vector Machine (Linear kernel) (98.23%)	Random Forests (10 trees) (70.44%)	K-Nearest Neighbour (1 neighbour) (84.73%)	Random Forests (40 trees) (78.19%)
Third best-performing classifier (Accuracy)	Random Forests (50 trees) (67.91%)	K-Nearest Neighbours (3 neighbours) (98.04%)	Support Vector Machine (Linear kernel) (70.15%)	Support Vector Machine (Linear kernel) (84.52%)	Random Forests (10 trees) (78.10%)

The best-performing classifier for classification into the main classes was K-Nearest Neighbours (1 neighbour), achieving an accuracy of **70.49%**. For the Herbaceous wetland subclassification, the same method, K-Nearest Neighbours (1 neighbour), delivered the highest accuracy at **98.82%**. In the Tree cover subclassification, Random Forests (20 trees) emerged as the top performer with an accuracy of **71.03%**. Similarly, for the Bare or sparse vegetation subclassification, K-Nearest Neighbours (3 neighbours) achieved the best result, with an accuracy of **85.32%**. Finally, for the Build environment subclassification, Random Forests (20 trees) again proved to be the best classifier, with an accuracy of **78.30%**.

Land cover maps through web application

The created maps can be accessed through a web application. If readers who have previously never used Google Earth Engine want to access this application, they must first register in GEE, which can be done here.

A snapshot of the resulting application can also be seen in Figure 8, where the main land cover map of the dry season of 2024 is selected. The dropdown menus visible on the right can be used to select the following images:

- The composite images can be accessed using the dropdown next to 'Composite satellite images: '
- The land cover maps similarly can be accessed using the dropdown next to 'Main classes: '
- Finally, the sub land cover maps can be accessed using the dropdowns next to '(class) subclasses: '

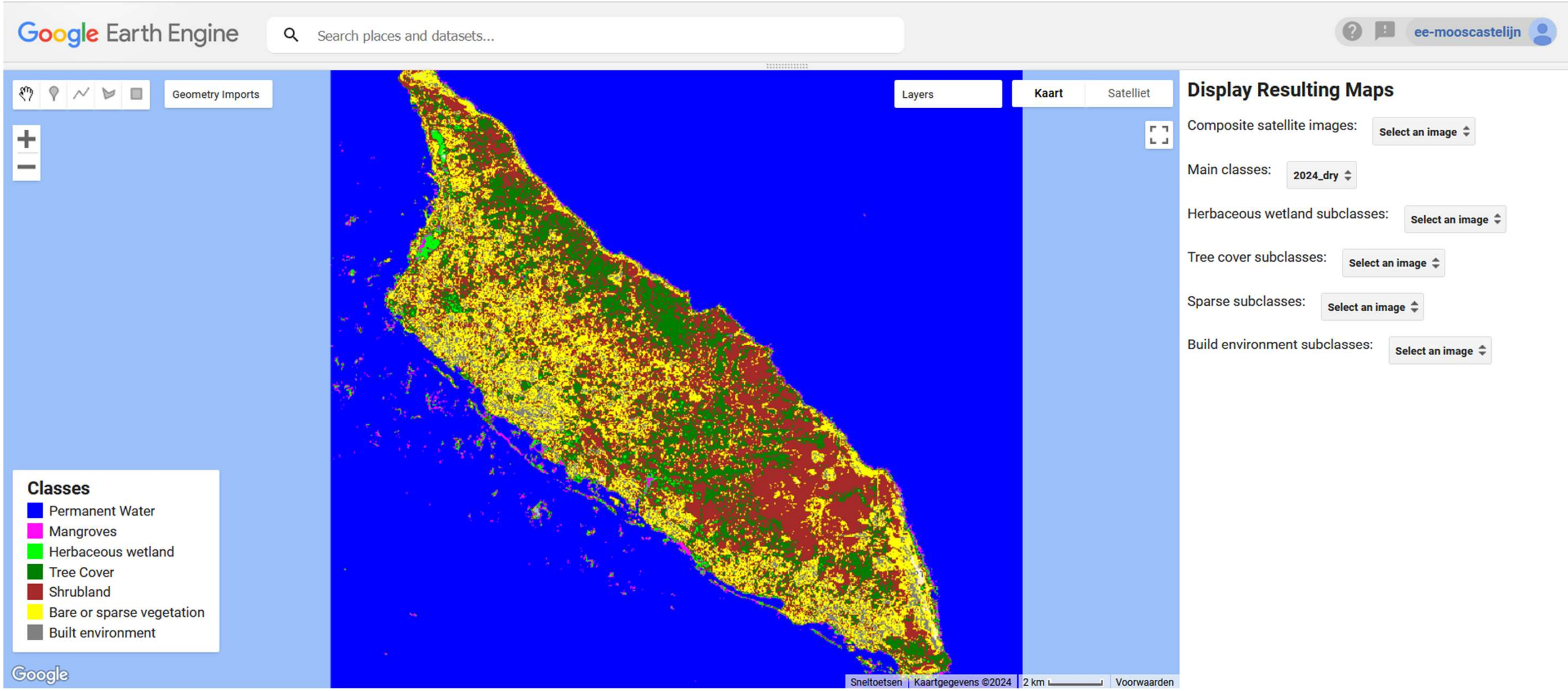


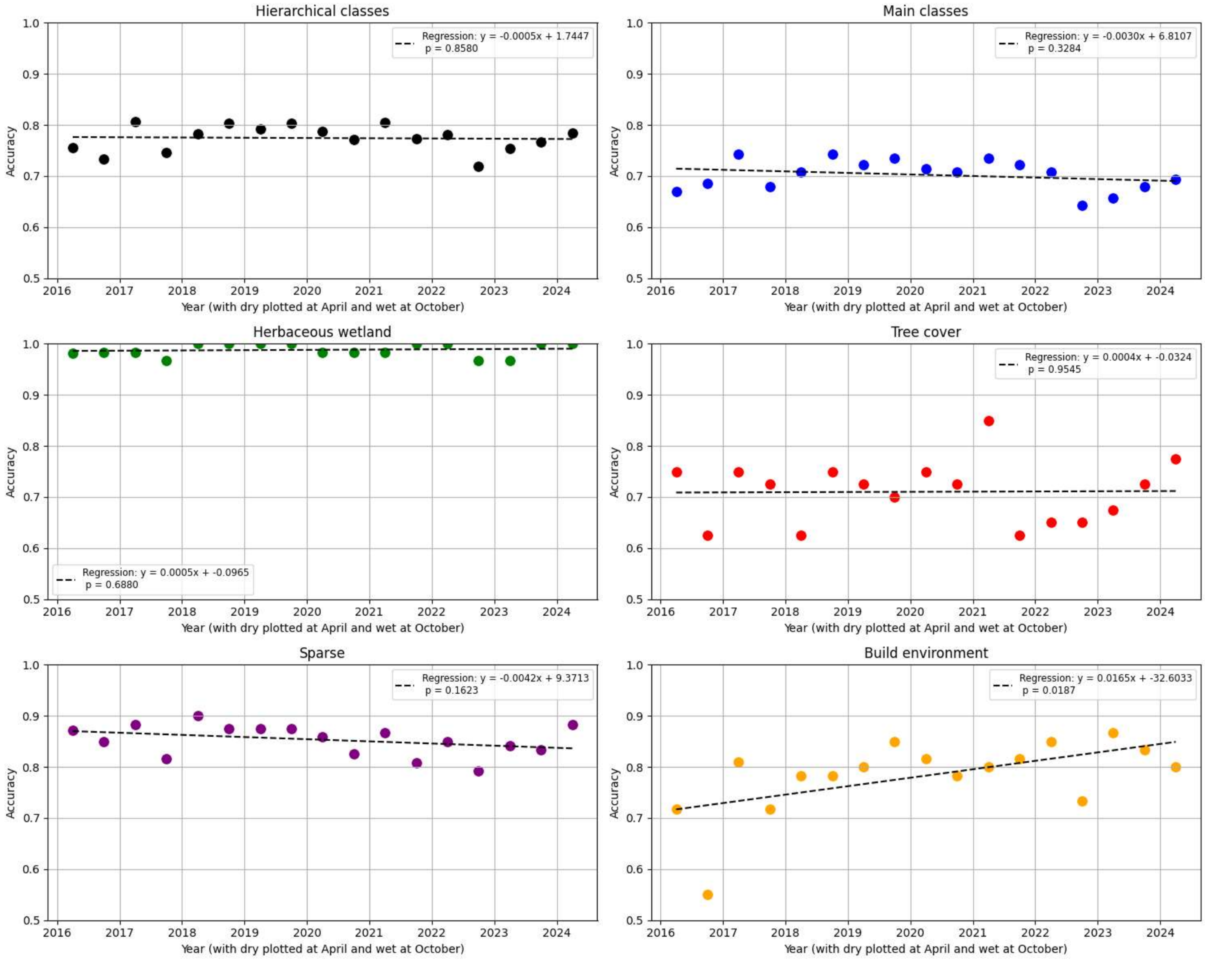
Figure 8. Google Earth Engine application for visualizing and navigating satellite images and classification images. The widget on the right can be used to select the desired image. Currently, the main land cover map 2024 is selected.

Performance for classifiers with the highest accuracy

The metrics calculated to assess performance can be found in this section.

Whilst the mean accuracies of each of the temporal classification problems were already known, as can be seen in **Table 5**, a more comprehensive overview of the error of each problem can be viewed in **Figure 9**. Here, the error for every year for every problem is given, along with a regression line to see if performance was worse for older imagery.

Figure 9. Accuracies of all classification problems over time



Note: accuracy over time for each problem with the best-performing classifier. A regression line is included for each problem to see if accuracy was worse for older imagery.

In the hierarchical classification problem, the highest accuracy was achieved during the 2017 dry season at 0.806, and the lowest was observed in the 2022 wet season at 0.719. Although there are some fluctuations year over year, the model performed consistently above 0.72, indicating a reliable classification process across different time frames.

