Dune vegetation classification using UAV-LiDAR point clouds

A Machine Learning assessment using structural properties of vegetation obtained from a point cloud

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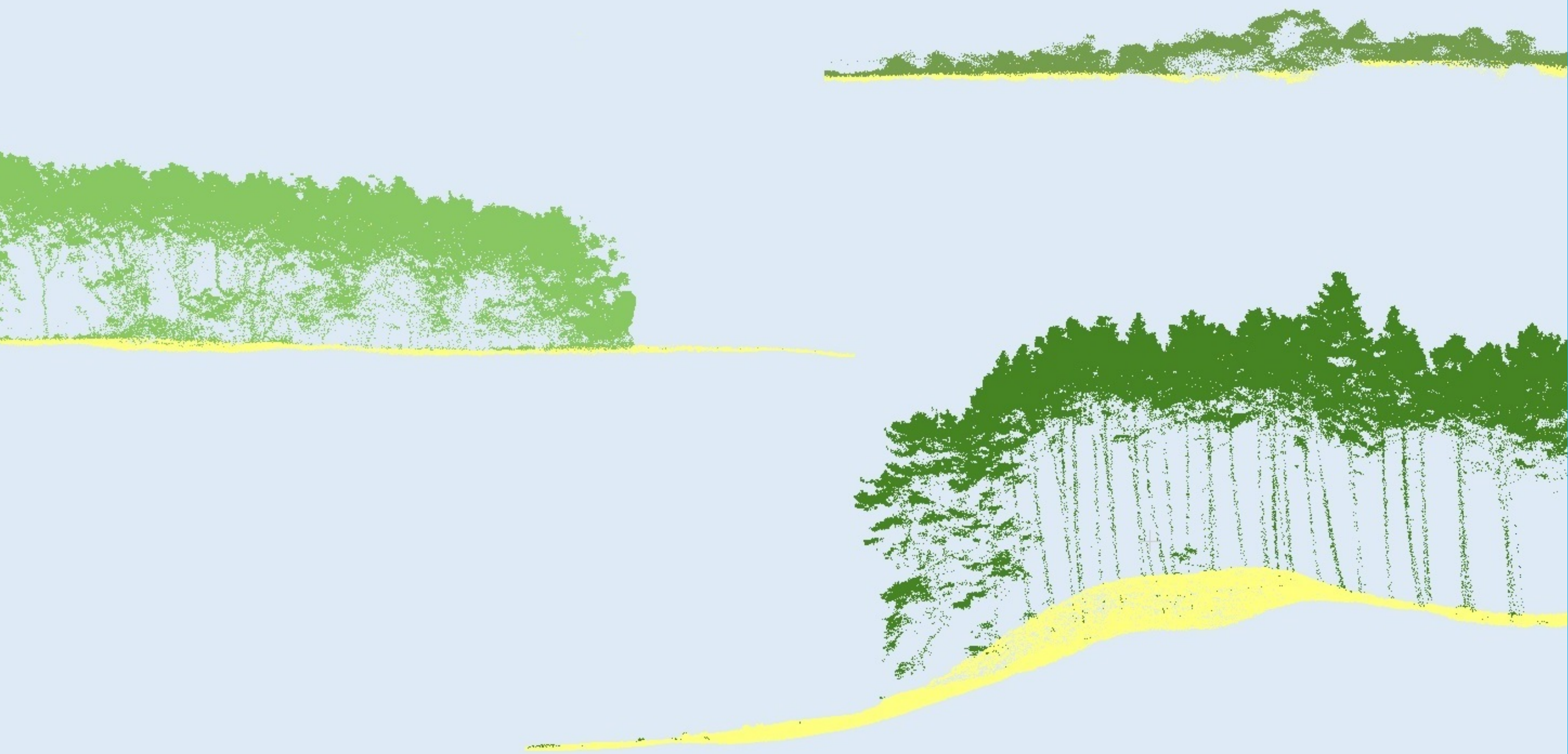

TU Delft

Shore Monitoring & Research

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A Machine Learning assessment using structural properties of vegetation obtained from a point cloud

by

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Master Civil Engineering
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Abstract

For European Union member states, it is mandatory to assign Natura 2000 areas and regularly monitor them. Currently, vegetation mapping is done mainly manually, which is a time-consuming and expensive practise. Unmanned Aerial Vehicles (UAVs or drones), manoeuvrable vehicles with which high-resolution measurements can be done, could increase automation in this process. Combining RGB imaging from drones with Machine Learning has already shown promising results. However, RGB imaging has limitations; there should be sufficient daylight, and only the upper layer of vegetation can be monitored. The use of LiDAR could complement the use of RGB imaging due to its ability to penetrate through different layers of vegetation and due to the fact that it does not depend on light conditions. This thesis investigates the contribution that LiDAR point clouds could have in mapping vegetation in typical Dutch Natura 2000 areas, which are typically in coastal dunes.

In this thesis, a method is proposed to classify vegetation into herbaceous, shrub, deciduous and coniferous vegetation classes. First, a method is developed to obtain the height of the vegetation. Using the height of the vegetation, the vegetation is divided into two classes: high vegetation (coniferous and deciduous trees) and low vegetation (herbaceous vegetation and shrubs). In this way, different layers of vegetation can be classified. For the classification of high vegetation, the points from the top of a raster cell to 5 metres below the top are considered. For the classification of the low vegetation, the points in the lower 2 meters of the vegetation are considered. Features are designed that summarise the vertical distribution of points in different ways. These features are used as input to a random forest classifier.

Using this classification method an accuracy of 85% could be reached to classify the higher vegetation into deciduous and coniferous trees. Using the method, spatial patterns in deciduous and coniferous trees are clearly visible; however, when looking at individual tree levels, still improvements can be made. For the lower vegetation, an accuracy of 73% could be reached to divide the vegetation into classes of shrubs, herbaceous vegetation and bare ground. The method generally performed well for the shrubs, but herbaceous vegetation and bare ground still was mixed at some points by the model. For both classification algorithms, the results and behaviour of the model showed high sensitivity to the training data.

This study has shown the potential of the use of LiDAR in the field of vegetation monitoring, especially in areas where cameras cannot reach, where LiDAR could have added value in vegetation monitoring.

Preface

This thesis was written to complete the master of Geoscience and Remote Sensing at the Civil Engineering Faculty of the Delft University of Technology. During this thesis I have learned a lot about point clouds. The use of point clouds is relatively new and still a lot about this topic can be researched. Although sometimes point clouds were a source for different headaches, I really enjoyed playing around with them and looking at what information could be retrieved. I have spent a year looking at the clouds now, and I think this was just the tip iceberg, and still many master theses and researches will follow on this topic.

I would really like to thank my thesis supervisors who have had to endure a lot of chaos with me. Thank you Roderik for the discussions we had and the insights you brought me to. Thank you Sean for guiding me and for at some points, when I got lost a bit too much in my mind, saying the right words. And also Sierd thanks you, we did not have many interactions, but the few times that I passed by, you were always enthusiastic.

Next to that, I would like to thank some people around me who supported me and gave insightful comment on my thesis, such as, Daan, my father, Goof and Emma. And last, but not least, I would like to thank the employees of the company *Shore Monitorin & Research*. Thank you for letting me run around in your company and involving me in the work that you do. It was really nice to be able to do something else than working on my thesis every now and then.

A.L.S. (Anna Lisa Sebastiana) Labaar
Delft, December 2022

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List of Abbreviations

AI	Artificial Intelligence
CART	Classification and Regression Trees
CHM	Canopy Height Model
CSF	Cloth Simulation Filter
DSM	Digital Surface Model
DTM	Digital Terrain Model
EU	European Union
FN	False Negative
FOV	Field Of View
FP	False Positive
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
K-z	Kennemerland-zuid (South-Kennemerland)
LiDAR	Light Detection and Ranging
ML	Machine Learning
MSL	Mean Sea Level
N2000	Natura 2000
NIR	Near-InfraRed (light)
NOx	Nitrogen Oxides
OOB error	Out-Of-Bag error
RD-coordinates	Rijksdriehoekscoordinates
RF	Random Forest
RGB	Red, Green, Blue (light)
RTK	Real Time Kinematic
THU	Theoretical Horizontal Uncertainty
TN	True Negative
TP	True Positive
TVU	Theoretical Vertical Uncertainty
UAS	Unmanned Aerial System (same as UAV)
UAV	Unmanned Aerial Vehicle

1 Introduction

1.1. Project description

Around 350 km of sandy beaches and dunes separate the Netherlands from the North Sea. This sandy border, mostly consisting of dunes, varies in width from 100 metres to over 10 kilometres. A large part of the dunes is still in a semi-natural to a natural state. The natural dune environment is managed for different purposes, such as the catchment of drinking water, the protection of the hinterland, nature recreation and the preservation and development of natural biodiversity (Doing, 1995). The dunes fulfil several essential functions for Dutch society which are summarised in Figure 1.1 below. The importance of these functions has always been acknowledged in the past. As a result, the coastal dune landscape is relatively undeveloped and therefore represents important values for nature conservation and recreation (Arens, Mulder, Slings, Geelen, & Damsma, 2013).

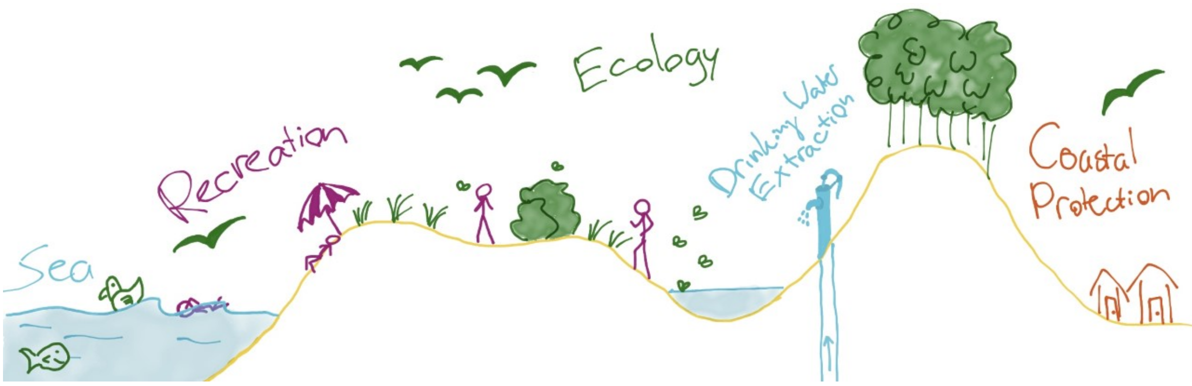


Figure 1.1: Dune-functions: Some of the different functions of the dunes

Several ecosystems in Europe, under which parts of the Dutch dunes, have been protected by the Natura2000 (N2000) programme. The EU set up the N2000 network of natural areas to protect certain habitats and bird species. Large parts of the Dutch dune system have been appointed as N2000 areas. Due to the deposition of nitrogen oxides (NOx) and the different functions of the dune system, the maintenance of certain species of fauna and flora forms a challenge. To get a better understanding of the flora and fauna, proper and regular mapping should be carried out (Van der Meulen, Van der Valk, & Arens, 2013). By mapping the ecosystems along the coast, the natural processes that form and sustain these ecosystems can be quantified (Grootjans, Geelen, Jansen, & Lammerts, 2002). This information contributes to targeted land management actions concerning the maintenance of biodiversity and other functions that the dunes serve. Currently, vegetation surveying still is done mainly by manually mapping the area. Because of the dynamic character of the dunes, this surveying needs to be done regularly, making it a costly and time-consuming practice (Suo, McGovern, & Gilmer, 2019; Doing, 1995).

With the rapid developments in remote sensing methods and platforms, interest in the application of this technique grows. The use of Unmanned Aerial Vehicles (UAVs or drones) can provide a fast and feasible method for vegetation monitoring. These vehicles can be used to obtain up-to-date information on changes in terrain and vegetation. Different measuring equipment can be mounted on a UAV. For example, a camera measuring in the Red Green Blue (RGB) spectrum could be used for imaging (combining these spectra shows images as we know from digital images). An extra band could be included in the images using a Near-infrared camera. However, point clouds could also be created by using Light Detection and Ranging (LiDAR) equipment. This is the measurement of the distance from a certain point using light.

Figure 1.2: The drone in action: The UAV of *Shore Monitoring and Research* equipped with a camera, positioning system (GNSS), motion sensor (IMU) and LiDAR in action. (see section 3.2.2 for further elaboration)

The company *Shore Monitoring and Research* has been using the drone in Figure 1.2 in the dunes. The drone is equipped with, among other things, a camera and a LiDAR sensor. The data obtained by this equipment could be used to classify the vegetation. The use of images for classification has already shown some promising results. Unfortunately, classification using images does have its limitations. The classification using images is highly dependent on the available light. Thus, the classification will show a different accuracy for different times of the day, different seasons or for different cloudiness. Especially the difference between coniferous and deciduous trees still seems to be difficult to find from RGB images. This problem could be solved by looking at the trees at different times of the year, but this would mean different flights during the year should be done. This would cost extra time and money.

The use of LiDAR point clouds to monitor and classify vegetation is undergoing a rapid development period as interest in big data increases (Guo et al., 2022). The advantages of LiDAR are that it is not dependent on lighting conditions and that it shows more than just information about the top layer since it is able to penetrate vegetation to a certain extent. Therefore LiDAR could both be used to develop and enrich data sets. Other extra information on vegetation can concern the vegetation height of grasses, shrubs, and trees, the canopy depth of trees and shrubs, and for example the Leaf-Area-Index. The extra information on vertical distribution also provides information on the trees growing in the area. This could make classification into coniferous and deciduous trees possible. Next to that, LiDAR could, due to its ability to measure through a canopy cover (to a certain extent), be able to classify different layers of vegetation. It could be interesting to see if for example shrubs or grasses underneath trees could be classified by using LiDAR point clouds.

1.2. Problem statement

For proper management of the dunes, the distribution of vegetation and the presence or absence of change in vegetation patterns should be known. To monitor this distribution and its changes, even today ecologists map vegetation could speed up this process and make it less sensitive to subjectivity. However, to make remote sensing useful, an accurate classification of the obtained data should be possible. For this research, vegetation is distributed in four classes: herbaceous vegetation, shrubs, deciduous trees and coniferous trees, as visualised in Figure 1.3 below.

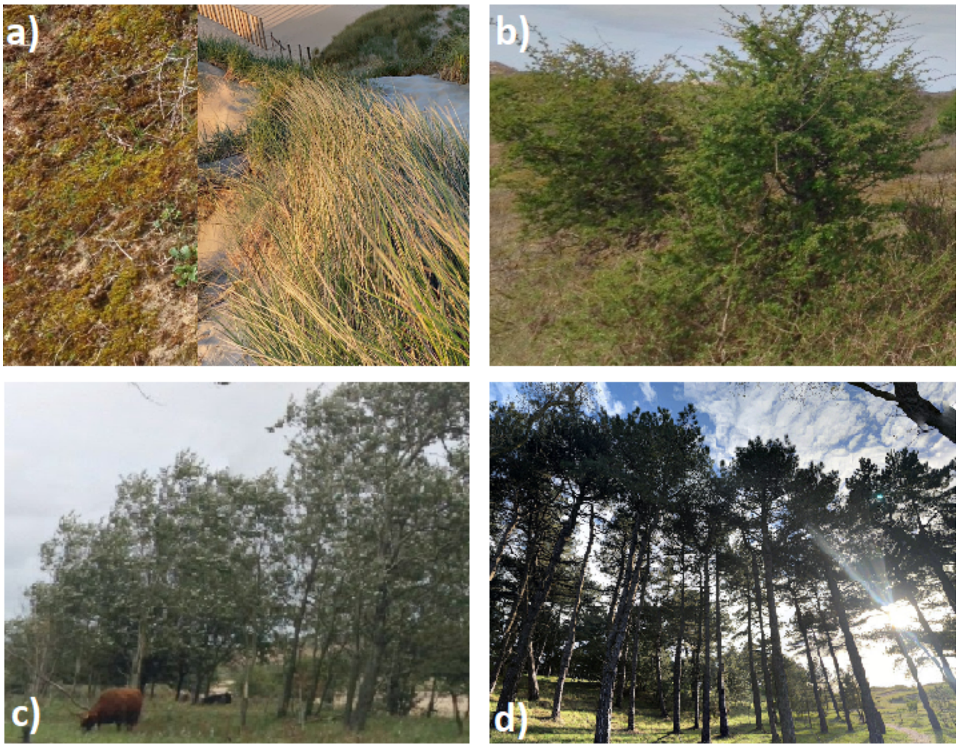


Figure 1.3: Vegetation classes to be classified
a) herbaceous; b) shrubs; c) deciduous trees; d) coniferous trees

Previous research has shown that the classification of vegetation using RGB imagery is showing promising results. However, this classification has several limitations. The goal of this thesis is to find what information concerning the vegetation can be obtained from a UAV LiDAR point cloud (an example of a slice of the point cloud can be seen in Figure 1.4 below). The next step is to find how this can be used to classify vegetation.

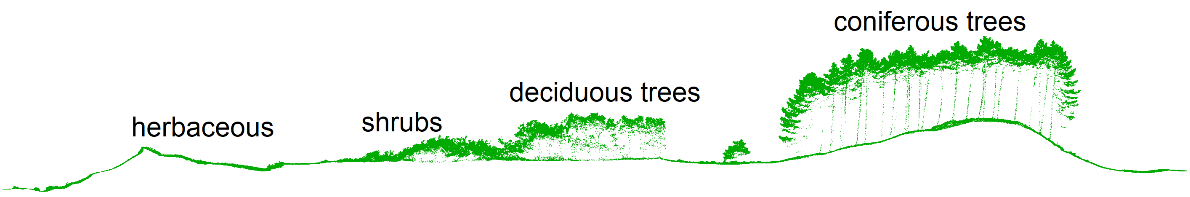


Figure 1.4: Side-view of some slices of point cloud containing all classes which need to be classified

1.3. Research questions

Based on the previously elaborated problems the proposed main research question is:

How can different vegetation types in the dunes be classified accurately and efficiently from UAV-LiDAR 3D point clouds?

To answer the main question, the project is divided into the following subquestions:

1. *How can the use of UAV-LiDAR point clouds improve existing dune vegetation classification methods?* Methods are already available to classify dune vegetation using different remote sensing methods. How can the use of UAV-LiDAR point clouds contribute to the classification of the vegetation of existing methods? What are the limitations of available methods, and what is the added value of the use of the UAV-LiDAR point cloud?
2. *What are the different vegetation types that should be classified, and what are their key characteristics?* From the point distribution, different characteristics can be obtained, such as point density and vertical point distribution. How can these characteristics summarise the different vegetation types.
3. *How will the quality of the result be assessed and what quality can be reached?* To assess the quality of classification results usually ground truth data is available. Since there is no ground truth data available this should be created by hand. How can this be done as accurately as possible? And how can this then be used to assess the accuracy of the classification algorithm?
4. *What are the limitations of using UAV-LiDAR point clouds for dune vegetation classification?* The use of UAV-LiDAR point clouds brings limitations. These are limitations in the equipment, but also limitations in the possibilities of point clouds. What are these limitations, and how do they affect the point cloud classfication.

1.4. Thesis structure

The thesis structure is given in table 1.1 below.

#	Title
2	Dunes and Monitoring
3	Area and Data
4	Methodology
5	Results
6	Discussion
7	Conclusion and Recommendations

Table 1.1: Thesis structure

Chapter 1 gives an introduction to the research and introduces the research questions. Chapter 2 gives some background information on the subject and insight into previously published research on this topic. In Chapter 3 the data and its properties to which the method will be applied are elaborated. In Chapter 4 the method that is proposed is explained and elaborated. In Chapter 5 the results of applying the method to the data are shown and in Chapter 6 these results are discussed. In Chapter 7 the conclusions that have been drawn from this and further recommendations are elaborated.

2

Dune Management and Monitoring

In this chapter background information on the research can be found. In Section 2.1 the Dutch dunes and their ecology and why monitoring is needed are discussed. Section 2.2 discusses different monitoring techniques that are currently used to monitor the vegetation on the dunes and nearshore coast. Section 2.3 elaborates on the current techniques used for vegetation classification using different remote sensing methods. The focus is mainly on classification using point clouds.

2.1. The role of the Dutch dunes

In this first section, a brief elaboration on the role of the Dutch dunes is given. The focus will be on the role of the vegetation in the dunes. Vegetation fulfils different roles in the coastal dune area. Vegetation protects the surface of the dunes from erosion and encourages the accretion of sand (Ranwell & Rosalind, 1986). Vegetation also plays an important role in the ecological system of the dunes. Different regulations and directives have been made on the dunes and their ecology. The first Subsection 2.1.1 will discuss the different zones in the dunes and their properties. Subsection 2.1.2 will discuss the different regulations concerning ecology management in the dunes.

2.1.1. Zones in the dunes

The dune area consists of different habitats distributed over different land-inward zones. In the dunes, several abiotic factors such as waves, tide, wind, soil salinity, grain size and dune morphology are typically arranged along a coast-inland gradient as is shown in Figure 2.1. Due to these gradients, zones with different characteristics are formed. An overview of the zones and their names can be seen in Figure 2.2 (Marcenò et al., 2018).

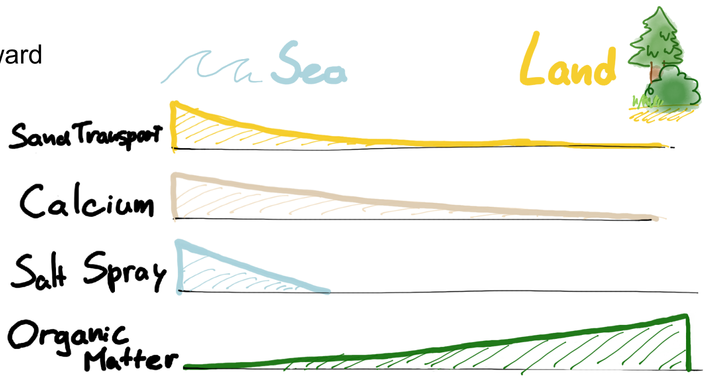


Figure 2.1: Abiotic gradients across coastal dunes (McLachlan & Defeo, 2018)

From the seaside land inward, the dunes are first in a developmental stage low in vegetation species in the embryonal dunes. Then the dunes become more stable and grasslands form in the grey dunes. When the soil gets more stable also more often the sea-buckthorn (duindoorn) is found, this is a type of shrub often found in the dunes. Due to an increase in nitrogen depositions, this shrub tends to overgrow parts of the grey dunes. Also present more inland are open waters, moist grasslands and lower swamp vegetation, this habitat type is called the humid dune slacks. When going more land-inward we find the wooded dunes containing forests. These forests include both deciduous and coniferous forests which often habit different fauna species(Marcenò et al., 2018; McLachlan & Defeo, 2018; Provincie Noord-Holland, 2017). For a more detailed overview of each zone Appendix **??** can be consulted.

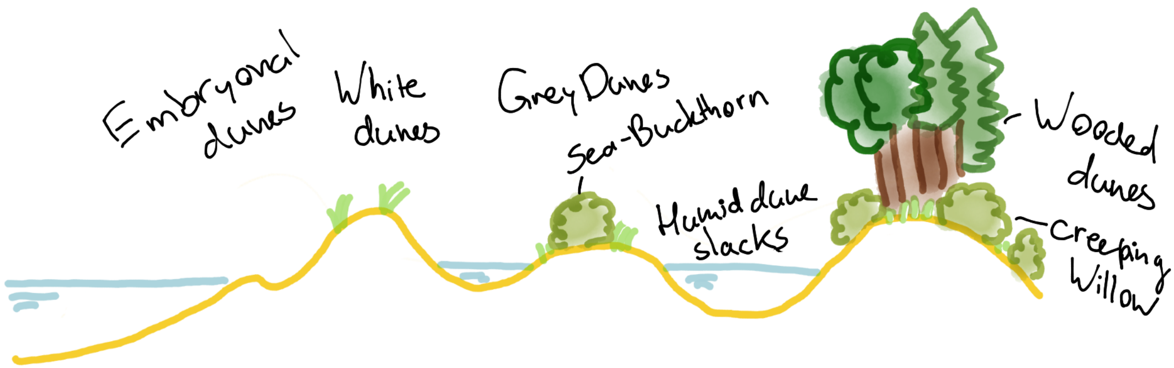


Figure 2.2: Habitat types in the dune system: the habitats and their spread land-inwards (Marcenò et al., 2018; Provincie Noord-Holland, 2017).

2.1.2. Natura 2000 and a new management approach

The dunes form an important habitat for several flora and fauna species. The natural coastal dune landscape has remained intact due to some previously acknowledged functions of the dunes. The dunes form a protective barrier against the sea and an area important as a drinking water production area. These functions have prevented urban and agricultural developments in this area. In addition to that, the dunes are becoming more important as a recreational area. Because of the many different purposes of the dune area, finding a management plan that adapts to the properties and requirements of these functions forms a challenge.

Current dune management is for a large part governed by the Natura2000(N2000) network. N2000 are bird-species and habitat directives, which are set up by the EU to prevent the loss of biodiversity within Europe. The objective of these directives is to achieve favourable conservation status of habitat types and flora and fauna species in Europe. In this way, the EU tries to ensure the long time survival of flora and fauna species, both within and outside the Natura 2000 (N2000) network. Each member state of the European Union is given the task of assigning N2000 areas within their European territories and monitoring and protecting the status of the species and habitat types in these areas. The results found by the monitoring should be reported back to the European Commission. Using this information, the European Environment Agency is able to determine the overall trends and conservation status of the different bird species and habitat types in all European territories. With the use of this feedback mechanism, it can be determined if the measures that are taken to sustain the N2000 area suffice and where additional measures are needed to ensure the survival of these habitat types and flora and fauna species. (Sundseth & Creed, 2008)

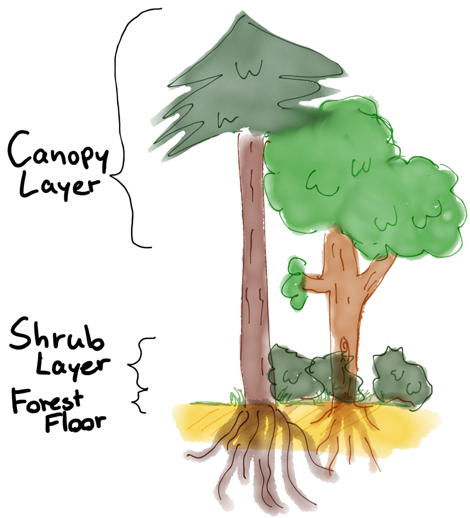


Figure 2.3: Vegetation layers in the forest. The shrub layer and the Forest floor together form the under-story

In the Netherlands, a large part of the dunes system has been assigned as an N2000 area. Especially the calcium-rich grey dunes are important. And habitats of different bird and animal species. This can be in the different layers of the forest. This also includes for example the vegetation on the forest floor, called, the understory. This layer can function as a habitat for, for example, smaller bird species and insects. But this can also function as the regenerative layer of the forest. (Van der Hagen, Geelen, & De Vries, 2008; Kremer et al., 2015)

2.2. Onshore coastal vegetation monitoring

This section discusses the ways in which vegetation in coastal areas is already monitored in general. Subsection 2.2.1 discusses the different sensing techniques that are available. The advantages and disadvantages of these techniques in current classification methods are discussed. Subsection 2.2.2 discusses the different techniques that are currently used for the N2000 habitat monitoring and where developments take place. The last Subsection 2.2.3 focuses on LiDAR and how this could benefit current classification methods.

2.2.1. Monitoring techniques available

Remote sensing is the technique to obtain information without making contact with the object. The objective of any remote sensing technology is to provide data on some physical parameter. When taking observations at different time periods remote sensing could be used to detect trends and changes in a certain area. The sensing can be performed from different platforms, such as a satellite, an aeroplane, or even from the ground. A short overview of the different sensing platforms and their properties is given in Table 2.1 below.

Applicability and operation aspects	Satellite (space-borne)	Airborne	UAV	Mobile/static (ground)
manoeuvrability	No/limited	Moderate	High	Limited
Observation space	Worldwide	Regional	Local	Local
Sensor diversity	MS/HSI/SAR	MS/HSI/LiDAR/SAR	MS (LiDAR/HSI)	MS/LiDAR (HSI)
Environment	Outdoors	Outdoors	Outdoors/indoors	Outdoors/indoors
Scale (inverse sensor range)	Small	Small/medium	Medium/large	Medium/large
Ground Coverage	Large (10 km)	Medium (1 km)	Small (100 m)	Small (50 m)
FOV	Narrow	Wide	Wide/super wide	Wide/super wide
Repeat rate	Day	Hours	Minutes	Minutes
Spatial resolution	0.30-300 m	5-25 cm	1-5 cm	1-5 cm
Spatial accuracy	1-3 m	5-10 cm	1-25 cm	3-50 cm
Deployability	Difficult	Complex	Easy	Moderate
Observability	Vertical/oblique	Vertical/oblique	Vertical/oblique/360^o	Oblique/360^o
Operational risk	Moderate	High	Low	Moderate
Cost	$$$$$*	$$$	$	$$

Table 2.1: Remote sensing platforms' properties. MSI:Multi-Spectral-Imaging; HSI:Hyper-Spectral-Imaging; SAR:Synthetic-Aperture-RADAR; LiDAR:Light-Detection-And-Ranging; (Toth & Jóźków, 2016)
It should be noted that the accuracy of all non-satellite platforms is not only determined by the precision of the sensor. Measurements of the positioning and orientation often also form a source of errors.
*This cost is usually at the tax-payer, a lot of satellite data is freely available

Specifically for vegetation monitoring, different sensing techniques can be used. The techniques mentioned in Table 2.1 can be used to examine different properties of vegetation. The most known is imaging, which we know from, for example, taking a picture with your camera. RaDAR could even be used to examine, for example, the water content of vegetation (Konings et al., 2021). Currently, a lot of developments are being made to monitor vegetation using different sensing methods. At the moment there is a lot of interest, especially in the application of the UAV as a platform. A UAV is a relatively low-cost platform with high manoeuvrability and with which a centimetre resolution can be reached.

