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Geographical Information Management and Applications

Using LiDAR in combination with aerial photographs to model and discriminate green small landscape elements

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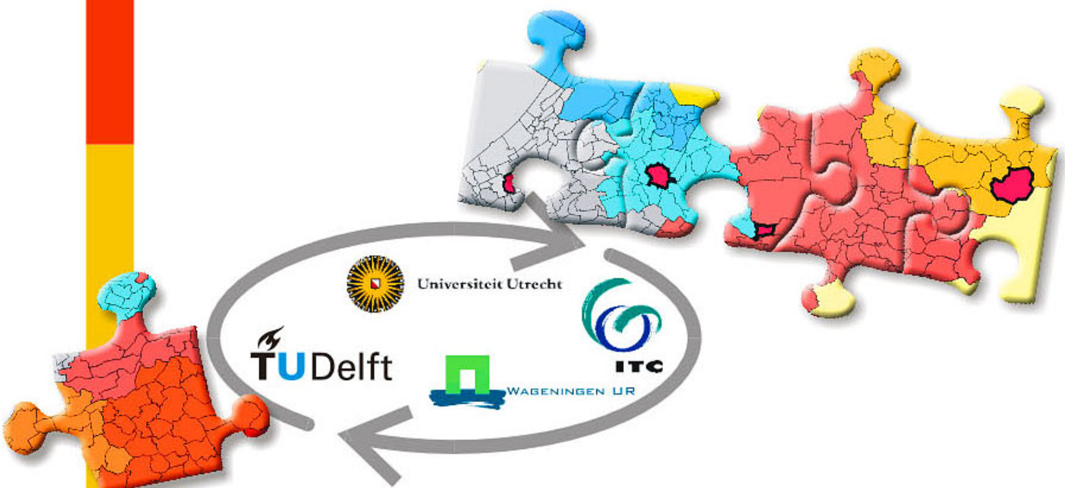

Using LiDAR in combination with aerial photographs to model and discriminate green small landscape elements

Master Thesis

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Abstract

Small landscape elements are an essential part of the Dutch landscape. They shape the identity of a region and landscapes in general. Small landscape elements prevent erosion, purify water, form a habitat for many animals and birds and contribute to the recreational attractiveness of landscapes. Because of industrialisation and the increasing scale of agriculture small landscape elements are under stress. The Dutch government is aware of the role that small landscape elements play in the quality of our landscapes. The government and organisations concerned with landscape management and policy support research and grant subsidies that help in the preservation of these landscape elements. It is however still difficult to monitor the state of different types of small landscape elements and the changes that are appearing. This is because there is no objective quantitative dataset with small landscape elements of the Netherlands available on a national scale. Therefore, the goal of this research is to make a model that can detect green small landscape elements.

Geographical Information Systems are used to make this model and several remote sensing techniques are combined to get the desired result. To discriminate small landscape elements segmentation techniques are used on LiDAR data. In the research two areas are used: a training area (Chaam) and a validation area (Wageningen). In both areas the accuracy of the model is tested by adding a false colour image to the LiDAR data to see if this improves the model. This research has shown that LiDAR is a very promising technique for classifying green small landscape elements. Adding a false colour image to the LiDAR data is especially useful in areas (such as the Wageningen area) where there are also man-made objects. There is however still work to be done to better detect tree rows and lanes. Future work can benefit from this model and improve it (for example by adding tree crown detection by using a region growing algorithm) so that all small landscape elements can be detected.

Keywords: GIS, LiDAR, remote sensing, landscape elements, segmentation, NDVI

Samenvatting

Kleine landschapselementen zijn een essentieel onderdeel van het Nederlandse landschap. Ze geven vorm aan het landschap en zijn bepalend voor de identiteit van een streek. Kleine landschapselementen gaan erosie tegen, zorgen voor de zuivering van water, vormen de habitat voor vele dieren en vogels en dragen bij aan de recreatieve aantrekkelijkheid van landschappen. De Nederlandse overheid ziet het belang van kleine landschapselementen in en beschouwt ze als belangrijke bouwstenen voor de kwaliteit van landschappen in het algemeen. De overheid en natuurbeheerorganisaties ondersteunen onderzoek en zorgen voor subsidies om deze kleine landschapselementen te behouden. Het is echter nog steeds moeilijk om de toestand van verschillende landschapselementen en de veranderingen erin te monitoren. Dit komt omdat er geen objectieve en kwantitatieve dataset van kleine landschapselementen van Nederland is op nationale schaal. Het doel van dit onderzoek is daarom het creëren van een model dat groene, kleine landschapselementen kan detecteren.

Geographical Information Systems worden gebruikt om dit model te maken. Hiervoor worden verschillende remote sensing technieken gecombineerd om het gewenste resultaat te krijgen. Om de kleine landschapselementen te kunnen onderscheiden wordt er een segmentatie model gebruikt met als belangrijkste input LiDAR data. In het onderzoek worden twee gebieden gebruikt: een training gebied (Chaam) en een validatie gebied (Wageningen). In beide gebieden wordt de nauwkeurigheid van het model getest door een false colour image toe te voegen aan de LiDAR data om te kijken of dit de uitkomsten verbeterd. Het onderzoek toont aan dat LiDAR een veelbelovende techniek is voor het classificeren van groene kleine landschapselementen. Het toevoegen van een false colour image is vooral nuttig in gebieden waar veel kunstmatige voorwerpen aanwezig zijn (zoals in de Wageningen dataset). Er is echter nog werk te verrichten om boomrijen en lanen beter te kunnen detecteren. Toekomstig onderzoek kan baat hebben bij dit model en het verder aanpassen (bijvoorbeeld door het toevoegen van *tree crown detection* door gebruik te maken van een *region growing algorithm*) zodat het model alle kleine landschapselementen kan detecteren.

Kernwoorden: GIS, LiDAR, remote sensing, landscape elements, segmentation, NDVI

Preface

This thesis was inspired by the research of Mücher et al. (2010) and their use of LiDAR to map and monitor habitats. I can still remember the first time I saw LiDAR data. Henk Kramer at Alterra, Wageningen, showed it to me. The level of detail and the fact that you could look at an object from every angle amazed me. I immediately saw the potential and relevance of LiDAR data for the detection of objects. Through the research of Mücher et al. (2010) I was inspired to expand my knowledge of LiDAR and the detection of green small landscape elements.

Through my work at Altenburg & Wymenga ecological consultants (A&W) I already knew about the important role that small landscape elements have on the quality of our landscapes. My colleagues who work in the field used the MKLE methodology already some years ago. With the gathered information our company helped farmers with submitting a request for a subsidy to preserve small landscape elements. In the last years A&W is also conducting research on the common redstart, whose habitat lies in small landscape elements. This made it clear to me that a model for the classification of green small landscape elements was needed.

This research could not have been possible without the very positive and to-the-point feedback of my supervisor Harm Bartholomeus. Thank you Harm, our Skype conversations were essential to solve the problems that every thesis writer encounters. I would like to thank Henk Kramer for joining the Skype sessions now and then and his help in acquiring the datasets of Chaam. I would also like to thank Arnold Bregt for his insight and feedback. He advised the use of the Wageningen dataset to validate the model.

I remember very well when I started with GIMA and I want to thank my employees at A&W for their support throughout the years. Also my father and girlfriend have been a very important factor to me in accomplishing this thesis research. Without them I would not have finished this thesis. Finally, I would like to thank everyone who assisted me in any way during my research.

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Colophon

Geo

AHN:	Actueel Hoogtebestand Nederland (van der Sande et al. 2010)
ALS:	Airborne Laser Scanning (Wehr and Lohr 1999)
CW:	Continuous Wave (Wehr and Lohr 1999)
DEM:	Digital Elevation Model (Burrough and McDonnell 1998) – page 99
DTM:	Digital Terrain Model (Burrough and McDonnell 1998) – page 99
GHC:	General Habitat Categories (Bunce et al. 2008)
GPS:	Global Positioning System (Lillesand and Kiefer 2000) – page 33-35
LiDAR:	Light Detection And Ranging (Lillesand and Kiefer 2000) – page 700-705
MPiA:	Multiple Pulse in Air (Roth and Thompson 2008)
NDVI:	Normalised Difference Vegetation Index (Baret et al. 1995)
TIN:	Triangular Irregular Networks (Burrough and McDonnell 1998) – page 99

Other

AC:	Ambtelijke Adviescommissie
BC:	Bestuurlijke Adviescommissie
Cb:	Collectief beheer
DKN:	Digitale Keten Natuur
DLG:	Dienst Landelijk Gebied
DR:	Dienst Regelingen
Nb:	Natuurbeheer
Nkw:	Natuurkwaliteit en monitoring
NVWA:	Nederlandse Voedsel- en Warenautoriteit
POP:	Plattelandsontwikkelingsprogramma
WUR:	Wageningen UR

1 Introduction

Small landscape elements are an essential part of our landscape. They have many functions such as prevention of erosion, purification of water and form the habitat for many animals and birds (Oosterbaan et al. 2004). Because small landscape elements are often related to small scale agriculture they keep disappearing. Therefore, more information about small landscape elements is needed to ensure their preservation. There is however no objective quantitative dataset with small landscape elements of the Netherlands available on a national scale. That is why the subject of this thesis is to make a model to detect green small landscape elements. To make such a model, Geographical Information Systems better known as GIS will be used. GIS covers a broad spectrum of spatial usage topics. One of these topics is remote sensing. There are many techniques within remote sensing, for example radar, satellite images, aerial photography and LiDAR, that can be used to detect small landscape elements. There is also earlier research done into this topic by Mücher et al. (2010) and Oosterbaan et al. (2004). Mücher et al. (2010) used LiDAR to map and monitor habitats. They encountered difficulties in implementing a good segmentation model that makes use of LiDAR data. They concluded that more research is needed to explore new possibilities. Oosterbaan et al. (2004) developed the methodology MKLE that functions as a monitoring network of small landscape elements. Data was collected by volunteers doing field surveys and entering the attribute data into a database and the spatial information in a shapefile. With this methodology it is however impossible to make a complete inventory of the Netherlands in a short time span. Instead the monitoring network will slowly be filled with the data of small inventories.