For the main classification, the best performance was observed in the 2017 dry season with an accuracy of 0.743 and the lowest in the 2022 wet season at 0.643. While the accuracies for main class classification were generally lower than for hierarchical classification, the results remained stable over the years, indicating that the model effectively distinguished between the broader class categories with only minor variations between wet and dry seasons.

Among the four subclasses, the Herbaceous wetland subclassification problem stood out, with near-perfect or perfect accuracy from 2018 onwards, achieving perfect accuracy in many cases.

For the Tree cover subclassification, the classification accuracy peaked at 0.85 in the 2021 dry season, while the lowest accuracies were recorded during the 2016 and 2022 wet seasons, at 0.625 and 0.65, respectively. Since there were only two subclasses for Tree Cover, these results indicate that the model struggled to differentiate between them, particularly during the wet seasons.

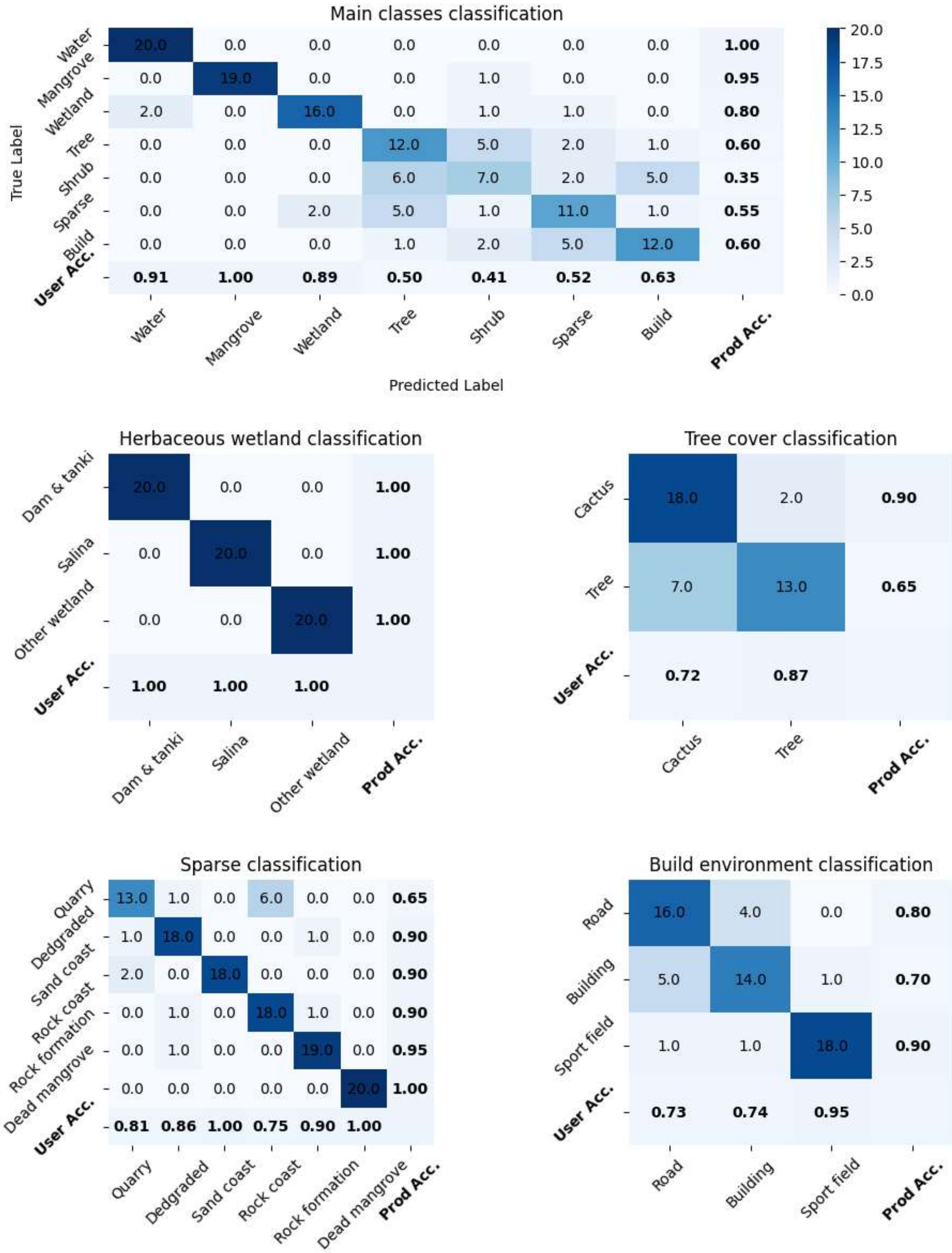
The Sparse subclassification performed well throughout the years, reaching a peak accuracy of 0.883 in the 2024 dry season. Although some minor fluctuations were noted, with the lowest accuracy at 0.792 during the 2022 wet season, the model proved to be reliable in identifying sparse vegetation or bare areas over time.

For the Built environment subclassification, the highest accuracy of 0.867 was recorded in the 2023 dry season, while the lowest accuracy of 0.55 occurred in the 2016 wet season. Despite this variability, accuracy consistently exceeded 0.70 in most cases, with the 2016 wet season being the only major outlier. The fluctuations in performance suggest potential challenges in distinguishing built environments from natural landscapes, particularly in earlier years or under wetter conditions. Notably, this was the only classification task that showed a statistically significant decrease in performance over time ($p = 0.0187$) when analysing data from the earlier years.

Overall, the machine learning model performed reliably, with accuracy generally improving in recent years, showing that the quality of the synthetic training points worsened farther back in time. Herbaceous Wetland subclassification was consistently strong, while Sparse subclassification showed stable results with minor variations. However, the model struggled to differentiate between the two Tree cover subclasses. Built environment subclassification had the greatest variability, indicating a need for further refinement to improve the detection of urban areas.

The second metric was confusion matrixes for each classification problem, combined with observations of the resulting land cover maps. The confusion matrixes can be seen in **Figure 10**, along with the associated user and producer accuracy.

Figure 10. Confusion matrixes for each classification problem



Note: These confusion matrixes are computed for the classification of the composite image of the dry period from 2024. Each matrix also contains the user and producer accuracy.

The main classification performed well for Permanent water, Mangrove, and Wetland classes, with high user and producer accuracies (>0.8). These results were reflected in the land cover maps, although there were some discrepancies. For example, Permanent water pixels appeared inland in areas expected to be Herbaceous wetland. Similarly, some Mangrove and Herbaceous wetland pixels were found inland at locations such as Bubali lake and the northern coast. These errors may be attributed to the low resolution of the data, which caused mixed-class pixels, particularly where moisture was present. However, the model struggled to differentiate between vegetation classes like Tree and Shrubland, where user and producer accuracies were below 0.6. Tree cover was often misclassified as Shrubland, and Shrubland was sometimes confused with Built environment, resulting in unexpected shrubland pixels in urban areas like Oranjestad. Additionally, Sparse and Built environment classes were often confused, with Sparse pixels incorrectly classified as Tree cover or Built environment due to spectral similarities between barren fields, dead mangroves, and urban rooftops.

The subclassification of Herbaceous wetland (Dam & tanki, Salina, and Other wetland) showed perfect performance, indicating clear separability of these classes. The land cover map confirmed that Salina and Other wetland pixels were predominantly in the correct locations, though Dam & tanki pixels were over-represented.

In Tree cover subclassification, there was a bias toward the Cactus class, with user accuracy of 0.9 compared to 0.65 for Deciduous tree, although the overall classification was still acceptable. On the map, cacti were more abundant and more frequent in the harsher northern coast, as expected, while trees were primarily located along the calmer southern coast.

The classifier performed well the Sparse subclasses Degraded land, Sand coast, Rock formation, and Dead mangrove, showing clear separation in the confusion matrix. However, the Quarry subclass was frequently misclassified as Rock coast, likely due to similar spectral signatures between barren quarries and rocky coastal areas. On the map, the Sparse class appeared in many locations, with Degraded land and Quarry pixels spread more widely than expected. Dead mangroves were also misclassified in some coastal areas with rocks or vegetation. Despite these issues, Sand coast and Rock coast were accurately mapped in their known locations along the western and northern coasts, respectively, while Rock formations were correctly identified inland.

In Built environment subclassification, distinguishing between Roads and Buildings was difficult due to the pixel size (10 meters), often resulting in mixed pixels. Consequently, the classifier struggled to separate these features accurately. While Sport field classification performed well, some confusion occurred between Sport fields and Buildings. On the map, Road pixels appeared randomly without following any clear pattern, and major roads were not identified. Sport field pixels were mostly accurate but appeared in unexpected locations, such as the airport.

Section 4.2) Land cover information

The values of the different land cover information desired by DNM can be found in this section.

Subsection 4.2.1) Environmental indicators

Here, the found values of the SDG 15.1.1, SDG 15.3.1 and GBF A.2 are stated. As part of this step, the value of land cover areas on the island of Aruba over time was computed. Since these may be useful by themselves, the values of the land cover can be found in Appendix 7).