Equipping a UAV with a camera can make imaging possible with a spatial resolution of up to a centimetre level. Using the Red-Green-Blue wavelengths can already give a lot of information about the vegetation types by looking at the colour distribution in certain vegetation types. Using a maximum likelihood classification algorithm on only RGB images of dune vegetation, a classification precision of 69% was reached for research done on dunes on the east coast of Ireland. Higher accuracy was already reached when including the vegetation height(Suo et al., 2019)

But rather than just using the colours to monitor the vegetation it would be interesting to look at the vertical vegetation structure. To get vertical dimensions, photogrammetry could be used or even LiDAR. A LiDAR instrument is often mounted to a UAV to get the terrain model and the height of the vegetation. However, much more information is obtained by a LiDAR instrument than just the upper (vegetation height) and lower (terrain level) points. A LiDAR is an instrument that sends out a laser and measures the time it takes for the laser to return to the point cloud. Using this method the distance to the object that reflected the laser can be calculated (distance = time/speed of light). By knowing the distance to the point of reflection and the orientation and location of the drone, the location of the point of reflection can be determined. But from just one laser that was sent out, multiple returns can come to the instrument. When many lasers are sent out and many multiple returns come back, many points can be measured. All these points together are called a point cloud. And from a point cloud, a lot of information about vegetation density and distribution could be obtained. In Figure 2.4 below this process of obtaining a point cloud is visualised.

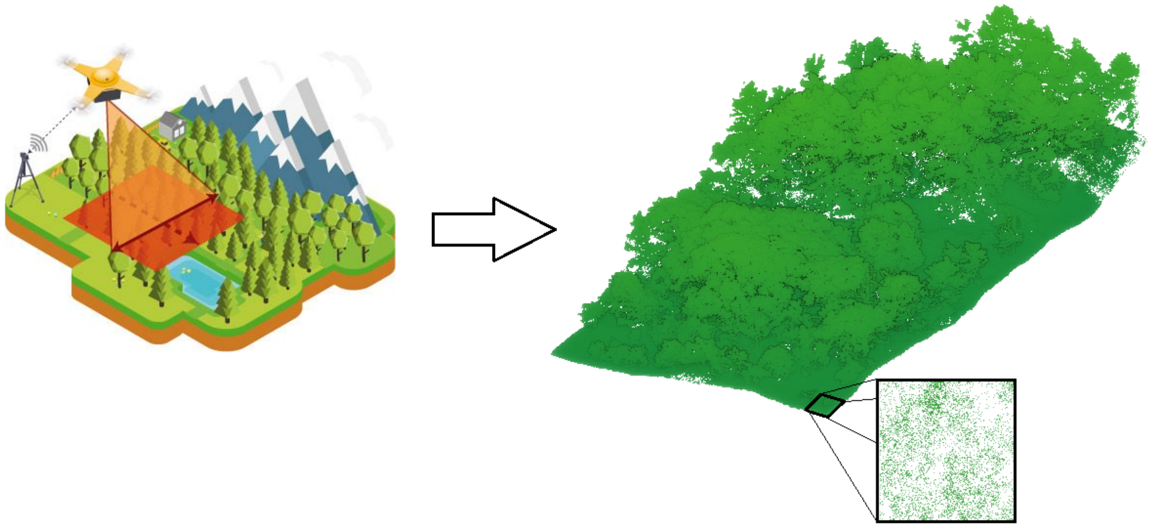


Figure 2.4: left: a UAV monitoring using LiDAR. Right: an example of a piece of a point cloud, when zooming in it can be seen that the full picture is built up of points

2.2.2. Habitat and vegetation surveillance and monitoring

Usually, habitat and species monitoring is done by ecologists. The first step in this process is to outline areas with different ecological properties by hand using different available maps. These can include topography maps, google earth, but also other available satellite imagery in other bands such as near-infrared or images in different bands from aerial photographs. When the outlining of the different areas has taken place, the findings should be recorded first, after which the classification takes place. This is done by going into the field. (Bunce et al., 2011)
A landscape or habitat is often characterised by different landscape elements, such as different types of land cover and forest patches. By monitoring the coasts, the development of the different habitat types can be quantified. To map the ecology it is becoming more common and feasible to use remote sensing. By combining remote sensing with machine learning classification could be automated. This then could be used to identify landscape change, this then can be used to make predictions using statistics and quantify the function of a landscape.

2.2.3. The use of LiDAR in coastal vegetation monitoring

LiDAR remote sensing shows great potential for integration with ecological research precisely because it is able to measure three-dimensional physical structures of vegetation that are comparable to basic plant community measurements that are of interest to ecologists. Until recently, canopies were measured and modelled mainly by hand. By reducing the time and effort associated with measuring canopy structures, LiDAR can foster the wider incorporation of a canopy science perspective into ecological research and place vegetation canopy structures squarely at the centre of efforts to measure and model ecological structures. (Lefsky, Cohen, Parker, & Harding, 2002)

2.3. Vegetation classification in LiDAR 3D point clouds

A 3D point cloud can represent almost any type of physical object, site landscape or geographic region or infrastructure. Simply said a point cloud is data represented by XYZ coordinates of points. Using these XYZ points different methods have already been found for the classification of objects in 3D point clouds. (Döllner, 2020; Bello, Yu, Wang, Adam, & Li, 2020)

However, LiDAR point clouds of vegetation do not show any geometrical behaviour, but rather chaos. LiDAR point clouds are mainly used as a classifier by looking at the geometric properties of the points. In a natural environment detecting geometries in vegetation will fail since vegetation is usually collected in a class with other objects showing no geometrical behaviour(Rutzinger, Höfle, Hollaus, & Pfeifer, 2008). Therefore, another approach should be searched. Usually in natural environments, point clouds are only used as a source to find the Vegetation Height or the Terrain Model. To assess how vegetation classification from 3D point clouds takes place, first the application of Machine Learning to point clouds, in general, is explained in Subsection 2.3.1. Then it is explained how a terrain model can be obtained 2.3.2. Then the properties of Vegetation are explained and then how this can be applied for classification.

2.3.1. Machine Learning algorithms and 3D point clouds

Because using LiDAR highly accurate and informative 3D information is provided it is changing the way we study and understand terrestrial ecosystems. Next to that, it forms a way to go from 2D to 3D observations. (Guo et al., 2020) These properties can be used for the classification of point clouds using a machine learning algorithm.

Some properties of point clouds form challenges in the application of machine learning to point clouds (see Figure 2.5). A point cloud is irregular, meaning that point cloud data is not sampled evenly across different regions. So same regions of the point clouds could show a very high point density while other regions have few points. A point cloud is unstructured, meaning there is no regularity such as a grid which you have in images. Each point is an individual measurement, and the space between points is variable. And a point cloud is, unordered, meaning that the order in which the points of a point cloud are presented does not change the image of the points.

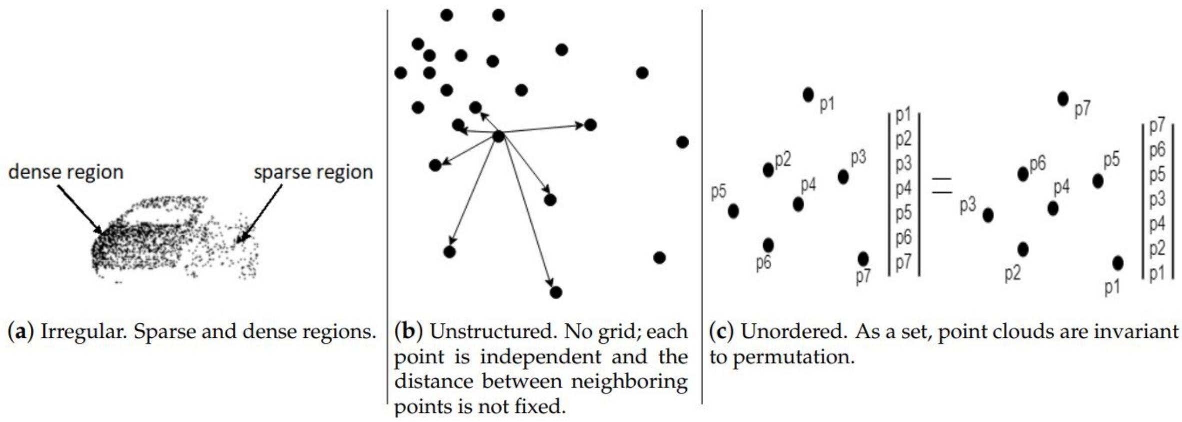


Figure 2.5: Challenges the application of machine learning to point cloud data (Bello et al., 2020)

These challenges could be solved in different manners. Points could be voxelized, meaning that a 3D raster can be placed over the point cloud, so known raster operation can be applied. Or groups of points could be looked at to find geometries. In this way the points in a 3D point cloud can still be structured to make them usable for a machine learning algorithm (Döllner, 2020; Bello et al., 2020). But since the interest is in classifying vegetation, which in a point cloud shows no geometrical behaviour (Rutzinger et al., 2008), a different approach should be searched than conventional methods to apply classifications in LiDAR point clouds.

For the use of LiDAR point clouds in ecological studies usually, another approach is taken than in the built environment. The steps taken for ecological studies usually include outlier removal, ground point filtering, obtaining the Vegetation height and extraction of the vegetation attributes. The classification algorithms that have been introduced can generally be divided into four categories: pixel-wise classification based on lidar-derived surfaces, object-based segmentation based on lidar-derived surfaces, hierarchical semantic segmentation based on lidar point clouds, and deep learning–based methods (Guo et al., 2020).

2.3.2. Ground filtering and vegetation height

Since we are dealing with a natural environment, all above-ground points are probably vegetation. Therefore, by determining the height of the terrain, and therefrom the height of the points above the terrain, the vegetation height can be determined. The height of the terrain in a point cloud is called the Digital Terrain Model (DTM), and the height of the vegetation is represented by the Canopy Height Model (CHM). (see Figure 2.6). To determine the CHM first, the DTM should be known. The DTM is usually determined by applying ground filtering. Ground filtering is usually based on the assumption that the ground is a continuous surface without sudden elevations and that for a certain surface area, the points with the lowest elevation are part of the ground. In the case of outliers with an elevation lower than the surface, this is not the case. (Ledoux, Arroyo Ohori, & Peters, 2021)

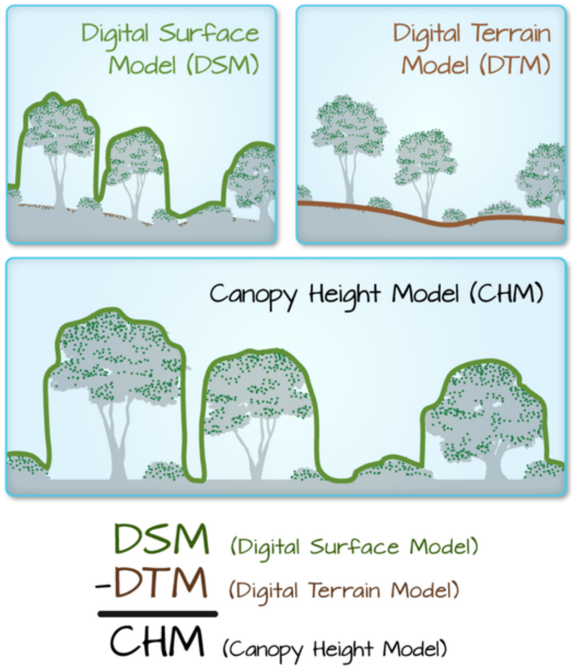


Figure 2.6: Canopy Height Model in a point cloud (Wasser, 2020).

A very common algorithm for doing this is the Cloth Simulation Filter (CSF). The idea of this algorithm is that a cloth is falling from below on the lowest points of the point cloud. But not too much stretch is allowed in the cloth, thus in larger objects such as houses, the cloth will not reach. (Zhang et al., 2016)

Since we are dealing with a natural environment the ground model can be pretty rough giving a second difficulty, thus the CSF does not always show a good fit. Next to that, we are also dealing with grasslands (thus lower vegetation, which could be seen as the ground) and steeper grounds. thus another terrain model than conventional terrain models should be used. Also, the terrain can be quite variable in the younger dunes near the sea due to sand transport changing the form of the dunes, which means that readily available terrain maps cannot be used. Comparable problems are seen in American salt marshes that have high variability due to extreme weather. For these marshes, an algorithm has been proposed taking into account the slope of the ground. This algorithm appeared to be able to estimate vegetation density and height.

The algorithm (see figure 2.7 puts a grid on the point cloud and then fits a plane to each cell using the minima of the 8 surrounding grid cells and the minima are given.
Then to each grid cell, a plane equation is fitted so a cell does not have an elevation but an equation. In this way, the elevation in each cell can be taken into account, and especially on slopes a smaller error in the vegetation height is encountered. (Pinton, Canestrelli, Wilkinson, Ifju, & Ortega, 2020)

2.3.3. Features for vegetation classification

During this thesis, different features of the point clouds are obtained from the point cloud for classification. Features that might be used for the classification of vegetation in a LiDAR point cloud include geometric and radiometric features. The geometric features describe the structure of the object that should be classified. These features describe the distribution of the points in the object in the 3D space. Especially the geometric features describing the internal structure of tree crowns appear to be useful in tree species classification. Radiometric features are represented by the intensity with which a pulse is returned. The use of radiometric features alone was found to show a lower accuracy than when using only geometric features. However, when using a combination of both a higher classification accuracy was reached. Note that results when applying these features varied a lot depending on forest type. (Michałowska & Rapiński, 2021)

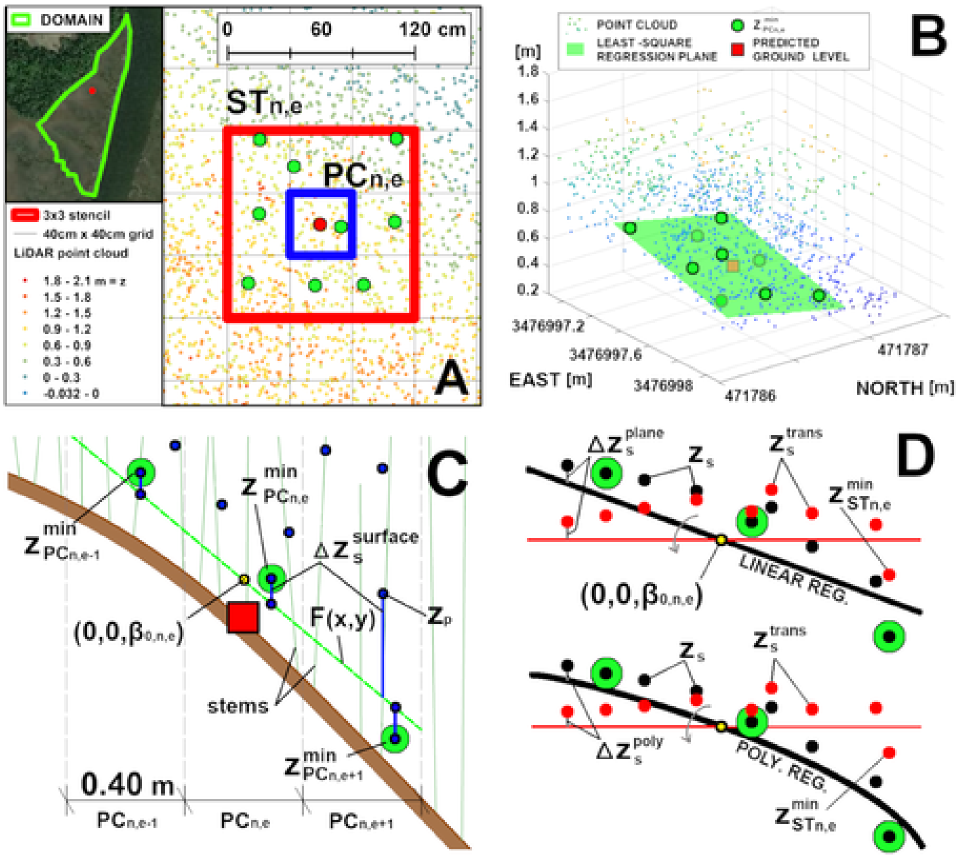


Figure 2.7: A: finding the minimum of each grid cell and taking the surrounding grid cells. B: Fitting a plane to the surrounding minima. C: Determining the distance of each point to the ground plane. D: Transforming the point cloud (bringing all points to ground 0). (Pinton et al., 2020)

2.3.4. Random forest

During this thesis, a random forest classification model is used. The random forest model is a method that combines multiple decision trees. In a decision tree, a decision is made on each node leading the attribute you put into it to a new branch. In the decision tree in Figure 2.8 for example based on height and vegetation features, it is decided to which class of vegetation each attribute belongs.

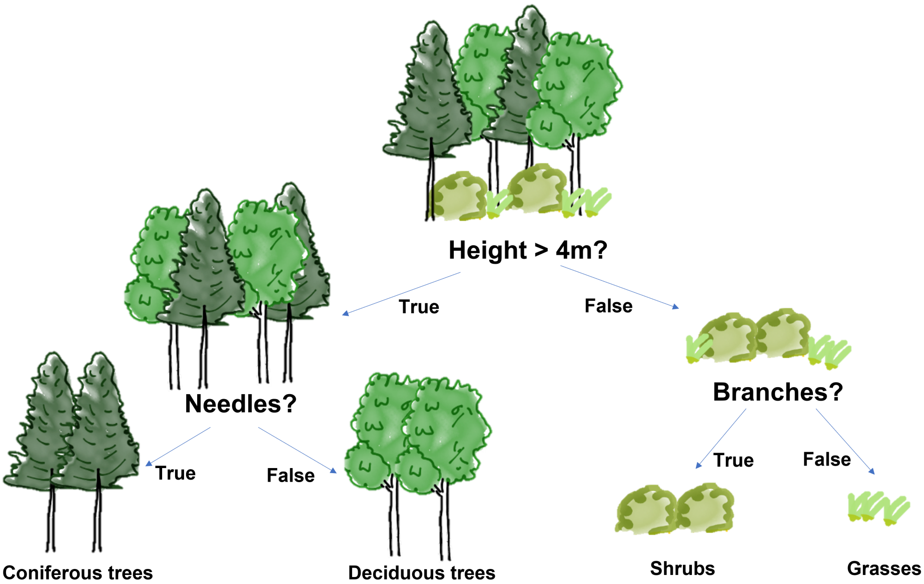


Figure 2.8: Example of a decision tree with some simplified features. Based on the properties of the vegetation the decision tree decides which vegetation class the vegetation belongs to.

Using the Gini impurity, a decision tree can be. The Gini impurity is a value that determines the best split. A low Gini impurity indicates the probability that an instance is incorrectly classified by the tree.(Breiman, Friedman, Olshen, & Stone, 1984) Growing multiple decision trees and letting them vote the class by majority vote (see Figure 2.9) have resulted in significant improvements in the classification accuracy (Breiman, 2001).

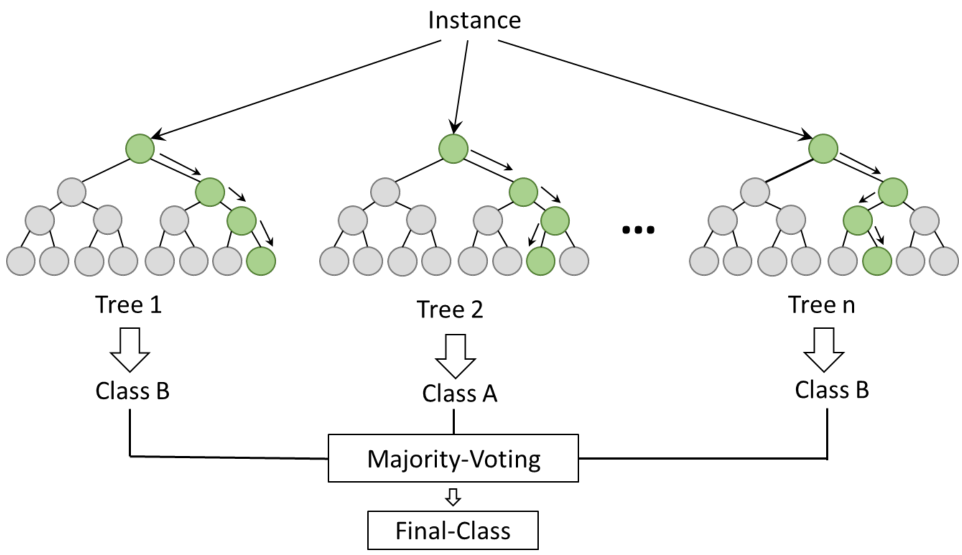


Figure 2.9: Simplified example of how a random forest works.

A random forest is after it has been trained able to indicate the importance of the features it used to build the decision trees in the forest. This means that if it has built the conclusions on only one feature, this can be evaluated, and changes in the features put in the model can be adapted to this. This makes interpretation of the model easier than when, for example, using a deep learning model where it is not known what the features are doing. This makes the approach of classification models more intuitive by increasing the correct estimation rate. To ensure the adequacy of the model can be tested more accurately by applying the generated model of the obtained point clouds from different areas (Zeybek, 2021).

The random forest can be tuned by changing parameters such as the number of trees, tree depth and the maximum features. A single tree tends to build a tree for that specific case (overfitting), this effect reduces when increasing the number of trees, but with more trees, the computational effort increases. Then there is the depth of the tree, which defines the number of nodes where decisions are made in a tree. A higher tree depth means more decisions are made and thus that the tree is more complex. This, however, does not mean a better fit is made. A more complex tree tends to overfit for specific cases. Then there is also the maximum number of features that can be chosen to increase randomness in the model.

2.3.5. Training and validating the model

The value of a map is a function of the accuracy of the classification. Accuracy assessment is therefore a fundamental part of any thematic map. There is no standard method of accuracy assessment. A confusion matrix is often the core of an accuracy assessment and is used to provide a site-specific assessment of the correspondence between classification and ground conditions. The confusion matrix could summarize the class allocation made by classification and the basis for many qualitative classification metrics. (Foody, 2002)

A random forest model can be evaluated using test data. To train the model, training data is created. This is data in which the class is indicated so the model can be trained based on this data. Usually, the training data is split into training and test data. In this way, the model can be evaluated after the random forest has been created. Using the test data, some statistics concerning the accuracy of the model can be created. This can be used to evaluate, for example, how well the model works on average, but also per class, so if the model mixes up certain classes.

		Predicted class	
		Positive	**Negative**
True class	**Positive**	TP	FN
	Negative	FP	TN

Table 2.2: An example of a confusion matrix with TP indicating the True Positive prediction, TN, the True Negative prediction, FP, the False Positive prediction and FN the False Negative prediction

Another technique to evaluate the model is bootstrapping. This means that a random subset of the training data is used to build the trees, and the trees are evaluated using the other part of the data that was not used to build the tree (the out-of-bag). Using this method, the Out-of-bag(OOB) error can be calculated. The OOB error is the percentage of wrong predictions in the OOB sample. This OOB can be used to predict the performance of the model. However, it should be noted that the OOB may overestimate the true prediction error, especially in the case of, for example, small sample sizes and a large number of features used for the prediction(Janitza & Hornung, 2018).

2.4. Shore Monitoring & Research

This thesis is written in collaboration with the company Shore Monitoring & Research. Shore Monitoring & Research is a survey- and consultancy company focused on the hydraulic engineering market. The company was founded in 2009 and is located in The Hague, Netherlands. In-depth knowledge of a wide range of survey techniques are combined with knowledge and insight into the hydraulic domain. The services of Shore vary from a single survey to arranging, executing and analysis of complete integral survey campaigns and long-term monitoring projects. Shore differentiates itself from its competitors by the availability of bathymetric and topographic survey solutions which can be combined for the acquisition of integral underwater and above-water data from coastal and river systems.

As a spin-off from the Delft University of Technology, Shore has always remained closely related to the Delft University of Technology, particularly in the field of knowledge development and innovation. Based on its own experiences and market demands, Shore carries out innovation and pilot projects to constantly optimise the range of available survey solutions. Innovation and pilot projects are carried out independently or in collaboration with knowledge institutes and industry. This results in an up-to-date and innovative range of survey solutions with which the customer can be supported in the most efficient way and according to the latest developments. (Shore Monitoring and Research, n.d.)

2.5. Summary

In this chapter background information concerning the research was presented. The reason for the need for the monitoring of habitats in the coastal regions is the Natura 2000 habitat directive. This monitoring is even nowadays for large parts done by hand by ecologists. But with the increase in the availability of remote sensing and machine learning methods, this could be done in a much less labour-intensive way. Current dune vegetation classification algorithms mainly focus on classification using RGB imagery. But using imagery does have its limitations. Point clouds could form a solution. Point clouds are mainly used as an information source to find the DTM and CHM. But much more information could be obtained from point clouds. But using point clouds in conventional Machine Learning algorithms brings an extra difficulty because of for example the unordered point clouds. And because we are dealing with a natural environment, we also need to deal with the unorderdness of the natural environment. Using techniques such as voxels, features can be extracted from the point clouds to make classification of the vegetation possible. This will be done using a random forest algorithm. This model will be trained and validated using test and training data.

3 Area and Data Properties

In this chapter, the research area and properties of the data are discussed. In Section 3.1 the study area is shown. In Section 3.2 the data that is used for the classification and the platform that has obtained this data are described. The data used to validate the results and create the training data are discussed in Section 3.3. Section 3.4 gives an insight into the software that was used for the research. A summary of this chapter can be found in the last Section 3.5.

3.1. Study area

The study area is the Zuid-Kennemerland national park as shown in Figure 3.1. The park has been designated a Natura 2000 area, which means that its habitats must be monitored. Additional information on this area and its role in the Natura2000 network can be found in Appendix A.

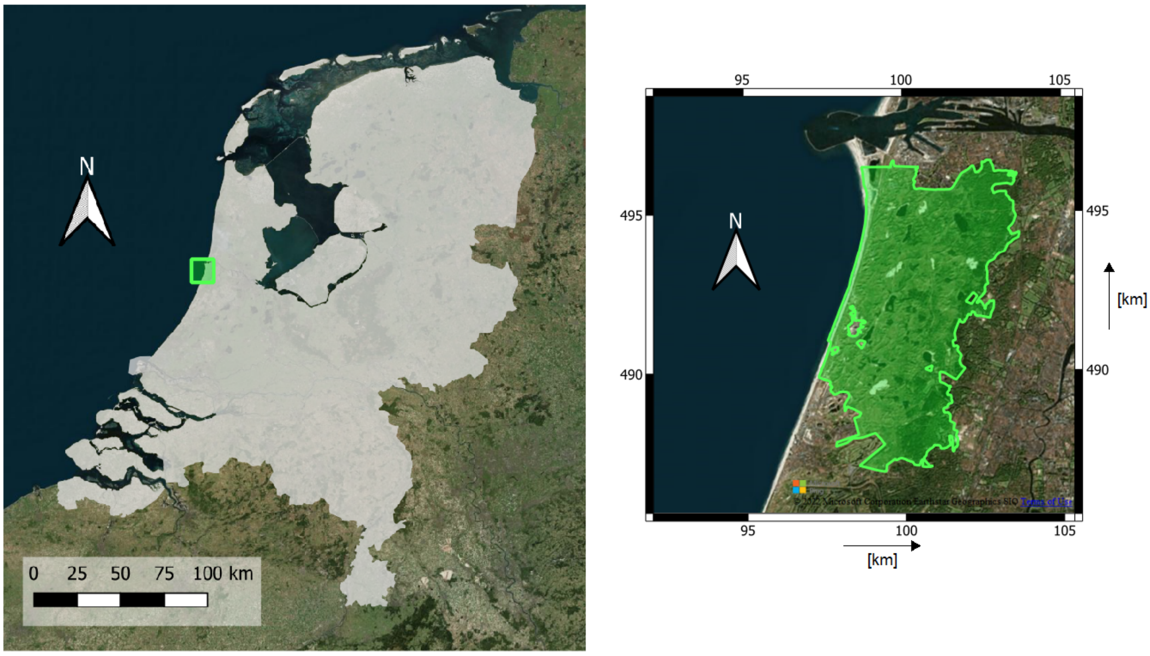


Figure 3.1: Location of the study area, the Zuid-Kennemerland national park, in the Netherlands.(MEZK, 2013; Earthstar Geographics, 2022) Coordinates are given in the RD-coordinate system.

The Zuid-Kennemerland national park has a surface area of about 38km^2. Not the full park was scanned using the UAV. The area covered by the measurements of the UAV is about 2.7km^2 (See Figure 3.2).

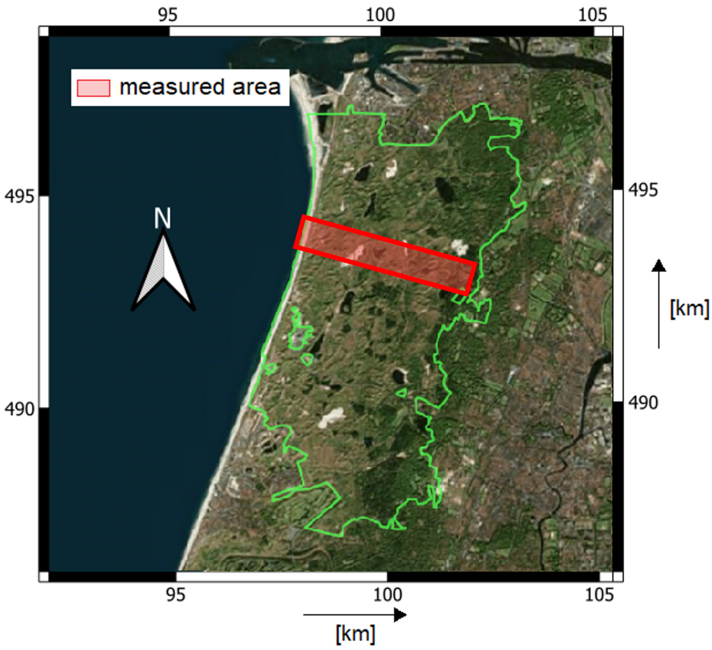


Figure 3.2: Area that has been scanned using the UAV (Earthstar Geographics, 2022).