Due to increasing availability of LiDAR data and new functionalities in programs such as eCognition it is now possible to deal with previous unanswered questions. With the current available techniques I want to make a model for automated classification of green small landscape elements. With this model it will be possible to make an objective quantitative dataset, which is useful for the government, scientists, nature managers and the public. The need for an automated and quantified model that can detect green small landscape elements is of a great need for standardisation and usage by governmental organisations (Krause et al. 2010). In the Netherlands there are various subsidies for green small landscape elements. Before a subsidy will be approved the request needs to be verified. The verification is time consuming and lacks automation. Therefore, it is important to give the government a tool that can automatically derive the elements and crosscheck this with the request in quicker and quantitative way. The dataset can give up to date information and it will help in the signalling of developments (deterioration or progress) in small landscape elements.

To make this model several remote sensing techniques are combined. Remote sensing can be divided in to active and passive sensing (Turner et al. 2003). Both remote sensing types are usually operated from an airplane or satellite. Although it is also very well possible to make field measurements, due to the smaller coverage area this method is most of the time used for ground truthing. The passive remote sensing sensors are able to record reflection (e.g. false colour image) in digital numbers. In a false colour image the vegetation has a higher reflectance in the nir-band compared to bare earth and man-made objects. Many other bands (e.g. yellow and red edge) are available these days, all covering their own bandwidth. Active remote sensing emits a pulse and later measures the energy returned or bounced back to a detector (e.g. LiDAR and radar). Vegetation structure and ground surface elevations are often measured using active sensors. Light Detection and Ranging (LiDAR) systems operate in visible to near-infrared wavelengths, while radio detection and ranging (radar) emits radiation in longer microwave wavelengths (Turner et al. 2003). The last ten years LiDAR has made a rapid development, resulting in improved datasets with a higher density of points and lower cost due to a bigger market and a growing usage in commercial applications. In the Netherlands the AHN is used and covers the complete country. The density of the AHN dataset in 1996 was one point per 16 square metres. This is at least a factor 10 improved in the new AHN2 dataset, with an average of 9-10 points per square metre. This dataset became available for different parts of the Netherlands between 2007 and 2012.

Airborne laser scanning (ALS), also called Airborne LiDAR, is an active remote sensing technique that measures range to and reflectance of objects on the earth surface (Wehr and Lohr 1999). LiDAR is less influenced by weather conditions compared to passive optical remote sensing instruments. The objects on the earth surface can be measured in two ways. The first method, also firstly commercial available (Flood 2001), is by discrete return also described in literature as pulsed ranging. This method records the travel time from a sensor to a target object. Discrete return systems typically allow for one, two or a few returns to be recorded for each pulse during the flight (Lim et al. 2003). The second method is known as full-waveform and makes use of continuous waves (Wehr and Lohr 1999). Full-waveform LiDAR samples at GHz rate the entire reflected waveform for computer intensive postprocessing and extraction of points and elaborate waveform features (Korpela et al. 2009). A full waveform system senses and records the amount of energy returned to the sensor for a series of equal time intervals (Lim et al. 2003). This is a recent development that has become commercially available somewhere around 2004 (Flood 2001; Mallet and Bretar 2009). The accuracy of X/Y pulse centres is typically 0,1-0,5m and depends on the flying height (Korpela et al. 2009). The vertical accuracy is usually < 0,2m. This shows the high accuracy of LiDAR data.

LiDAR data can be used to generate a Digital Elevation Model (DEM) of the ground surface, though there are landscape elements (e.g. ditches, slumps, riverbeds) that will influence the quality of the DEM (Carson et al. 2004). To improve the DEM special editing for these elements is needed. A DEM of the ground surface is needed for detecting and analysing of vertical structures. The information from vertical structures bridges the gap between local precision and reality, and landscape generality (Graf et al. 2009). Next, LiDAR was being researched for usage in habitat detection. It started with relating habitats to heights as described by Lefsky et al. (2002). For monitoring European habitats, the usage of LiDAR was further investigated by Korpela et al. (2009). In his research he derived several key variables that are of importance for classification of green small landscape elements. The decision tree for high level divisions, which form the basis for the General Habitat Categories (GHCs) as described in Bunce et al. (2008) has been adapted and used by Mücher et al. (2010). Here they successfully integrated the model for usage with LiDAR. Mücher et al. (2010) focussed mainly on the green small landscape elements.

Although LiDAR-based classification often provides a good way of distinguishing between buildings and trees, it is error-prone when the spatial properties of vegetation and buildings become very similar. This kind of problem typically occurs with dense, trimmed hedges, in sparsely sampled regions, with buildings having a weirdly shaped roof, etc. In order to be able to classify those objects correctly, more information may have to be used (Schenk and Csatho 2006). One of the sources for providing extra spatial information besides LiDAR are false colour images. The spectral information of houses and vegetation differs and when combined with LiDAR information it can increase accuracy (Schenk and Csatho 2006). Important parameters for analysis and suitability for monitoring small landscape elements (MKLE) are: length, width, height and openness (Oosterbaan et al. 2004).

Digital topographic maps as top10nl are not complete, not accurate for a larger scale then 1:10.000 and therefore cannot be used for classification. Monitoring of small landscape elements was introduced by Alterra in partnership with Landschapsbeheer Nederland. The landscape with the green small landscape elements, is unique and preserved. Preservation is maintained with the use of subsidies from the government. This is why it is very useful to have a model which is possible to create a national dataset for control. By setting a standard for capturing small landscape elements the growing dataset has a better accuracy and includes more information on type, location, composition, quality and maintenance. It is also more time effective.

The combination of multispectral aerial photographs (or satellite images) and LiDAR data can deliver improved classification of green small landscape elements (Bradbury et al. 2005; Hill et al. 2002). The height combined with reflection of green objects should result in an improved automatic classification of these green small landscape elements. Because the ideal outcome of the classification gives information about area and maybe even volume I decided to make use of object-based classification. Another advantage of the object-based (segmentation) approach is its flexibility, it is possible to combine multiple types of datasets for classification.

1.1 Problem definition

There is a need for automation of detecting green small landscape elements described by the MKLE methodology (Oosterbaan et al. 2004; Oosterbaan and Pels 2007) and by Krause et al. (2010). Due to increasing availability of LiDAR data (Flood 2001) such as AHN2 data, adoption of LiDAR by the commercial sector, more awareness by end users and more powerful computers software vendors are releasing new versions of their software with better integration for raw LiDAR data. These new functionalities were not available at the time during earlier research by Mücher et al. (2010). Therefore, consecutive research is needed to deal with the unanswered questions described in the recommendations by Mücher et al. (2010). The following problems need to be dealt with:

- Proper mapping unit for green small landscape elements is still unclear.
- There is no model for automated classification of green small landscape elements.
- It is unclear whether object-based processing of LiDAR in combination with false colour images increases the quality of the outcome.
- Validation is missing.

1.2 Research objective

The main objective of this research is to create an automated model that will be able to discriminate green small landscape elements. The model uses LiDAR data and NDVI derived from a false colour image. Making use of segmentation techniques the model classifies green small landscape elements. Many organisations concerning landscape management and policy can benefit from the results of the model and use it for the signalling of developments in small landscape elements and thus better preserve and maintain them.

1.3 Research questions

The main research question of this project is:
Is it possible to automate a classification model for green small landscape elements with an object-based approach on LiDAR data, making use of segmentation?

To answer the main research question, the following sub-questions need to be answered:

1. *Can segmentation techniques be used to classify green small landscape elements?*
2. *How accurate is the model?*
3. *Is the accuracy improved when combining a NDVI derived from a false colour image with LiDAR data?*

1.4 Scope

This research will focus on green small landscape elements as in spots and lines, according to Oosterbaan and Pels (2007) they can be arranged as shown in Table 1. This research will be limited to model and identify only a few green small landscape elements; these are marked green in Table 1.

Table 1: Overview of green small landscape elements (< 5 ha), points and lines

	Spots (points)	**Lines**
Green elements	Tree	Tree row
	Group of trees	Lane
	Shrub	Tree row with shrub layer
		Hedge(row)
		Alder row

		Shrub row
		Coppice row
		Dike

The first method for discriminating these elements is by making use of segmentation. Because of limitations in software another approach will also be used like raster analysis. In this research two areas are used. The first is a training area used for making the model. This area is divided in small areas of interest and lies near Chaam, not far from the Dutch-Belgium border in the province of Noord-Brabant. The area is an agricultural area, mainly consisting of arable land and pastures, with a fair amount of linear landscape features such as hedges and lines of trees, and surrounded by forests and some remaining patches of heathland (Figure 1). The site is approximately 3 km x 3 km.