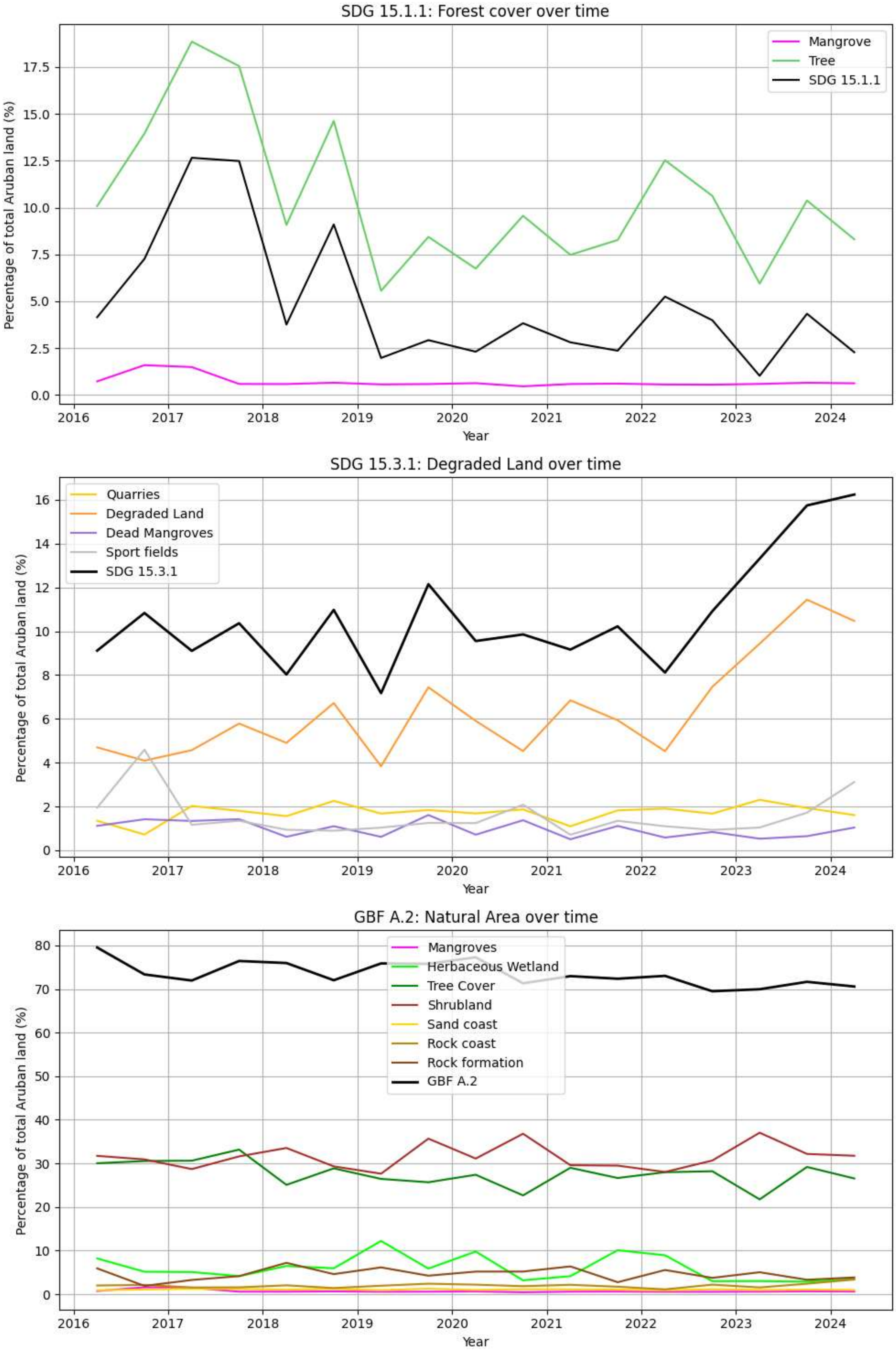
The focus groups yielded the (sub)classes for both indicators SDG 15.3.1 and GBF A.2. For SDG indicator 15.1.1. the values are picked by me, since for this a very strict definition of Forest is used. However, it became clear in the focus group that this narrow definition of 'Forest' was too limiting and did not capture all land cover types locally perceived to be forest. More on this can be found in the relevant discussion in Subsection 5.2.1). The utilised (sub)classes for each of the indicators can be seen in **Table 6**.

With these classes, the values of the indicators were calculated. The values of the indicators over the period for which Sentinel-2 pictures were available can be seen in **Figure 11**. Here, the area of the constituent (sub)classes are also plotted. The exact values for the dry season of 2024 can be seen in **Table 6**. The exact values for all years can be found in Appendix 8).

Table 6. Classes and subclasses perceived to belong to the indicators

	SDG 15.1.1	SDG 15.3.1	GBF A.2
Classes & Subclasses	Mangrove, Deciduous tree dominated	Quarries, Degraded land, Dead mangrove, Sport field	Mangrove, Herbaceous wetland, Tree cover, Shrubland, Sand coast, Rock coast, Rock formation
2024 indicator value [% of Aruban area]	2.28%	16.24	70.57

Figure 11. Environmental Indicators over time



Note: Showing the calculated values of SDG 15.1.1, SDG 15.3.1 and GBF A.2 starting from 2016 until 2024. Every indicator is in the percentage of the total Aruban area.

SDG 15.1.1, which measures forest cover as a proportion of total land area, showed considerable fluctuations across the years and seasons, which makes the values of this indicator over earlier years at least questionable. For later years, the indicator value was around 2.5%. The constituent mangrove class always had a small area, contributing little to the indicator value, meaning that the indicator was mainly determined by the extent of the Deciduous tree class. Interestingly, the indicator value is below the Deciduous tree area, indicating that the constraint of only including connected areas larger than 5000 m^2 had a significant impact on the indicator.

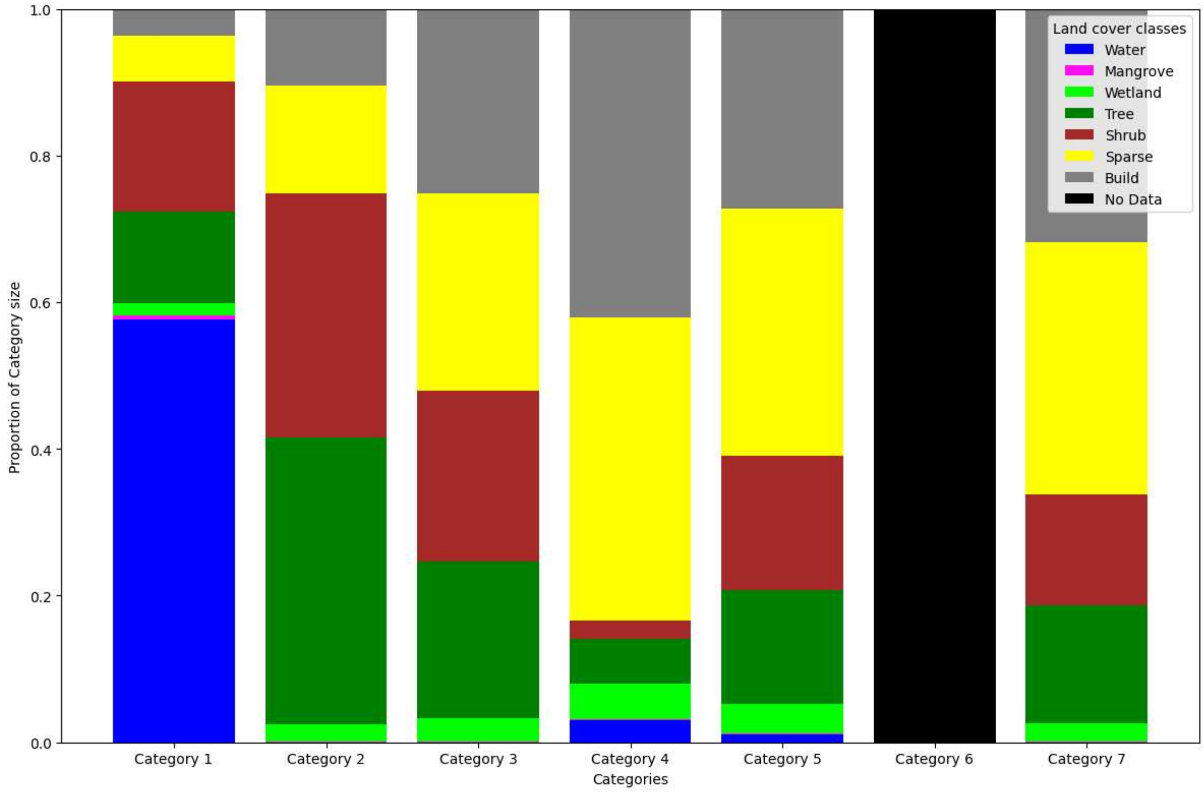
SDG 15.3.1, which measures the proportion of land that is degraded, exhibited some fluctuations, with a noticeable increase starting from 8.12% in the dry season of 2022 to 16.24% . The subclass largely determining this indicator was the Degraded land subclass, whose perceived increase in recent years also explained the recent increase. However, the land cover map which shows the Sparse subclasses of 2024 showed that Degraded land was present in many locations, also where it was not expected, decreasing the confidence in the found indicator.

GBF A.2 measuring natural area as a proportion of total land area remained relatively high and constant across the whole period, with values always above 69%. This was largely due to the size of two constituent classes, namely Tree cover and Shrubland, which collectively already made up 60% of the Aruban environment.

Subsection 4.2.2) Linking to Build with Nature

The second information that the DNM wanted from processing the land cover maps were area estimates for the Build with Nature zones for the year 2024. The function from the zones to the categories can be seen be found in Appendix 9). The resulting land cover areas within each of these categories can be seen in **Figure 12**. The actual sizes for each of the areas within the category, see the Appendix 9).

Figure 12. Land cover classes within each of the Build with Nature categories for the year 2024



First, it should be noted that none of the zones of category 6 were present on the zoning map (**Figure 2**), meaning that no area estimates for this category could be done. These zones were 'Infrastructuur' ('Infrastructure') and 'Hoofdwegen' ('Main roads') and were maybe not on the map given the narrow size of elements belonging to these zones. Water was almost exclusively present within the first category, matching the 'Marine Park' and 'Overig kustwater' ('Other coast water') zones. The Mangrove class has such a small area on Aruba that it is almost unnoticeable in every category. Wetland was present in an almost equal proportion in the different categories. Tree cover was present more in the earlier categories (particularly in the first if we disregard water), matching that these categories are meant to contain more natural land cover. The same holds for the Shrubland class, although it stays more present than the Tree cover class in later categories. The Sparse and Build environment class showed an opposite pattern, becoming more abundant in later categories.

Chapter 5 Discussion

Section 5.1) Land cover maps

First, general discussion points regarding the creation of land cover maps will be stated.

Complex methodology

What this methodology tried to do was the following: instead of answering a single question to be answered by remote sensing classification, formulate comprehensive land cover maps capable of answering a multitude of questions identified at DNM. One the one hand this comprehensive method is powerful, and Gisbert (DNM manager) was a supporter of this since it closely mirror how they work. This has the advantage of answering many needs all at once and even yielding information for needs not identified when the land cover maps were created. However, this does create land cover maps that are not optimized for any specific question. If this is desired, a more streamlined classification procedure is recommended.