3.2. The data

The point cloud is obtained by a LiDAR sensor on an Unmanned Aerial Vehicle (UAV), which in this case is a drone. The drone is equipped with different sensors, of which the precision and use are elaborated on in this section. The first Subsection 3.2.1 will explain the vehicle itself. Subsection 3.2.2 the sensors the vehicle is equipped with. In Subsection 3.2.3 the properties of the data are discussed

3.2.1. The vehicle

The platform used is a rotary-wing drone. This means that the drone is able to take off vertically. Vertical take-off and landing indicate that no runway is needed for take-off. Because of the size of this drone, it is able to lift the equipment needed for monitoring. The rotary-wing drones are generally more suitable for achieving high spatial resolution measurements. A limiting factor of the drone is its power source. The available power in the batteries affects the endurance of the flight and therefore the drone must return regularly to the base to change batteries (Tang & Shao, 2015). There are also some regulations around flying drones. To fly the drone, a certified drone operator is required. Next to that regulations are different for different countries. These regulations concern restrictions regarding flight permission, flight height and the maximum distance from the operator. On a regular basis, these regulations are updated and changed. Therefore, when preparing the drone for a survey, regulations should be regularly reviewed.

3.2.2. The equipment of the vehicle

To monitor the area, the drone is equipped with different sensors. First, the RTK-GNSS antenna is on top of the drone (as visible in Figure 3.3), so the signal to positioning satellites to determine its positions is as undisturbed as possible. GNSS, short for Global Navigation Satellite System, is the term used for systems with global coverage that use satellites to provide autonomous geospatial positioning. Examples of GNSS systems are the USA's GPS, Europe's Galileo, Russia's GLONASS and China's BeiDou.

This vehicle is also equipped with two IMUs. IMU stands for Inertial Measurement Unit. This is an electronic device that measures and reports the roll, pitch and yaw (also see Figure 3.4)of the object by using a combination of accelerometers, gyroscopes and sometimes also magnetometers. In the case of drones, IMUs are typically used to manoeuvre the drones. The acceleration data can be used to support the positioning of the drone.

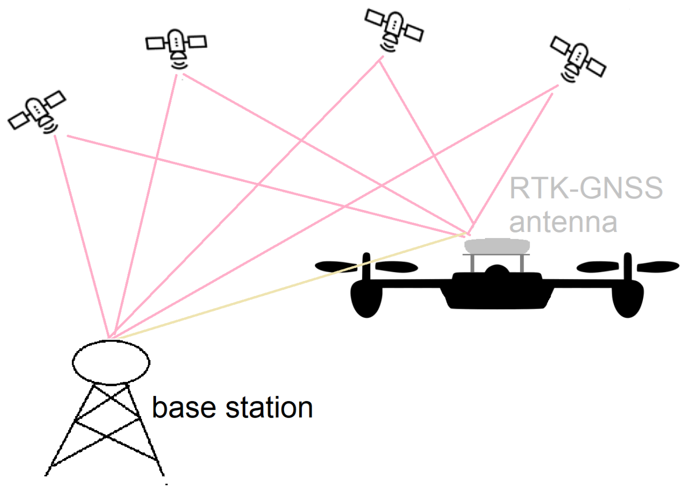


Figure 3.3: Positioning using GNSS: The drone determines its position using GNSS, to correct for atmospheric errors and get to a more accurate position a base station is used.

Typically, an IMU records the acceleration data and rotation rates at a sampling rate of up to 1000 Hz (1000 times per second).
Each IMU fulfils a different function. One IMU is used for drone orientation of the drone itself and to support flying, this IMU is not very precise. The other IMU is embedded in the LiDAR system. This is a much more precise IMU. This is needed to estimate the direction of the laser pulse that is sent and received as precisely as possible.

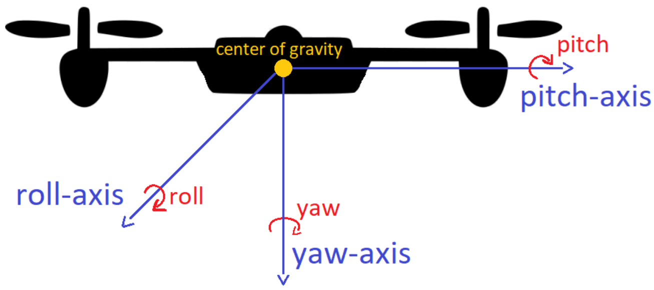


Figure 3.4: Rotation axis in an IMU: The roll, pitch and yaw angles on the drone that are measured by the Inertial Measurement Unit.

The total accuracy of the GNSS system with the LiDAR system combined is given in Table 3.1 below.

THU (95%CI)	7.17 cm
TVU (95%CI)	4.93 cm

Table 3.1: Accuracy of the drone (Shore Monitoring and Research, 2021) (THU: Theoretical Horizontal Uncertainty, TVU: Theoretical Vertical Uncertainty)

The UAV is equipped with a LiDAR system with a wavelength of 903 nm. The data is collected using the Phoenix Scout-32. This system collects survey data and combines it. So the LiDAR data is combined with GPS data and the IMU measurements. The accuracy of this LiDAR system is given in Table 3.2 below.

Velodyne HDL32E LiDAR Sensor Resolution	2 cm
NovaTel GNSS	10mm+1ppm
Post-Processed Attitude/Heading Error	0.019^o

Table 3.2: Accuracy mobile lidar (Shore Monitoring and Research, 2021)

3.2.3. Spread of the point cloud

To assess the spread of the obtained point cloud, we look at surfaces that should approximately be seen as flat surfaces with little to no deviation. With a flat surface, something like what is meant in Figure 3.5 below.

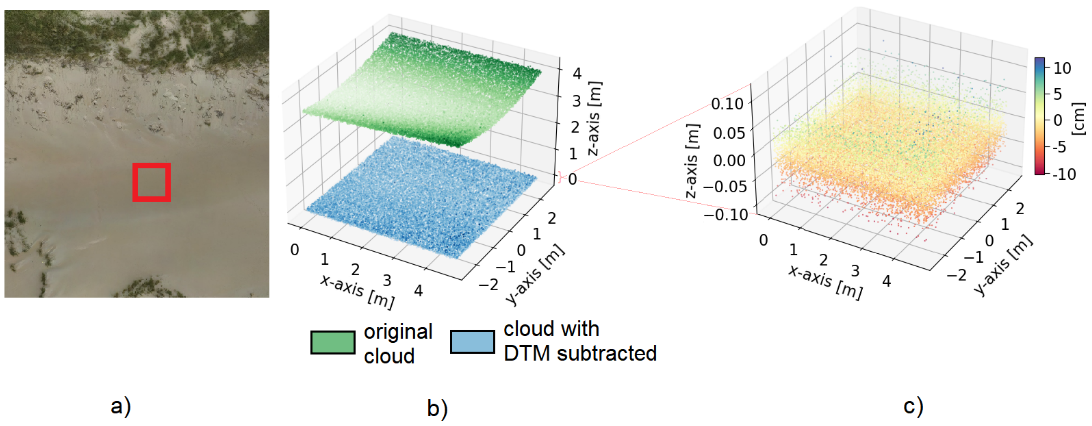


Figure 3.5: Zoom to a piece of a point cloud of a flat surface: a) orthophoto and outline of the piece of point cloud; b) original point cloud and point cloud after the DTM is removed; c) zoom to a normalised point cloud.

In figure 3.5b the removal of the DTM is made visible. This is done using a regular cloth method. In Figure 3.5c, the normalised point is zoomed in. Here, it can be seen that there is a spread around the zero axis and that the points are not perfectly flat. To quantify this spread some more pieces which should show an approximate zero surface were moved to zero. The surfaces in the area that should be flat include cobblestones and more sandy areas; furthermore, there were no real flat roads in the area. The spread shown on these types of surfaces has been visualised in Figure 3.6 below.

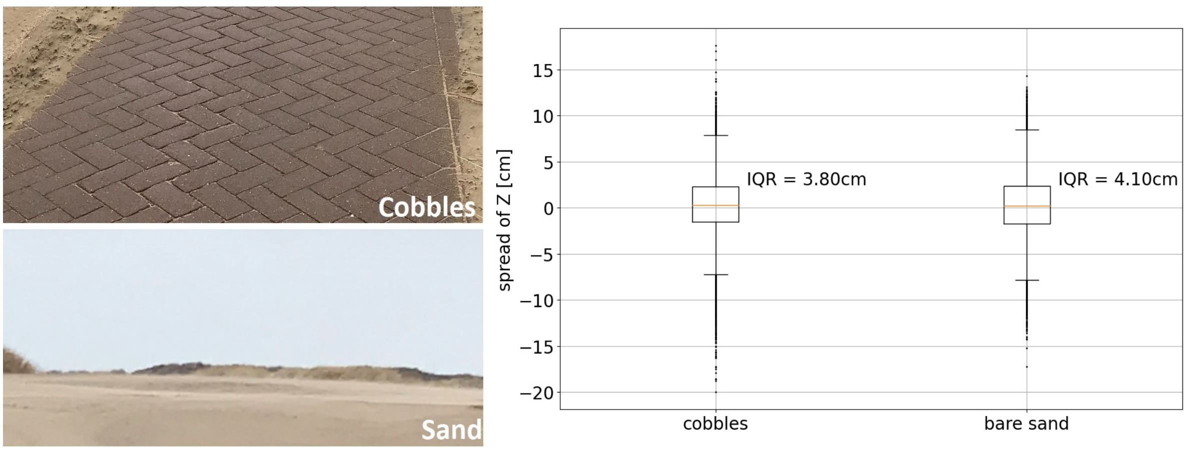


Figure 3.6: Boxplots of point spread on a flat surface with the Inter Quartile Range (IQR= upper 75% bound - lower 25%bound of the data) shown for both cobbles and sand

3.2.4. Reach of the LiDAR under vegetation
Because of the density of the vegetation in some areas, the LiDAR laser does not fully penetrate the bushes in these locations. To confirm this some ground points have been measured in the field using GPS, as can be seen in Figure 3.7. This should be taken into account when determining the height of the ground and from that the vegetation height.

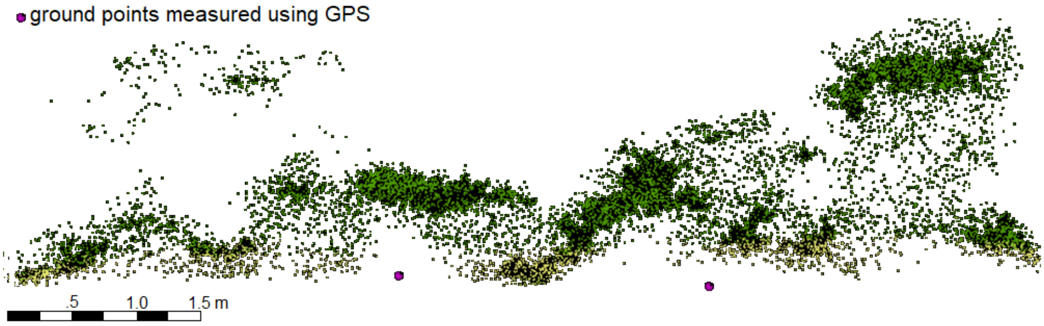


Figure 3.7: LiDAR and dense vegetation: in pink some hand-measured GPS points of the ground are visible. From those points it can be clearly seen that the LiDAR does not reach the ground

3.3. Training and validation data
When performing different algorithms, the models should be trained and the result should be validated. This is done using data from different sources. The properties of the data used for validation and its sources are elaborated on in this section.

3.3.1. Validation of the digital terrain model
Instead of using an external terrain model to find the ground elevation, the ground elevation will be determined using the terrain model. To validate this obtained terrain model a comparison will be made with a terrain model created using airborne LiDAR data from the 28th of April 2021. The data has got a point density of 10-14 points per square meter. The points have a systematic error of 5 cm and a stochastic error of also 5 cm, meaning that at least 68.7 % of the points have a precision of 10 cm.

3.3.2. Ground truth for the classification
To find the validation data of the vegetation classification results, satellite data was used. Available land cover maps, such as the Copernicus land cover map or Corine, are not accurate enough. In these datasets, many parts of the N2000 dunes are classified as only dunes or as croplands, which are not present in N2000 areas these N2000 areas. Added to this is the fact that the resolution was often quite coarse, usually in the 10s of metres. The resolution of data that is obtained by the drone is in the cm's range. Therefore, not the land cover maps were used, but the ground truth was made by hand. Making the ground truth was done using different open-source data such as Google Maps, Google Earth and Google Street View and an aerial image in March 2021 half a year after the LiDAR data was obtained. Also, an orthophoto was taken when the LiDAR data was obtained. An advantage of using images from March is that the deciduous trees do not have leaves yet and it is thus easier to separate the deciduous trees and coniferous trees. Also, the area management provided a vegetation map of the area of 2018 from which some information could be obtained the maps for these different vegetation types can be found in Appendix B. Using this information, comparisons were made, such as in Figures 3.8 and 3.9 were made to determine the class of vegetation at different locations of the point cloud.

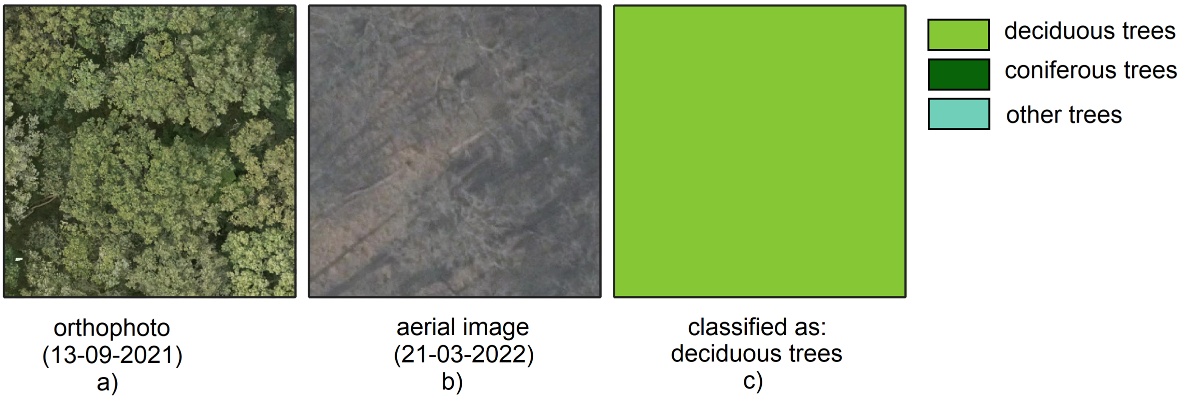


Figure 3.8: Sources to find the ground truth for the classification of deciduous trees; a) orthophoto obtained at the same moment as the point cloud; b) aerial image obtained by a plane (Beeldmateriaal Nederland, 2022); c) vegetation map of the area of the year 2018

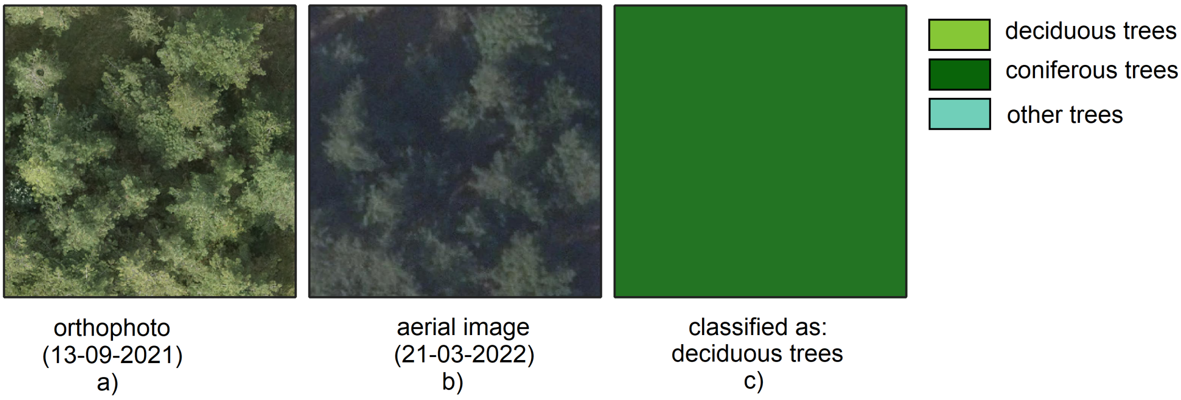


Figure 3.9: Sources to find the ground truth for the classification of coniferous trees; a) orthophoto obtained at the same moment as the point cloud; b) aerial image obtained by a plane (Beeldmateriaal Nederland, 2022); c) vegetation map of the area of the year 2018

3.4. Software

In the process of the LiDAR data, different tools have been used. For the visualisation and some basic handling of the data *CloudCompare* was used. Since we are dealing with a large point cloud (2 milliard points), the data was split into pieces to make the data processable. To do this, the programme *FME* was used. For the classification steps and algorithms, the programming language *Python* was used. In *Python*, several packages were used such as *NumPy* and *pandas* for the more general data processing. Some more specific packages that were used are the package *laspy* to load .LAS files, the package *sklearn* to apply Machine Learning and *watershed* from *skimage.segmentation* for tree delineation. To visualise the results, *QGIS* was used.

3.5. Summary

In this chapter, the data and the region of interest are discussed. The region of interest to which the method was applied concerns a region stretching from dunes at the shoreline to the dune forests in the hinterland. The data in this area are obtained by a LiDAR mounted to a drone with an overall spread of about 4cm, which was evaluated by looking at approximate flat surfaces. The system accuracy is influenced by a combination of the GNSS system, IMU and the LiDAR system. To validate the results of the methods data should be validated. To do this, different data sources are used. To evaluate the DTM a DTM from a different time of the year is used. To evaluate the classification results different open-source data and orthophotos taken by the drone at the same time as the LiDAR data are used.

4

Methodology

Vegetation classification using UAV-LiDAR point clouds is in an experimental phase with room for development (Beland et al., 2019). This chapter proposes a method to classify vegetation in UAV-LiDAR point clouds. Next, a method to assess the accuracy of the results is discussed. To get an overview of the entire method, the workflow is presented in Figure 4.1. The first steps involve preparing the point cloud for classification. This includes rasterisation (Section 4.1) and obtaining the height of vegetation (Section 4.2). In Section 4.3 the structural features of the different types of vegetation that are used for the classification are discussed. To validate the obtained results some sort of reference is needed, the data that is used as a reference and how it is used is proposed in Section 4.5. A short overview of the entire chapter, and thus the method, can be found in Section 4.6.

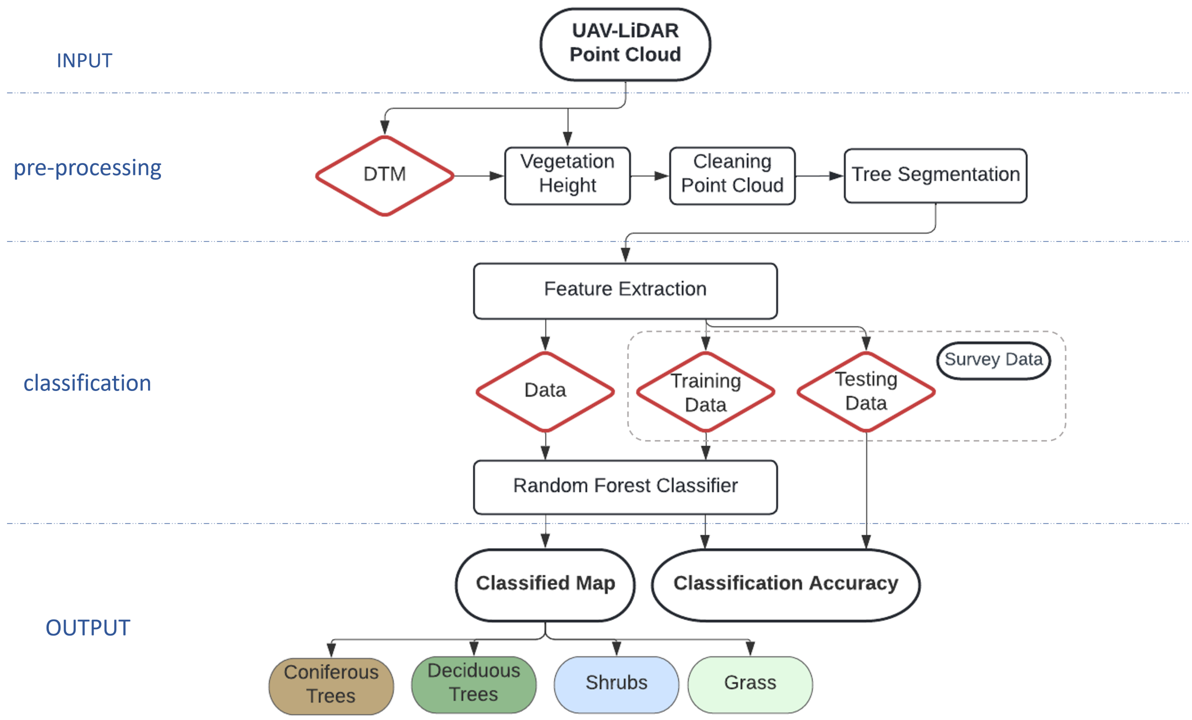


Figure 4.1: Workflow with the steps that are proposed to get from an UAV-LiDAR point cloud to a vegetation map. The pre-processing steps

4.1. Rastering the point cloud

The different methods proposed in this thesis use a raster on the point cloud. To group the points in the point clouds, the index of the raster cell of each point is used, are visualised by numbers 0 to 8 in Figure 4.2. To determine the index of a raster cell corresponding to a point in the raster, first, its column and row are determined using the x and y values (see Equation 4.1). To find the columns and rows first the point cloud is translated to zero by subtracting the minimum x and y values of the point cloud. The columns and row numbers are then determined by dividing the translated x and y values by the dimensions of the raster cells (Δx_{cell},Δy_{cell}). To get the integer values (whole numbers) of the columns and rows, the largest integer less than these values is taken (floor()).

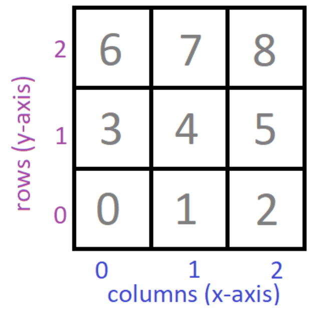


Figure 4.2: Raster indices of the points in the point cloud after applying Equation 4.1 and Equation 4.2

$$\begin{aligned} col &= \text{floor}((x - x_{min,pointcloud})/\Delta x_{cell}) \\ row &= \text{floor}((y - y_{min,pointcloud})/\Delta y_{cell}) \end{aligned} \tag{4.1}$$

To group the points, the raster index is used. The index can be computed by filling in the obtained row and column numbers in Equation 4.2 below.

$$ind = col + row \cdot (col_{max} - col_{min} + 1) \tag{4.2}$$

4.2. Obtaining vegetation height

Since we are dealing with a natural environment, it is assumed that the points in the point cloud are either terrain or part of the vegetation. The height of the points above the terrain represents the height of vegetation. To find the elevation of the terrain usually, a Digital Terrain Model (DTM, see Subsection 2.3.2) is used. This terrain model is usually created using the lowest points of a point cloud. But not everywhere in the point cloud the ground is reached by the LiDAR pulse (see Subsection 3.2.4). With a lack of points on the ground, conventional DTM algorithms predict that the terrain is higher than it is, meaning that the vegetation height is estimated lower. This problem occurs mainly under denser vegetated shrub areas. Therefore a new method to approximate the DTM was developed which is explained in Subsection 4.2.1 below.

4.2.1. A new model to estimate the DTM

To determine the DTM an algorithm that was proposed to find the DTM from point clouds in salt marshes (Pinton et al., 2020) is used. In this algorithm, a raster is put over the data. The lowest point of each raster cell is used in the next step to estimate the DTM. For each raster cell and its surrounding cells (thus 9 points) Equation 4.3 or 4.4 is fitted. Also, see Subsection 2.3.2. To reduce the influence of outliers only the points inside the range mean$\pm 2.7\cdot$std of the points are used for the fit. Since there are some points in the data where the light has not reached the ground, a hybrid version of this algorithm is proposed (Figure 4.3). Two different raster cell sizes with both the first-order polynomial fit (Equation 4.3) and the second-order polynomial fit (Equation 4.4) are used. The smaller cell size has a higher resolution, but the larger cell size has the ability to bridge areas with fewer points on the ground. On the smaller cell Equation 4.3 is fitted. Since the larger cell occupies a larger area, and therefore, probably more variation will be present in the terrain, the second-order fit (Equation 4.4) is fitted to the larger cell. Both of these methods are applied to the point cloud to calculate the DTM. To find where the larger cell size bridges the smaller cells, the distance dz between the rasters is calculated. To preserve spatial resolution usually the smaller grid is used, but if the distance dz of the smaller grid above the larger grid comes above a certain threshold the larger grid is used. To get a better overview of the method in the workflow in Appendix C can be consulted.

$$z = a + b \cdot x + c \cdot y \tag{4.3}$$

$$z = a + b \cdot x + c \cdot y + d \cdot x^2 + e \cdot y^2 + f \cdot x \cdot y \tag{4.4}$$

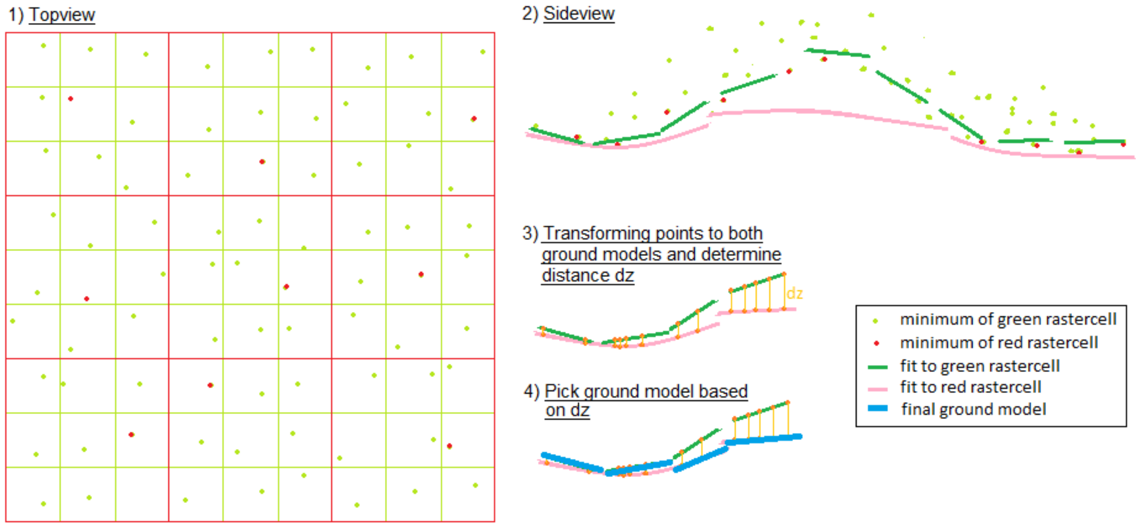


Figure 4.3: Ground estimation model: 1) Topview of the point cloud with a raster put over it, 2) To the smaller green raster cells Equation 4.3 is fitted and to the bigger red raster cells Equation 4.4 is fitted. 3) transform points to ground height and determine dz between the two fits. 4) use the smaller raster fit unless dz is above the threshold value, then fit the larger raster should be used.

4.2.2. Obtaining CHM

The model containing the vegetation height is called the Canopy Height Model (CHM). Subtracting the terrain (DTM) from the surface (DSM) should give the vegetation height (CHM). This is illustrated in Figure 4.4 below.

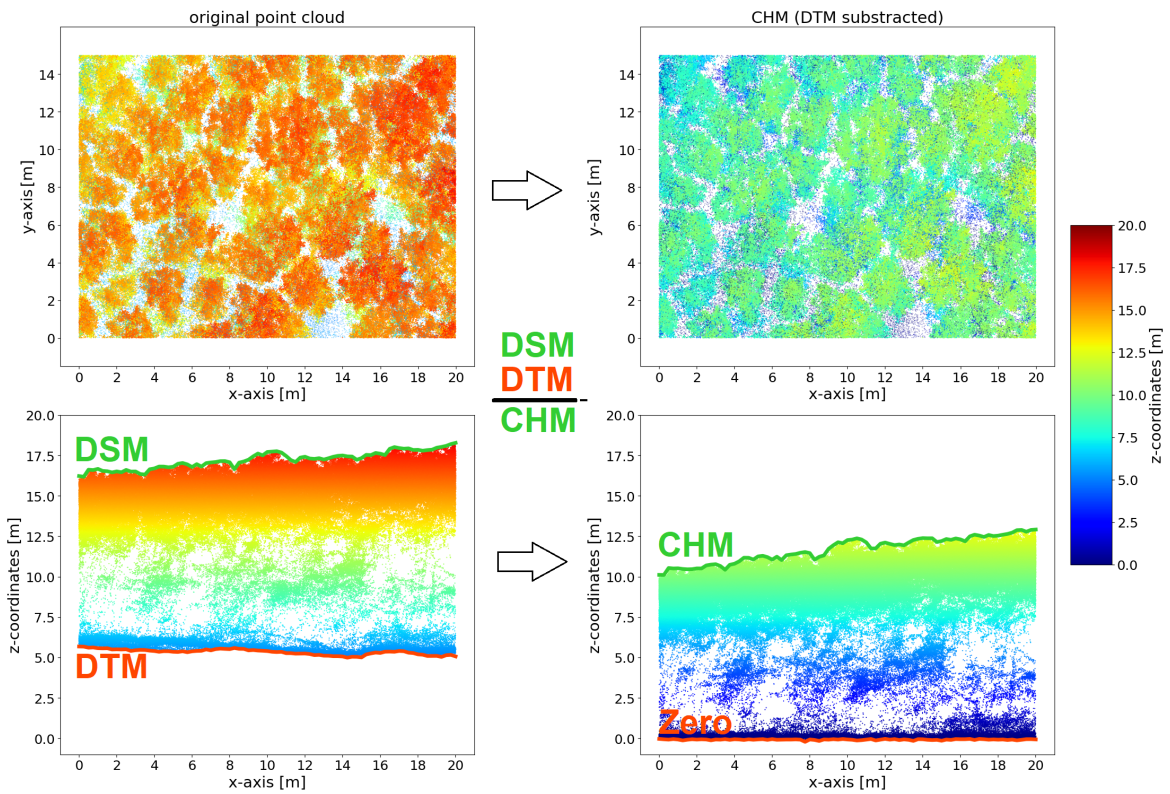


Figure 4.4: Obtaining CHM using DTM; Up: Top view, Down: Side view

4.3. Classifying vegetation

This section discusses the classification of vegetation. The goal is to classify the point cloud into four classes: coniferous trees, deciduous trees, shrubs and herbaceous vegetation. To classify the point cloud the vertical distribution of the points is considered. The vertical distribution is taken per unit area. To obtain this unit area, a grid is placed over the point cloud as can be seen in Figure 4.5. To rasterise the data the method explained in Section 4.1 is used.