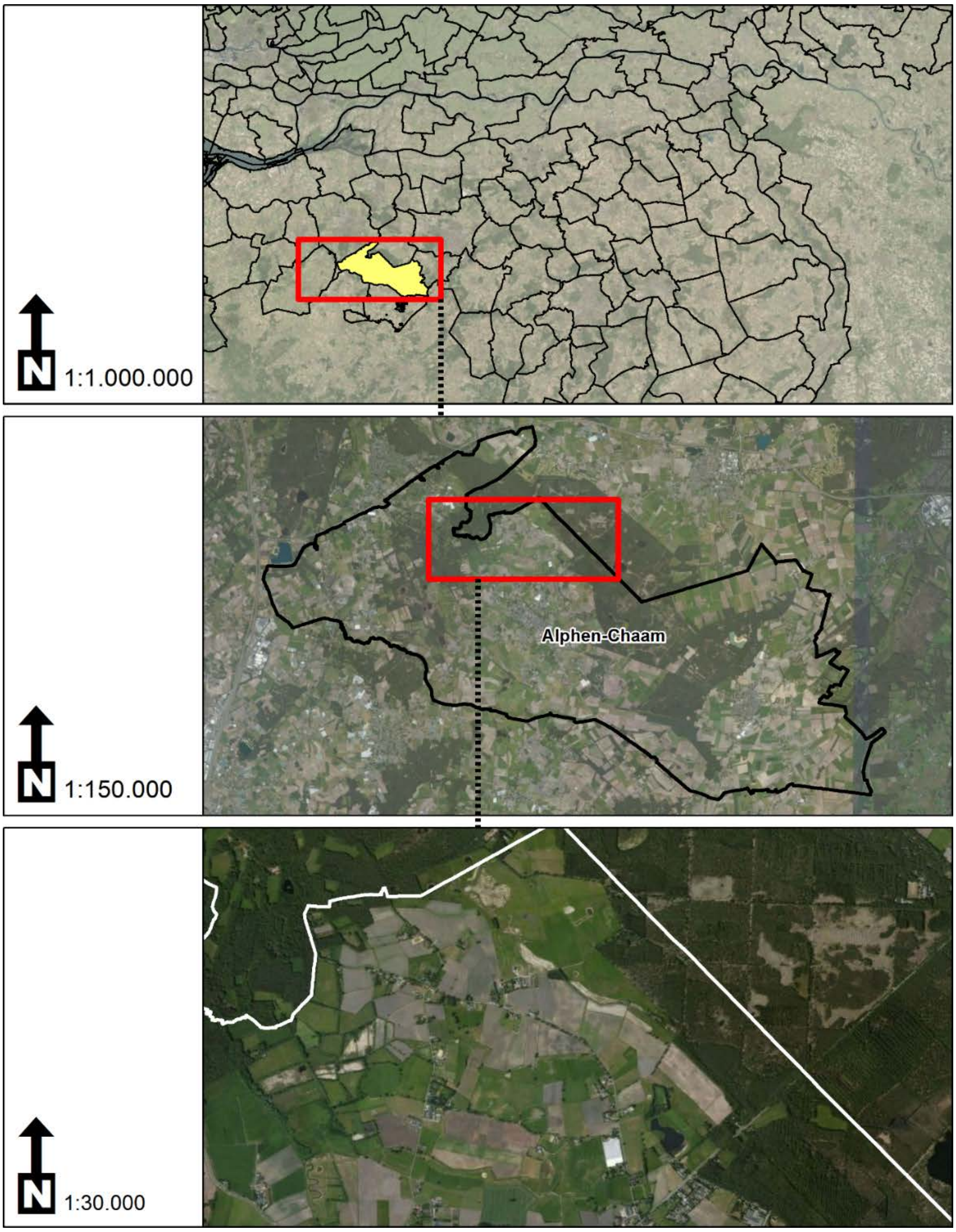


Figure 1: Location of study area Chaam

The second area is used for validating the model and lies in the Wageningen UR area within the province of Gelderland. This is an area where the university is situated surrounded by a green environment. It has a diversity of green small landscape elements and man-made objects, see Figure 2. Therefore, it is used for validating the model. The site is approximately 650 m x 500 m.

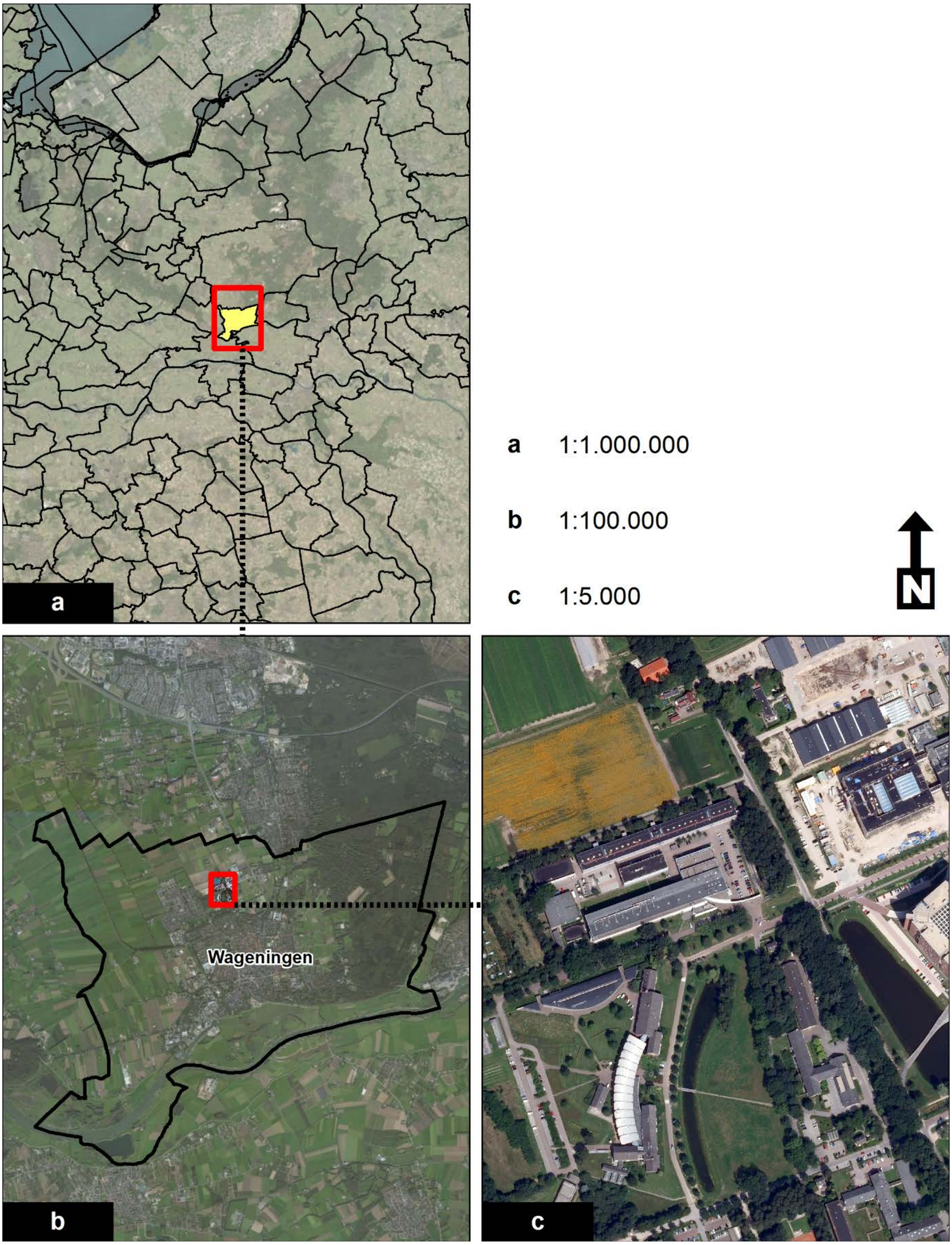


Figure 2: Location of study area Wageningen UR

2 Methodology

2.1 Introduction

The project is divided in two phases. The first phase will focus on the theoretical background in combination with applied research. The tools used by Mücher et al. (2010) will be used as a starting point for further development of a model.

This model is based on the methodology described by Sithole (2005) and adapted with segmentation methodology described by Mücher et al. (2010) and Krause et al. (2010). The same references are also used as a starting point for recognition criteria. The methodology described by Sithole (2005) can be divided in three steps (Figure 3). The first step is creating a filter framework, once this is done it will be the base for further analysis. The framework has several steps and each step makes use of minimal one segmentation methodology followed by classification of objects. The diagram from Sithole (2005) is mainly based on detecting bridges. In the scope of this research the bridges are not relevant, but instead the natural objects are to be extended. Furthermore an extension will be made to take into account false colour. Datasets derived from false colour aerial photographs are for example NDVI and Leaf Area Index (LAI). These datasets can help discriminate vegetation from buildings (Mücher et al. 2010; Suarez et al. 2005). This research will not take LAI into account because it is a complex and time consuming method. Another method can be used where one takes measurements in the field, this methodology is not suitable for large areas according to Wilhelm et al. (2000). The disadvantage of the methodology described by Suarez et al. (2005) in which they use LiDAR combined with aerial photography, is that in some cases it can underestimate the value of LAI in very dense canopies. Besides the fact LAI will not be taken into account the disadvantage will probably not rise on green small landscape elements, because these elements don't tend to be very dense. Furthermore the focus of the research is on LiDAR and therefore also the indirect method is too time consuming for the available time.