Collaborative research

A unique aspect of this research is the incorporation of local information needs into the environmental classification process. This approach was taken to ensure that classified images are actually used for questions deemed relevant by people in charge of the local environment. This aids in overcoming the technical difficulties associated with remote sensing analysis (Nandasena et al., 2023), making them more knowledgeable about the possibilities and impossibilities of this technology, and that the results tailer most to the needs of local environmental actors. Research of this type is highly relevant and should be practised more wide spread, to ensure that scientific advancements are adopted by developing countries which could benefit a lot from these technologies.

Subsection 5.1.1) Hierarchical set of Land Cover classes incorporating local needs

Implications

This research formulated a novel methodology for creating a hierarchical land cover classification system incorporating land cover classes recognised by actors responsible for land cover management. This was done in two stages, first local policy makers had to select WorldCover classes they recognized to be present on Aruba, after a subclassification of classes that they thought were too broad was developed.

This method filled a research gap within landscape ethnoecology by facilitating the creation of hierarchical classification systems tailored to the needs of local policymakers. Prior research focussed on applying Landscape Ethnoecology methods to indigenous communities (Jiang, 2003; Libakova & Sertakova, 2015; Riu-Bosoms et al., 2015). However, this thesis demonstrates the effectiveness of applying these methods to policy makers, as it results in land cover classes both related to their views on nature and their particular land cover information needs. This information can then immediately inform policy or monitor land change.

A key strength of this methodology is that it ensures a comprehensive land cover classification system by starting with main classes that were previously developed for global application. This approach allows for the immediate adaptation of a localised hierarchical land cover classification system to vastly different regions around the world. Hierarchical systems like this are available (Di Gregorio & Jansen, 1998), most notably by the FAO (Latham et al., 2002), but these have as of yet failed to capture views of local stakeholders. This methodology uniquely produces a hierarchical classification system that is both comprehensive and aligned with land cover classes recognised by selected stakeholders, including policymakers and indigenous communities. This tailored land cover information can then be directly incorporated into policy decisions.

The results also have implications. Locations that are similar in land cover and desire similar information can use the developed hierarchical classification system immediately as the present local classes. For example, neighbouring Curacao and Bonaire, which have similar natural land cover to Aruba following the identical climate (Schmutz et al., 2017), and experiencing similar land cover change pressure due to tourism (Dinica, 2006; Schep et al., 2013). However, the developed system can also serve as a starting point for other regions, provided that researchers and local stakeholders determine its relevance. This decision should be based on an evaluation of the locally occurring land cover and whether the recognised classes meet the needs of stakeholders in the new location.

Furthermore, the developed system can serve as a starting point for further studies on land cover change in Aruba, by the DNM or other agents interested in land cover on the island. For example, the system can be utilised for a detailed analysis of how land cover changes impact ecosystems, biodiversity, and natural resources. Or, knowledge about specific classes can be expanded, to learn more specifically what is monitored within each class.

Top-down approach

A potential drawback of the employed methodology is its predominantly top-down approach. By beginning with predefined main classes, it may influence local perceptions of these classes rather than adopting a fully bottom-up approach. While this method ensures comprehensive coverage, it may not fully align with locally recognised classes if the research focuses on understanding and incorporating local perspectives.

Although this was not experienced to be a drawback here, this should be considered if research wants to focus more completely on locally recognized classes. If so, the research of Riu-Bosoms et al. (2015) offers a suitable methodology. Here, field listings are employed without a starting point, thus offering a truly bottom-up approach.

Subsection 5.1.2) Machine learning based classification of the Aruban environment

Utilised Remote Sensing Data

The Sentinel satellite was utilised since this was the satellite data with the highest temporal and spatial resolution available through Google Earth Engine. There are some potential biases associated with these images however, which will now be addressed.

First, whilst clouds were attempted to be masked through the creation of a composite, it can be observed that this was not sufficient for all pictures. Specifically, for dry_2023, some gaps in the composite map result where clouds were present in all pictures. The land cover maps from this composite therefore have also gaps at these locations. Measures to mitigate this such as using a longer time period, using interpolation techniques, or applying higher threshold cloud masks (Zekoll et al., 2021) can be considered if these gaps are a problem. For this research, since it concerned only small gaps in an older composite image, these were accepted. This can be defended by noticing that the accuracy for none of the classification problems was noticeably worse for the dry composite of 2023, which implies that the effect of these gaps on classification was minimal.

Secondly, sub-grid variability is expected to have had a noticeable impact on the accuracy of classification for certain land cover classes in this study. The variability within a single pixel led to classification challenges, as mixed land cover types within a pixel reduced the model's ability to accurately assign a single class. Despite the relatively high spatial resolution of Sentinel-2, the mixed nature of these pixels introduces uncertainty in classification results. For example, urban areas often contain a mix of built structures, vegetation, and bare ground within the same 10-meter pixel, which can result in misclassification. Since ground truthing points are picked at locations which are not mixed, this uncertainty is not quantified in any performance metrics. Future research should be conducted to see when mixed pixels are classified into which class.

Lastly, sensor drift is expected to have impacted the results minimally, as rigorous radiometric and geometric calibration is regularly performed by the ESA.

If even finer spatial resolution is desired for the resulting land cover maps, starting with composite images which have a smaller spatial resolution, such as WorldView-3 data can be bought (Longbotham et al., 2015). These are not automatically available in Google Earth Engine. However, after manually creating the composites using tools like GIS and uploading them to Google Cloud, the classification code written in this thesis can be used again with minimal changes.

Number and quality of training and ground truth points

In this study, 20 training and 20 ground truth points were used for each class and subclass in the land cover classification. While this meant a feasible number of points for each class were gathered, it may not fully capture the variability within more complex or heterogeneous classes. Additionally, the selection of 20 points per class could introduce bias if the chosen points do not adequately represent the full spectrum of conditions within each class. Finally, it reduced confidence in the computed accuracies, as the limited number of ground truth points could also lead to biases here. Future work should consider vastly increasing the number of ground truth points collected, in such a way that an acceptable margin of error of the computed accuracies is known beforehand (Fitzpatrick-Lins, 1981).

Furthermore, points were chosen based on the current state of the island, but ideally it should be checked whether the points match the classes they represent for the entire period composite images are classified. For example, using the current methodology it may be the case that points representing Build environment are placed in buildings that were not there in the first composite image from 2016. Exactly this may be the reason for the lower accuracy in Build environment subclassification for earlier years.

Performance of different classifiers

Two classifiers outperformed all others in all of the classification problems, namely the k-Nearest Neighbour and Random Forest algorithm, with Support Vector Machine also being up there in the classifier rankings. This matches the results of Khatami et al. (2016), who found that exactly these three methods generally outperform other classifiers in land cover classification.

Specifically, k-Nearest Neighbour has been previously found to perform highly accurate with smaller datasets (Peterson, 2009), which was the case within this study. For Support Vector Machine and Random Forest the good performance is matched by other research such as Nguyen et al. (2020), who found accuracies of 80% in creating land cover maps of Dak Nong Province in Vietnam. Interestingly, Thanh Noi & Kappas (2017) found my results in reverse, with highest accuracy for SVM, followed by RF and finally kNN. These conflicting results once more support the finding of Maxwell et al. (2018) that there exists no general optimal classifier. What my study has at the very least demonstrated is that k-Nearest Neighbour should not be disregarded in Land cover classification problems, as not all studies comparing classifiers in Sentinel even include kNN (For example: Forkuor et al. (2018)).

Comprehensive accuracy assessment

Finally in this research performance was only measured with the accuracy and confusion matrix. Other measures are available such as the kappa score and the fscore. These both offer more comprehensive performance, since they address imbalances in class occurrence. However, the way that ground truth points were gathered in this work make these measures unsuited. Specifically, these correct for the fact that if a class occurs a lot more in the environment, the model accuracy would increase simply if it would predict just that class most of the time. These metrics then punish for just choosing the most occurring class. However, this assumes that more ground truth points indicate more occurrence of that class in the environment. This is not the case in my work since every class has an equal number of ground truth points, so these more extensive metrics were unsuited. For this reason, collecting ground truth points after classification by fixing random points along a grid (stratified random sampling) can be more suited, since then the occurrence of a class is contained in accuracy assessment. The current approach resulted in the calculated high accuracy not being reflected in the land cover maps.

Quality of land cover maps

Evaluation of the land cover maps demonstrates that while the mapping of certain land cover classes, like Permanent water, Mangrove, and Wetland, performed well, challenges arose with more complex features, particularly in distinguishing between vegetation types and Built environment categories. The results highlight the limitations of low-resolution data in the real world, where mixed pixels, especially in urban or transitional areas, can introduce noise into classifications. For example, the confusion between Tree cover and Shrubland and the misclassification of Sparse land as Tree cover illustrates how spectral similarities can affect classifier performance, leading to inaccuracies in areas with mixed vegetation or barren land. In a practical context, this limitation could hinder land management decisions that rely on precise vegetation mapping.

Moreover, the confusion between Roads and Buildings reflects a broader issue when applying land cover maps in real-world urban planning or environmental monitoring. The inability to clearly separate these classes suggests that higher resolution data or more targeted training data are necessary for better accuracy. This is particularly important for urban planning or conservation efforts that depend on clear differentiation between infrastructure and natural features. The accurate classification of wetlands and cacti, however, shows that some land cover types can be reliably mapped, offering valuable insights into habitat conservation and ecosystem services. Overall, the maps provide a useful tool for understanding Aruba's land cover, but their application in real-world scenarios should account for the noted classification challenges, particularly in urban and transitional environments.

Google Earth Engine application

The created composite images and land cover maps can all be viewed an investigated using the created Google Earth Engine application. A valuable addition to the current application would be that if a new composite could be computed (so the next one being in February, when the picture wet_2024 can be calculated), this was done automatically. Furthermore, the land cover images for this composite could also be calculated automatically. This would continually supply the DNM with up-to-date land cover classes to be used for the same purposes as highlighted within this thesis or any new purposes they see fit.