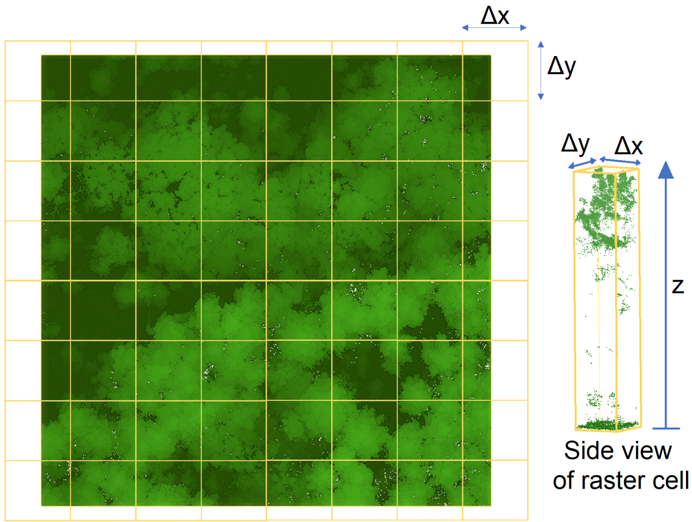


Figure 4.5: A raster put over a piece of the point cloud. Cell size is given by Δx and Δz, as Δx = Δy. Note that in reality, the raster cells are much smaller. In this image, the raster is formed by 8x8 cells, while in reality the raster is formed by 250x250 cells.

Since shrubs and herbaceous vegetation can grow below trees, the vegetation classes are divided into two layers of vegetation: high vegetation which is in the upper layer of the point cloud and low vegetation, which is in the lower layer of the point cloud. High vegetation includes trees with the classes coniferous and deciduous. The low vegetation includes shrubs and grasses. To the low vegetation class, also bare sand with no vegetation is added. To look at the point distribution of the low and high vegetation the raster is used. For low and high vegetation, another height is used in the raster (Figure 4.6). For the lower vegetation, the point distribution is examined from the lowest height until the maximum height. When determining this height the point should be as little as possible affected by the canopy of trees, so also under trees, the lower vegetation can be determined. For trees, the maximum height is looked at until a certain depth, which should not be affected by the ground.

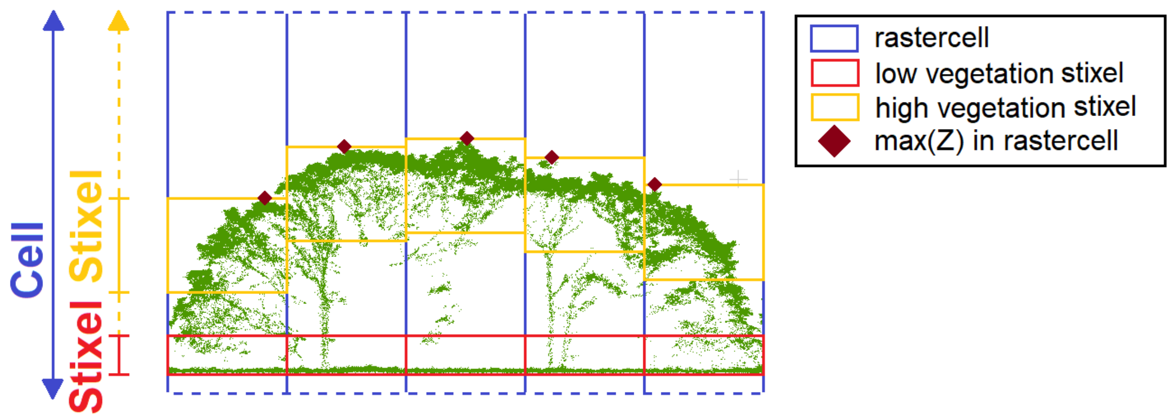


Figure 4.6: Upper and lower stixels that were used for classification of the two different vegetation layers

For trees, the classification takes place per tree, but for shrubs and herbaceous vegetation (also underneath trees), this takes place per raster cell. In Subsection 4.3.1 the tree delineation algorithm is explained. 4.3.3 4.3.4

4.3.1. Delineating trees

It is assumed that trees have a height of at least 4 metres. This is of course not always the case, but a line needs to be drawn somewhere. Using the raster as shown in Figure 4.5 first the raster cells with no points above the 4 metres are removed. These cells do not contain trees. To classify different types of trees and get an as precise as possible estimation First the trees are delineated so classification occurs per tree. Most methods using LiDAR data use the CHM, represented by a raster. Usually, peaks in the CHM are used as a basis, but because of multiple peaks in some tree crowns, this can cause one tree to be classified as multiple. Each tree delineation algorithm reacts differently to another forest structure. The accuracy of the tree delineation method is determined by determining the F score (4.7) using the recall r (4.5) and precision p (4.6). These values are determined using correctly detected trees or True Positives (TP), trees that are detected but are not there or False Positives, and trees that have not been detected but are present or False Negatives (FN). The F score is found by looking at the harmonic mean of r and p. Improving the F score can be done by looking at different tree delineation algorithms, but also by smoothing window sizes and looking at the consistency of the DTM (Mohan et al., 2021).

$$r = TP/(TP + FN) \tag{4.5}$$

$$p = TP/(TP + FP) \tag{4.6}$$

$$F = 2 \cdot r \cdot p/(r + p) \tag{4.7}$$

Since the area of interest is dealing with different forest types the method that was easiest showed the best overall accuracy over different forest types and that was not too difficult to implement was used. This method is the watershed algorithm. Currently, using the F-score, an accuracy of up to 80% can be reached using a watershed algorithm, which is good enough for the classification in the next step.(Wu, Shen, Cao, Wang, & Cao, 2019)

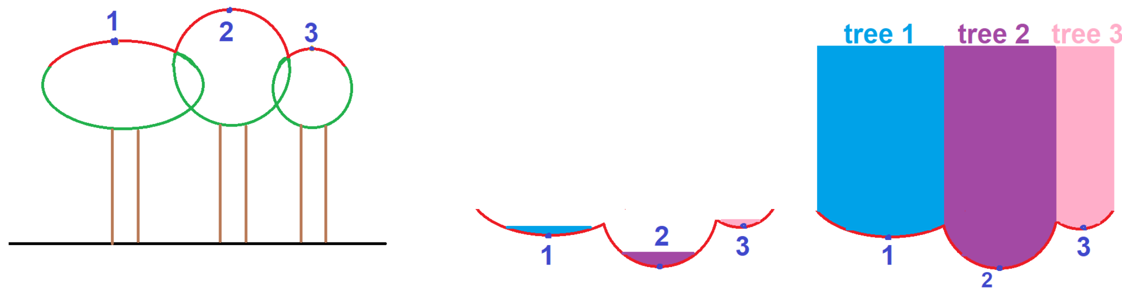


Figure 4.7: The watershed algorithm, 2D side view

The watershed algorithm is created to determine the watersheds of a river. In this algorithm, the CHM is turned upside down and from the peaks of the basins, or in this case, the trees are filled with water until it overflows. Each basin has its own watershed or tree. In Figure 4.7 a 2D visual overview of the steps is visible.

4.3.2. Using a raster to classify trees

In the next subsection, the features of the trees are discussed, but over which part of the trees these features are taken can differ. Since a raster was used to obtain the features the classification of the trees can be done by classifying the trees in different manners. In Figure 4.8 these manners are visualised. The first way is by making the classification take place per raster cell and using a majority vote of the classified cells to determine the tree classification. This means the raster is trained per raster cell and the classification also takes place per raster cell. The second method is to classify the tree by taking the average of the features in all cells. The last method is by first determining which raster cells belong to the tree and then using all points in the raster cells belonging to the tree to calculate the features of the tree. For the second and the third method, the classifier is trained per tree and also the classification takes place per tree.

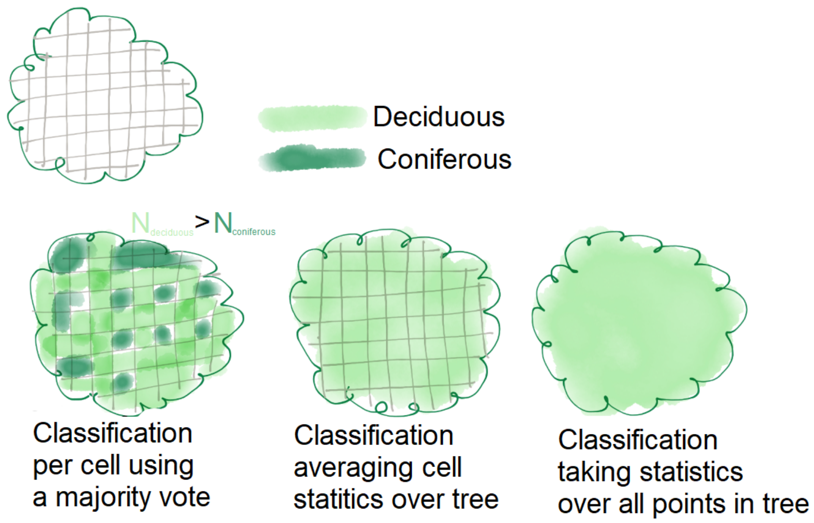


Figure 4.8: Different methods look at statistics in trees: Using all points in a tree, taking the average statistics of the grids cells, looking per raster cell

4.3.3. Features trees

For classification, the vertical distribution of the points is used. For deciduous trees and coniferous trees, a different vertical distribution of the points is expected due to a difference in canopy type and cover and structure in the trees. To assess this, a histogram of the upper 10 metres (top-down) of a group of deciduous trees and coniferous trees is compared in Figure 4.9.

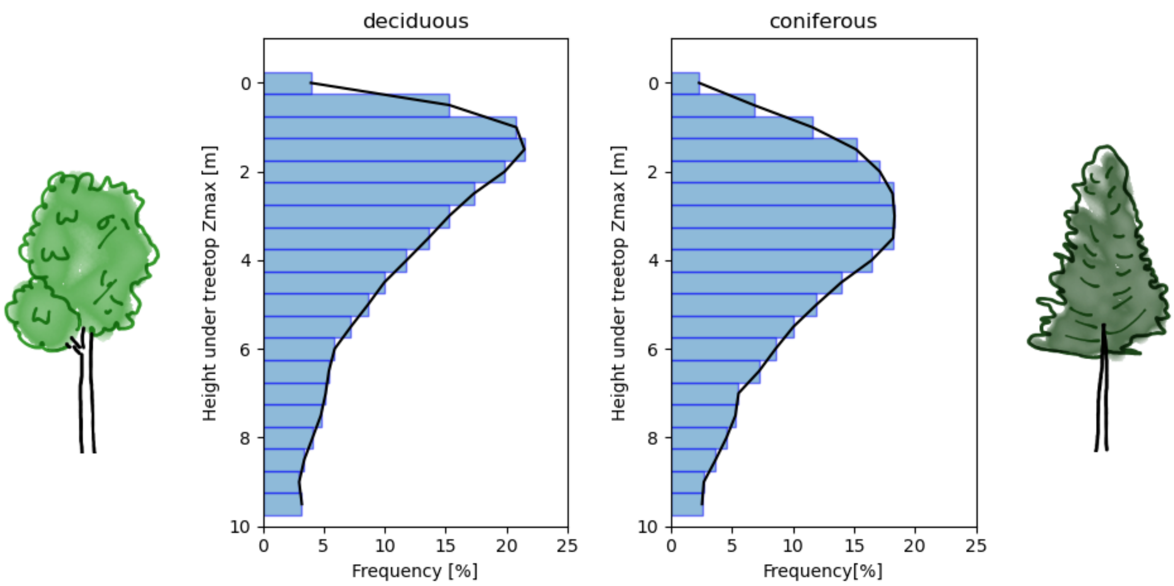


Figure 4.9: Point distribution in coniferous and deciduous trees: Histogram of point distribution in the top 10 meters of deciduous and coniferous trees.

To quantify these differences in the histogram distribution, a skewed normal fit (see Equation 4.8) is fitted to the histograms at different heights. The results of this can be seen in figure 4.10.

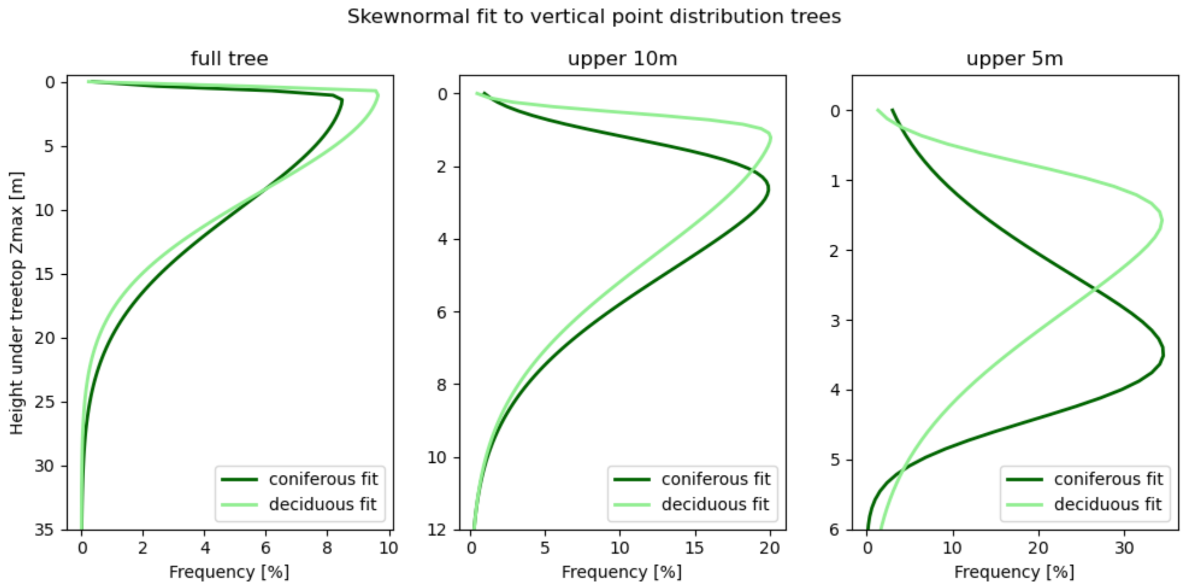


Figure 4.10: Skew-normal fit to histograms of the point distribution starting from the top down. From left to right taking all points, in the middle a fit to the distribution to the points in the upper 10 meters and on the right a fit to the distribution to the points in the upper 5 meters.

$$f(x) = 2\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}\int_{-\infty}^{\alpha\frac{x-\mu}{\sigma}}\frac{1}{\sqrt{2\pi}}e^{-\frac{t^2}{2}}dt \tag{4.8}$$

With x indicating the vegetation height μ, the mean of the variables σ, the standard deviation of the variables and α indicating the skewness of the graph. A negative α indicates that the graph is negatively skewed (to the lower values) and a positive α indicates that the graph is positively skewed. For an α of zero, the data is normally distributed (Azzalini & Capitanio, 1999)).

When looking at Figure 4.10 it can be seen that in the upper 5 meters the difference in the variation in the height distribution the distributions of the coniferous fit and deciduous fit become clearly distinguishable. The skew-normal fit to the deciduous points seems to be inversely skewed compared to the skew-normal fit to the coniferous data.

Based on the result of Figure 4.10 structural features that are used for classification are taken in the top 5 meters. To calculate the structural features the formulas given in Table 4.1 are used. For the z values (note that these are the CHM values) of the points in the upper meters of the canopy, the parameter h is used. H indicates the total height of the tree. Note that in the right of figure 4.11 the canopy starts at zero metres. This is done to prevent the algorithm from classifying trees by solely their height. Thus, for example, classifying a high tree as coniferous and a low tree as deciduous. To ensure that the height of the trees does not influence the classification, the two methods of normalising and not normalising the features are compared.

$$h_{normalised} = h - (H - 5) \tag{4.9}$$

An overview of all the features used is visible in Table 4.1 below.

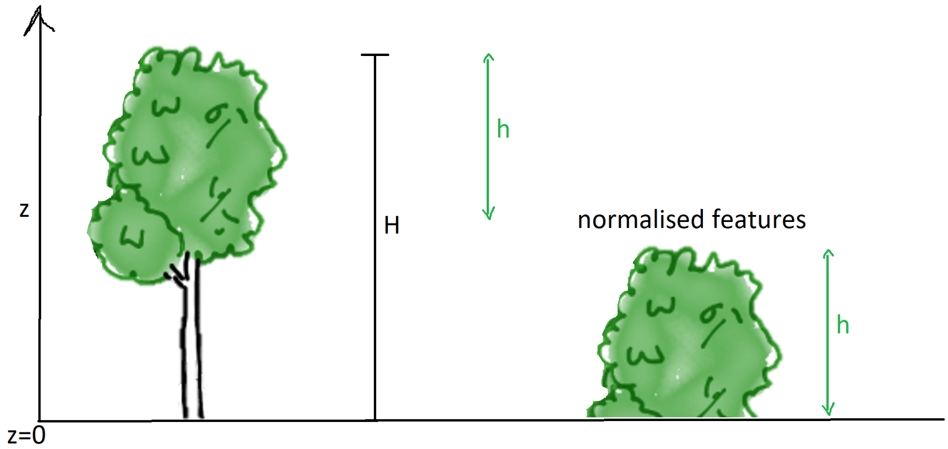


Figure 4.11: Features from a tree, normalised vs not normalised.

Variables	Formula
h_{mean}	$\frac{\Sigma_1^n h_i}{n}$
h_{std}	$\sqrt{\frac{\Sigma(h_i - h_{mean})}{n}}$
h_{skew}	$\frac{\frac{1}{n}\Sigma_1^n (h_i - h_{mean})^3}{[\frac{1}{n-1}\Sigma_1^n (h_i - h_{mean})^2]^{3/2}}$
h_{CV}	h_{std}/h_{mean}
ph	Ratio of 25, 50, 75, 95 height percentile of points
hist values	Histogram values of the upper meters

Table 4.1: Overview of structural features used to classify trees: tell what variables are

A short description of all features can be found below. The parameter h_i indicates the height above the DTM. Note that when normalising the tree H-5 is removed from h_i. h_i n indicates the number of points an equation is used on.

Mean

The mean of the trees, thus the average height, is given by Equation 4.10 below.

$$h_{mean} = \frac{\Sigma_1^n h_i}{n} \tag{4.10}$$

Standard deviation

The overall standard deviation of the top, thus the spread, is given by Equation 4.11 below.

$$h_{std} = \sqrt{\frac{\Sigma(h_i - h_{mean})}{n}} \tag{4.11}$$

Coefficient of Variation (CV)

The coefficient of variation or the relative standard deviation gives the ratio of the standard deviation relative to the mean as shown in Equation 4.12.

$$h_{CV} = \frac{h_{std}}{h_{mean}} \tag{4.12}$$

Skewness

The skewness is, as explained above, indicated by the value α in Equation 4.8. This value can be approached using Equation 4.13 below.

$$h_{skewness} = \frac{\frac{1}{n}\Sigma_1^n(h_i - h_{mean})^3}{[\frac{1}{n-1}\Sigma_1^n(h_i - h_{mean})^2]^{3/2}} \tag{4.13}$$

Percentile heights/ranges

The hypothesis is that the point density in the upper part is higher for deciduous trees than for coniferous trees. To evaluate this in the point cloud the percentile heights, thus the height under which a certain percentage of the point is. Different percentile heights are looked at. This is done by using equation 4.14 below. Here N_points, is given by the total number of points, P, is the percentile value, thus a certain percentage. This formula returns the point number, for the point increasing in point number with height. $h_{percentileranges}$ is determined by taking the height of the point number coming out of the formula.

$$h_{percentile\ ranges} = (\frac{P}{100} \cdot N_{points}) \tag{4.14}$$

Histogram values The histogram values are represented by the percentage of points relative to the total points in a certain bin. For the high vegetation, a bin width of 1 meter is taken.

$$N_{points,H_{max}-i-1)<h<(h_{max}-i)}/N_{h_{max}-x<h<h_{max}} \tag{4.15}$$

Intensity

The intensity is between *'s because this feature influences the classification a lot. Intensity is the strength with which the pulse is coming back. The intensity is influenced by three main factors, spherical loss, topographic loss, and atmospheric effects. The effects of these factors can be reduced by using a range dependency. (Höfle & Pfeifer, 2007) However, obtaining the range from the point-cloud data was not figured out, and therefore reducing this effect was not achieved. Since this value appeared to have such a big influence on the classification, the effect of both including and excluding this feature on the classification is researched.

4.3.4. Features low vegetation

The low vegetation is divided into the classes of bare sand, herbaceous and shrubs. For low vegetation, the features will be comparable to those of high vegetation. But since generally speaking a difference in vegetation height between bare sand (no vegetation), grass (relatively low vegetation) and shrubs do say something about which vegetation the vegetation height is not normalised. On the basis of this, the features as shown in Table 4.2 are proposed for the classification of the low vegetation. The only type of road present in this area was cobble or sand roads. The cobbles showed little to no difference from the sand (see Subsection 3.6). Therefore, it was decided not to include the road as a class.

Variables	Formula
h_{mean}	$\frac{\Sigma_1^n h_i}{n}$
h_{std}	$\sqrt{\frac{\Sigma(h_i - H_{mean})}{n}}$
h_{skew}	$\frac{\frac{1}{n}\Sigma_1^n(h_i - h_{mean})^3}{[\frac{1}{n-1}\Sigma_1^n(h_i - h_{mean})^2]^{3/2}}$
H_{CV}	H_{std}/h_{mean}
PH	Ratio of 25, 50, 75, 95 height percentile of points
Intensity	*not structural*

Table 4.2: Overview of structural features used to classify low vegetation: tell what variables are

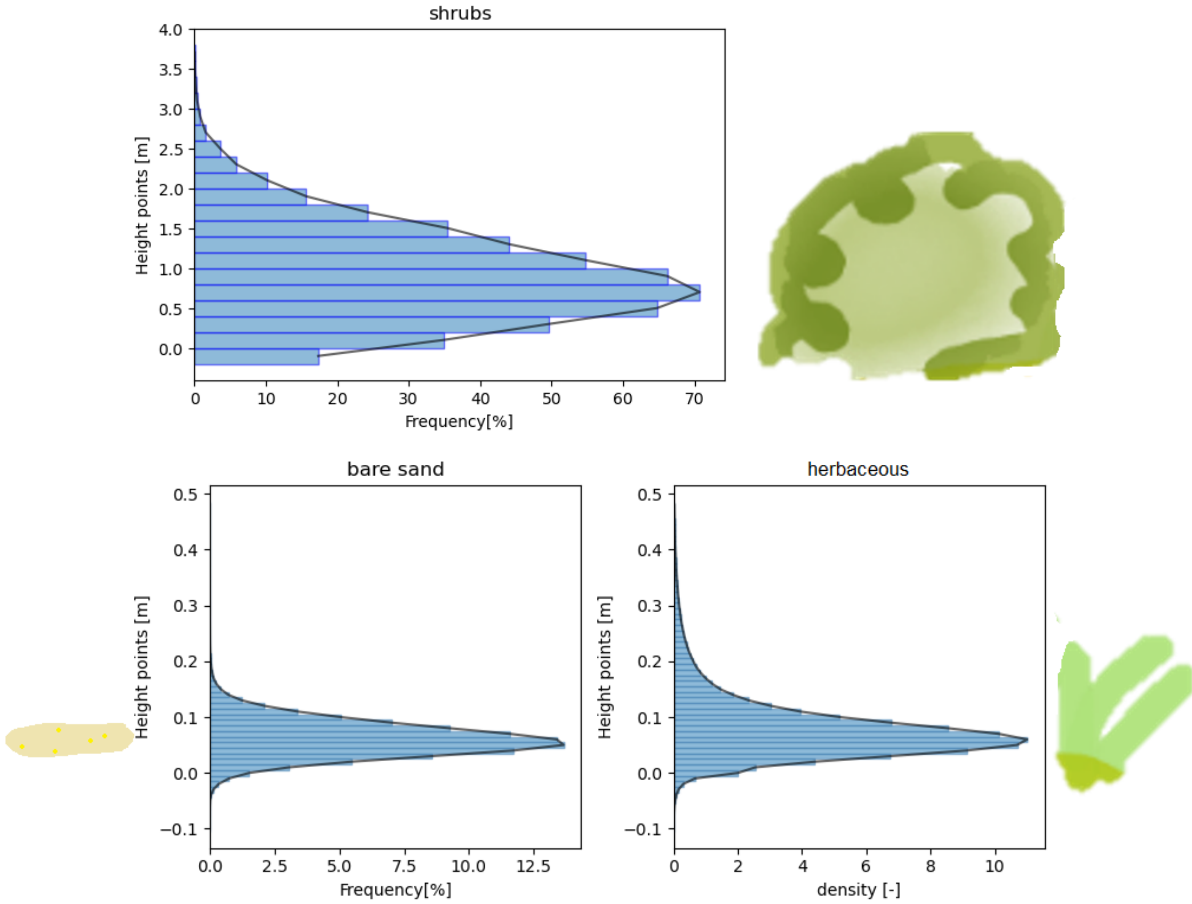


Figure 4.12: Density distribution bare sand and grass

4.3.5. Random forest classifier

As a classification algorithm, the random forest classification algorithm (Breiman, 2001) was used. This classifier is explained in detail in Subsection 2.3.4. The random forest can be tuned by different parameters. The parameters used to tune the model are described in this document. The random forest classifier has different parameters with which the model can be tuned. By adopting these parameters, the model should be improved. But when tuning the possibility of model over-fitting on the training data should be considered. Mainly the maximum depth of the tree and the maximum number of features per tree can increase the effect of over-fitting. The number of trees generally does not increase over-fitting, but more trees mean that computational time is increased, so when no improvement in classification accuracy is seen for more trees, it is better to limit the algorithm to that number of trees. The maximum depth and maximum number of features can, however, increase the possibility of over fitting. Therefore not a too large depth of the tree should be used. To determine the best values for these parameters, the OOB error (see Subsection 2.3.4) was used and visualised. An example of this can be seen in Figure 4.13. The different parameters that are visible include the OOB error on the y-axis, the number of trees in the model on the x-axis, and the maximum depth and maximum number of features in different graphs. The maximum number of features per decision tree was set to 'sqrt' and 'None'. 'sqrt' means that the maximum number of features is the square root of the number of features. For this case, 'sqrt' was always 3. None meant that no maximum number of features was set, and each tree could use an unlimited amount of features.

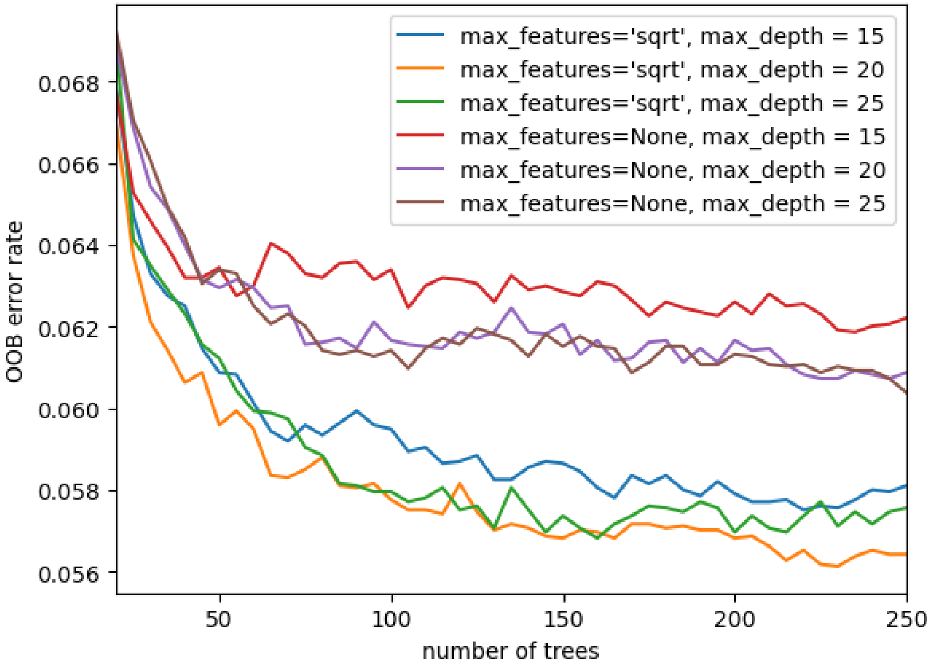


Figure 4.13: OOB-error for low vegetation. For both the randomness was controlled by defining the random state. The low vegetation OOB stagnates from around n_estimators = 150

By creating the graphs as shown in Figure 4.13 for the different models the best parameters for the different random forest models were determined. An overview of these paramters can be found in Table 4.3

	# trees	maxfeatures	maxdepth
percell	120	'sqrt'	15
cellavg	100	'None'	15
pertree	150	'sqrt'	20
lowveg	150	'sqrt'	20

Table 4.3: Best parameter for the Random Forest

4.4. Training data selection

The training data are selected as explained in Subsection 3.3.2. To select the training data, it was tried to use different sources. Thus different types of coniferous and deciduous trees and different locations of bare sand, herbaceous vegetation and shrubs. To see the training data that were used, Appendix D can be consulted.

4.5. Assessment and validation of the method

To substantiate a method, evaluation and validation of its results are needed. In this section, a method is proposed to assess the different

4.5.1. Evaluation of the proposed DTM algorithm

To assess a digital terrain model, it should be compared to a reference model. The problem here is that if you try to improve a model, this model will probably show its flaws. The raster might have another spatial resolution, and the measuring equipment with which the other model is measured might show other properties. The main goal of the proposed new model is to determine the height of the terrain under the shrubs where the LiDAR does not penetrate until the ground. But in winter these shrubs do not have leaves. Therefore the model is compared to the winter measurements.

4.5.2. Evaluation of the tree delineation

The tree delineation is used as a method to ease the classification. This is why trees are not classified as both coniferous and deciduous trees. The applied method should still be validated. A not so densely vegetated area is used as a reference. The delineation can go wrong in two ways, this has been visualised in Figure 4.14 If some isolated trees are classified as more trees than one this means the algorithm is over-delineating or over-segmenting trees. And if some trees near each other are classified as one tree the algorithm is under-delineating or under-segmenting trees. Of course, a densely vegetated forest will show some different structures than loose trees. However, since this dense structure also makes the evaluation harder, an evaluation using loose trees is seen as the best evaluation method.