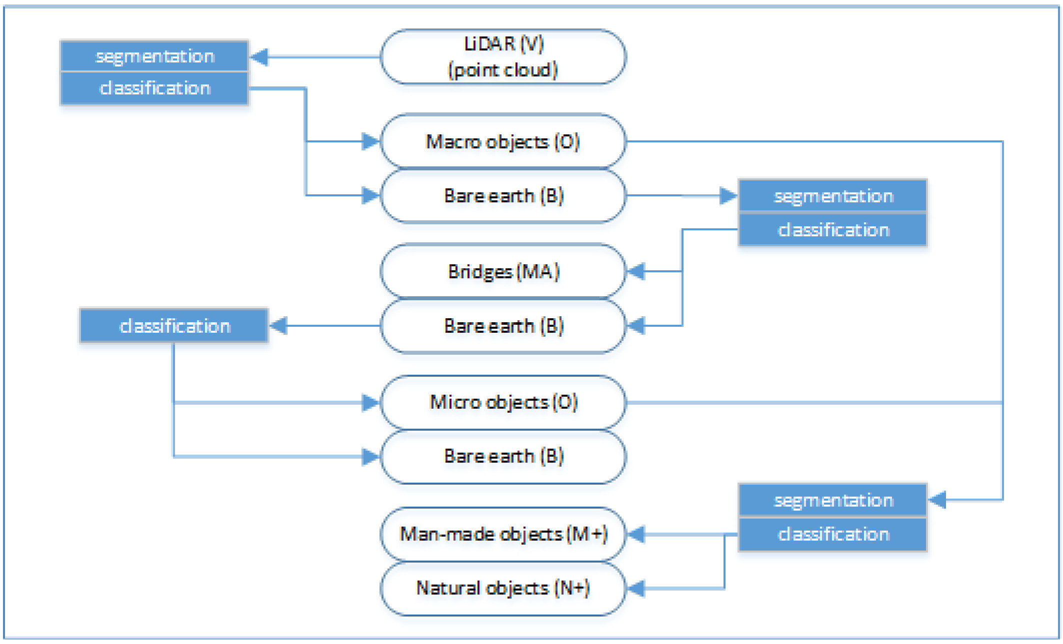


Figure 3: Methodology by Sithole (2005)

The second phase deals with the analysis of the research outcomes of the first phase. The accuracy of the classification results will be assessed by making use of the following datasets:

- Aerial digital photographs of Chaam (May 2008) by Eurosense B.V.
- LiDAR dataset of Chaam (May 2009)

- Ground truth dataset Chaam (December 2009 and February 2010)
- Aerial digital photographs of Wageningen UR area (2008)
- LiDAR dataset of Wageningen UR area (2012)

Besides the user, producer and overall accuracy, a normalised accuracy will be calculated by making use of an iterative proportional fitting procedure (IPFP). This accuracy method is defined by Congalton (1991). The normalised classification accuracy can be defined as shown in formula (1) and (2) from Norman (1999).

$$\mathrm{P}ij(k+1) = \left[\frac{\mathrm{P}ij(k)}{j\ \mathrm{P}ij(k)}\right] * Qi \qquad (1)$$

$$\mathrm{P}ij(k+2) = \left[\frac{\mathrm{P}ij(k+1)}{i\ \mathrm{P}ij(k+1)}\right] * Qj \qquad (2)$$

Where $\mathrm{P}ij(k)$ is the matrix element in row I, column j and iteration k. Qi and Qj are the pre-defined row totals and column respectively. Equations (1) and (2) are employed iteratively to estimate new cell values and will theoretically stop at iteration m where: $j\mathrm{P}ij(m) = Qi$ and $i\mathrm{P}ij(m) = Qj$.

This research is based on segmentation. Although it is possible to have a multiplicity of inputs, for example raster and vector, this research uses mainly raster as an input for segmentation. The output will be vector objects.

2.2 Sub-question 1

In chapter 5 and 6 the first sub-question will be discussed. Chapter 5 deals with the segmentation techniques that can be used to classify green small landscape elements. It is divided into five sections. The first section is a short introduction. The second section will discuss segmentation techniques. The third section will discuss green small landscape elements and how they can be defined. The best threshold for contrast split segmentation is discussed in section four. The fifth section will briefly discuss the segmentation. Chapter 6 deals with classification and is divided into four sections. The first section will give an introduction to the classification model used. The second section will deal with detecting natural objects (solitary tree, tree row, lane and group of trees) through segmentation from the LiDAR dataset. Section three adds a false colour image. And the last section will have a discussion on the accuracy.

2.3 Sub-question 2

The second sub-question will be answered in chapter 7 section 2, it will discuss the outcomes of the classified elements by making use of segmentation and will look at the accuracy of the outcome of the model visually and by means of field data. It will look at the results from Chaam based on LiDAR only.

2.4 Sub question 3

The third sub-question will be answered in chapter 7 section 3. It tries to give an answer concerning the accuracy of the outcome and compare a 'LiDAR only' model with a false colour image with LiDAR data model and discuss the outcome of the comparison. It will look at results of Chaam based on LiDAR combined with a false colour image. In the fourth section a comparison of both methods will be described. The fifth section will deal with the validation by making use of a different area. The last section will discuss the results.

3 Green small landscape elements

3.1 Introduction

Small landscape elements are part of our history, they played an important role in different land use systems (Oosterbaan and Pels 2007) and are also an important terrain type for several birds as they are used as corridors (Fernandez-Juricic and Jokimäki 2001). Small landscape elements can be solitary trees, rows of trees and ponds. In Table 2 a list of small landscape elements shows 24 green elements, eight types of water and three infrastructural elements.

Table 2: List of small landscape elements (< 5 ha) by Oosterbaan and Pels (2007)

	Spots (points)	Lines	Areas
Green elements	Tree	Tree row	Broadleaved forest
	Group of trees	Lane	Conifer forest
	Shrub	Tree row with shrub layer	Mixed forest
		Hedge(row)	Tree meadow
		Alder row	Alder brook
		Shrub row	Willow shrubs
		Coppice row	Coppice wood
		Dike	Holm
			Special garden
			Farmyard
			Reedland
			Heathland
			Moor/bog
Water	Pond	Creek	Fen
		Brook	Moor
		Meander	Pingo
		River	
Infrastructure		Footpath	
		Cycle road	
		Sand road	

Because the landscape elements are often related to small scale agriculture they keep disappearing. This has to do with industrialising and an increasing scale of agriculture. The problem is that it is unknown what the state of different types of small landscape elements are and what kind of changes are appearing at what rate (Oosterbaan et al. 2004). It is clear that many are managed inadequately, so there was a need for change (Oosterbaan and Pels 2007). In 2002 the first subsidies came to protect, improve and maintain the existing small landscape elements. During the next years several governmental organisations supplied subsidies.

3.2 History

Since 1970 nature conservation has been of interest in the Netherlands. This is due to the fact that typical landscapes were disappearing because of land consolidation, road construction, housing and an increasing scale of agriculture (Baas et al. 2005). This is the reason that people got more involved with nature conservation, for example in the form of a paid membership to support organisations like Staatsbosbeheer, Natuurmonumenten and many others. The Dutch government wanted a better understanding of the changes that occur in landscape quality, and the roll small landscape elements play in this (Oosterbaan et al. 2004). That is why in 2002 the government decided to support a research project initiated by Landschapsbeheer Nederland (a private foundation for stimulating landscape management), aimed at establishing a system to monitor changes in the quantity and quality of small landscape elements in the Netherlands (Oosterbaan and Pels 2007). In the years 2002 – 2004 research was carried out in three test municipalities to provide answers for the following questions:

- What are the objectives of a monitoring system for small landscape elements?

- What is the monitoring system going to monitor? What classification of small landscape elements should lie at its base?
- How can data be collected, stored, analysed and reported reliably, repeatedly and cost-efficiently? What methodology should be used?

Since 2005 the attention for small landscape elements has increased. New groups of landscape elements have come to people's attention, together with new literature which led to new insights. The following points give a good overview of the importance to maintain these unique cultural and historical small landscape elements:

- The small landscape elements are an archive and historical library of our past.
- Some small landscape elements contribute to rare ecosystems.
- They have a positive experience on people that live in or visit these areas. People intend to like it.
- From an ecological perspective the small landscape elements are stepping stones to larger nature areas.
- The agricultural sector finds the small landscape elements important to fight diseases and pests.
- Small landscape elements have a positive effect on the air quality.

3.3 Current usage

Besides the known stakeholders concerning the small landscape elements there are quite a few new organisations that got involved over the last five years. These organisations are concerned with policy and management of landscape and are generally interested in information about the spatial distribution, the character and the condition of small landscape elements as well as the changes of these aspects (Oosterbaan and Pels 2007). These concerned parties see a need in a monitoring system for small landscape elements (Oosterbaan and Pels 2007). Oosterbaan and Pels (2007) made an overview including a short description on purpose, see Table 3.