Difficulties in using locally recognised classes

A limitation encountered within this research is that local perceptions of subclasses may yield subclasses that are too similar. Specifically, that machine learning based land cover classification cannot distinguish one subclass from another. This is supported by Gavish et al., (2018) who found that thematically distinct but spectrally similar classes had a high degree of misclassification. To mitigate this, researchers could employ an initial analysis of representative points for subclasses to see whether the difference in spectral signatures is deemed sufficient. Another method is proposed by Balarabe and Jordanov (2024), who developed a method for combining similar subclasses into superclasses.

A second limitation is that certain perceived subclasses are too small for the resolution of the utilised remote sensing imagery. An example of this in this thesis is that of the Degraded land subclass of the Bare or sparse vegetation class. It is rarely the case that an entire pixel is only filled with the land degraded by UTV vehicles, such degraded land is never 10 metres wide which means that a certain pixel is only rarely fully filled with this class. This subclass then cannot really be expected to be classified.

A third limitation to keep in mind when applying this methodology is that some subclasses that local agents strongly feel belong to a certain overarching class can negatively impact the classification procedure by reducing accuracy. This is expected to have been the case with the Sport field subclass, which was thought to be a subclass of Build environment due to being created by humans. This resulted in the Build environment class containing pixels from Sport fields, which broadened the distribution of spectral signatures within the Build environment class and reduced accuracy of Build environment and bare and sparse vegetation classification significantly.

Section 5.2) Using Land cover maps in environmental management

Subsection 5.2.1) Environmental indicators

The indicators should be investigated before they are submitted. One way this can be done is by looking at the classes underlying the indicators on the map and seeing whether this matches known conditions. For example, The SDG 15.3.1: degraded land was seen to increase heavily over the last few years (starting from the dry season of 2022), due to a large increase in Degraded land (By UTV traffic). However, upon viewing the land cover map, the value of this class was seen in many cases where it is known not to be present. This makes the value of the indicator questionable and indicates that future research into suitable classes and classification for this indicator needs to be done.

A further point of discussion is the restrictive definition of Forest as utilized within SDG 15.1.1.: “Land spanning more than 0.5 hectares with **trees** higher than 5 meters and a canopy cover of more than 10 percent, or **trees** able to reach these thresholds *in situ*. It does not include land that is predominantly under agricultural or urban land use (UN, n.d.-a)”. Notice the word tree here. Locally, cacti are also perceived to fill similar functions as trees by providing shade, habitat and structural stability. Given that trees are explicitly stated in the definition and cacti are not trees, they are not allowed to be counted in calculating the indicator. But this is ignorant of the local context, which is a large problem in SDG indicators in general (Kulonen et al., 2019). To illustrate the effect of including the local context, a value of SDG 15.1.1 including the cacti was also calculated and yielded a value in the dry season of 2024 of 20.18% (for values of all years, see Appendix 8)). This was significantly higher than the non localized value of SDG 15.1.1 in the dry season of 2024, which was 4.15%! The large discrepancy observed once again calls for increased inclusion of local context within the SDG indicators.

Subsection 5.2.2) Build with Nature

In order to improve the link between the policy aims of the Build with Nature policy figure (**Figure 2**) and the zoning map (**Figure 3**), utilising the same classes in both would help. Now, for instance, the environmental classes within zone six could not be measured, since none of the areas mentioned within **Figure 3** correspond to zones in **Figure 2**. However, matching the found Build environment within the categories to goal of maximum build environment leads us to conclude based on this data that the goals are currently satisfied, and that policy should aim to keep this.

Chapter 6 Conclusions

This research aimed to develop land cover maps for Aruba that incorporate classes recognized by the Department of Nature and Environment (DNM) and to use these maps to provide the desired land cover information. The research questions were addressed as follows:

The study successfully created current and historical land cover maps for Aruba, classifying Sentinel-2 imagery using a hierarchical set of land cover classes developed in collaboration with DNM. A total of 11 main classes, subdivided into 17 subclasses, were recognized as relevant to the island's landscape. These classes reflect both the local environmental characteristics and the policy needs of the DNM. The best-performing machine learning classifiers were K-Nearest Neighbours and Random Forest, achieving classification accuracies ranging from 70% to 98%, depending on the class. Herbaceous wetland and Sparse vegetation classes were classified with high accuracy, while more complex classes, such as Tree cover and Built environment, posed challenges due to spectral similarities between their subclasses.

The recognized land cover classes for Aruba included Mangrove, Herbaceous wetland, Tree cover (dominated by cacti and deciduous trees), Shrubland, Bare or sparse vegetation (with subclasses like Degraded land and Quarries), and Built environment (subdivided into Roads, Buildings, and Sport fields). These classes aligned closely with local ecological and policy needs, providing a detailed framework for monitoring and managing Aruba's environment. In terms of classifier performance, K-Nearest Neighbours and Random Forest classifiers were most effective, with K-Nearest Neighbours performing particularly well for the main classification and subclassification of Herbaceous wetland and Sparse vegetation, while Random Forest showed strong results for subclassifying Tree cover and Built environment.

The land cover maps generated through this research were also used to calculate environmental indicators desired by DNM, particularly the SDG indicators and the GBF A.2 indicator. For SDG 15.1.1, which measures forest cover, the calculated value remained low at around 2.28%, with the limited extent of Deciduous tree cover contributing most to the indicator. For SDG 15.3.1, which measures degraded land, the value increased significantly from 8.12% in 2022 to 16.24% in 2024, largely due to the rise of the Degraded land subclass. However, discrepancies in the land cover maps suggest that this indicator may be overestimated, warranting further refinement of the classification system. GBF A.2, which measures natural area, remained consistently high, with natural areas accounting for 70.57% of Aruba's total land area, supported by the large presence of Shrubland and Tree cover classes.

In relation to the Build with Nature policy, the land cover maps provided area estimates for the different zones established by the policy. Water, Tree cover, and Shrubland were predominantly found in the earlier, more natural zones, while Sparse vegetation and Built environment dominated the later zones.

Overall, this research provided DNM with a functional and relevant land cover classification system that helps fill important knowledge gaps about Aruba's environment. While the classification system proved effective, further refinement is recommended, particularly for distinguishing complex land cover types like degraded land and urban infrastructure. Nevertheless, the land cover maps and findings offer a valuable resource for future environmental management and policy decisions on the island.

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Appendix

Appendix 1) Internship Agreement

Internship agreement

This Internship Agreement is entered into between Department of Nature and Environment (DNM), Aruba and Moos Castelijn, Master student Sustainable Development in Utrecht.

1. Duration

The internship will commence on **05-02-2024** and conclude on **19-04-2024**, unless elongated as per the terms outlined in this agreement.

2. Supervision and Mentorship

The DNM will appoint a supervisor to oversee the intern throughout the internship.

The first day of the internship will begin with an orientation session, where the intern is acquainted with the organization's operations, policies, and workplace culture. Furthermore there will be a session where the intern will present their current project plans, which may be modified to better suit DNM's objectives.

Subsequently, regular meetings, either weekly or bi-weekly, will be organized. These sessions are designed to monitor the intern's progress, address any emerging issues, and ensure that the intern's efforts are consistently aligned with DNM's operational requirements.

3. Interviews

The intern is allowed interviews several DNM employees to assist in the thesis of the intern.

4. Intellectual Property

Any work created by the intern during the internship have to become publicly available. This is a consequence of the intern conducting a master thesis. In the situation where the DNM or any other organization has private data which is useful the intern, this data it can remain private.

5. Elongation

If the research necessitates a longer duration to achieve the primary goal of providing additional value to the Aruban government, this can be discussed.

Moos Castelijn, Utrecht University

xxx.xxxx, Department of Nature and Environment

Appendix 2) Informed consent & information sheet

INFORMED CONSENT FORM (INTERVIEW)

In this study we want to learn about perceived classes of the Aruban environment by DNM employees. Participation in this interview is voluntary and you can quit the interview at any time without giving a reason and without penalty. Your answers to the questions will be shared with the research team. We will process your personal data confidentially and in accordance with data protection legislation (the General Data Protection Regulation and Personal Data Act). Please respond to the questions honestly and feel free to say or write anything you like.

I confirm that:

- I am satisfied with the received information about the research;
- I have no further questions about the research at this moment;
- I had the opportunity to think carefully about participating in the study;
- I will give an honest answer to the questions asked.

I agree that:

- the data to be collected will be obtained and stored for scientific purposes;
- the collected, completely anonymous, research data can be shared and re-used by scientists to answer other research questions;

I understand that:

- I have the right to see the research report afterwards.

Do you agree to participate? o Yes o No

INFORMATION SHEET **(INTERVIEW)**

INTRODUCTION

You are invited to take part in this study on collaboratively classifying remote sensing imagery. The purpose of the study is to learn about how classified remote sensing imagery can aid in environmental monitoring on Aruba. The study is conducted by Moos Castelijn who is a student in the Msc programme Sustainable Development at the Department of Sustainable Development, Utrecht University. The study is supervised by Britta Ricker.

PARTICIPATION

Your participation in this interview is completely voluntary. You can quit at any time without providing any reason and without any penalty. Your contribution to the study is very valuable to us and we greatly appreciate your time taken to complete this interview. We estimate that it will take approximately 60 minutes to complete the interview. The questions will be read out to you by the interviewer. Some of the questions require little time to complete, while other questions might need more careful consideration. Please feel free to skip questions you do not feel comfortable answering. You can also ask the interviewer to clarify or explain questions you find unclear before providing an answer. Your answers will be noted by the interviewer in an answer template. The data you provide will be used for writing a Master thesis report and may be used for other scientific purposes such as a publication in a scientific journal or presentation at academic conferences. Only patterns in the data will be reported through these outlets. Your individual responses will not be presented or published.

DATA PROTECTION

The interview is also audio taped for transcription purposes. The audio recordings will be available to the Master student and academic supervisors. We will process your data confidentially and in accordance with data protection legislation (the General Data Protection Regulation and Personal Data Act).

Audio recordings will be deleted when data collection is finalized and all interviews have been transcribed.