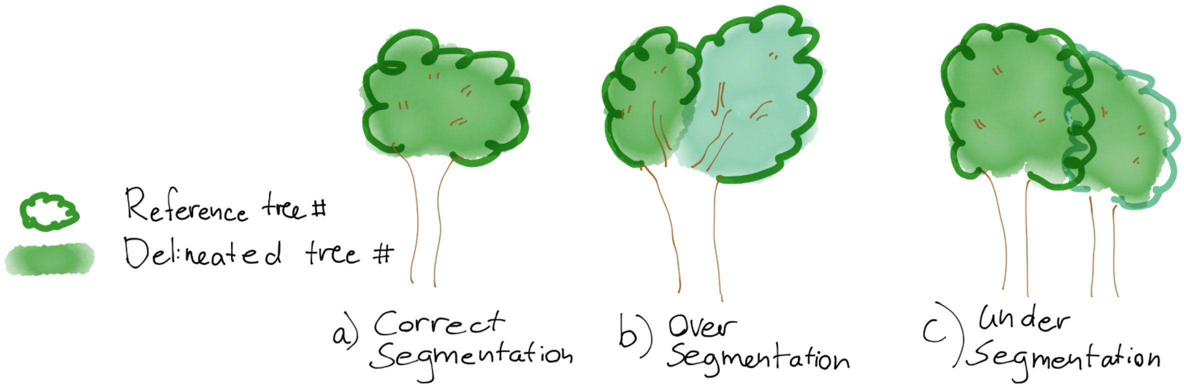


Figure 4.14: Possible problems when delineating trees: a) correct; b) over-segmentation, meaning multiple trees are seen in one tree; c) under-segmentation meaning multiple trees are seen as one tree.

4.5.3. Evaluation of the classification

Evaluation of the classification already takes place when running the random forest algorithm. Before running this algorithm the data is split into test and training data. The training data is used to train the random forest and the test data is used to create a confidence matrix. But, since training and test data come from the same set of trees, the algorithm may overfit itself for these areas. Therefore for each class 3 tiles containing vegetation of just one class are selected. For the trees, a tile size of 50mx50m is used. An example of these tiles containing the orthophoto of the survey is visible in Figure 4.15 below.

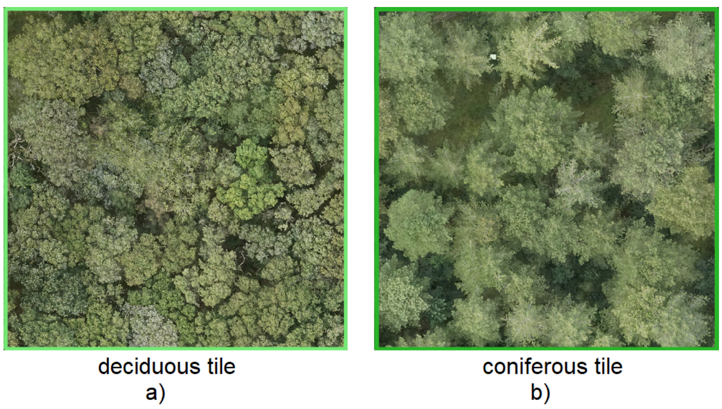


Figure 4.15: Tiles for tree classification evaluation: Two example tiles of 50mx50m were used for validation of the trees. To validate each class properly the tile should either be fully coniferous or fully deciduous trees.

For the for the validation tiles of the low vegetation the same approach as for the trees was used. But since no large areas containing only one class were present tiles with the size of 25x25 metres were use. An example of such tiles is visible in Figure 4.16.

bare sand tile
a)

herbaceous tile
b)

shrub tile
c)

Figure 4.16: Tiles used for low vegetation classification evaluation: Two example tiles of 25mx25m were used for validation of the lower vegetation. When classification takes place the full content of the tile should be either bare sand, grass or shrub.

An overview of the location of all tiles that were used can be found in Appendix D.

4.6. Summary

The method proposed to classify the data is subdivided into the steps of pre-processing, classification and evaluation. The pre-processing includes all steps that are needed to prepare the data for classification. This includes obtaining the vegetation height. Since the area contains little to no urban objects such as buildings and cars in the area it is assumed that the area is a natural environment. In a natural environment, it can be assumed that the points in a point cloud are either part of the ground or of the vegetation. Thus, when the terrain model is known, it can be assumed that all points at a certain height above this model (depending on the precision of the point cloud) are part of the vegetation. Obtaining the terrain model is made a bit more difficult since points do not have a very good ability to penetrate through some vegetation types first the DTM is determined. For the classification of the high vegetation, the trees in the data are delineated as individual trees so that a better classification can take place. To classify the vegetation, different features are created by looking at the vertical point distribution. As a classification algorithm, the Random Forest Classifier is used. As training data, hand-made training data is used this is also used as test data. This was created by looking at different sources. The evaluation takes place by looking at parts of vegetation with a sole vegetation type.

5 Results

This chapter provides the results from the methods proposed in Chapter 4 applied to the available data. The first Section 5.1 discusses the results obtained by the ground model. The second Section 5.2 discusses the results obtained for the high vegetation (trees). And Section 5.3 will discuss the results obtained for the low vegetation. And last Section 5.4 will shortly summarise the obtained results.

5.1. Integral method to obtain DTM

In Section 4.2 the new method, which we will call the integral method, is proposed to make a better estimation of the DTM, especially under bushes where the LiDAR was unable to penetrate through the canopy. In this section, the new method is compared to the originally used cloth method (Subsection 2.3.2). To evaluate the improvements of the newly proposed method both the cloth method and the integral method are compared to a DTM obtained by measurements that were made by a plane a few months earlier in the winter of 2021. At this time, due to the time of the year, less vegetation and leaves were present, thus it was easier to reach the terrain using LiDAR. The DTM of the winter data for comparison is made by using the cloth method, but since there is less vegetation now present, the problem that occurs under dense vegetation should not form a problem.

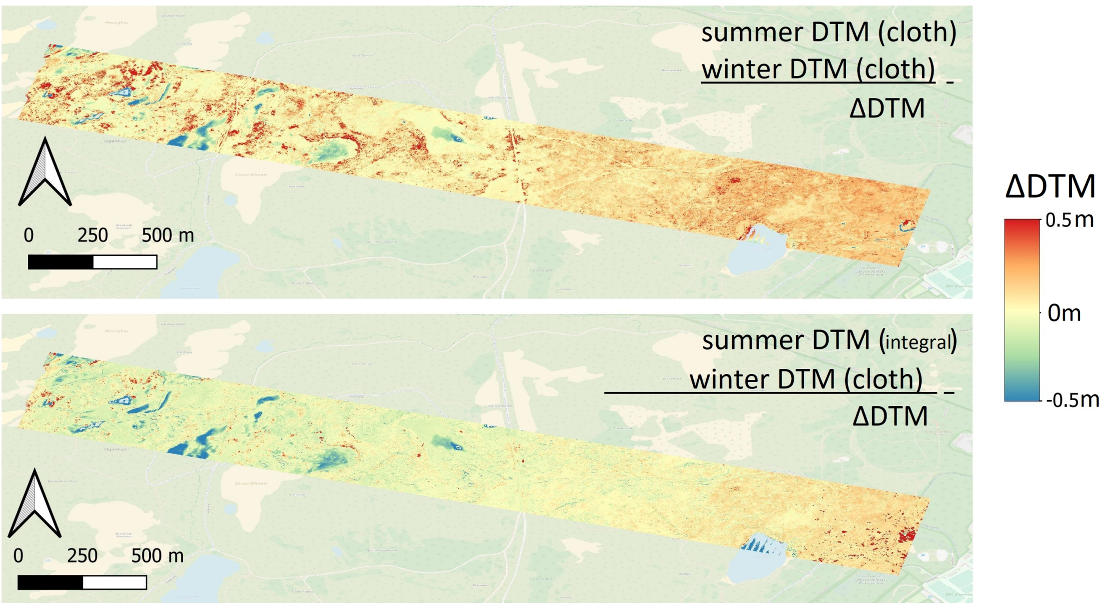


Figure 5.1: Map to evaluate the DTM algorithm: the DTM from the UAV LiDAR data compared to the DTM from the aeroplane data (up: cloth method, down: integral method)

Figure (5.1) shows the results of both methods with the obtained DTM compared to the DTM obtained by using the LiDAR from the plane is visible. To get to this values Equation 5.1 below was used:

$$\Delta DTM = DTM_{summer} - DTM_{winter} \tag{5.1}$$

This means that too high estimates will show positive values, this is what is seen in the shrubs, and too low estimates show negative values, this is especially seen in areas where sand is blown away in the west of the area. To see the distribution of the differences a histogram was plotted in Figure 5.2 below.

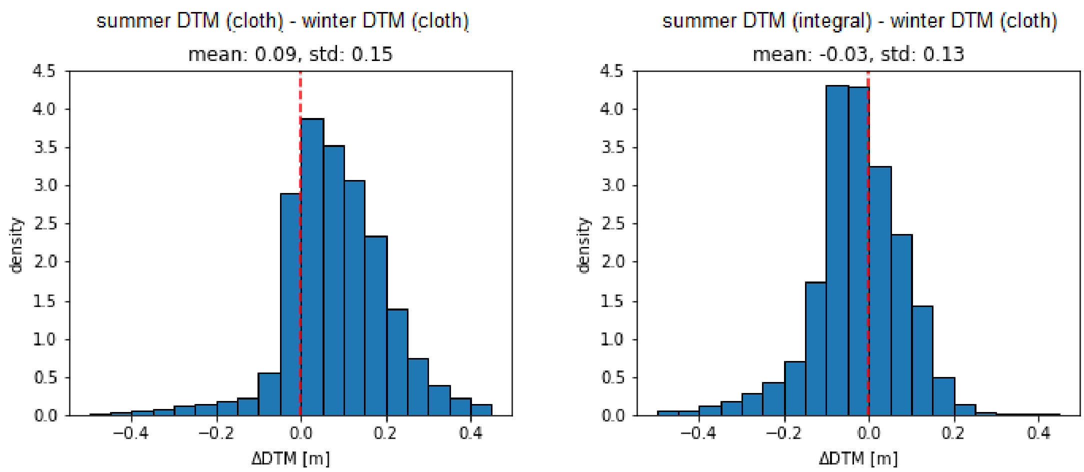


Figure 5.2: Histogram to evaluate DTM algorithm: Distribution of the ΔDTM with on the left the cloth method on summer data minus the cloth method on the winter data and on the right the integral method compared on the summer data minus the cloth method in winter data

In the histogram in Figure 5.2, it becomes visible that the estimate of the height of the ground using the cloth method is usually a bit on the high side, while when using the cloth method this estimate lays more around the zero. Since this is the histogram of the full area and a lot of different sites with loose sand to wooded dunes and a lot of shrubs are represented in this histogram no specific conclusions can be drawn from it. Therefore some case studies of different sites are done.

5.1.1. Case studies

Since the area consists of different vegetation and ground types a few case studies are done on several specific topics. One of these studies concern the shrubs. This is the area where we are most interested since this shows the biggest deviation from the True DTM in the cloth method and specific objects such as buildings. In Appendix E some more figures of shrub cases can be found.

Shrubs
First, the shrubs are evaluated. Actually, at almost all locations of the shrubs, the deviation of the true DTM has not fully gone away. But with an improvement in the mean of about 35cm (see Figure 5.3) the DTM using the integral method has indeed improved. It should be noted though that this method does not show a DTM as smooth as the cloth model. But depending on the goal of your DTM this does not have to be a problem. For the goal of this research, these blocks in the DTM show no problem.

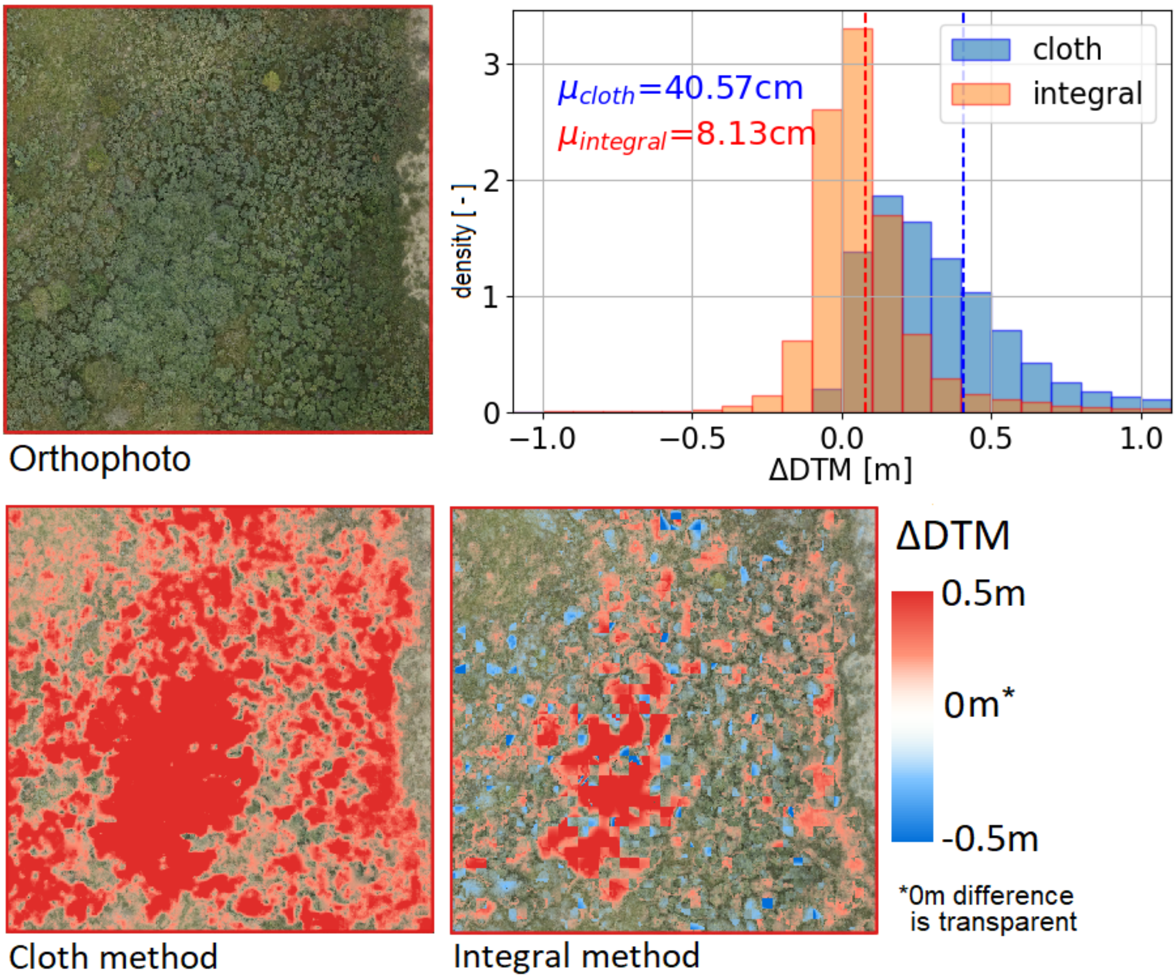


Figure 5.3: Case study: shrubs.
Left top: orthophoto made at time of LiDAR retrieval;
Right top: histogram of difference of each method with the winter measurements. The spread of the cloth method is going up to a meter in difference, while the integral method stays in the range of half a meter.;
Left bottom: Difference between the cloth method and the winter measurements, note that almost the full image is red indicating the estimate of the terrain is too high;
Right bottom: Difference between the integral method and the winter measurements. The red as reduced a lot but now patches of blue (too low estimates) have become visible.

Objects
Objects on the terrain form a problem for the integral method. An example of this are houses, as can be seen in Figure 5.4 below. If there is vegetation on the top of such an object, for example on an old ruin or bunker, this could be useful for vegetation classification. But this would mean that the terrain model should properly follow the outlines of the object, which in this case is not fully the case. When looking at the edges of the building it is visible that the sudden elevation formed a problem. On the edges of such an object the vegetation height would thus be incorrect when using this model. It could of course also be the case that you want to exclude objects, in that case it would be better to remove this object. This could also be done before processing the point cloud by using the Kadaster.

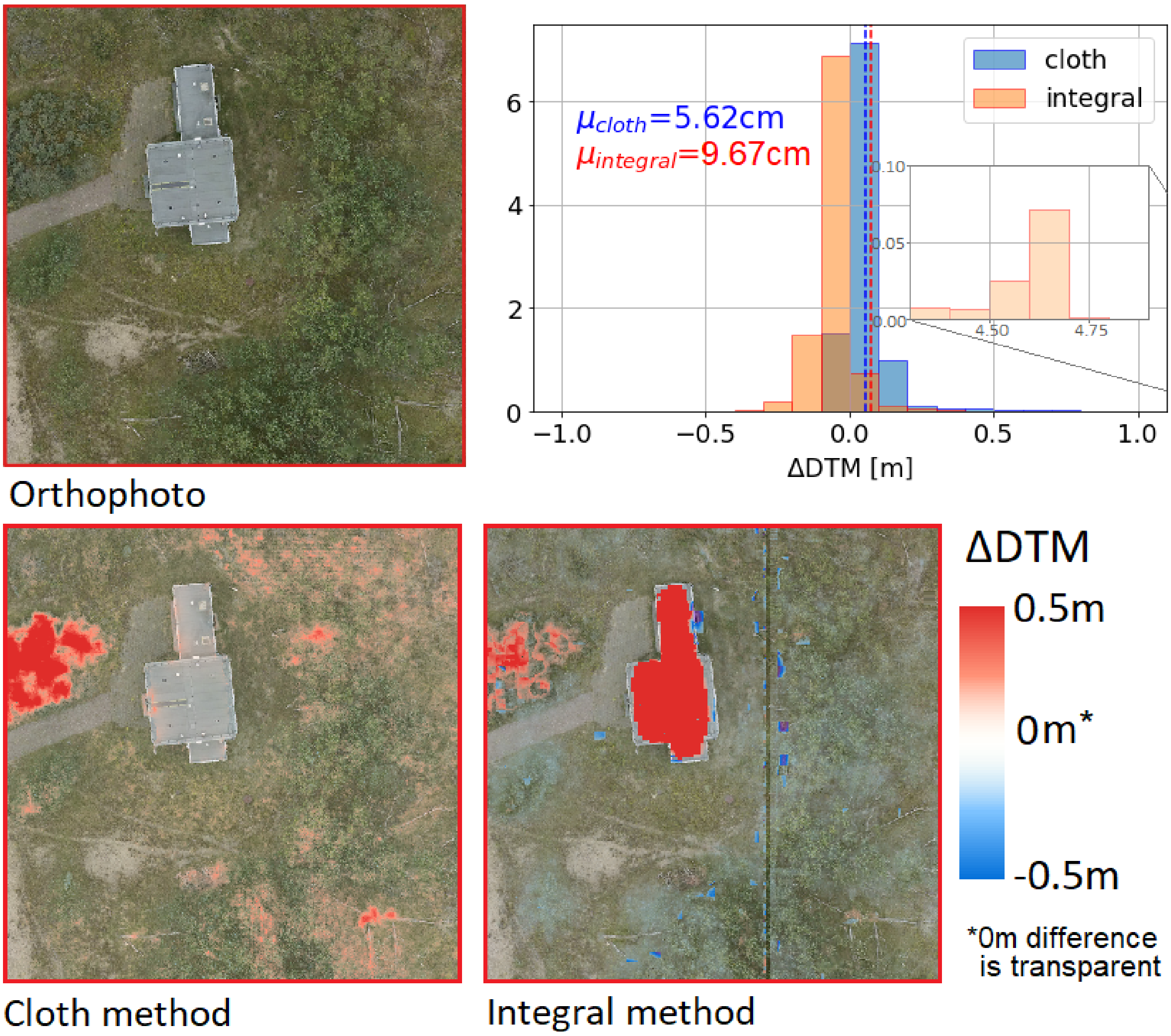


Figure 5.4: Case study house Left top: orthophoto made at time of LiDAR retrieval;
Right top: histogram of difference of each method with the winter measurements. Note that the histogram of the integral method still has values at 5 meters, while the cloth has most of its values concentrated around zero.;
Left bottom: Difference between the cloth method and the winter measurements on the tiles: note that no height difference is visible in the building.;
Right bottom: Difference between the integral method and the winter measurements. The building is now fully red. The vertical line in the centre of the image is caused by different bordering tiles.

Cross sections

From the cases above also some cross-sections were made. In the cross-section of the first case in Figure 5.5 it is visible that indeed the integral method is estimating the ground to be below where the cloth is estimating the ground to be. It also shows that still, this method is not perfect, but definitely, an improvement was made on the cloth method here. Something else that stands out here is that the line of the integral method is irregular compared to the cloth method. This is because each cell on its own is looked at again. This could be reduced by applying for example something like a smoothing filter. But when applying a smoothing filter other terrain information could be lost, so it is case-dependent if this is an option.

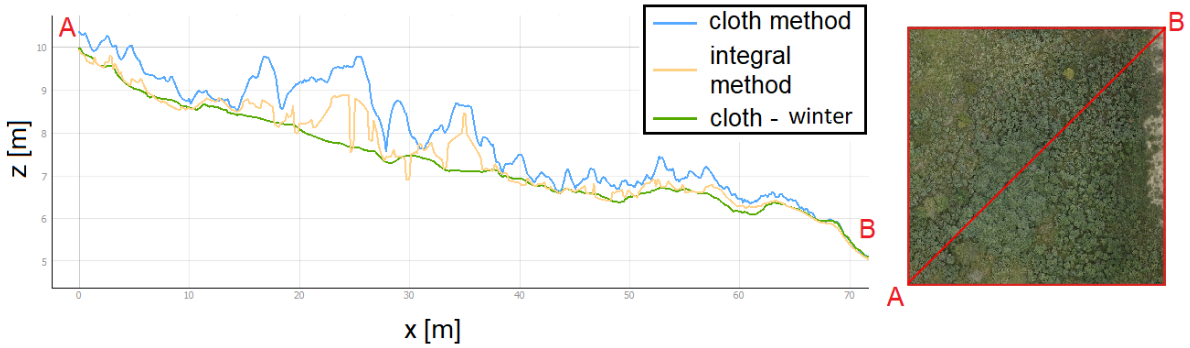


Figure 5.5: Cross section of the DTM under shrubs as obtained by the different methods

For the second method in Figure 5.6 the expected raise in terrain is visible at the location of the building. Next to that, something else is visible. When zooming in it becomes visible that the cloth method is always about 6 cm above the integral method. This probably has to do with the fact that the integral method does not take point densities into account, it just uses the lowest points. When looking at the point cloud height on flat surfaces, in Section 3.6 there is indeed a reach of about 6 cm below the visible median.

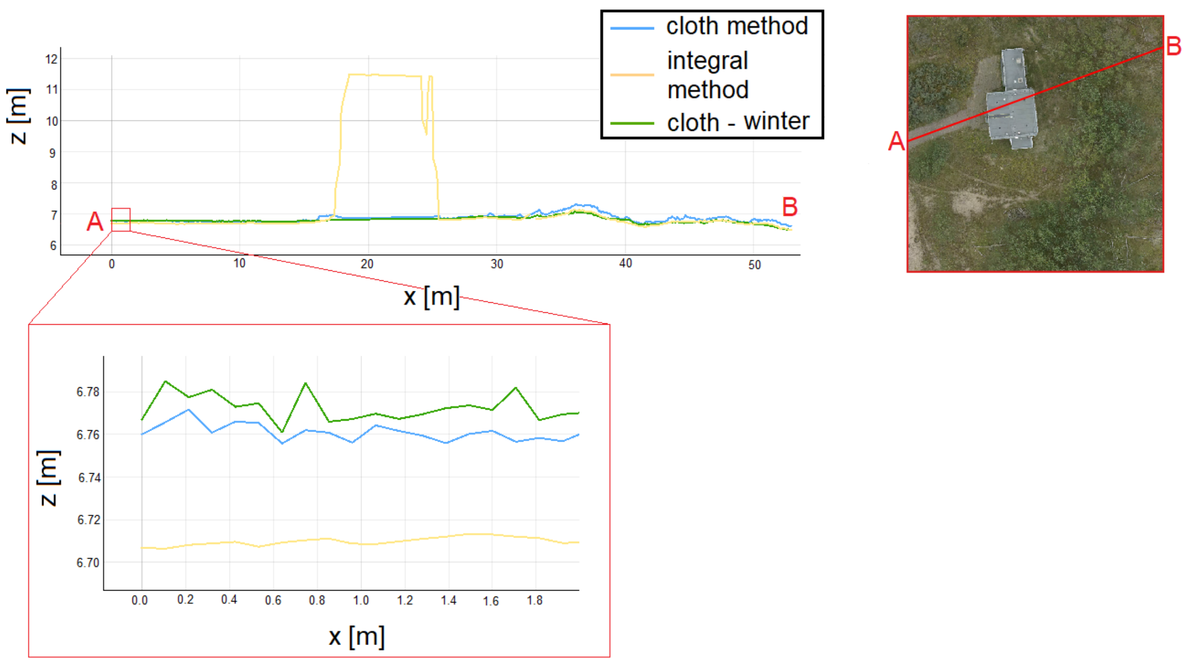


Figure 5.6: Cross section of the DTM obtained around an object

5.2. Results of the high vegetation classification (trees)

As was shown in the methodology the vegetation was subdivided into high and low vegetation. First the results of the method to classify the high vegetation will be discussed in this section, the results to classify the low vegetation will be discussed in the following section.

5.2.1. Tree delineation

To classify the trees as a cluster instead of per raster cell it was proposed to delineate the trees before the classification. In Figure 5.7 the result of the delineation is visible. Each colour represents a tree that is classified. In this specific example under-segmentation is visible. The tree numbered one and four are classified as one tree (left image orange), when looking at the point cloud these clearly are two trees (orange and turquoise).

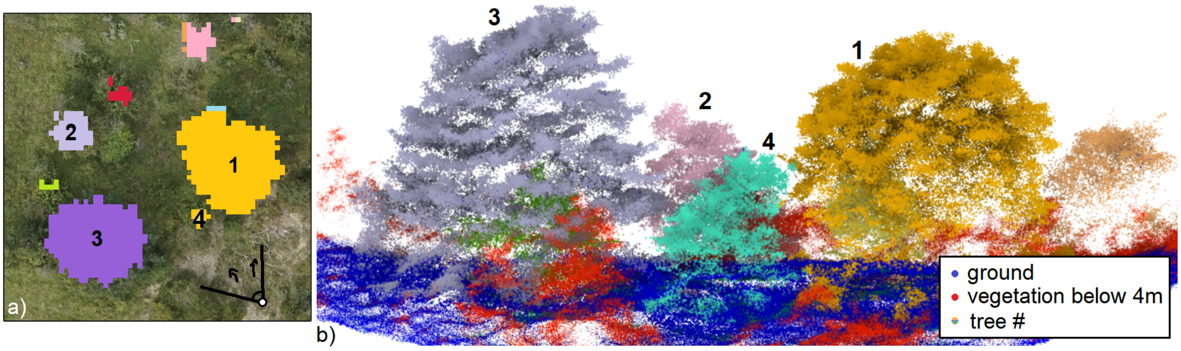


Figure 5.7: a) Tree delineation result b) trees delineated by hand in the point cloud.

5.2.2. Tree classification

The goal was to divide the trees into two groups, coniferous and deciduous trees. It was decided to do this by looking at the vertical distribution of points in the upper 5 meters in the tree. In Subsection 4.3.2 three different methods have been proposed to classify the trees using the same features. For all different methods, a Random Forest model was created. All models showed a high importance of the intensity if this was included as can be seen in an example of the feature imporance's in Figure 5.8.

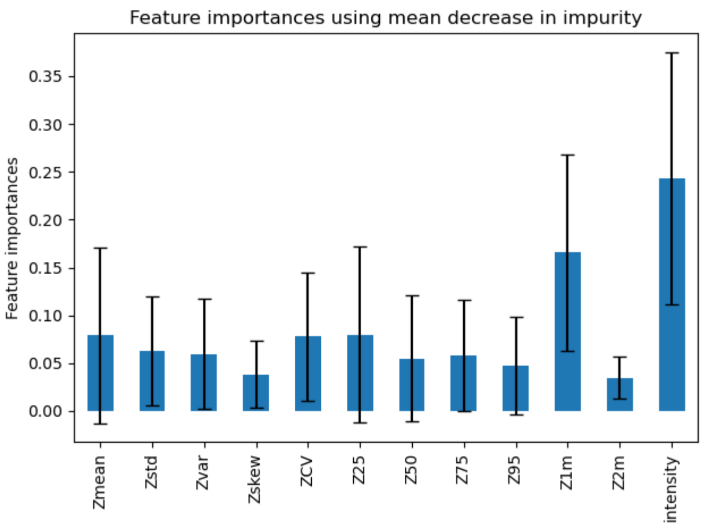
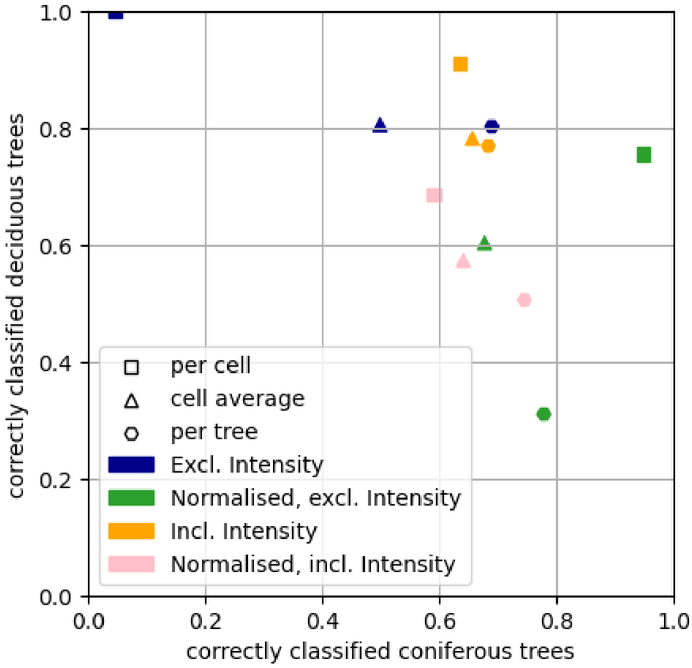


Figure 5.8: Example of feature importance's trees for the classification using the features from all points in a tree, including the intensity and normalising the tree. Percentile features are represented by Z25, Z50, Z75 and Z95. Histogram features are represented by Z1m and Z2m

From these feature importance's it can be seen that the skewness has less importance than would be expected, when looking at the difference in skewness in Section 4.3.3. What does stand out is that the importance of the histogram value for the first meter (Z1m) seems to show a high importance. For the classification histogram features until 4m depth were finally used, but this Z1m seemed to keep a high importance for all methods (next to the intensity). This could indicate that the upper layer of the tree canopy has the highest difference in point density when looking at the difference between coniferous and deciduous trees. Usually, the data to train the model is split into test and training data and than the model is evaluated using a confusion matrix. But since the first model makes this random forest model based on the features of the raster cells and the second and third models based on the full trees they can not really be compared using the confusion matrix as created by the random forest model. Thus as explained in 4.5 some tiles were used to evaluate the classification for the different features and models. The results of the predictions can be seen in Figure 5.9 below.



	per cell	cellavg	per tree
norm. ex.int.	.52	.65	.75
ex int.	.85	.64	.54
norm. inc.int.	.77	.72	.73
inc.int.	.64	.61	.63

Figure 5.9: Comparison of different feature extraction methods for trees, norm. indicates normalised tree, ex. int. indicates excluding intensity, inc. int indicate including intensity. Left: Average correctly classified coniferous and deciduous trees for the 6 test tiles of 50x50 meters. (3 containing coniferous and 3 containing deciduous trees); Right: accuracy per method

In this figure, it can indeed be seen that the classification per cell for some methods shows higher accuracy than was found using the confusion matrices. But it also becomes visible that, especially for the classification of deciduous trees, the precision is very low. By combining the results the accuracy is determined for each method, this is shown on the right of Figure 5.9 By using these results it was decided to continue with the method with the highest accuracy. This is the method in which the trees are classified by classifying all raster cells individually and then taking the majority vote (per cell). The variant in which the trees were normalised and where the intensity was not included worked best. This was method was used to classify the full area, the result can be seen in Figure 5.10 below. Using this figure different cases were looked selected where the algorithm seemed to function good, or where interesting results are shown.