Table 3: Organisations concerned with policy and management of landscape and their interest in a monitoring system for small landscape elements (Oosterbaan and Pels 2007)

Organisation	Purpose(s)
Nature managers	• Defining nature management objectives and activities; • Planning and implementing landscape management systems; • Guidelines for management of specific types of small landscape elements; • Assessing the extent and cost of restoration requirements.
Policymakers (in general)	• Gather information for policymaking; • Early identification of problems; • Assessment of cost-efficiency of subsidies (i.e. for the construction and management of small landscape elements); • Monitoring and evaluation of policies.
Municipalities	• Assisting in the exploration of municipal strategies in landscape development; • Envisaging the enhancement of the local landscape; • Implementation of physical planning policies, as set down in regional and local development plans; • Framing landscape development plans as framework for assessing requests for permits; • Assessing the extent and cost of restoration requirements; • Planning and implementation of landscape management systems.
Physical planners and consultancy firms	• Framing landscape development plans; • Framing land development projects; • Basic information for the construction and management of small landscape elements.
Provincial policymakers	• Assistance in distribution of funds/subsidies;

	• Framing provincial regulations for subsidies; • Monitoring changes; • Policy evaluation.
Public	• Information about and increased interest in landscape; • Interpretation and education.
Volunteers	• A detailed knowledge base on the location, nature and character of small landscape elements; • Guidelines for volunteer involvement with management and restoration of small landscape elements.
Scientists	• Increasing the body of knowledge concerning small landscape elements and the changes in their spatial distribution and condition; • Identifying the causes of these changes; • Increasing the body of knowledge of the relationship between small landscape elements and biodiversity as well as related actual and potential ecological values.

The national government is interested in the role of small landscape elements in the change of landscape. If a method can be defined for automatic classification, it will be very helpful in framing, monitoring and evaluating landscape species (Oosterbaan and Pels 2007). Since 2004 the small landscape elements are being monitored by MKLE methodology. This methodology monitors quality, condition of maintenance, location, dimensions in the field and will be stored in a GIS. This is a very cost ineffective method because the data is collected by people doing field surveys where they manually fill in the survey forms. Afterwards the obtained data has to be entered into a database and into a GIS. With the MKLE methodology it is difficult and therefore very expensive to keep the GIS up to date.

3.4 Subsidy

There have been numerous types of subsidies for the preservation of small landscape elements. To give an insight in all the different geographic delimited types a summary follows (not pretending this list is complete).
Subsidies for maintenance of existing small landscape elements:

- Stimuleringsregeling onderhoud landschapselementen (SOL)
  - Since 1993
- Subsidieverordening onderhoud landschapselementen Drenthe
  - 2002 – 2007
- Subsidiestelsel Natuur en Landschap (SNL) →Subsidie landschapsbeheer
  - Since 2010
- Almost every province has its own subsidy

Subsidies for the creation of new small landscape elements:

- Vergoeding voor Aanleg Kleine Landschapselementen (KLE)
- Stimuleringsfondsen Erfbeplantingen en Haagbeplantingen
  - Since 2004
- Stimuleringsfonds Bossingels en Houtwallen
  - Since 2005
- Almost every province has its own subsidy

The most important subsidy at the time of writing is Subsidiestelsel Natuur en Landschapsbeheer (SNL) (Lubberink 2011). Figure 4 shows all stakeholders concerned with SNL. Especially the stakeholders in the domain of control services will have many advantages using an automated model that classifies green small landscape elements. To make the flow of communication between stakeholders more clear a management organisation was appointed. In the diagram the management organisation is split in three domains, which consists of the following:

System and Index
Consultation between governments and managers. This is primarily focused on the policy content management system, the Index Nature and Landscape, the Blue Green Catalogue Services and the standard cost system. The 'field' (managers, conservation organisations and interest groups) is well represented here.

Arrangements and DKN
Consultation between provinces themselves. This is about decision-making and implementation of the SNL schemes and the technical management of the Index Nature and Landscape and the Green Blue Catalogue Services. The Digitale Keten Natuur (DKN) was made for a better collaboration between stakeholders. In the DKN relevant processes and information are united and presented in one language, with the same map representation and one monitoring system. It is an unambiguous and uniform information provision for nature policy.

Control Services
Consultation between different governmental organisations themselves. Involved with the technical execution of the system and control of the executive departments.

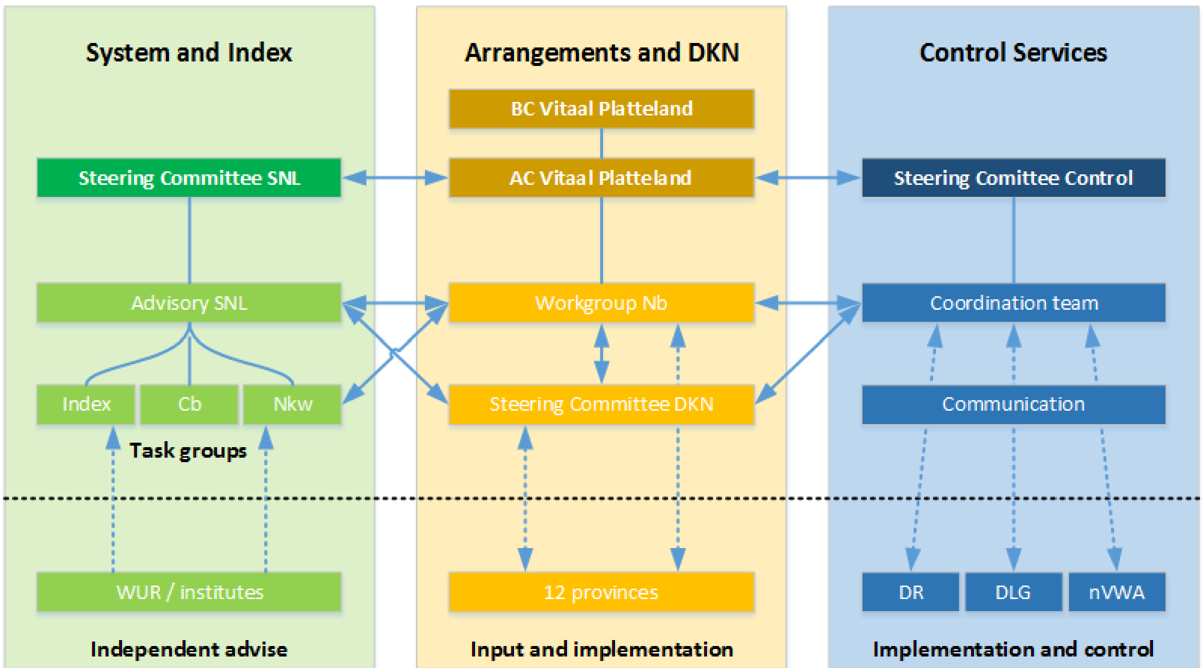


Figure 4: Overview of stakeholders concerned with SNL

All these stakeholders (Figure 4) can benefit from a quantitative dataset containing the green small landscape elements. SNL is part of the European Plattelandsontwikkelingsprogramma (POP2). SNL uses the classes defined by POP2 to grant subsidies. These classes will be used in the model for classifying green small landscape elements. Table 4 shows the SNL classes in relation to the classes that will be used in the model.

Table 4: Relation between SNL classes and the classes defined in the model

SNL class	Model class(es)
L01.02	Wooded bank, shelterbelt
L01.04	Group of trees
L01.06	Hedgerow
L01.07	Lane
L01.13	Solitary tree, tree row

4 Filter

4.1 Introduction

This chapter deals with assumptions and describes the filter framework that is used. Assumptions are made and are of great importance, because the real world is too difficult to be caught into a model. It helps maintain the scope of research. The framework shows the segmentation and classification steps that are needed to identify the green small landscape elements.

4.2 Assumptions

To be able to make a model that can classify defined green small landscape elements, some assumptions are described. They help to define the scope of the model and are made with the Dutch landscape in mind. The following assumptions are taken into account in this thesis research:

1. In a neighbourhood points that meet the condition for a certain height range are considered to be bare earth.
2. The bare earth is in general flat.
3. Man-made objects and natural objects are distinguishable by their roughness: man-made objects by design tend to have smooth surfaces, whereas natural objects tend to be rough.
4. Man-made objects and natural objects are distinguishable by their radiometry (if every point in a point cloud is associated with a reflectance or RGB value).
5. Man-made objects have crisp borders.
6. Man-made objects have a lower NDVI value compared to natural objects.
7. Natural objects have a maximum relative height.
8. Natural objects have a relatively high NDVI value compare to man-made objects and bare earth.
9. Natural objects have fuzzy borders.
10. Solitary trees don't exist within other natural objects.
11. Solitary trees don't touch the boundaries of other natural objects.
12. Solitary trees have a minimal height of 6 metres.
13. When there are more than two solitary trees located closely together, it is classified as a group of trees.
14. A group of trees have a minimum area of 500 m^2.
15. A tree row is greater in length than in width.
16. A tree row with a shrub layer has a width at 1 metre above bare earth.
17. A lane consists of minimal two parallel tree rows.
18. A lane with a shrub layer has a width at 1 metre above bare earth.
19. Points inside closed edges belong to objects.
20. All LiDAR points in a dataset are free of systematic errors.
21. If corresponding first and last returns are spaced far apart, then the first return is an object.

Sithole (2005) made a nice comment in his report, he wrote: "A cursory examination of a point cloud gives the impression that filtering is a relatively simple task. This is because the human cognitive skills and intuition are applied to the task. However, duplicating human cognitive skills and intuition is not simple. The best that can be done is to define and apply simple rules on the radiometry, geometry, and topology of sample points abstracted from the landscape." This shows that simple steps need to be taken in building the model.