Appendix 3) Non-disclosure agreement DNM data

Directie Natuur en Milieu
Ministerie van Transport, Integriteit,
Natuur en Ouderenzaken

GEHEIMHOUDINGSOVEREENKOMST VOOR ONDERZOEKSDATA

Tussen **Directie Natuur en Milieu** (de "Verstrekker") en **Moos Castelijn** (de "Ontvanger").

Datum: 19 februari 2024

Doel van de Overeenkomst:
De Ontvanger krijgt toegang tot vertrouwelijke onderzoeksdata voor het uitvoeren van een specifiek project.

Gebruik en Openbaarmaking:
De verstrekte informatie wordt alleen gebruikt voor het onderzoek. Openbaarmaking aan derden is niet toegestaan zonder schriftelijke toestemming.

Duur van Geheimhouding:
Verplichtingen blijven geldig gedurende het project.

Ondertekening:
Bevoegde vertegenwoordigers namens beide partijen bevestigen de overeenkomst.

Naam Bedrijf: Directie Natuur en Milieu Naam Stagiair: Moos Castelijn

Handtekening: ________________________ Handtekening: ________________________

B v/d Veen Zeppenfeldtstraat 7, San Nicolaas ARUBA tel: (297) 584-1199
www.dnmaruba.org Find us on

Appendix 4) Specification of environmental classes

Now, for each of the WorldCover classes, a discussion about if this class occurs on Aruba, if so if there is a subclassification in order and where the representative points for the class/subclasses can be found.

1) Permanent water

Figure 13. Water bodies example from the western coast of Aruba. Picture taken by the researcher.

The island is surrounded by the sea, and at various locations there occurs water year round, which was chosen to be the only real example of this category on Aruba by DNM employees. There are other permanent water bodies on the island of Aruba, but their shallowness made the DNM employees decide that these bodies fitted better at the 'Herbaceous wetland' category.

2) Mangrove

Figure 14. Mangrove example from the Spanish lagoon. Picture taken by the researcher.

Mangrove forests occur on Aruba as barrier islands along the southern coast, and as forests on the southern coast. Locations where these occur are Mango Halto, the Spanish lagoon and in the south of Savaneta. The species they wanted as defining a mangrove ecosystem are the red mangrove (*Rizophora mangel*), black mangrove (*Avecinnia germinans*) and white mangrove (*Laguncularia racemose*).

3) Herbaceous wetland

Figure 15. Herbaceous wetland example from Bubali. Picture taken by the Aruba Tourism Authority (n.d.).

DNM employees wanted to include this section, but recognized distinct subclasses which should all fall under this category. Namely, the subcategories of Dam & Tanki, Salina and Other Wetlands were recognized. The difference between these categories are that the first constitutes year round rainwater deposits, the second are shallow or dry coastal salt pans and the third is Bubali, a deeper year round wetland consisting partly of waste water.

3.1) Dam & tanki

Figure 16. Dam and Tanki example from Rooi Afo. Pictures taken by the researcher

The "Dam & Tanki" subclass refers to a unique type of wetland landscape found on Aruba, characterized by either man-made or natural rainwater catchments. This subclass includes two main types, which were DNM saw as looking similar but having a very different cause. The first is Dam, which are Man-made structures designed to capture and store rainwater. These are typically constructed for purposes such as water supply or flood control. The second are the Tanki, natural depressions in the landscape that collect and retain rainwater. These are often smaller and can be seasonal, filling up during the rainy season and drying out afterward. Both Dams and Tanki’s hold cultural significance on Aruba as they are integral to the island's water management systems. The knowledge of their locations and uses reflects historical and contemporary practices in water conservation.

3.2) Salina

Figure 17. Salina example from north of Westcoast. Picture taken by the researcher.

The “Salina” subclass represents coastal wetlands that are significantly drier compared to other wetland types. These areas are characterized by the accumulation of salt and are influenced by their proximity to the coast. Salinas have a much drier environment compared to other wetlands due to the high evaporation rates and salt content. Typically surrounded by more salt-tolerant flora adapted to the harsh, saline conditions.

3.3) Wetland other

Figure 18. Other wetland example from Bubali. Picture taken by the Aruba Tourism Authority (n.d.)

The “Wetland Other” subclass was formulated following the wish to separate the only true historic wetland, Bubali, from the other subclasses. This was done because the vegetation of Bubali was thought to be truly different from that of the other two categories.

4) Tree cover

Figure 19. Tree cover example from forest near Savaneta. Picture taken by the researcher.

Class representing the areas on Aruba covered with trees. Table 7 captures what the DNM employees considered to be the trees present on Aruba. Besides species internationally recognized as trees, DNM employees felt that locally cacti were also deserving to fall under this land cover. This is because cacti on Aruba of their significant size, long lifespan, and crucial ecological role in providing shade, habitat, and structural stability in the island's arid environment.

Local Name	Scientific Name

Breba	Cereus repandus
Breba di pushi	Pilosocereus lanuginosus
Cadushi	Stenocereus griseus
Huliba	Quadrella odoratissima
Kwihi	Prosopis juliflora
Pal'i siya blanco	Bursera karsteniana
Watapana	Caesalpinia coriaria
Wayaca	Guaiacum officinale

Table 7. Trees present on Aruba

To distinguish these different types of large vegetation, they decided a subclassification was in order, into Cactus dominated and Deciduous tree dominated areas.

4.1) Cactus dominated

Figure 20. Cactus dominated example from the north coast. Picture taken by the researcher.

On large parts of Aruba large cacti are the dominant large vegetation. In particular, the Breba (*Cereus Repandus*), Breba di Pushi (*Pilosocereus Lanuginosus*) and Cadushi (*Stenocereus Griseus*) can be found in abundance.

4.2) Deciduous tree dominated

Figure 21. Deciduous dominated example from forest near Savaneta. Picture taken by the researcher.

On other parts, deciduous trees are the dominated large vegetation. The species representing this subcategory are the Kwihi (*Prosopis juliflora*), Pal'i siya blanco (*Bursera karsteniana*) and the Watapana (*Caesalpinia coriaria*).

5) Shrubland

Figure 22. Shrubland example from the north coast. Picture taken by the researcher.

Many areas on Aruba are dominated by shrubs, these areas are captured in the shrubland class. The species DNM employees considered as represented this class for the Aruban environment can be seen in Table 8.

Local Name	Scientific Name
Aloe	Aloe vera
Basora preto	Cordia curassavica
Betonica	Melochia Tomentosa

Bringamosa	Cnidoscolus urens
Flor di sanger	Lantana camara
Shrubland Hubada	Vachellia tortuosa
Seida	Jatropha gossypiifolia
Taya	Erithalis fruticosa
Tuna	Opuntia caracassana
Walishali	Croton flavens

Table 8. Species representing the shrubland class

6) Grassland

Grassland was thought to have too much overlap with the shrubland and bare/sparse vegetation classes, there was no desire for one more class between these.

7) Cropland

Whilst there is some Cropland on Aruba, these areas are very tiny, and analysis of cropland on Aruba was thought to fall more in the jurisdiction of Santa Rosa, the Directorate of Agriculture, Livestock, and Fisheries, and Market Halls.

8) Bare or sparse vegetation

Figure 23. Bare/sparse vegetation example from the north coast. Picture taken by the researcher.

DNM recognizes the Bare or sparse vegetation class to be present on the island of Aruba. However, many different types of these were recognized. Namely, this class is split into six subclasses, Quarries, Degraded land, Sand coast, Rock coast, Rock formations, Build environment.

8.1) Quarry

Figure 24. Quarry example from the Butucu excavation. Picture taken by the researcher.

The DNM recognizes quarries as a suitable subclass of the bare or sparse vegetation main class on Aruba because these areas, heavily disturbed by human activity, exhibit minimal to no plant cover. Quarries are characterized by exposed rock and soil, aligning with the environmental conditions of sparse vegetation where natural regrowth is limited due to the harsh, dry climate and ongoing extraction activities. This subclass highlights the impact of human land use in transforming once-vegetated areas into barren landscapes.

8.2) Degraded land

Figure 25. Degraded land example from the north coast. Picture taken by the researcher.

The DNM classifies UTV track degraded land as a subclass of bare or sparse vegetation due to the significant vegetation loss and soil disruption caused by off-road vehicle use, leading to barren, degraded areas. Desired to be quantify the effects of UTV on the natural environment.

8.3) Sand coast

Figure 26. Sand coast example from Eagle beach. Picture taken by the researcher.

The DNM considers the sandy coast a subclass of bare or sparse vegetation on Aruba due to the minimal plant cover found in these areas, where the loose, shifting sands, high salinity, and constant wind create inhospitable conditions for most vegetation to thrive. These coastal zones are naturally barren, with only a few hardy species able to establish themselves, aligning with the characteristics of sparse or bare vegetation across the island.

8.4) Rock coast

Figure 27. Rock coast example from the north coast. Picture taken by the researcher.

The DNM classifies the rocky coast as a subclass of bare or sparse vegetation on Aruba because the rugged, exposed rock surfaces, combined with strong winds, salt spray, and lack of soil, create conditions unsuitable for most vegetation. These coastal areas are characterized by minimal plant life, with only a few specialized species able to survive in the harsh environment. As a result, the rocky coast is largely barren, fitting within the sparse vegetation classification due to its limited capacity to support plant growth. Mostly consistent of limestone.

8.5) Rock formation

Figure 28. Rock formation example from Ayo rock formations. Picture taken by the researcher.

The DNM classifies rock formations as a subclass of bare or sparse vegetation on Aruba because these areas consist of exposed, solid rock surfaces with little to no soil, making it difficult for most plants to take root. The harsh, dry conditions around these formations limit the presence of vegetation, resulting in a largely barren landscape. While some small, resilient plants may survive in crevices, the overall vegetation cover is minimal, aligning with the characteristics of sparse vegetation. Perceived as different from Rock coast since here the rocks consist mostly of limestone, where rock formations consist primarily of igneous rocks like diorite and quartz diorite.

8.6) Dead mangrove

Figure 29. Dead mangrove example from Mango Halto. Picture taken by the researcher.