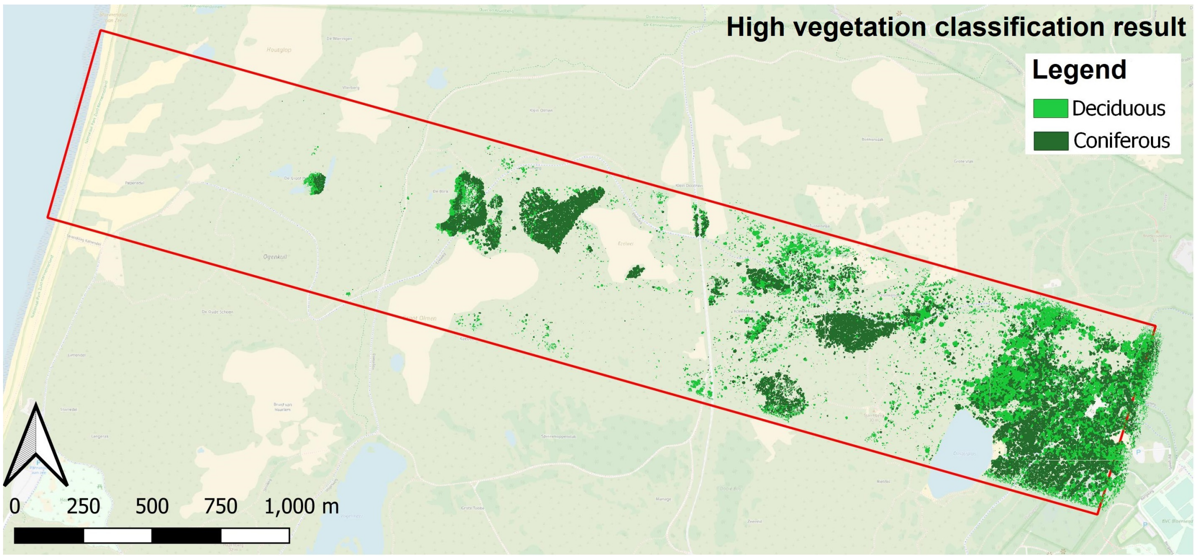


Figure 5.10: Map of the classification of the trees

Both deciduous and coniferous

Looking at the classification in Figure 5.11 it becomes visible that indeed a rough estimation of the locations of the trees is correct. The diagonal line of coniferous trees is indeed represented. But when looking around this diagonal line of coniferous trees in Figure 5.11c no green, thus no coniferous trees are visible, while in the classification result in Figure 5.11 these trees were classified as coniferous trees.

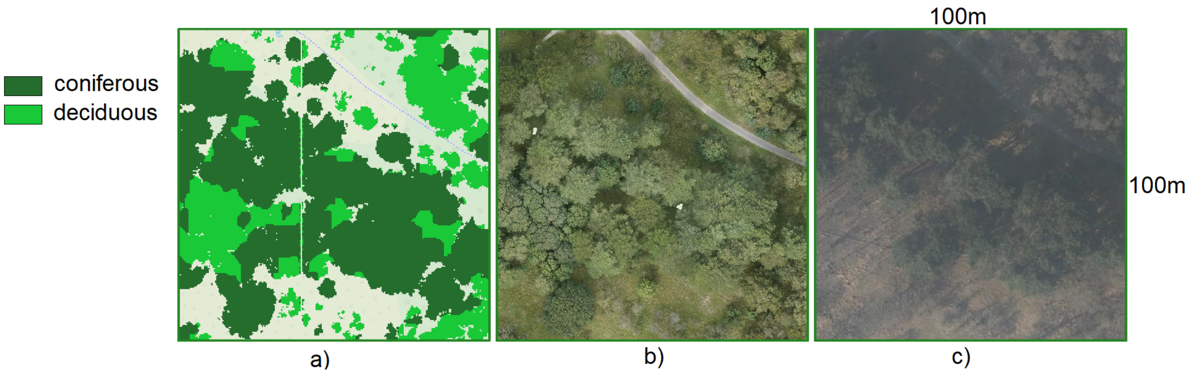


Figure 5.11: Case with both coniferous and deciduous trees. a) classification of the trees into coniferous and deciduous; b) orthophoto of the drone made at the same time as the point cloud was obtained on the 19th of September 2021; c) orthophoto taken at the 21st of March 2022, everything that is green in this image is assumed to be a coniferous tree since the deciduous have not grown leaves yet at this time of the year.

A deciduous tree

In Figure 5.12 it can be seen that in the middle of a coniferous forest a tree was classified as deciduous. As can be seen in Figure 5.12b the drone image was not of great quality here, so no conclusion could be drawn there. But when looking at Figure 5.12c indeed at exactly the location where the tree was classified as deciduous there is a change in colour visible. To really confirm this case fieldwork is needed, but it can be said that indeed a change is visible in the tree structure which was detected correctly by the classification algorithm.

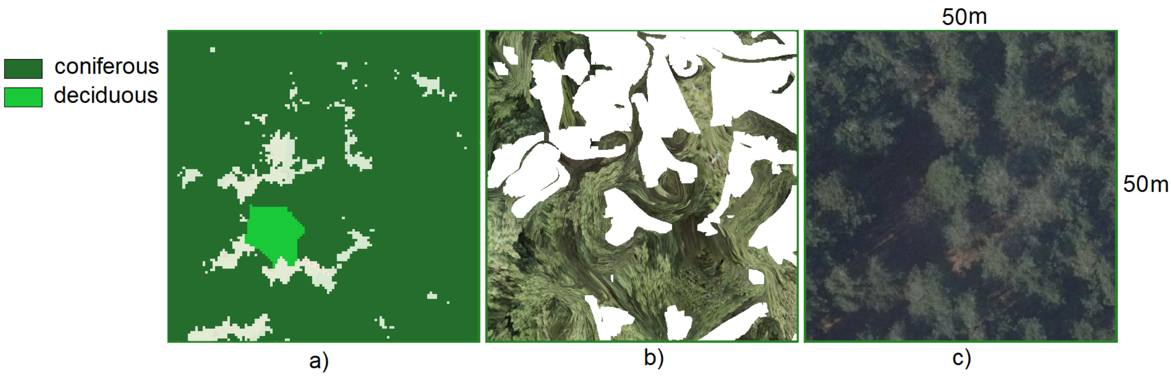


Figure 5.12: Case with one tree classified as deciduous in a coniferous forest. a) classification of the trees into coniferous and deciduous; b) orthophoto of the drone made at the same time as the point cloud was obtained; c) orthophoto taken at the 21st of March 2022

A deciduous forest

The classifier appeared to have especially problems with deciduous trees. This is clearly represented in some deciduous forests such as the one in Figure 5.13. But there is a clear transition line visible from deciduous to coniferous classification. There is another forest a little to the East showing exactly the same pattern. This could perhaps be caused by this specific deciduous tree structure.

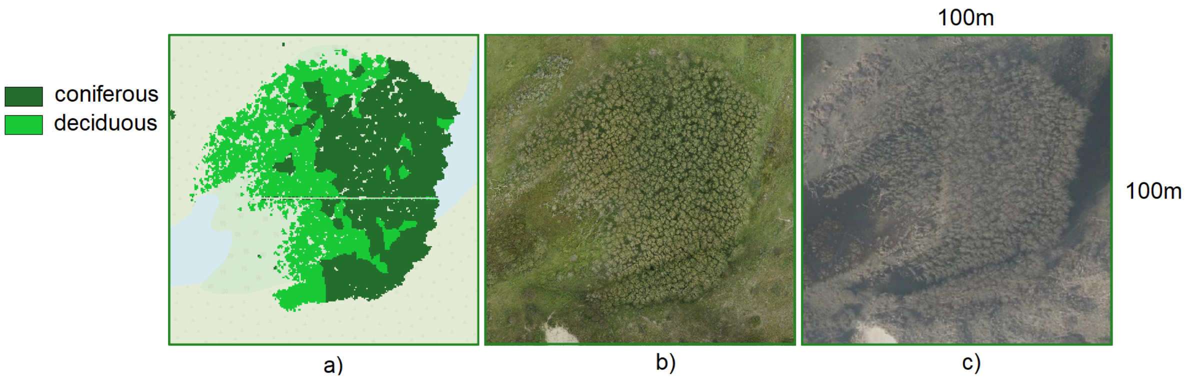


Figure 5.13: Case of the deciduous forest. a) classification of the trees into coniferous and deciduous; b) orthophoto of the drone made at the same time as the point cloud was obtained; c) orthophoto taken at the 21st of March 2022

5.3. Results of the low vegetation classification (understory)

Classifying the low vegetation from images has already been done. Therefore, the most interesting part of this classification is if it would be possible to classify the vegetation under the trees, which we will call the understory. This class is divided into 3 different classes. Bare Sand/No vegetation, herbaceous vegetation and shrubs.

To find the best parameters for the low vegetation classification model, a confusion matrix was created for different parameters. The result of this is visible in Figure 5.14.

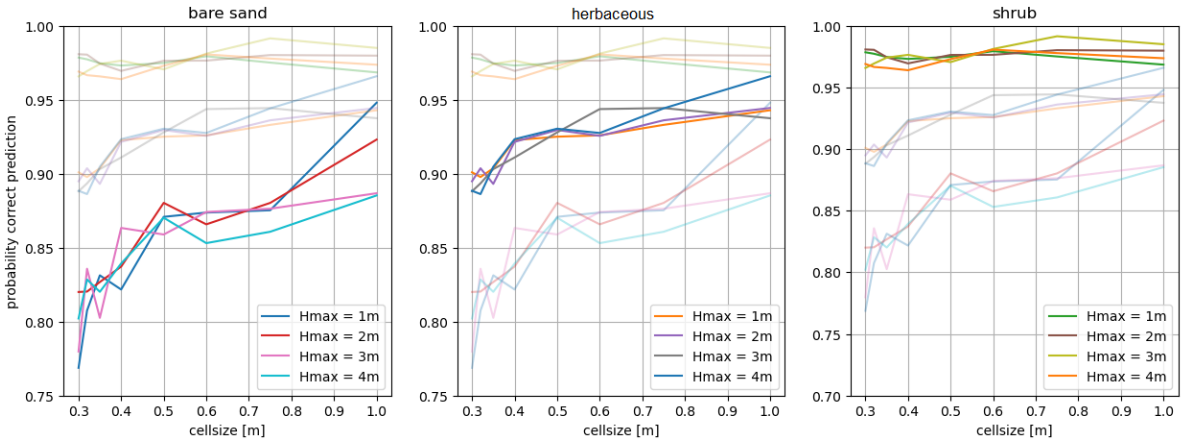


Figure 5.14: Confusion matrix results for different maximum heights of the bottom cell and different cell sizes of the raster

It can be seen that for a higher raster cell size, thus for a lower spatial resolution, the best results were found. Therefore, it was decided to continue with raster cell sizes to obtain the features of 0.5 meters, and an maximum stixel height of 2 meters. When running training the random forest model using these parameters the confusion matrix and parameters as visible in Figure 5.15 are given.

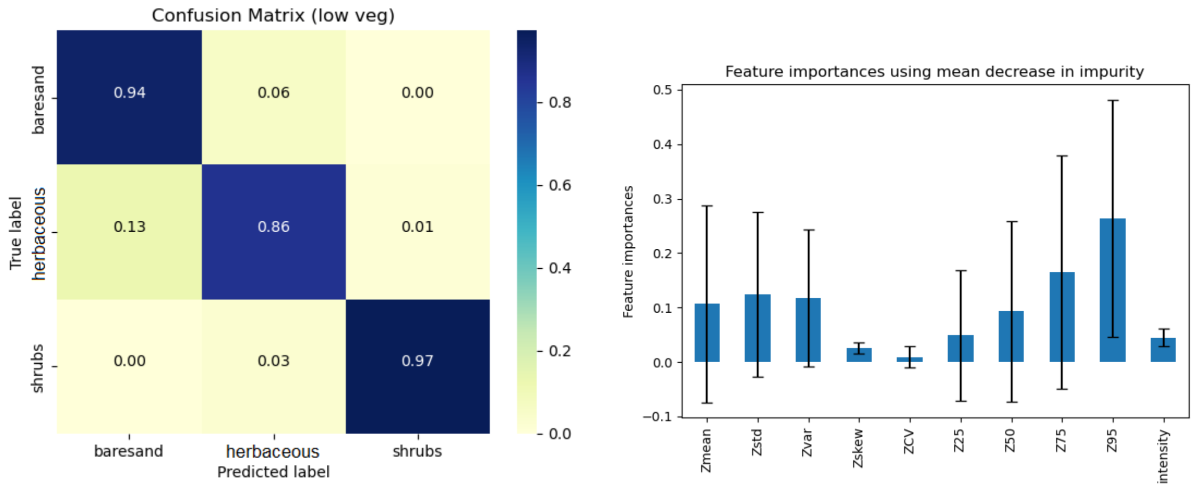


Figure 5.15: Low vegetation classification performance

Except for the Z95, the 95 percentile height, which is practically the maximum height of the points the feature importance's are pretty evenly distributed. The high importance of the 95th percentile is not strange since this the main difference between bare sand, herbaceous vegetation and shrubs seems to be their height. It does stand out that the importance of the intensity in these features low, while this was the other way around for the trees.

To validate the results the model was run on the test tiles. The result of this can be seen in Table 5.1 below. in this table it can be seen that the classification of herbaceous vegetation showed a low accuracy in the tiles, with an average of 53%. The shrubs and the sand, however, showed accuracy of above the 80%.

	tile 1	tile 2	tile 3	avg
Bare sand	.69	1.00	.95	.88
Herbaceous vegetation	.53	0.53	0.33	.49
Shrubs	.72	.77	.96	.82

Table 5.1: Total tree, inc intensity

When applying this algorithm to the full area an map as shown in Figure 5.16 is created. Using this map some cases with interesting results are chosen. These are elaborated below.

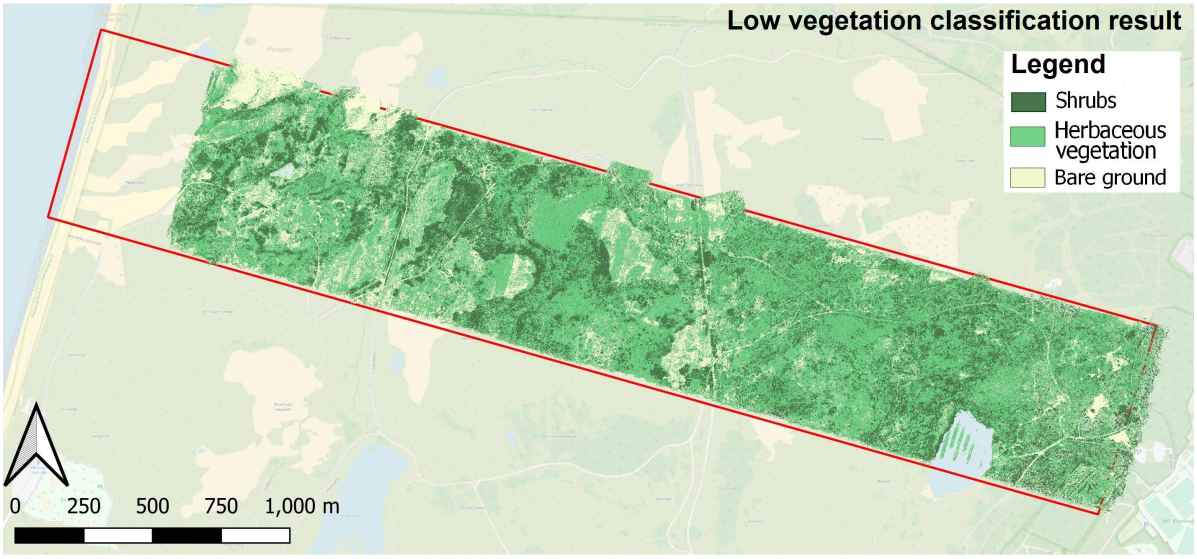


Figure 5.16: Map of the classification algorithm applied to the full area

5.3.1. Case studies

All classes

When looking at Figure 5.17 a mix of shrubs, bare sand and herbaceous vegetation is visible. On the left an image from the drone is visible and on the right, the predicted outcome is based on the point cloud. On the transition from sand to grass, some mix-up can be seen. This could be due to the fact that the sand perhaps is a little rougher around the vegetation edges. In between the shrubs, there also seems to be some mix-up where shrubs seem to be classified as grass. But when taking a closer look at the image it seems that there are indeed grasses growing in between the shrubs.

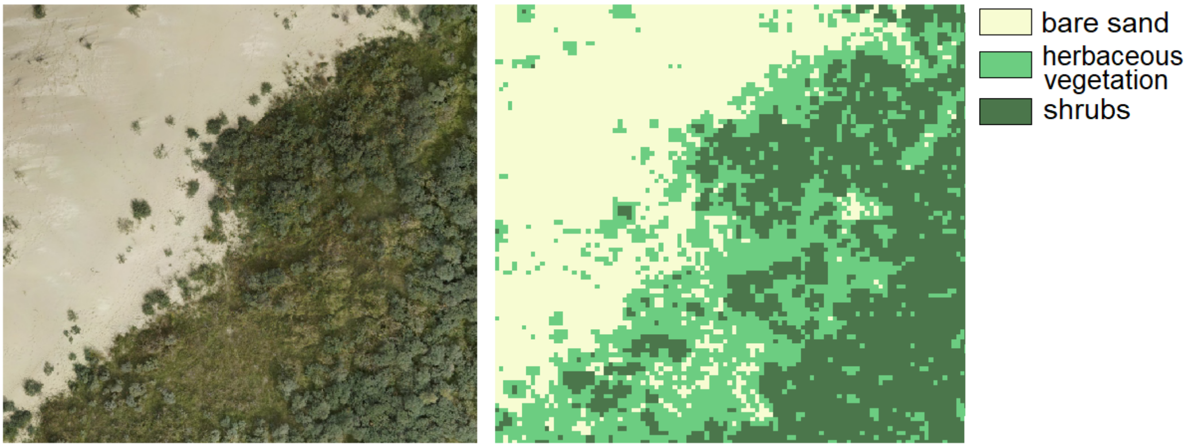


Figure 5.17: An overview of a tile containing all classes that were classified left: orthophoto; right: classification result

Overlapping flight paths

At the location where the drone has passed multiple times, it becomes visible that points that were previously classified as sand are now classified as grass. This could be due to an increase in deviation in the vertical distribution of the point that occurs. This increase in deviation can occur due to different effects, but this does result in a different classification.

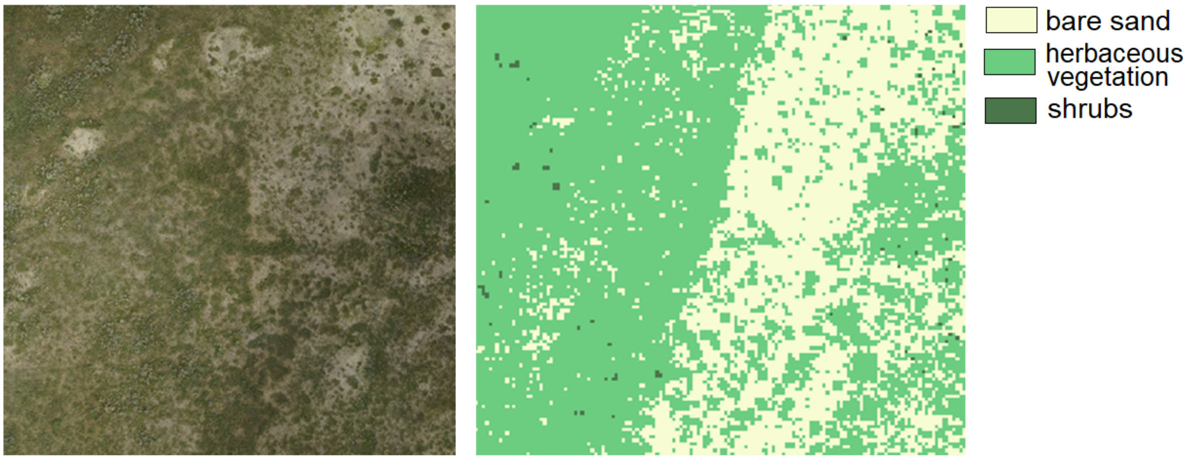


Figure 5.18: Classification of sand and grass where flight paths overlap left: orthophoto; right: classification result

Under trees

Since classifying sand, shrubs and herbaceous vegetation has already been done many times from images. The added value here would be to look where a camera can't and that is for example below a forest canopy. A result of this can be seen in Figure 5.19. When looking at the image in Figure 5.19b these results can not be evaluated, due to the canopy of the trees. Therefore in Figure 5.19a a piece of point cloud is made visible which is classified in vegetation and not-vegetation objects. When comparing his to Figure Figure 5.19c at the location of these vegetation objects shrub classification is visible, meaning that indeed patterns of the vegetation can be seen under the trees. This can also be seen by looking at the bare sand class, this seems to form a path on the left side of the image.

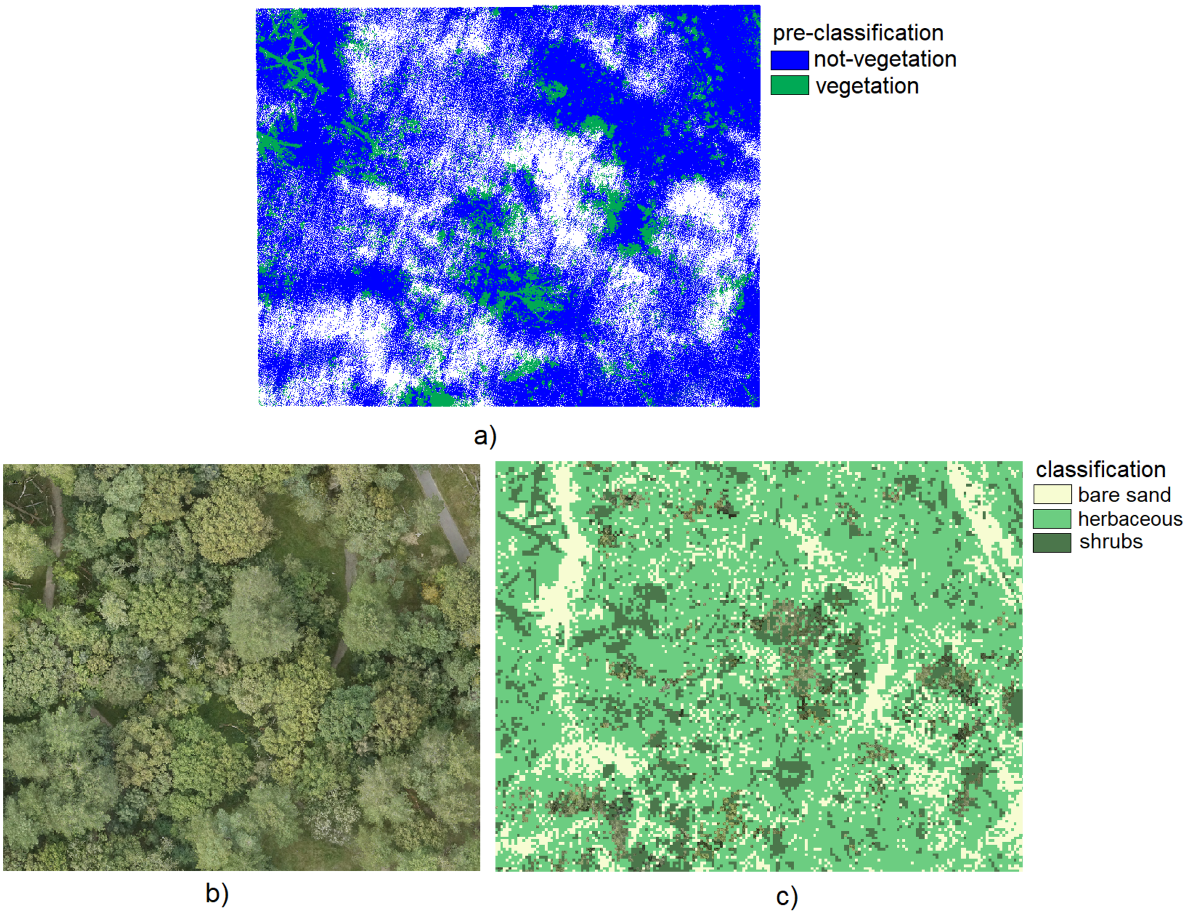


Figure 5.19: The classification under the trees a) point cloud with a pre-classification into vegetation-not vegetation; b) orthophoto of the trees, here it can be seen that in the image the layer under the tree canopy is little visible; c) Classification of the vegetation under the trees using the point cloud.

When combining the results obtained by the tree classification and the low vegetation, the occurrence of each low vegetation class under trees can be found The occurrence of the low vegetation classes under the tree classes is shown in Table 5.2. When looking at these results, it should be noted that both the tree and the low vegetation classifiers are not yet perfect, so there is probably a bias present. This part is just to show the possibilities.

	coniferous	**deciduous**
bare ground	5.30%	5.02%
grass	65.72%	62.00%
shrubs	28.98%	32.98%

Table 5.2: Occurrence of the different low vegetation classes under the two classes of trees.

Treetrunk problem

Then there is also the treetrunk problem. Under trees we find treetrunks, but because of (probably) their height they are classified as shrubs. An example of this can be seen in figure 5.20. As can be seen in the point cloud on the left there are no shrubs present in this piece of point cloud. But the classification maps do seem to indicate many small parts of shrubs. This is probably caused by the treetrunks under the trees. A solution for this method could be filtering the trunks using a moving window, this would however mean that a certain level of detail will be lost. Another class in which treetrunks are classified could also be added. Or round geometries under the tree canopies could be searched. This would, however, (probably) take great computational effort.

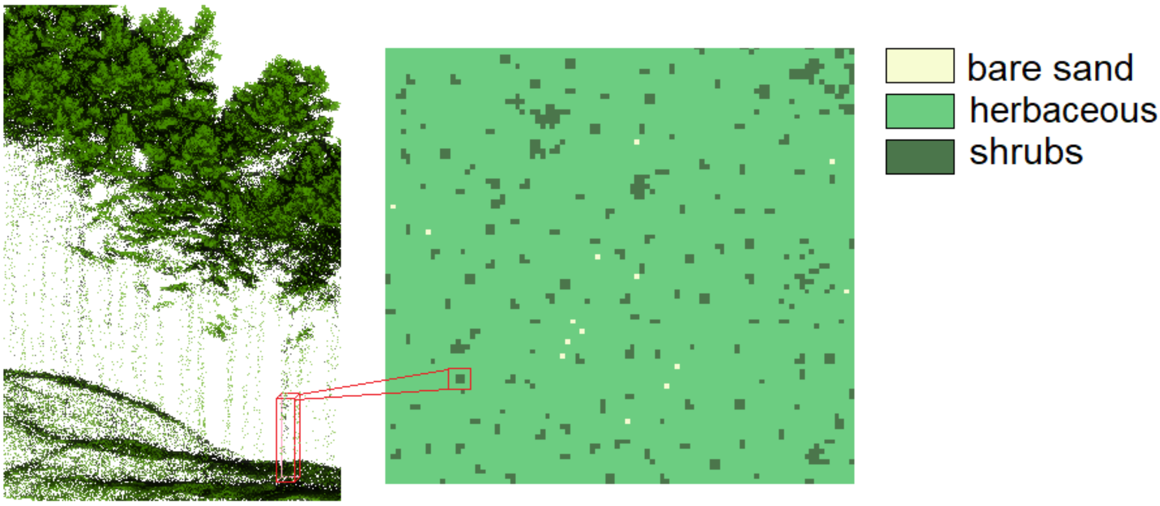


Figure 5.20: Treetrunk problem

5.4. Summary

The proposed method for the ground appears to set an improvement for the determination of DTM under shrubs, which was a problem. This could mean that a better estimate of vegetation height of shrubs could be made. When looking at the results of the trees, it is found that the method proposed to first classify all the cells in a tree and then determine the majority seems to provide the best results. With an overall accuracy of 85% when looking at the tiles, it seems to be the best method. For low vegetation, the algorithm shows some promising results. Although still some problems are seen, especially for the rougher sand or the shorter herbaceous vegetation. Next to that, there is the problem of the tree trunks being classified as shrubs.