4.3 Used filters

Before LiDAR can be used for analysis a few standard layers will be created from LiDAR, these are: digital surface model (DSM), digital elevation model (DEM) and normalised digital surface model (nDSM). As shown in Figure 5 the DSM (a) and DEM (b) have holes in the dataset, this is due to the density of the points. It gives an example of the converted LiDAR data and the interpolated DSM (c) and DEM (d). Therefore another calculation on the dataset is required. It needs a simple interpolation that fills up the spaces.

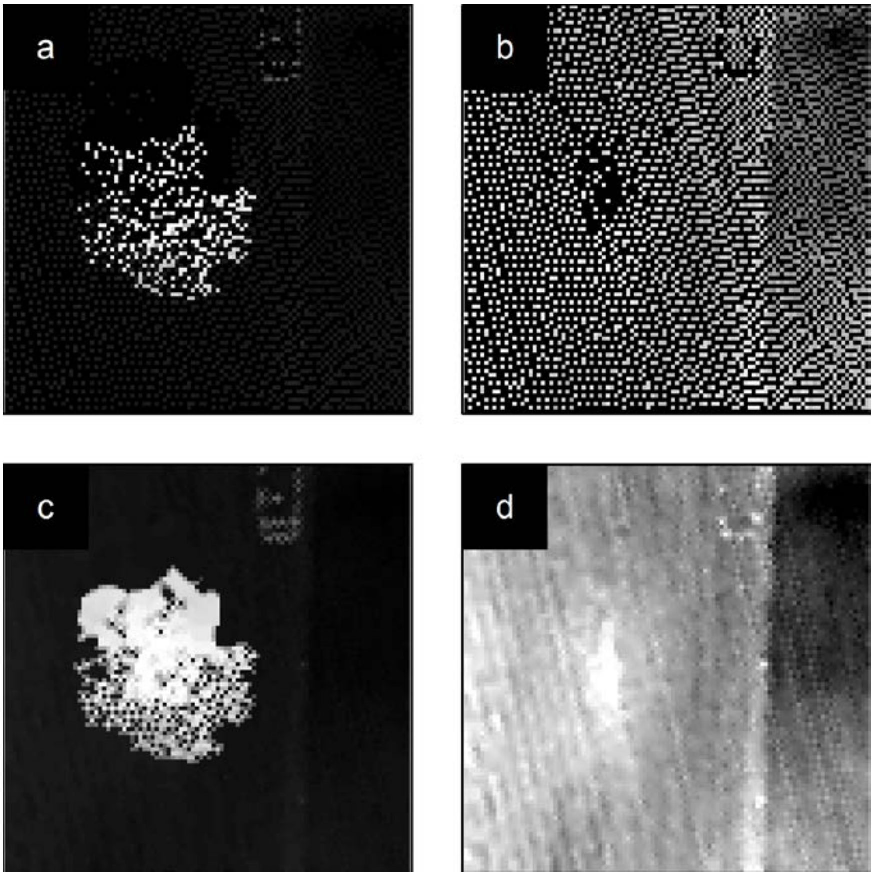


Figure 5: Convert and interpolate: (a) maximum height from all LiDAR returns converted to DSM. (b) average height from all class 2 LiDAR returns converted to DEM. (c) interpolated DSM. (d) interpolated DEM.

The interpolated DEM (d) shows some noise due to density and flight direction. Because bare earth is a continuous surface we can use some filtering for smoothing. Therefore a convolution filter with a Gauss Blur algorithm was used. With this algorithm the kernel size is of importance. The kernel size influences the degree of smoothing, as it defines the box with which the individual pixel is compared as shown in Figure 6. The higher the kernel size, the more the data is smoothed.

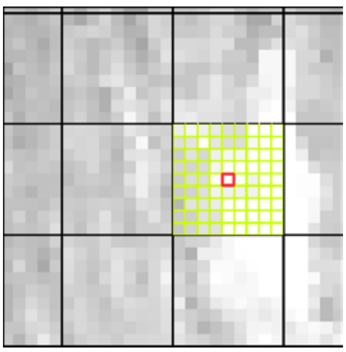


Figure 6: Diagram of kernel size of 9x9.

After testing some parameters of different kernel sizes, as shown in Figure 7, a kernel size of 5x5 (b) was decided on. This is because a kernel size of 9x9 makes the interpolated DEM too smooth. This leads to the disappearance of the variation in height (c). It is, for example, difficult to distinguish hedgerows during classification due to fuzzy borders and smoothing.

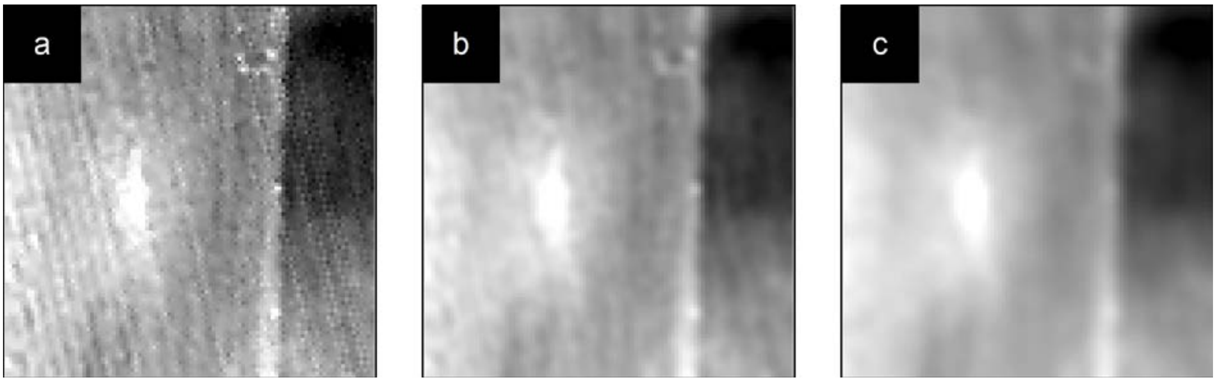


Figure 7: Different kernel sizes: (a) interpolated DEM. (b) smoothed interpolated DEM with a kernel size of 5x5. (c) smoothed interpolated DEM with a kernel size of 9x9.

4.4 Framework

Based on the assumptions an overall filter process is made (Figure 8). The figure shows five steps. Each step does a segmentation on the data and a classification is made.

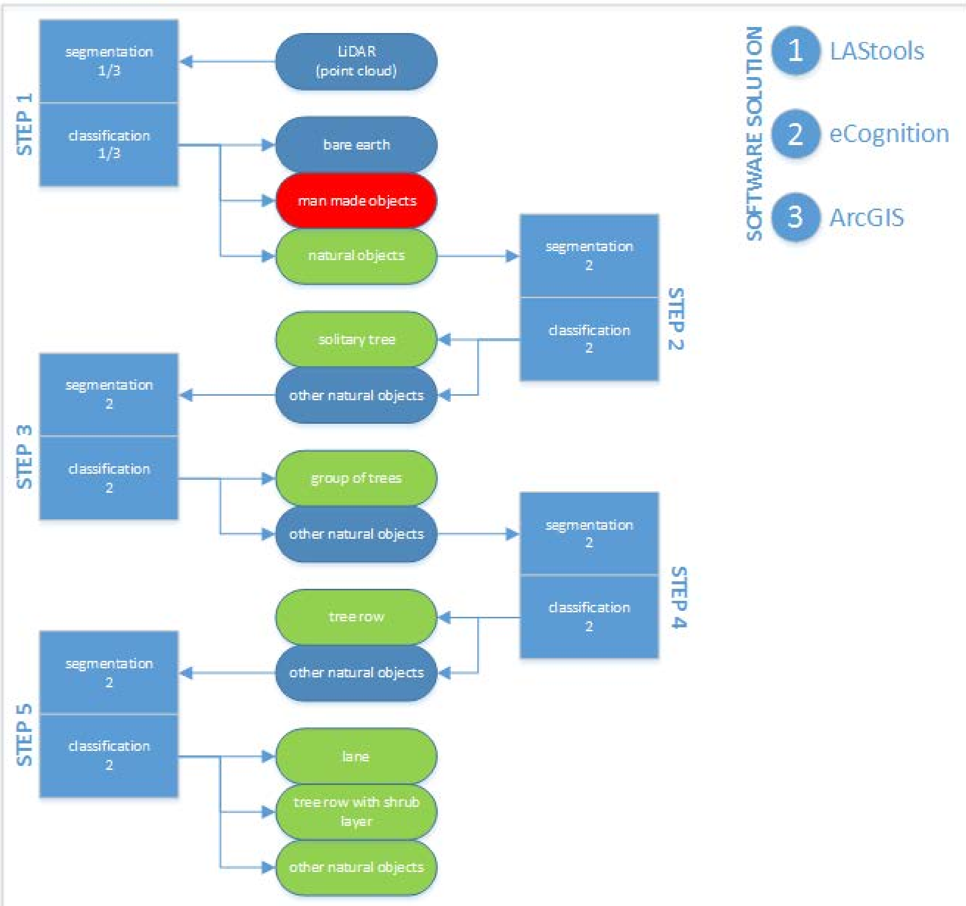


Figure 8: Filter process

For every classification different segmentation procedures are used. The reason to do so will be explained in chapter 5.

5 Segmentation

5.1 Introduction

As stated in the main research question the methodology is based on object-based image analysis (OBIA) instead of pixel-by-pixel image analysis. This is because OBIA can take into account real world situations. A bottom-up segment distinguishes the landscape element from bare earth and man-made objects (Figure 9). These segments are combined to meaningful objects. As you can see in Figure 9c the natural objects are classified as a group of trees and a tree row.