The DNM classifies dead mangrove areas as a subclass of bare or sparse vegetation on Aruba due to the absence of living plant life in what were once dense, thriving mangrove ecosystems. These areas have been degraded by factors such as changes in water salinity, pollution, and coastal development, leaving behind barren landscapes with little to no vegetation. The once lush mangrove roots and trees are now dead, creating a stark contrast to the island's remaining vegetated zones and fitting the characteristics of sparse or bare land.

9) Built environment

Figure 30. Build environment example from Oranjestad. Picture taken by the researcher.

The DNM recognizes the Build environment class to be present on the island of Aruba. This class was thought to deserve a subclassification into three classes namely Road, Building and Sport field.

9.1) Road

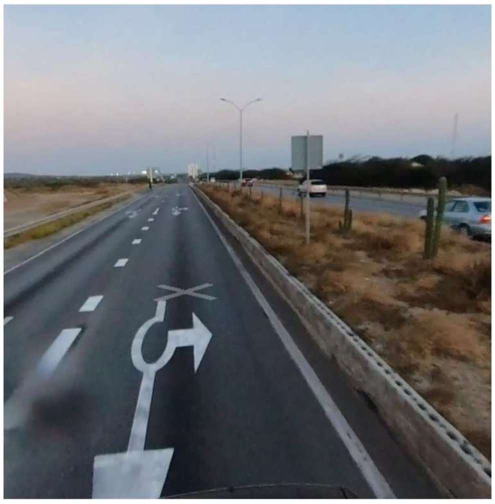


Figure 31. Road example from Route 1. Picture taken by researcher (left). Points representing road (right).

The DNM classifies roads as a subclass of the built environment on Aruba because they are man-made structures that transform the natural landscape into paved, functional spaces for transportation. Roads significantly alter the land, removing natural vegetation and replacing it with asphalt or concrete, which limits the capacity for plant life to thrive. These constructed surfaces are integral to human infrastructure but disrupt the ecological balance, placing them within the broader built environment classification.

9.2) Building

Figure 32.Building example from Oranjestad. Picture taken by the researcher.

The DNM classifies buildings as a subclass of the built environment on Aruba because they are permanent, human-made structures that replace natural landscapes with developed areas. Buildings disrupt the natural vegetation and soil, introducing constructed materials such as concrete, steel, and wood, which are central to human habitation and activity. These structures significantly alter the environment, reducing biodiversity and creating artificial spaces, fitting them within the built environment classification.

9.3) Sport field

Figure 33. Sport field example from Santa Cruz. Picture taken by the researcher.

The DNM classifies sports fields as a subclass of the built environment on Aruba because these areas are artificially created and maintained for recreational activities, replacing natural landscapes with levelled, often baren or synthetic surfaces. As human-made spaces, they fit within the built environment category due to their constructed and managed nature.

10) Snow and Ice

Given the arid climate on Aruba, these are very rarely present. Therefore, these classes are excluded from the classification

11) Moss and Lichen

The Moss and Lichen class are deemed to be not to be present on Aruba by the DNM due to the island's arid climate and lack of consistent moisture, which are unfavourable conditions for the growth and proliferation of these organisms.

Appendix 5) Methods used to collect training and ground truth data for each land cover class

In **Table 9Error! Reference source not found.**, the methodologies used to gather training and ground truth data for each land cover class are detailed. The complete methodologies are described in the Methods section under Training and ground truth points.

Table 9. Table showing how training and ground truth points were selected for the different classes and subclasses. Colours are used to distinguish the different overarching classes. For classes containing subclasses, the training and ground truth points for the subclasses are used as points for the main class, which is why these are not shown explicitly.

Class/Subclass	Employed methodology to collect training and ground truth data
Permanent water	GEE
Mangrove	PICTURES + FIELDMAPS
Dam & Tanki	PICTURES + GEE
Salina	GEE

Wetland Other	GEE
Cactus dominated	PICTURES + FIELDMAPS
Deciduous tree dominated	PICTURES + PICTURES
Shrubland	PICTURES
Quarry	PICTURES + GEE
Degraded land	GEE
Sand coast	PICTURES+ GEE
Rock coast	GEE
Rock formations	PICTURES + FIELDMAPS
Dead mangrove	FIELDMAPS + GEE
Road	FIELDMAPS + GEE
Building	GEE
Sport field	FIELDMAPS + GEE

Appendix 6) Classification accuracies

Table 10. Mean accuracy of classification into main classes

Classifier	Mean Error (%)
K-Nearest Neighbours (1 neighbour)	70.49
Random Forests (40 trees)	68.51
Random Forests (50 trees)	67.91
Random Forests (30 trees)	67.47
Random Forests (20 trees)	67.31
K-Nearest Neighbours (3 neighbours)	66.76
Random Forests (10 trees)	65.57
K-Nearest Neighbours (5 neighbours)	65.41
Gradient Boosted Decision Trees (30 trees)	64.77
K-Nearest Neighbours (7 neighbours)	64.77
Gradient Boosted Decision Trees (50 trees)	64.77
Gradient Boosted Decision Trees (40 trees)	64.65
Support Vector Machine (Linear kernel)	64.37
Gradient Boosted Decision Trees (20 trees)	64.22
Gradient Boosted Decision Trees (10 trees)	63.18
Classification and Regression Trees	62.91
Support Vector Machine (RBF kernel)	28.24

Table 11. Mean accuracy of classification into Herbaceous wetland subclasses.

Classifier	Mean Error (%)
K-Nearest Neighbours (1 neighbour)	98.82
Support Vector Machine (Linear kernel)	98.23
K-Nearest Neighbours (3 neighbours)	98.04
Random Forests (30 trees)	98.03
Random Forests (50 trees)	97.93
Random Forests (40 trees)	97.72

K-Nearest Neighbours (5 neighbours)	97.16
Random Forests (20 trees)	97.14
K-Nearest Neighbours (7 neighbours)	96.96
Random Forests (10 trees)	96.74
Classification and Regression Trees	96.55
Gradient Boosted Decision Trees (40 trees)	96.26
Gradient Boosted Decision Trees (20 trees)	96.16
Gradient Boosted Decision Trees (30 trees)	96.16
Gradient Boosted Decision Trees (50 trees)	96.06
Gradient Boosted Decision Trees (10 trees)	95.96
Support Vector Machine (RBF kernel)	46.46

Table 12. Mean accuracy of classification into Tree cover subclasses.

Classifier	Mean Error (%)
Random Forests (20 trees)	71.03
Random Forests (10 trees)	70.44
Support Vector Machine (Linear kernel)	70.15
Random Forests (30 trees)	70.15
Random Forests (50 trees)	69.85
Random Forests (40 trees)	69.26
Gradient Boosted Decision Trees (50 trees)	69.26
Gradient Boosted Decision Trees (20 trees)	68.68
Gradient Boosted Decision Trees (40 trees)	68.68
Gradient Boosted Decision Trees (10 trees)	68.53
Gradient Boosted Decision Trees (30 trees)	68.38
K-Nearest Neighbours (1 neighbour)	67.94
Classification and Regression Trees	67.94
K-Nearest Neighbours (3 neighbours)	66.76
K-Nearest Neighbours (5 neighbours)	65.44
K-Nearest Neighbours (7 neighbours)	65.44
Support Vector Machine (RBF kernel)	57.5

Table 13. Mean accuracy of classification into Sparse subclasses.

Classifier	Mean Error (%)
K-Nearest Neighbours (3 neighbours)	85.32
K-Nearest Neighbours (1 neighbour)	84.73
Support Vector Machine (Linear kernel)	84.52
K-Nearest Neighbours (5 neighbours)	83.6
K-Nearest Neighbours (7 neighbours)	82.86
Random Forests (50 trees)	82.72
Random Forests (40 trees)	82.67
Random Forests (30 trees)	82.67

Random Forests (20 trees)	82.03
Gradient Boosted Decision Trees (20 trees)	81.2
Random Forests (10 trees)	81
Gradient Boosted Decision Trees (50 trees)	80.96
Gradient Boosted Decision Trees (30 trees)	80.76
Gradient Boosted Decision Trees (40 trees)	80.71
Gradient Boosted Decision Trees (10 trees)	80.07
Classification and Regression Trees	77.65
Support Vector Machine (RBF kernel)	28.68

Table 14. Mean accuracy of classification into Build environment subclasses.