6
Discussion

This chapter provides a discussion concerning the different aspects of this research. In Section 6.1 the effect of the data quality and processing on the results are discussed. Section 6.2 discusses the proposed method. Section 6.3 discussed similar results and compares their results to the results that were obtained in this research. In Section 6.4 the approach of the chat GPT is discussed..

6.1. Data quality and processing

The quality of the data and how the data is processed have an influence on the results of the classification and the resolution of the classification. Therefore their effects are shortly discussed in this section. In Subsection 6.1.1 the quality of the LiDAR data is discussed, in Subsection 6.1.2 the effect of the way the data is handled in voxels, and in Subsection 6.1.3 the quality of the data that was used to train the model is discussed.

6.1.1. The LiDAR data

In Section 3.6 it was seen that the LiDAR has a precision of several centimetres. This precision can go up or down depending on the height of the UAV and the angle with which the pulse is returned. As was seen with the low vegetation, the higher-angle areas show a larger spread. This is mainly a problem when trying to distinguish grasses from sand. To solve this problem, it could be interesting to see if the angle of the pulse could be included in the classification in some sort of way. Next to the precision, also the reach of the LiDAR formed a problem at some points. The dense canopy of, for example, shrubs, but also some trees made an estimation of the terrain at some locations quite difficult.

6.1.2. Rasterisation

It was decided to use a raster to group points in the point cloud for all methods. This means that certain geometric information in the XY plane was not used, only the geometric information in the z plane was used. Since vegetation shows little geometric behaviour this was not a too big problem. But of course, there is a whole lot of information neglected by doing this. Also, the resolution is reduced to the cell size when using rasterisation. A lower resolution means a bigger cell size and thus more points and thus more accurate point distribution values. So a balance had to be found between these two.

6.1.3. Training Data

Picking training data was one of the most important factors for the results. The training data is obtained only from the Zuid-Kenenmerland area. Because the clearly distinct coniferous and deciduous forests are not in abundance in this area, there was not much training data available. If one of the two classes was overly represented in the training data the model fitted most vegetation towards the class that was in majority. Therefore, it was quite important to check whether the training data met the requirements. In addition, for low vegetation, the training data could have a large influence on the results. For example, including sand in overlapping LiDAR clouds (as was shown in Section 5.3), made the algorithm classify a lot more grass as sand since a higher spread over the vertical axis was expected. It was found that random forest model of high and low vegetation is quite sensitive to training data.

6.2. Method and results

In this section, the method and the results are discussed. The method used has different properties which should be considered, such as computational time, which is discussed in Subsection 6.2.1. But also other parts of the method including the features that were used and how the trees have been delineated and the machine learning algorithm that was used.

6.2.1. Computational challenges

The different methods formed different computational challenges. First, there was the new ground method. Applying a least-squares fit is quite computationally expensive. Applying this for each raster cell is therefore quite a while. Since we are dealing with regions of squared kilometres the runtime is relevant. In figure 6.1 it can be seen that the runtime scales linearly for both DTM algorithms.

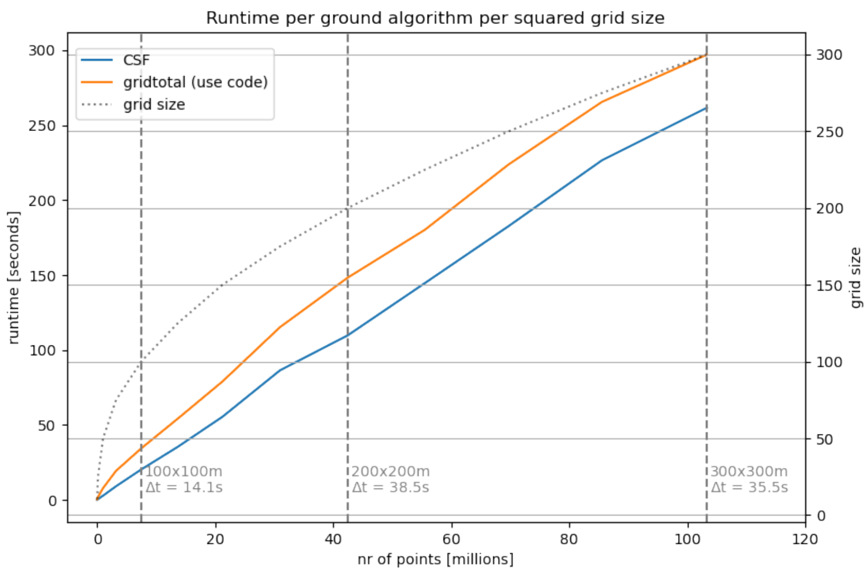


Figure 6.1: Runtime of the cloth algorithm and the integral method for a DTM with a resolution of 1cm

From this figure, it can be seen that indeed the newly proposed algorithm is slower, but this is not an insurmountable difference. Of course depending on the amount of data you want to apply the algorithm. Next to that, it should be taken into account that the integral method was created by a not-computer-science student so knowledge of efficient codes is not the expertise of the student.

Also when looking at the different tree classification methods it was found that first determining which points belonged to a certain tree was relatively computationally expensive. The more elements that belonged to a tree, the more computationally expensive it became. Thus, determining which raster cells belonged to a tree was much more computationally efficient. Therefore, applying the classification first to all cells independently and then determining which cells belonged to each tree was much faster than trying to obtain features from a full tree and classifying it at once.

6.2.2. Feature engineering

The random forest was used since it shows the importance of features and it was not yet known if the features of the proposed method would even show a difference between coniferous and deciduous trees. Based on this different features were formed to classify the high and low vegetation. The main features were based on the vertical point distribution. For future research, it would be interesting to see whether including intensity properly as a feature could improve classification. For the research, the intensity value itself was used, but the intensity value is very dependent on environmental parameters such as the distance the pulse travelled. For this research, it was not found that these parameters can be calculated and included, but for future research, it would be interesting to do so.

6.2.3. Limitations

The newly proposed terrain model seems to have improved the estimation of a DTM below shrubs. Although the DTM is a lot more irregular when looking below the shrubs. This could maybe be resolved by looking at a smoothing filter, but this would have an effect on the results, which then also needs to be assessed. In other parts of the area, especially when human-made objects such as buildings are in the field, the methods seem to show their limitations. In this section, the high vegetation is discussed. This will be subdivided into first discussing the tree delineation method, then the method and its results.

The watershed method can show different limitations. Since it uses the peaks of trees, this can cause an over-segmentation or an under-segmentation in the results. A tree with multiple peaks can show, as shown in the results. But a tree can also be over-segmented. This itself is not that big of a problem, but this could cause the same tree to be classified as a coniferous and deciduous tree as in Figure 6.2. If this problem occurs, it does form a problem.

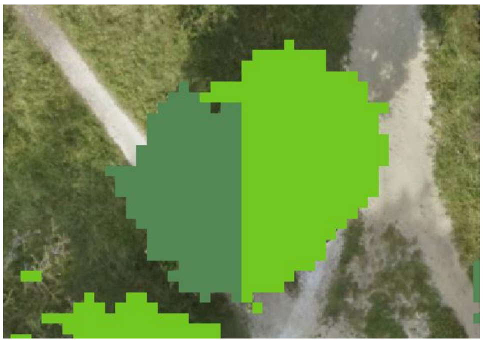


Figure 6.2: Tree classified both as coniferous and deciduous tree

For the tree classification into deciduous and coniferous trees was looked at the height distribution of points in coniferous and deciduous trees was. The hypothesis was that leaves reflect more light than needles because there is more surface area. But, of course, of large influence in this vertical distribution is the shape of the tree. And there are many different types of deciduous and coniferous trees. So it is possible that some deciduous trees are a bit shaped like a coniferous tree and a coniferous tree is a bit shaped like a deciduous tree. This could then also be the cause of the deciduous trees in Figure 5.13 which were classified as conifers. A solution to this problem could be to create subclasses in coniferous and deciduous trees, thus creating more classification classes.

6.3. Similar research

Interesting about the findings is that it contradicts some findings found by Wasser in 2013 (Wasser, Day, Chasmer, & Taylor, 2013). For this study airborne, LiDAR was used. According to their findings, the returns at the top of the canopy of conifers were much higher than at the bottom, while the returns at the top of deciduous trees were comparable to the returns at the bottom. This can also be seen in Figure 6.3. These findings contradict the findings and foundation of the classification features of trees used in this study as proposed in Subsection 4.3.3.

Other research that tried to classify trees reached a much higher accuracy than was reached in this research in both the tree delineation and classification by combining the structural features with imaging (Qin, Zhou, Yao, & Wang, 2022). So for tree classification it is intersting to continue with a combination of this research with images.

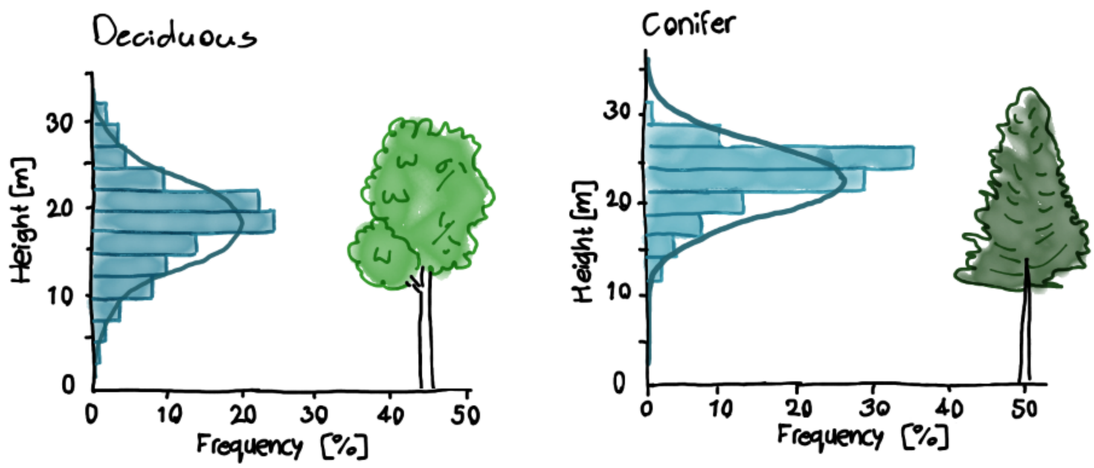


Figure 6.3: Histogram, as found in another research(Wasser et al., 2013), interesting is that in this research another point distribution was found in the trees.

6.4. What would chat GPT do?

In November 2022 chat GPT was launched. ChatGPT is an AI chatbox that is able to write reports and code, but also, to make an approach for a problem. So, as a test, I asked the bot what its approach would be asking it: *"How to classify deciduous and coniferous trees from LiDAR point clouds"*. Its response was as follows.

To classify deciduous and coniferous trees from LiDAR point clouds, you can use a machine learning approach. This involves the following steps:

1. *Collect LiDAR point cloud data of a forested area using a UAV or other means.*
2. *Pre-process the point cloud data to remove noise and artifacts, and to extract relevant features such as tree height, crown diameter, and canopy density.*
3. *Use the extracted features to train a machine learning classifier, such as a decision tree or random forest classifier, to distinguish between deciduous and coniferous trees.*
4. *Test the trained classifier on a separate set of point cloud data to evaluate its performance and fine-tune the model if necessary.*
5. *Use the trained and validated classifier to classify trees in the point cloud data and generate a map or other representation of the results.*

It is important to note that the specific details and approaches used in this process may vary depending on the specific dataset and goals of the study. It may also be necessary to incorporate domain knowledge and expert input to improve the accuracy of the classification results.

When looking at the approach of the bot actually all steps match the approach in this research. But, as the bot says in the conclusion, the process may vary depending on the specific dataset used. Thus a different result can be reached for different forest types.

7

Conclusion and Recommendations

The research is concluded with this last and final chapter discussing the conclusions that can be made and the recommendations for changes and further research.

7.1. Conclusion

In Section 1.3, the main research question was formulated as:

How can different vegetation types in the dunes be classified accurately and efficiently from UAV-LiDAR 3D point clouds?

To describe the characteristics of the different vegetation types features can be created. These features can be made based on the vertical distribution of points in stixels in the point cloud. To classify a point cloud a random forest can be trained accurately on labeled data containing different features extracted from the point clouds. By creating features the amount of data that the algorithm needs to process is reduced, increasing the efficiency.

1. *How can the use of UAV-LiDAR point clouds improve current dune vegetation classification methods?* It was shown that classification of low vegetation could be done underneath trees by just using point clouds. This is not possible using "mainstream" image classification algorithms. In addition, this classification method could be used independently of light conditions, where cameras are dependent on light to properly obtain information from an area. In addition to that additional information is obtained by looking at the vertical vegetation structures in the 3D space. This could have an added value to existing classification methods that only use the CHM in combination with imaging.

2. *What are the different vegetation types that should be classified, and what are their key characteristics?* The vegetation types are subdivided into high classification and low vegetation, which can exist together. Their characteristics are described by the features. Features are the basis of the classification model. On the basis of the features, a classification is done. In general coniferous trees are a bit higher than deciduous trees, but of course, there are also high deciduous trees and low coniferous trees. By making the features independent of the height of the trees (thus normalising the features), it was tried to prevent the model from linking these features to each other. However, this generally reduced the accuracy of the classification.

3. *How will the quality of the result be assessed and what quality can be reached?* The quality is assessed in different ways. First, the confusion matrix given by the random forest test data provides a quality check. Next to that, an extra assessment takes place by looking at tiles of one vegetation class. An accuracy of up to 85% could be reached in tree classification. For the lower vegetation, this accuracy was a bit different. Depending on the training data the bare sand and herbaceous vegetation got an accuracy of 40 to 80%, the shrubs on the other hand always got an accuracy of about 73%.

4. *What are the limitations of using UAV-LiDAR point clouds for dune vegetation classification?* One of the limitations in the use of UAV-LiDAR point clouds is that the LiDAR cannot reach everywhere, so certain parts of the vegetation lacked information. Next to that because of the unstructuredness of the point cloud a way to structure the information is searched. However, when structuring the cloud information does get lost.

7.2. Recommendations

This research was mainly focused on what the possibilities were in vegetation classification using LiDAR point clouds. Further research could go in several directions. First of which the research could go further by looking into the use of point clouds as a sole source in vegetation classification. In this case, I would advise improving the intensity feature by taking into account several atmospheric factors that affect the intensity. Next, the influence of other vegetation structures than only vertical structures could influence the classification. So rather than just looking at the structure in the densities in the z direction also the xy directions could be included.

Also, during this research, only one machine learning algorithm was used, which was the Random Forest. It would be interesting to see what the effect of the use of other classification algorithms would be on the accuracy of the results.

And last, there has already been some research looking at the combination of LiDAR structural features with images. If images are available in combination with structural features from LiDAR point clouds (thus not solely the vegetation height), it would be interesting to combine these two. This means that the structural features could be used as extra layers of information in existing classification methods, but also the other way around.

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A

Zuid-Kennemerland

In this appendix, some background information concerning the Zuid-Kennemerland area is given.

A.1. The research area

The location of the area is in the southwest of the province Noord-Holland. On the north side, the park borders the city of Ijmuiden, on the east side, it borders the city of Haarlem, on the south, it borders Zandvoort, and on the west, it borders the North Sea.

A.2. Ecology in the area

The area has been appointed a N2000 area, based on the habitat directive (not the bird directive). An overview of the habitats present in the park can bee seen in Figure A.2 below. In the area, some specific protected species of flora and fauna are also present (see Figure A.1). The Yellow widelip orchid is a protected fauna species. This plant is one of the rarest orchid species in Europe. In Zuid-Kennemerland a few grow on the more nutrient-poor ground like the grey dunes. If too much moss grows in a location or shrubs succeed, this ground becomes uninhabitable to the orchid. Therefore, especially nutrient-poor grasslands such as the grey dunes should be maintained.

Under the protected fauna species we find the pond bat and the narrow-mouthed whorl snail. The pond bat is one of the rarest bat species in Europe, which during the summer uses different parts of the dunes as its habitat. These bat nests in lowland regions provide water, meadows, and woods, which are exactly the habitat types that the Dutch dune system offers. So for this bat actually a good combination of all habitat types should be present. The Narrow-mouthed whorl snail lives mainly next to water in lower vegetated areas. As a habitat for this snail mainly the humid dune slacks should be maintained. But this snail is a special case of its own. It is unsure if its protected status is actually valid. This specific type of snail appears to be very good at hiding itself. So for the N2000 directive, different habitat types should be present in the area. To ensure all habitat types stay in a good condition regular monitoring and, if needed, interferences should take place.

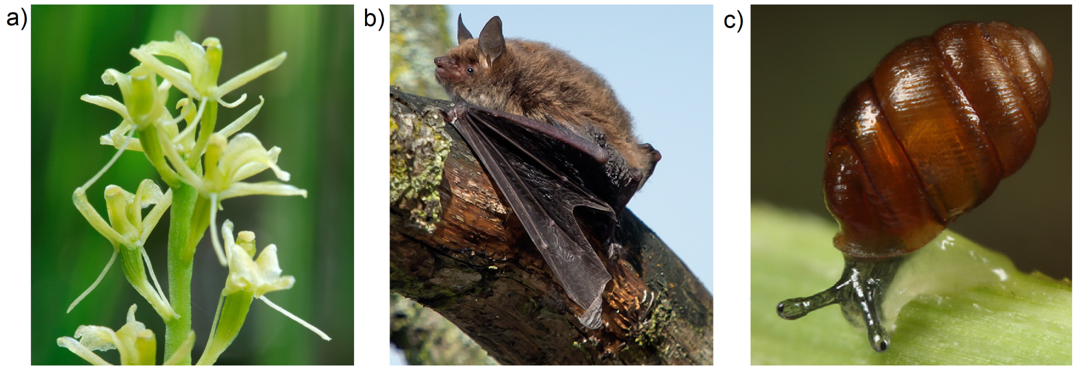

Figure A.1: Protected species in the Zuid-Kennemerland N2000 area: a) yellow widelip orgid, b) Pond bat, c) narrow-mouthed whorl snail (Vlaanderen, n.d.; anonymous, 2015; Faasen, 2011)

Figure A.2: Overview of the Natura 2000 Habitat types present in the Zuid-Kennemerland area. (Objectives: = Maintainance, > extension/improvement).
* For this type of habitat there is a 'sense of urgency '.
** Some degradation in favour of White dunes(H2120), Grey dunes (H2130) or humid dune slacks (H2190) is permitted.
*** Some degradation in favour of Humid dune slacks (H2190) is permitted.

B

Data used for validation

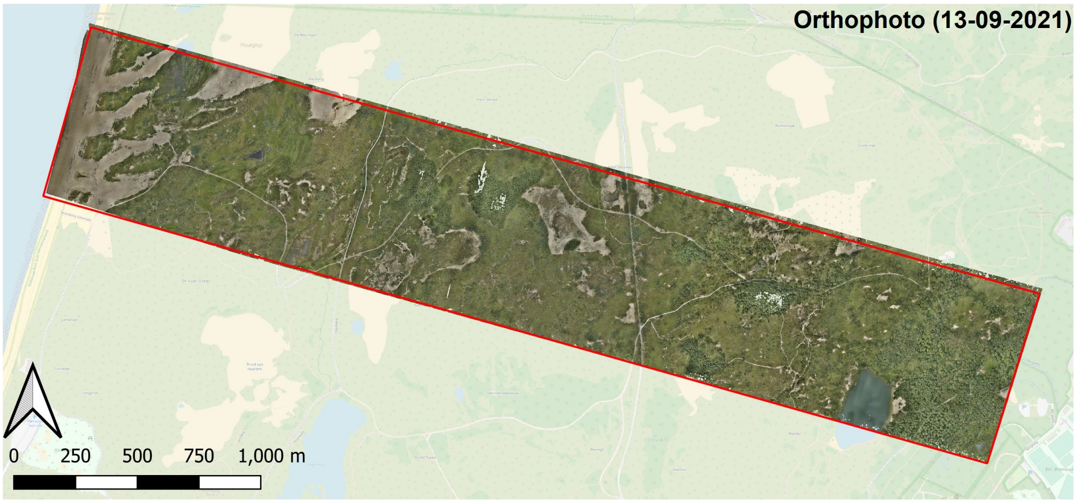

Figure B.1: Orthophoto drone September 13th 2022

Figure B.2: Orthophoto aeroplane march 20th 2022 (Beeldmateriaal Nederland, 2022)

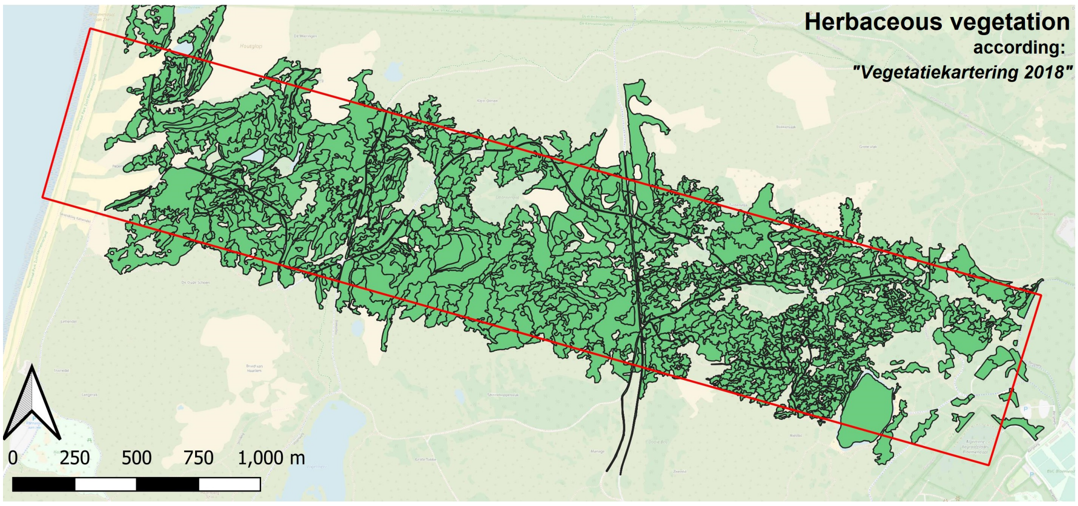

Figure B.3: Herbaceous vegetation (Kartering: "Bloemrijke graslanden", "Duingraslanden en rompgemeenschappen", "Kalkarme duingraslanden" and "Kalkrijke duingraslanden")

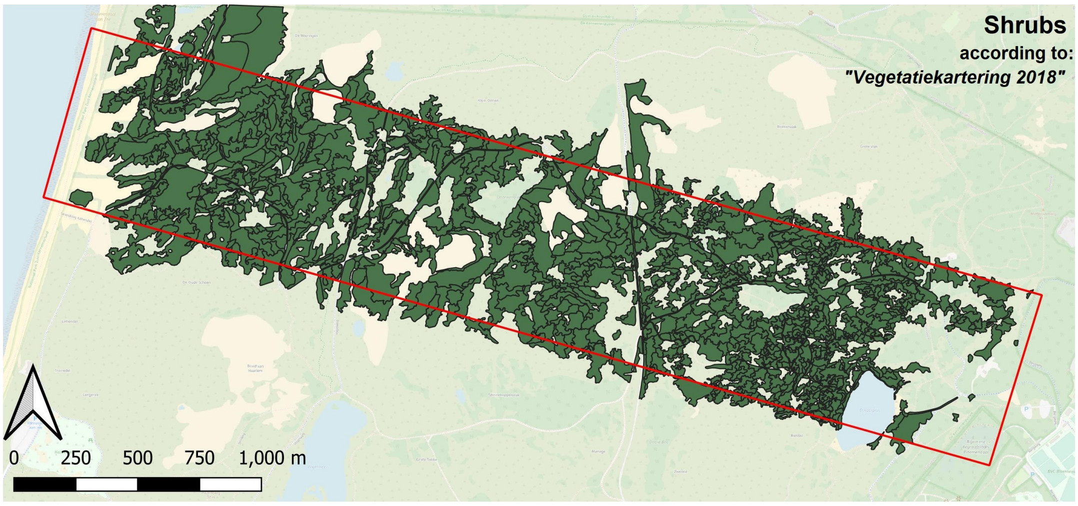

Figure B.4: Shrubs (Kartering 2018: "Duinroos, Kruipwilg- en braamstruweel" and "Struwelen")

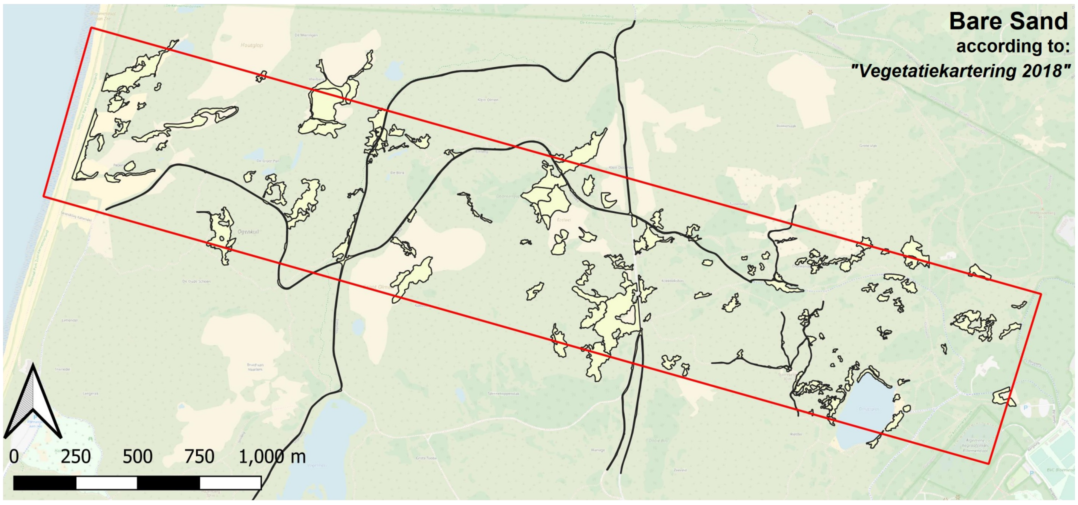

Figure B.5: Bare sand (Kartering 2018: "Kaal zand")

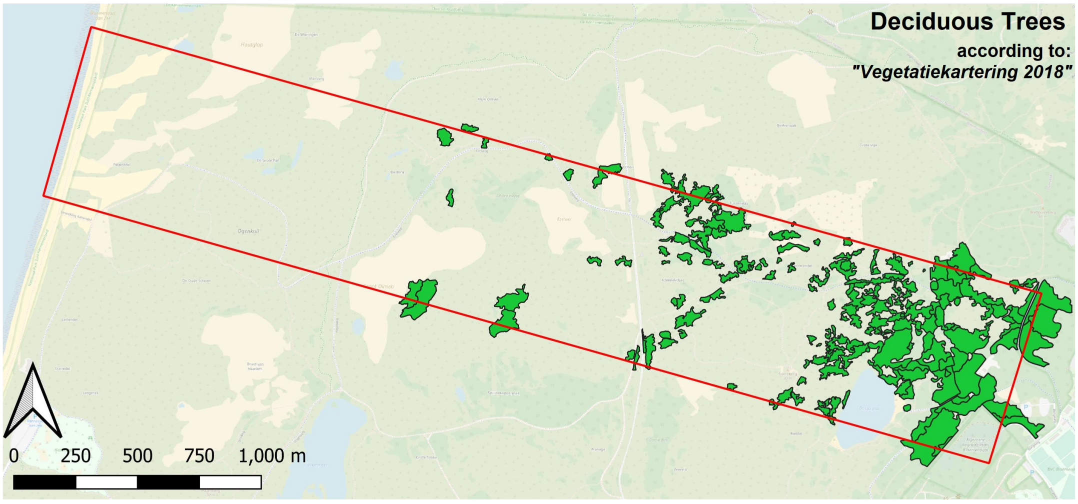

Figure B.6: Deciduous trees (Kartering 2018: ”Loofbossen”)

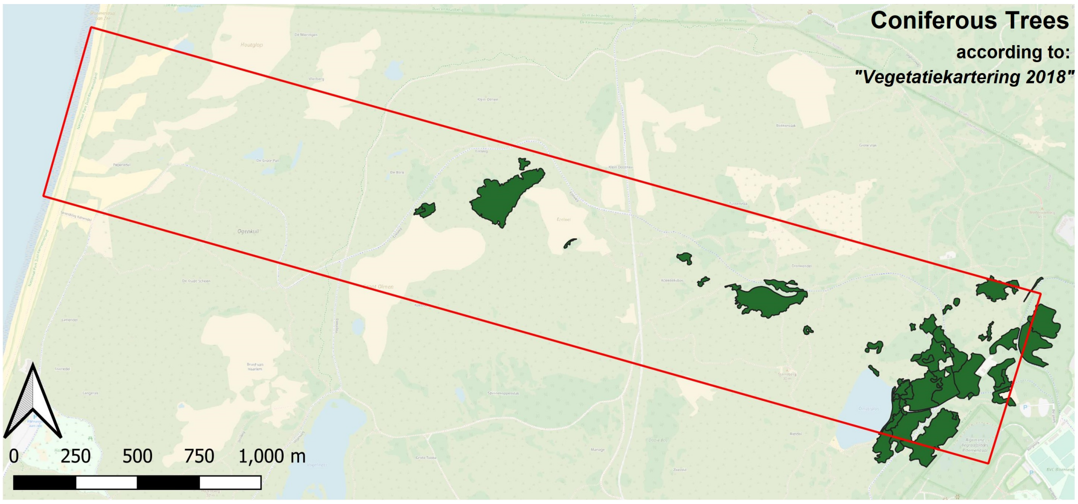

Figure B.7: Coniferous trees (Kartering 2018: ”Naaldbossen”)