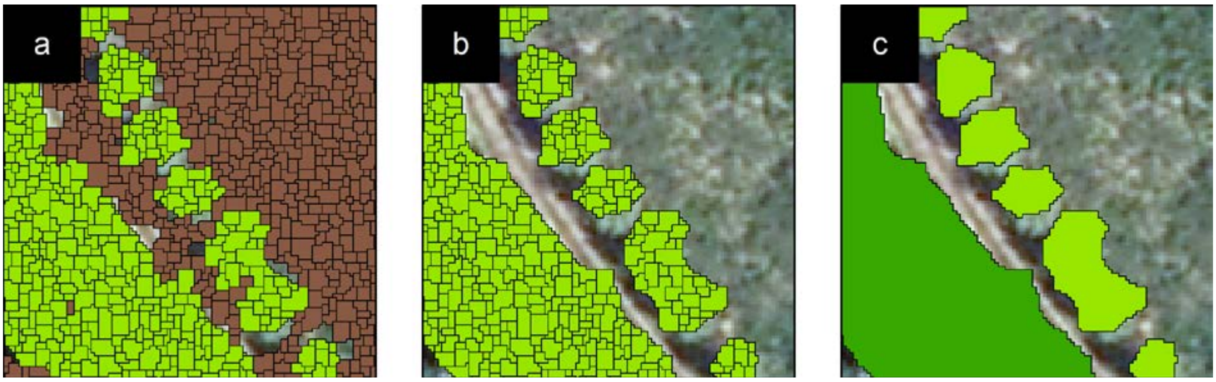


Figure 9: Bottom-up segmentation: (a) bare earth and natural objects. (b) natural objects. (c) group of trees and tree row.

Segmentation refers to the process of partitioning a digital image into multiple segments (set of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Segments are regions which are generated by one or more criteria of homogeneity in one or more dimensions (of a feature space) respectively. Thus segments have additional spectral information compared to single pixels (e.g. mean values per band, and also median values, minimum and maximum values, mean ratios, variance etc.), but of even greater advantage than the diversification of spectral value descriptions of objects is the additional spatial information of objects (Blaschke 2010). Figure 10 shows schematically the relationship between the spatial resolution and an object.

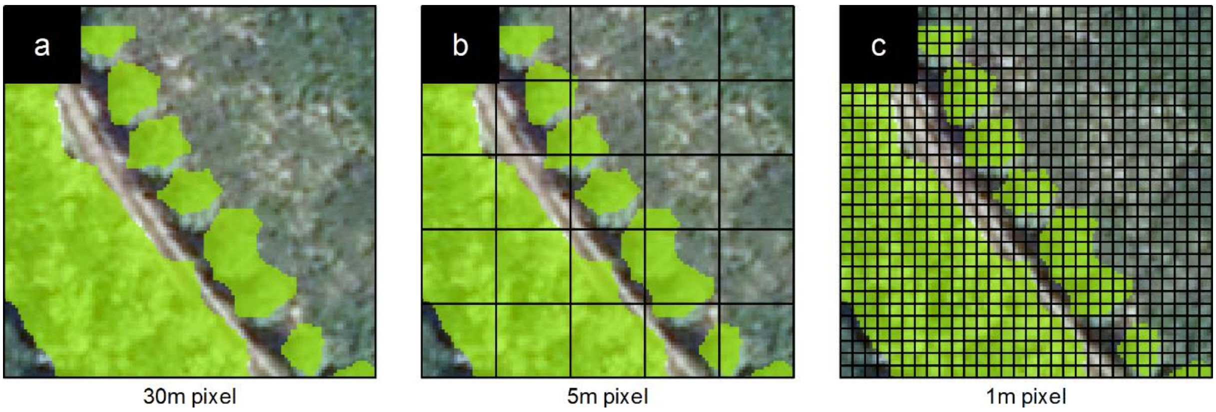


Figure 10: Relationship between objects under consideration and spatial resolution: (a) low resolution: pixels significantly larger than objects, sub-pixel techniques needed. (b) medium resolution: pixel and objects sizes are of the same order, pixel by-pixel techniques are appropriate. (c) high resolution: pixels are significantly smaller than object, regionalisation of pixels into groups of pixels and finally objects is needed (Blaschke 2010).

The next paragraph will describe the used segmentation methods. In this research a combination of methods are used: contrast split segmentation, multiresolution segmentation and the merge algorithm.

5.2 Segmentation techniques

Image objects are typically produced by an initial segmentation. They are based on shape, size, colour, and pixel topology controlled through parameters set by the user. Every step deals with new questions and therefore a combination of methods has been used. By applying the most suitable method for a realistic outcome, a deterministic approach is used. To find the best parameters for these methods and to get the best results, a trial and error process is used to see if the output is close to the real world representation. If this is not the case the parameters are adjusted to get a better outcome or a different method is used. In the eCognition software this process is also referred to as strategy. Figure 11 describes the process for creating a strategy to define a rule set.

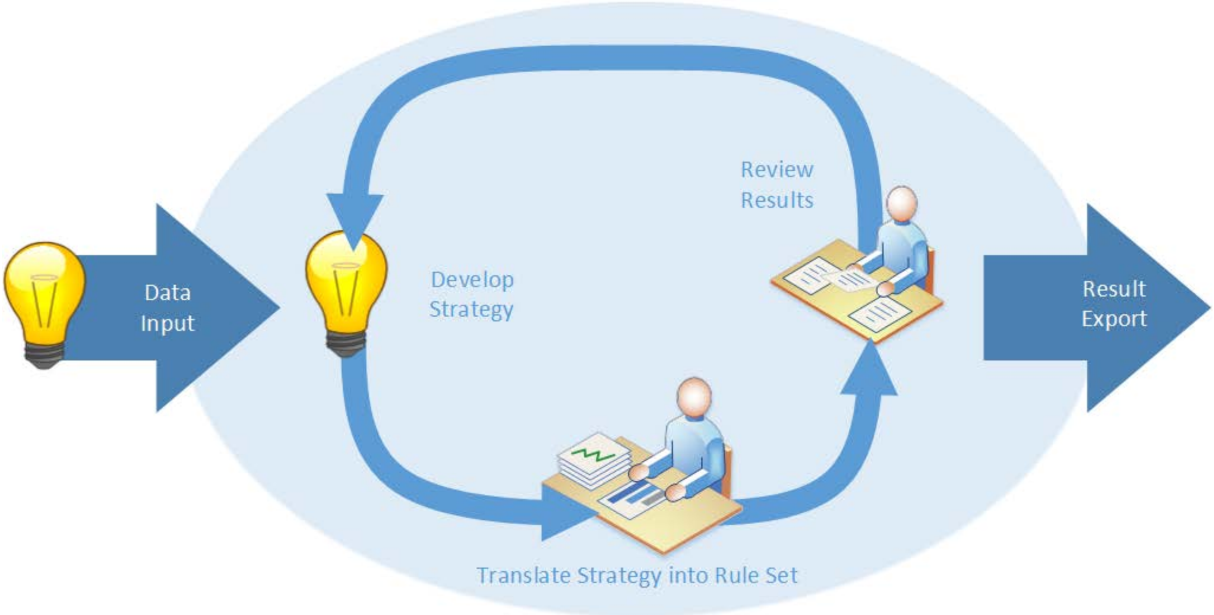


Figure 11: Rule set development

There are quite a few segmentation methods. This chapter deals with the bottom-up, top-down and reshaping algorithms. The three domains have their own methods; an overview of these segmentation methods is given in Table 5.

Table 5: Segmentation methods

Segmentation	Methods
Top-down (TD)	chessboard segmentation
	quadtree based segmentation
	contrast filter segmentation
	contrast split segmentation
Bottom-up (BU)	multiresolution segmentation
	multi-threshold segmentation
	spectral difference segmentation
Reshaping Algorithms (RA)	merge algorithm
	grow algorithm

Top-down segmentation is mostly used when the user already knows what he wants to extract from the image, but he doesn't know how to perform the extraction (Yan 2003). The different methods are shown in Figure 12. For the model contrast split segmentation is used because it is a quick method to divide ground from other objects like natural or man-made objects.

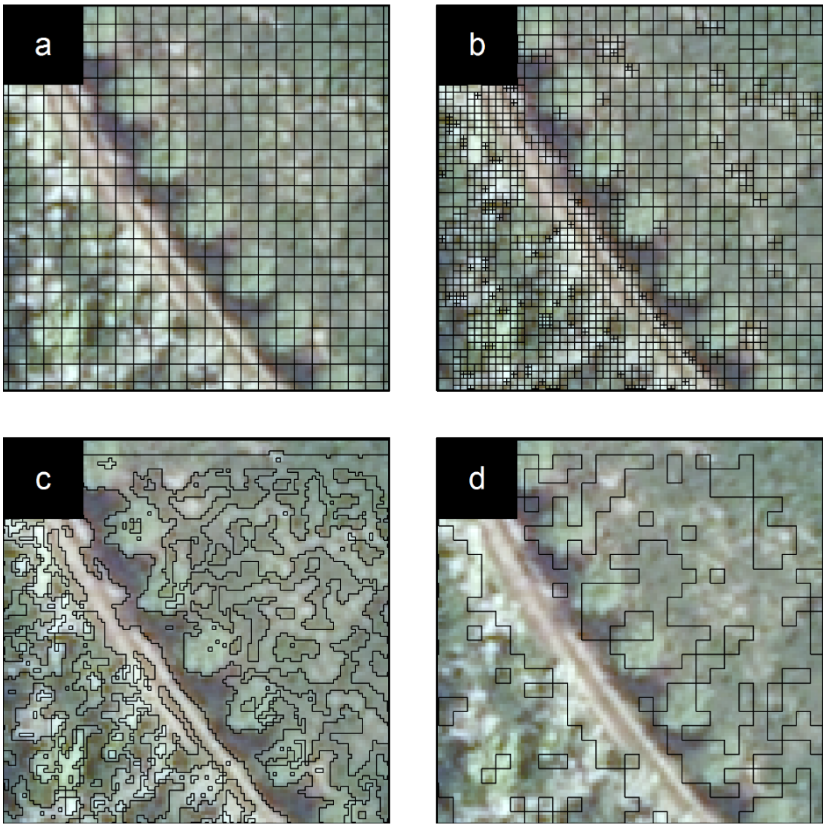


Figure 12: Example of top-down segmentation methods: (a) chessboard segmentation. (b) quadtree based segmentation. (c) contrast filter segmentation. (d) contrast split segmentation.