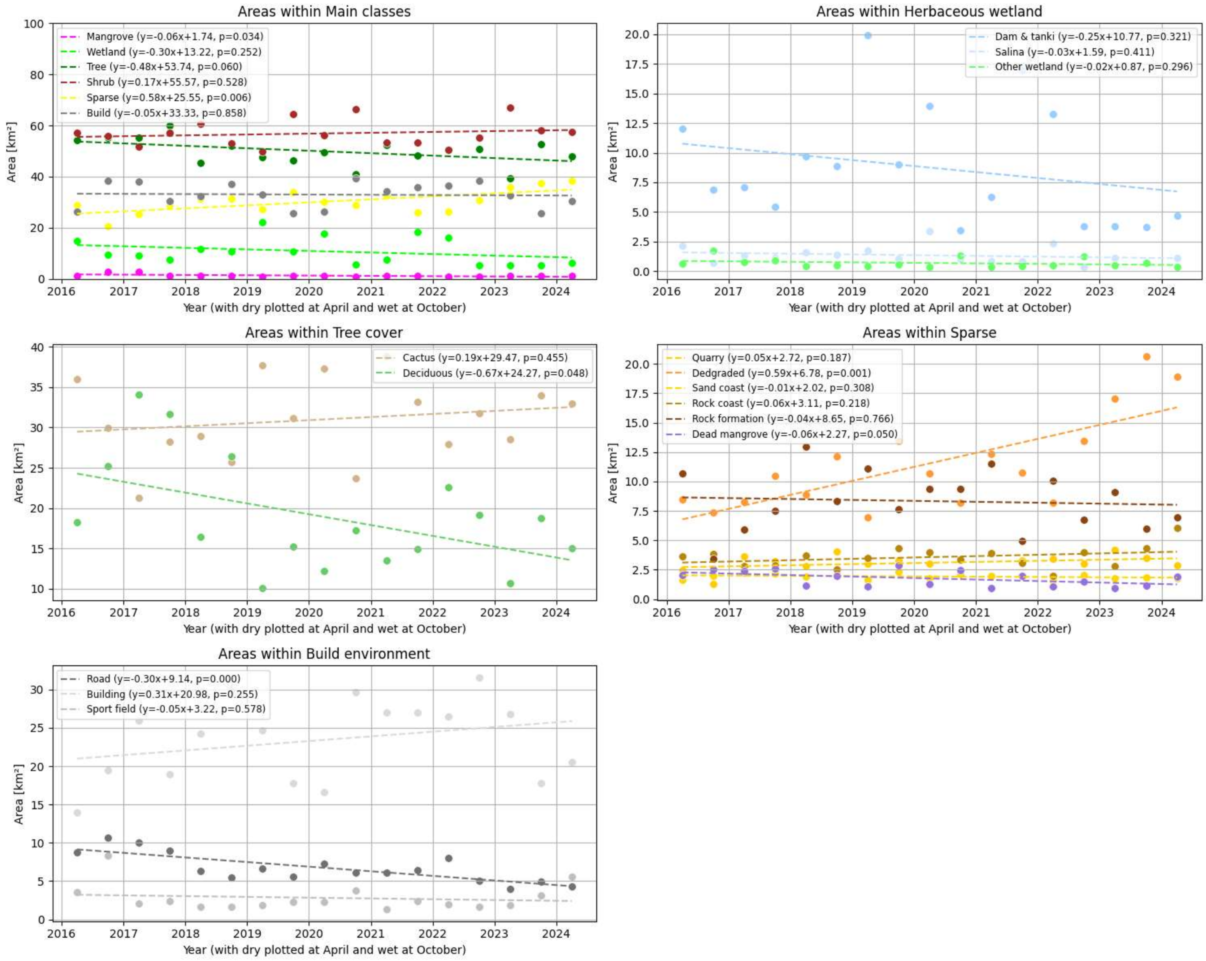
Classifier	Mean Error (%)
Random Forests (20 trees)	78.3
Random Forests (40 trees)	78.19
Random Forests (10 trees)	78.1
Random Forests (30 trees)	78
Random Forests (50 trees)	78
K-Nearest Neighbours (5 neighbours)	77.31
Gradient Boosted Decision Trees (30 trees)	77.21
K-Nearest Neighbours (3 neighbours)	77.2
Gradient Boosted Decision Trees (40 trees)	76.91
Gradient Boosted Decision Trees (50 trees)	76.82
Gradient Boosted Decision Trees (10 trees)	76.82
Gradient Boosted Decision Trees (20 trees)	76.82
K-Nearest Neighbours (7 neighbours)	76.42
K-Nearest Neighbours (1 neighbour)	75.33
Classification and Regression Trees	74.74
Support Vector Machine (Linear kernel)	69.74
Support Vector Machine (RBF kernel)	44.89

Appendix 7) (sub)class area values for all years

Table 15. Table showing the area estimates for the different (sub)classes in the different years

Date	Man-grove	Wet-land	Tree	Shrub	Sparse	Build	Dam & tanki	Salina	Other wet-land	Cac-tus	De-cidu-ous	Quarry	Ded-graded	Sand coast	Rock coast	Rock for-mation	Dead man-grove	Road	Build-ing	Sport field
2016 dry	1.31	14.8	54.23	57.3	28.88	26.23	12	2.14	0.66	36.03	18.2	2.44	8.49	1.63	3.61	10.7	2.02	8.73	13.98	3.51
2016 wet	2.87	9.31	55.16	55.82	20.53	38.42	6.86	0.69	1.76	29.97	25.19	1.3	7.39	1.96	3.87	3.44	2.56	10.68	19.45	8.3
2017 dry	2.69	9.19	55.29	51.82	25.26	38.05	7.08	1.3	0.8	21.24	34.05	3.66	8.25	2.24	2.79	5.9	2.42	10	25.95	2.11
2017 wet	1.05	7.48	59.89	57.08	28.77	30.32	5.43	1.12	0.92	28.21	31.69	3.26	10.45	2.16	2.85	7.49	2.57	8.93	18.94	2.44
2018 dry	1.05	11.68	45.29	60.56	31.36	32.31	9.72	1.57	0.4	28.91	16.38	2.82	8.86	1.9	3.69	12.99	1.12	6.33	24.28	1.7
2018 wet	1.17	10.73	52.12	52.94	31.27	37.13	8.86	1.4	0.47	25.71	26.41	4.07	12.13	2.2	2.55	8.32	1.99	5.52	29.99	1.62
2019 dry	1.01	22.06	47.75	49.91	27.34	33.1	19.95	1.7	0.41	37.71	10.03	3.03	6.93	1.64	3.52	11.1	1.11	6.6	24.62	1.87
2019 wet	1.05	10.61	46.37	64.43	34.02	25.65	9.01	1.04	0.57	31.14	15.23	3.32	13.44	2.32	4.36	7.67	2.91	5.61	17.78	2.26
2020 dry	1.13	17.67	49.47	56.18	30.08	26.15	13.92	3.36	0.38	37.29	12.17	3.04	10.67	1.75	3.95	9.37	1.29	7.28	16.63	2.25
2020 wet	0.83	5.76	40.93	66.45	28.83	39.44	3.44	1.03	1.29	23.66	17.27	3.37	8.18	2.09	3.33	9.38	2.48	6.07	29.61	3.76
2021 dry	1.05	7.46	52.35	53.44	32.68	34.33	6.24	0.87	0.35	38.85	13.5	1.98	12.36	2	3.9	11.51	0.91	6.08	26.97	1.29
2021 wet	1.09	18.22	48.12	53.26	25.99	35.79	16.94	0.83	0.45	33.19	14.93	3.29	10.72	1.9	3.1	4.97	2.01	6.4	26.95	2.43
2022 dry	1.01	16.13	50.53	50.61	26.24	36.42	13.29	2.34	0.49	27.91	22.62	3.44	8.17	1.54	2	10.03	1.06	8	26.43	1.99
2022 wet	0.99	5.39	50.93	55.37	30.81	38.3	3.81	0.33	1.24	31.75	19.18	3.03	13.48	2.06	3.97	6.77	1.51	5.01	31.6	1.68
2023 dry	1.06	5.44	39.28	66.88	35.8	32.69	3.79	1.14	0.51	28.55	10.73	4.16	17.03	1.75	2.8	9.1	0.96	4.04	26.78	1.88
2023 wet	1.17	5.2	52.7	58.1	37.51	25.74	3.69	0.78	0.73	33.97	18.74	3.49	20.66	1.86	4.35	5.98	1.17	4.89	17.74	3.1
2024 dry	1.12	6.24	47.94	57.34	38.48	30.47	4.7	1.14	0.39	32.94	15	2.91	18.91	1.78	6.08	6.94	1.88	4.31	20.53	5.63

Figure 34. Overview graph of area sizes over time, allong with regression lines to investigate whether perceived change in area was significant.



Appendix 8) Values of all environmental indicators for all composite images

	SDG 15.1.1 (international)	SDG 15.1.1 (local)	SDG 15.3.1	GBF A.2
2016 dry	4.15	20.18	9.12	79.52
2016 wet	7.26	19.54	10.83	73.34
2017 dry	12.66	21.02	9.1	71.95
2017 wet	12.48	22.12	10.36	76.43
2018 dry	3.76	15.81	8.03	75.96
2018 wet	9.1	18.18	10.97	72.02
2019 dry	1.97	19.21	7.17	75.87
2019 wet	2.92	16.18	12.15	75.77
2020 dry	2.31	19.71	9.55	77.27
2020 wet	3.83	13.22	9.85	71.32
2021 dry	2.81	21.7	9.16	72.95
2021 wet	2.36	16.31	10.22	72.36
2022 dry	5.25	16.73	8.12	73.02
2022 wet	3.99	13.38	10.91	69.49

2023 dry	1.02	11.34	13.31	69.95
2023 wet	4.33	18.53	15.74	71.65
2024 dry	2.28	15.86	16.24	70.57

Appendix 9) Build with Nature support

Table 16. Function from zones to categories.

Category	0	1	2	3	4	5	6
Zones	"Marine park", "Marine-zones", "Natuur en landschap", "Natuur-gebied", "Strand"	"Landelijk gebied"	"Woon-gebied met waarden"	"Haven-front Oranje-stad", "Toeris-tisch gebied westkust", "Toeris-tische zone oostkust"	"Bedrijven-terrein Barcadera", "Bedrijven-terrein Barcadera", "Luchthaven"	-	"Centrum Oranjestad", "Centrum San Nicolas", "Stedelijk woongebied", "Transformatie-gebied"

Table 17. Precise sizes (percentages) of the environmental classes in the different areas.

	Category 0, [m^2] (%)	Category 1, [m^2] (%)	Category 2, [m^2] (%)	Category 3, [m^2] (%)	Category 4, [m^2] (%)	Category 5, [m^2] (%)	Category 6, [m^2] (%)

Permanent water	1084343 (57.65)	16 (0.01)	68 (0.01)	142 (2.98)	1029 (1.08)	0 (0.0)	10 (0.01)
Mangrove	10520 (0.56)	76 (0.03)	615 (0.13)	9 (0.19)	143 (0.15)	0 (0.0)	196 (0.11)
Herbaceous Wetland	31168 (1.66)	6694 (2.39)	15255 (3.14)	231 (4.85)	3810 (3.99)	0 (0.0)	4492 (2.47)
Tree Cover	234722 (12.48)	109496 (39.16)	103790 (21.4)	289 (6.06)	14904 (15.59)	0 (0.0)	29190 (16.06)
Shrubland	333857 (17.75)	93055 (33.28)	112659 (23.22)	123 (2.58)	17462 (18.26)	0 (0.0)	27496 (15.12)
Sparse	116762 (6.21)	40926 (14.64)	130671 (26.94)	1969 (41.3)	32178 (33.66)	0 (0.0)	62606 (34.44)
Build environment	69450 (3.69)	29335 (10.49)	122047 (25.16)	2004 (42.04)	26081 (27.28)	0 (0.0)	57815 (31.8)