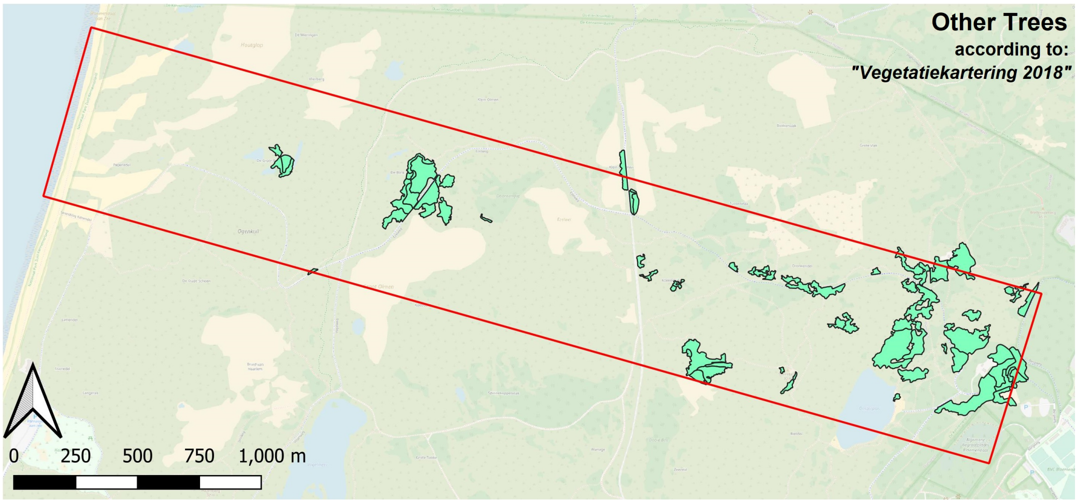

Figure B.8: Other trees (Kartering 2018: ”Overige bossen”)

C

Workflow to estimate DTM

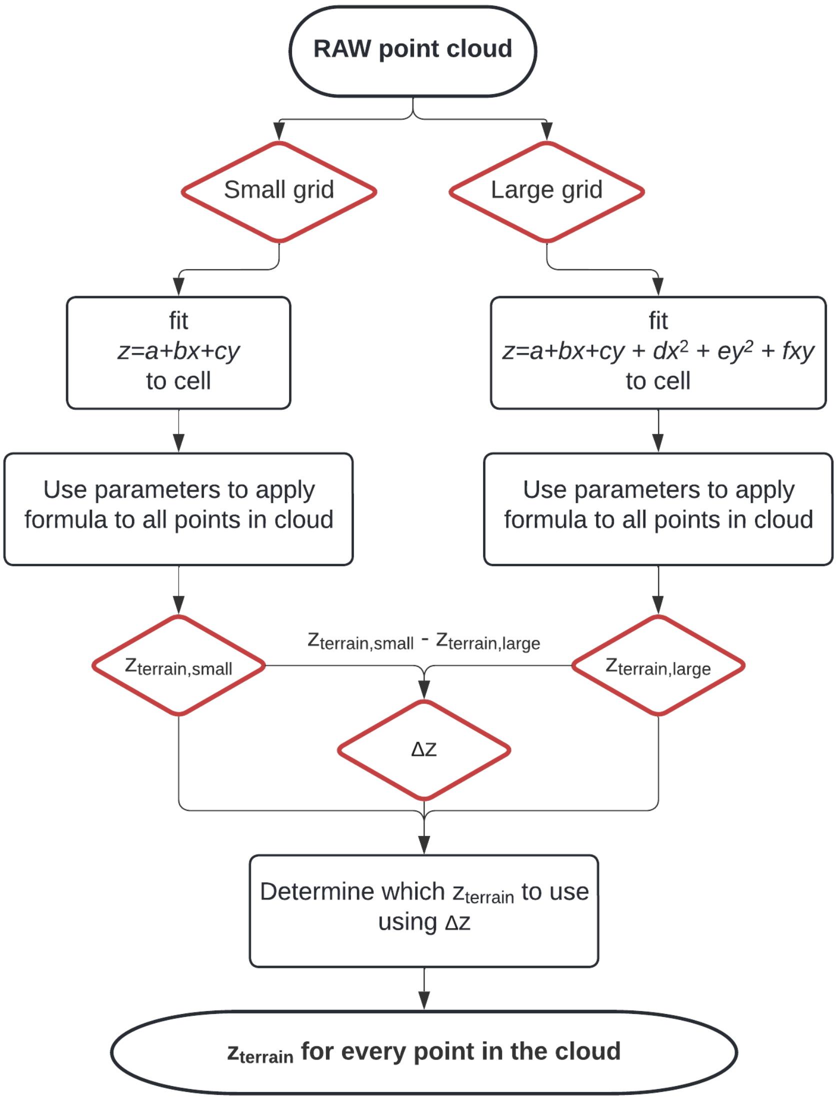

Figure C.1: Workflow summarising the steps of the newly proposed algorithm to estimate the DTM

D

Data overview

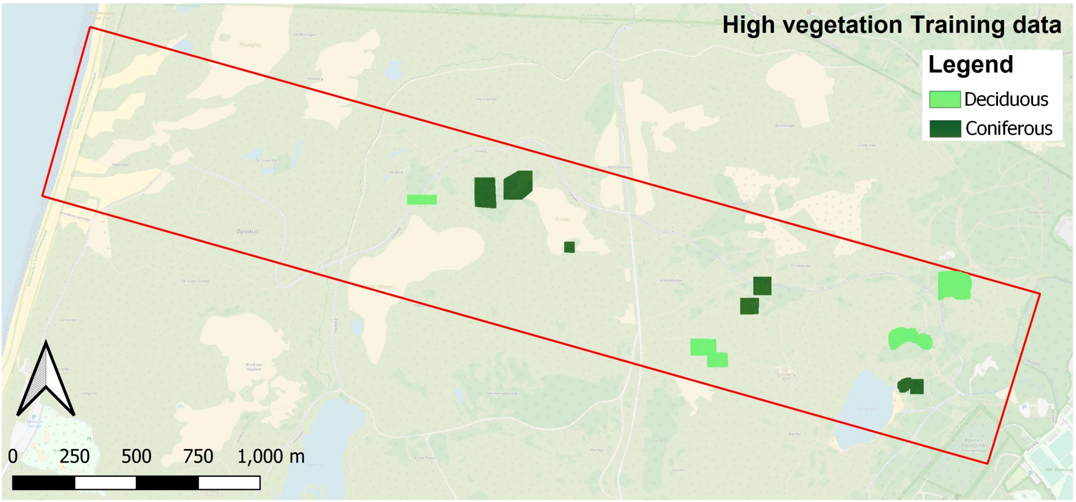

Figure D.1: Trainingdata trees

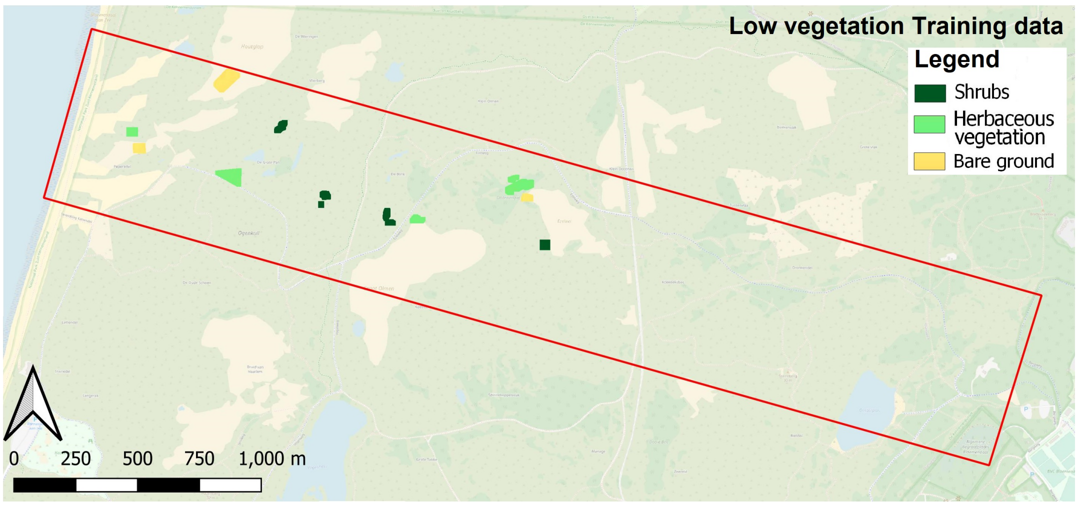

Figure D.2: Trainingdata low vegetation

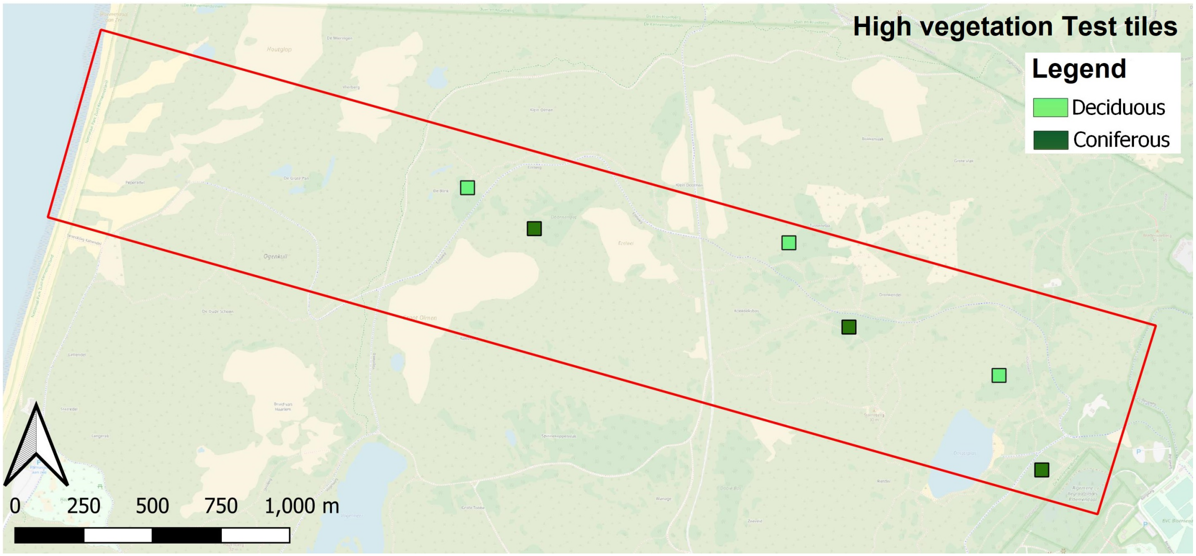

Figure D.3: Validatiaon tiles trees

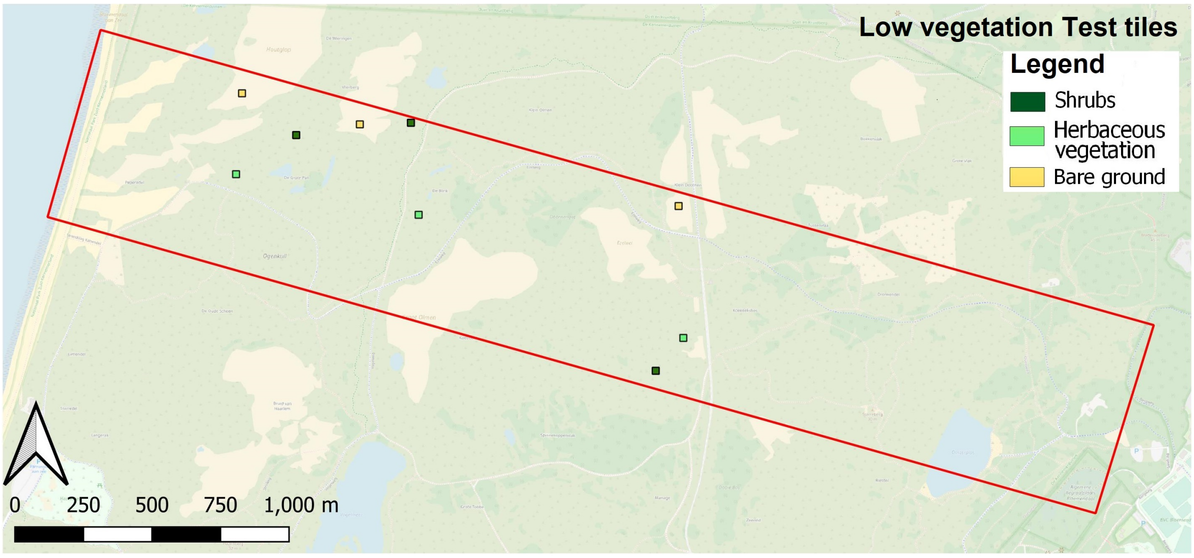

Figure D.4: Validation tiles low vegetation

E
Ground

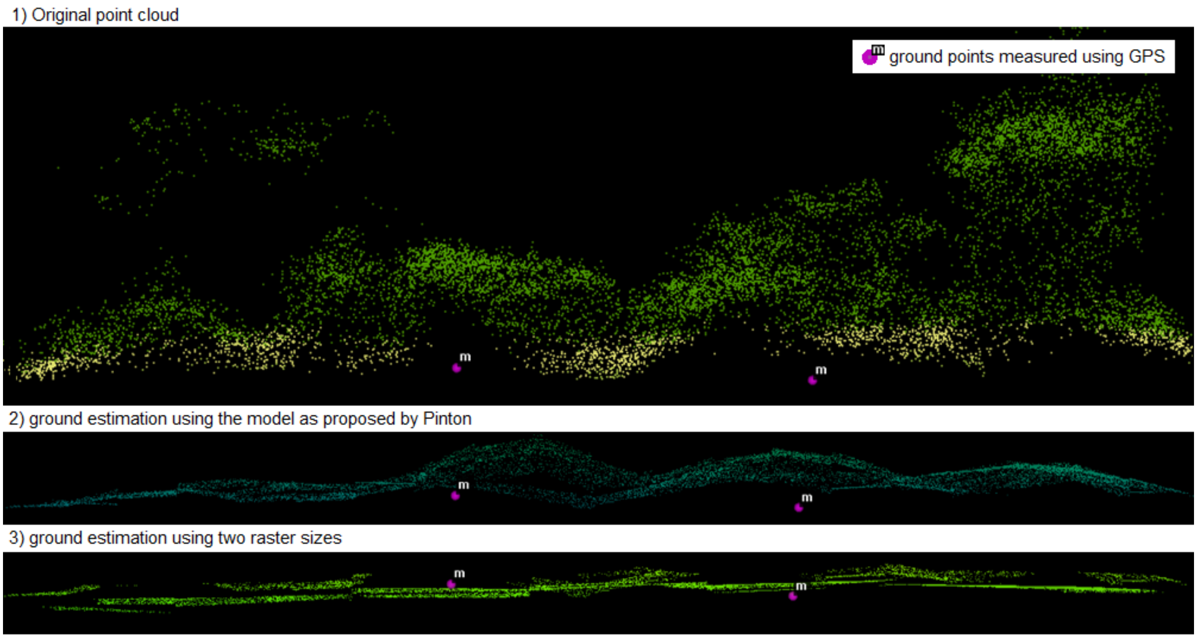

Figure E.1: GPS points in different DTM algorithms, up: original point cloud and GPS points; middle: DTM obtained by a cloth and GPS points; down: DTM obtained by integral method and GPS points

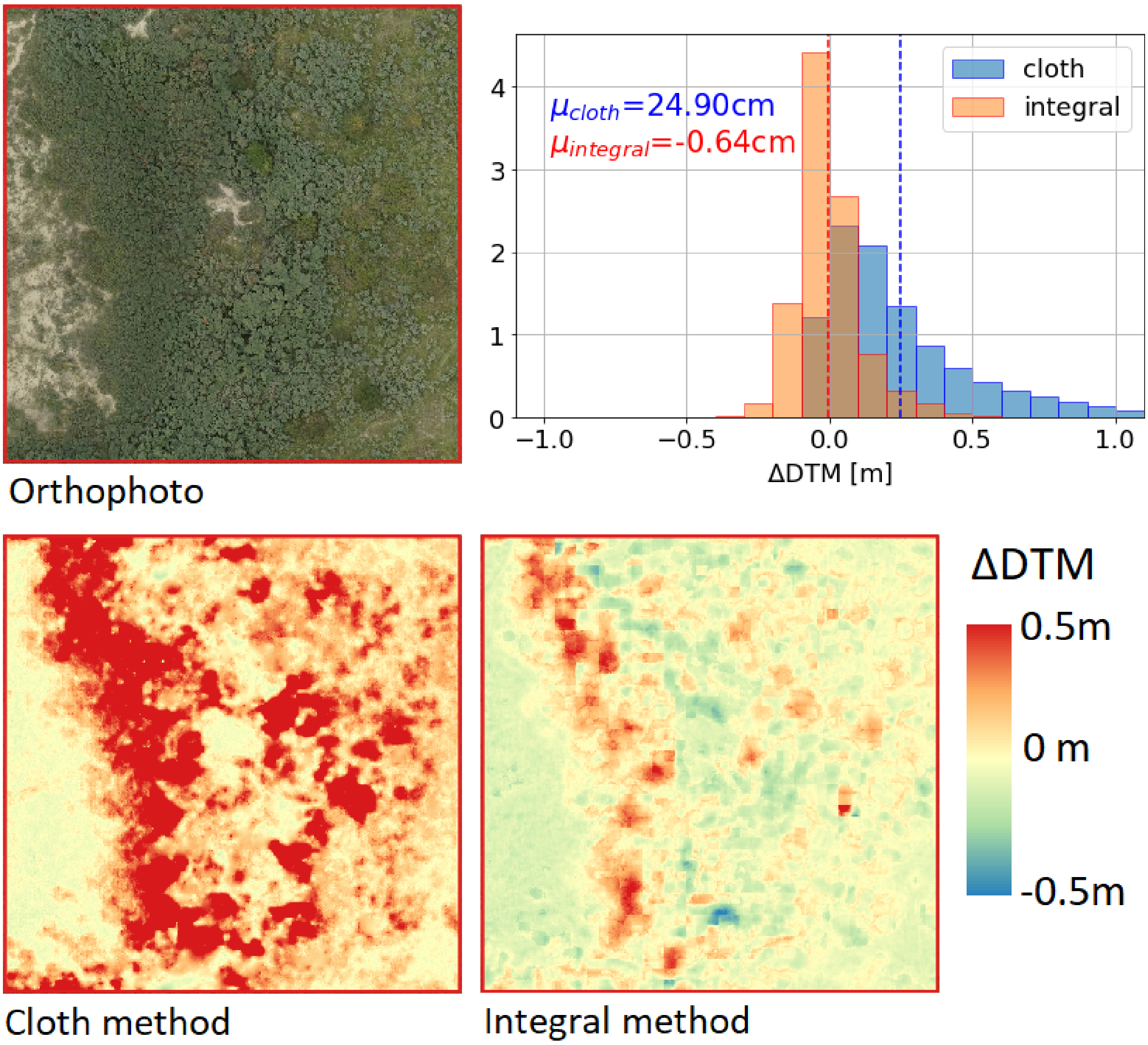

Figure E.2: Comparison of the ground model with AHN data measured in the winter, shrub case

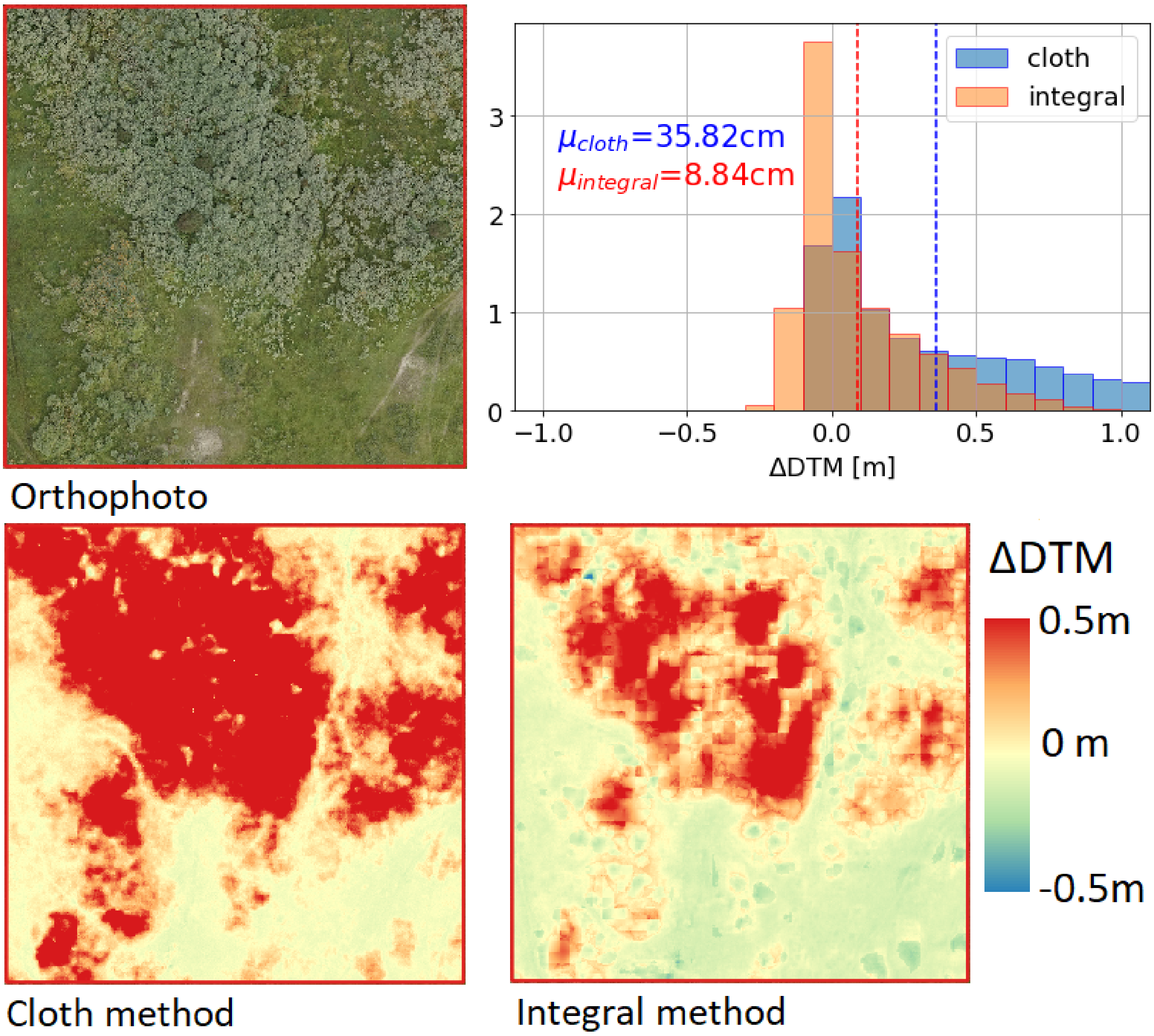

Figure E.3: Comparison of the ground model with AHN data measured in the winter, shrub case

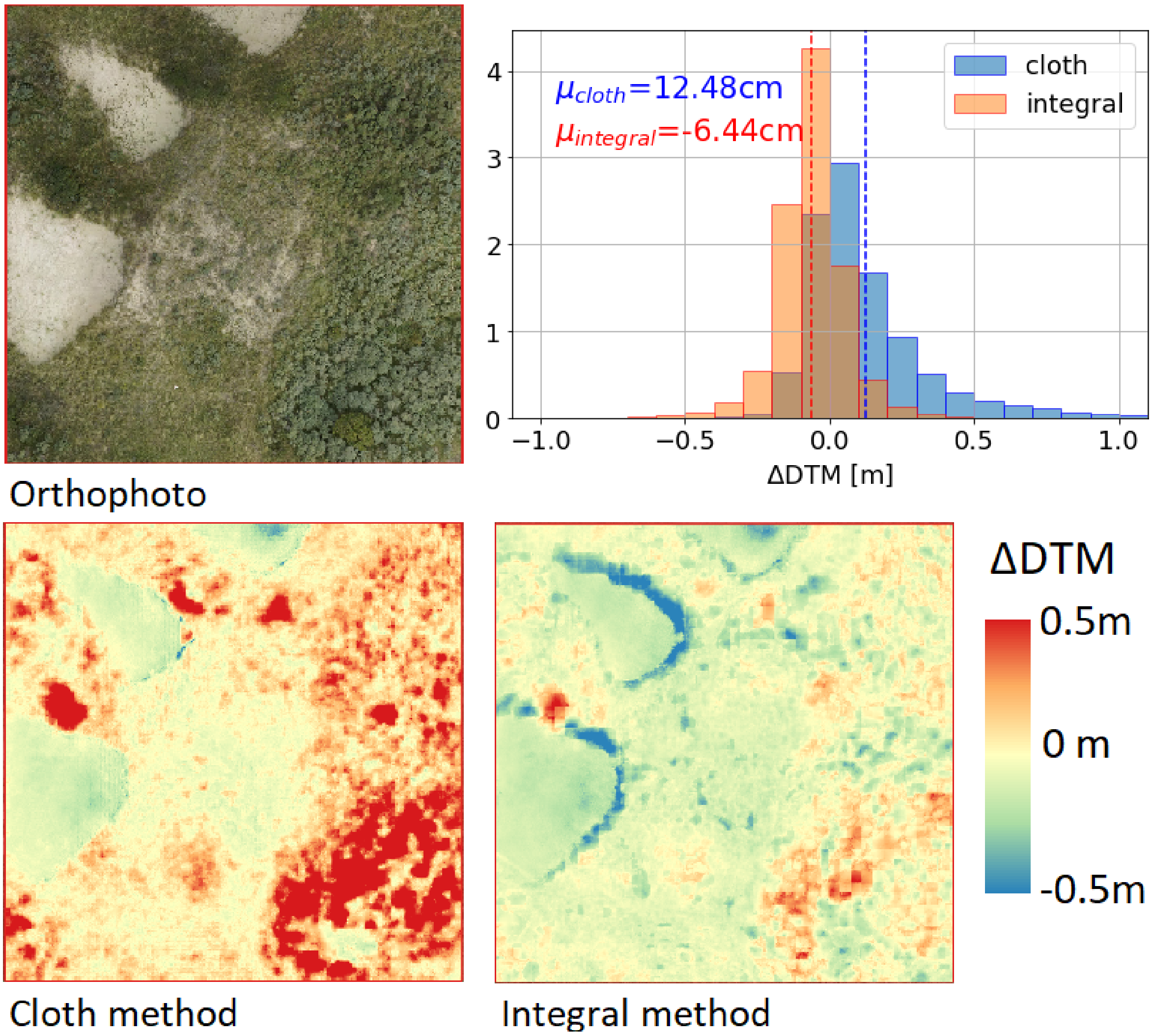

Figure E.4: Comparison of the ground model with AHN data measured in the winter, sand case

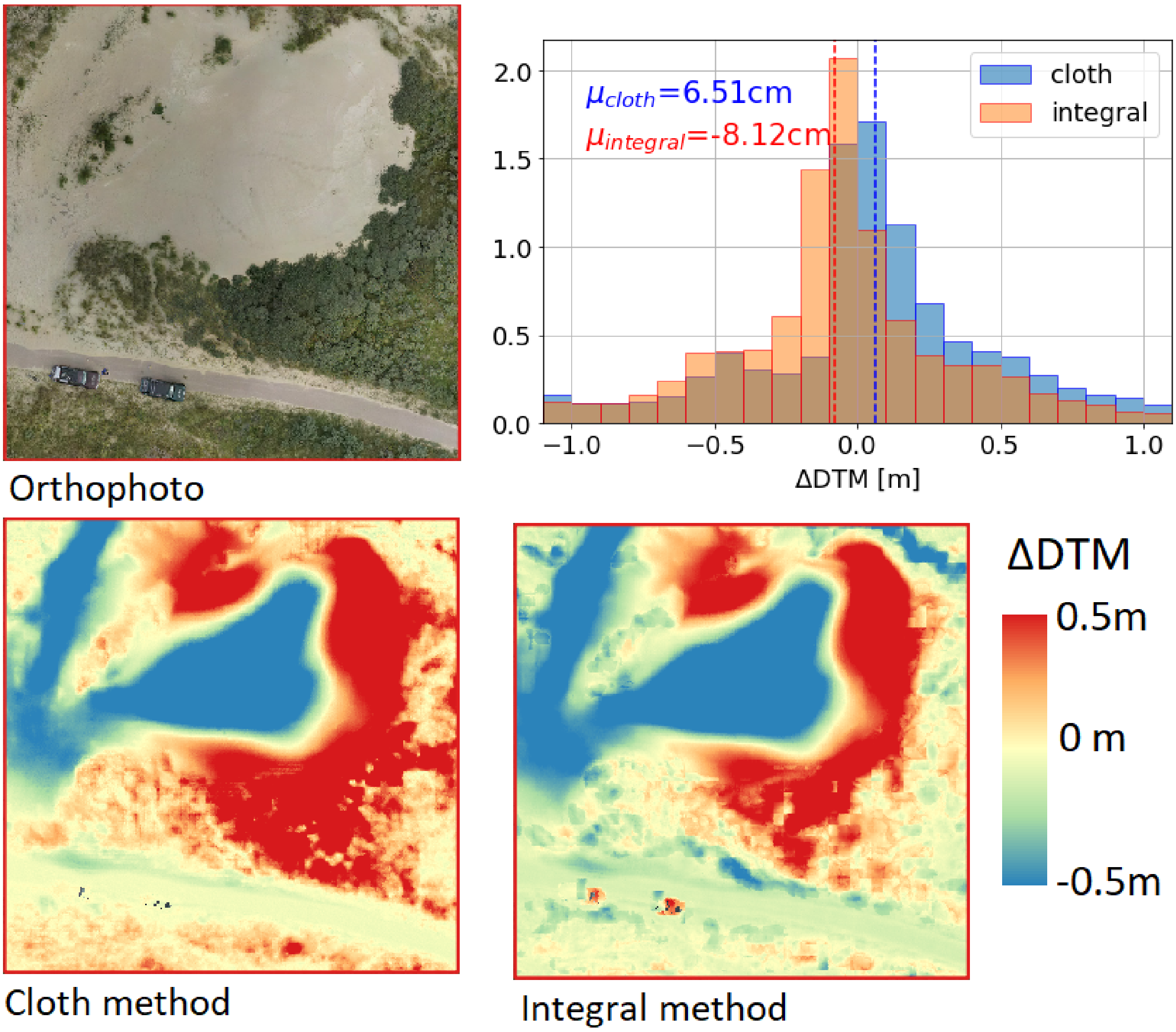

Figure E.5: Comparison of the ground model with AHN data measured in the winter, sand case, sand case. The sand show a high deviation because the sand is highly dynamic, and large differences can occur due to sand blowing on or away. Note the cars in the intgral method, these are seen as part of the DTM.