Bottom-up methods can be seen as a kind of data abstraction or data compression. As with clustering methods, in the beginning the generated segments are only image object primitives. It is up to the user to determine what kind of real world objects the generated image objects represent. Bottom-up methods perform a segmentation of the complete image. It groups pixels to spatial clusters that meet certain criteria of homogeneity or heterogeneity (Yan 2003). Figure 13 shows some examples of the different bottom-up methods. For the model a multiresolution segmentation is used, with this technique it is possible to take into account multiple layers (e.g. NDVI, nir and red band).

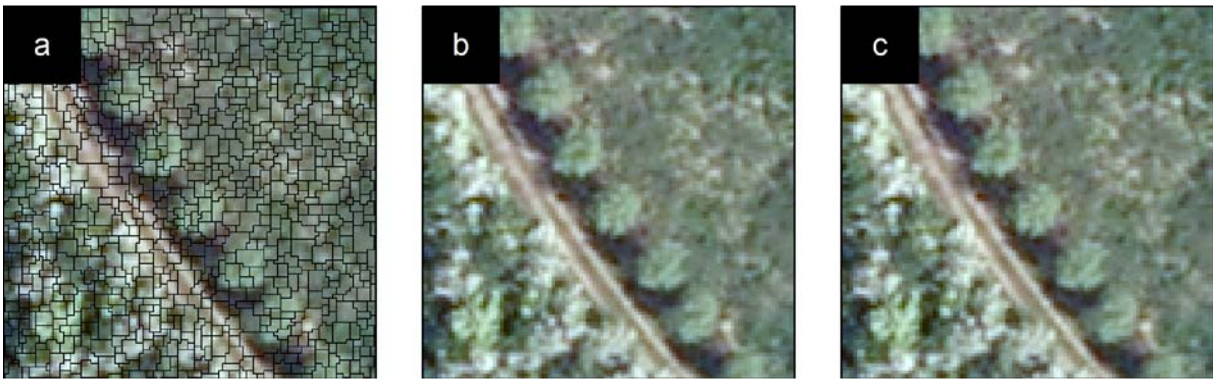


Figure 13: Example of bottom-up segmentation methods: (a) multiresolution segmentation. (b) multi-threshold segmentation. (c) spectral difference segmentation.

Besides the top-down and bottom-up segmentation methods there are reshaping algorithms. Reshaping algorithms cannot be used to identify undefined image objects, because these algorithms require pre-existing image objects. However, they are useful for getting closer to regions and image objects of interest. The merge region algorithm merges all neighbouring image objects of a class into one large object. Classifications are not changed; only the number of image objects is reduced (Trimble 2011). The grow region algorithm extends all image objects that are specified in the image object domain, and thus represent the seed image objects. They are extended by neighbouring image objects of defined candidate classes. Figure 14 shows how the merge and grow algorithm can produce the same outcome from multiple segments within a defined class. For the model a merge algorithm is used, because the segments in the model already have a classification and therefore they need to be merged so that it becomes a meaningful object.

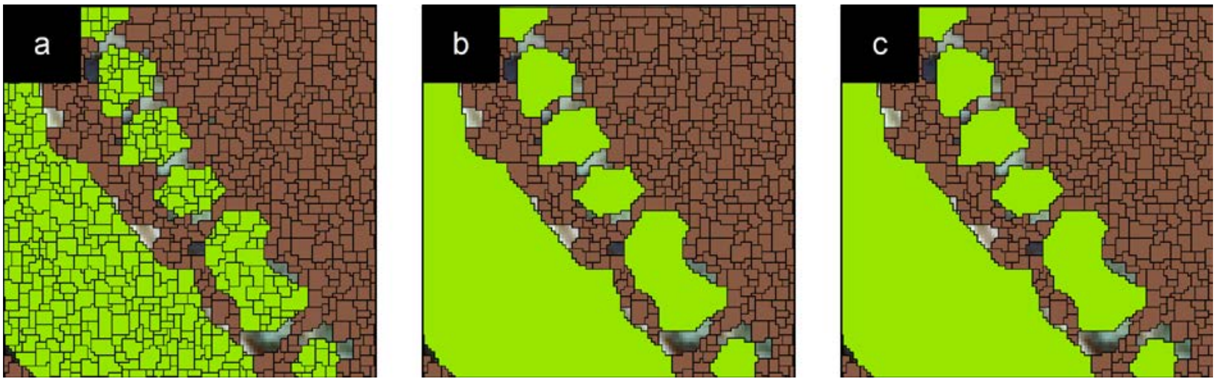


Figure 14: Example of reshaping algorithms: (a) input image for merge and grow algorithms. (b) merge algorithm. (c) grow algorithm.

5.3 Strategy for green small landscape elements

The strategy used for discriminating the green small landscape elements is divided in two parts. The first part of the classification is done with LAStools. LAStools is a collection of highly efficient, batch-scriptable, multicore command line tools (Isenburg 2013). It can handle large datasets with minimum hardware specifications. Processing a LiDAR dataset with the extent of the Netherlands is possible. Three tools are combined to prepare the LAS-dataset and make a first classification. The classification divides the dataset into four categories: bare earth, man-made objects, natural objects and unclassified. Although these are not the final classes I am looking for, the thus extracted natural objects are a good start for further questioning by model in eCognition. The order of usage for the three tools is as follows:

1. lasground
2. lasheight
3. lasclassify

A recent conference paper written by Ryan (2013) describes roughly the same workflow and shows that the software suite from Isenburg (2013) is an effective approach. Lasground extracts bare-earth, it classifies LiDAR points into ground points (class = 2) and non-ground points (class = 1). Lasheight computes the height of each LAS point above the ground. This assumes that grounds points have already been classified (class == 2) so they can be identified and used to construct a ground TIN. Lasclassify is a tool that classifies buildings and high vegetation (i.e. trees) in LAS/LAZ files. This tool requires that the bare-earth points have already been identified (e.g. with lasground) and that the elevation of each point above the ground was already computed with lasheight (which stores this height in the 'user data' field of each point). The tool essentially tries to find neighbouring points that are at least 2 metres (or 6 feet) above the ground and form '-planar 1' (= roofs) or '-rugged 0.1' (= trees) regions (Isenburg 2013). Now that the LAS-dataset is divided into four classes, it is used as input for segmentation. To translate real world information into a strategy for creating a rule set, the values presented by Krause et al. (2010) are combined with SNL rules (Braat 2009) and shown in Table 6. To discriminate green small landscape elements and classify these elements the outcome has to apply to these values.

Table 6: Specifications of green small landscape elements for deterministic modelling

	Feature						
	SNL code	**length (m)**	**width (m)**	**height (m)**	**area (m^2)**	**has tree**	**extra information**
Shelterbelt	L01.02		≥ 1 m ≤ 20 m	0-3 m		No	Has trees
Wooded bank	L01.02		≥ 1 m ≤ 20 m	3-6 m		No	Has trees
Solitary tree	L01.13	n/a	n/a	≥ 6 m		Yes	
Tree row	L01.13	≥ 100 m	≤ 20 m	≥ 6 m		Yes	≥ 8 trees / 100 m One row at most. If there is more than one row the object is seen as a lane.
Lane	L01.07	≥ 100 m	≤ 20 m (per tree row)	≥ 6 m		Yes	≥ 8 trees / 100 m Two rows at most. If there are more than two rows the object is seen as a group of trees.
Group of trees (line)	**L01.04**	**n/a**	**≤ 20 m**			**Yes**	Natural objects with variable heights.
Group of trees (grove)	L01.04	n/a	> 20 m		500 m^2	Yes	Natural objects with variable heights.

The LAS output from lasclassify is used as an input in eCognition. The software is able to convert the LiDAR to a raster dataset. Furthermore, it is possible to create new datasets from the LiDAR point attribute information. Based on the newly created datasets rule sets are created and applied for classification. A more detailed description of the rule sets and their parameters is described in chapter 6. Developing a rule set is an iterative process and therefore it is wise to start with the class that has the most significant features.

5.4 Optimal object size for contrast split segmentation

After preprocessing is done with LAStools the LiDAR data is ready for usage in eCognition. The next step is segmenting the LiDAR data. Therefore, a contrast split segmentation is used. This is done on the normalised digital surface model. The nDSM is important for detecting green small landscape elements. The height is used for discriminating natural objects from bare earth. During contrast split segmentation, of the areas of interest in Chaam, the algorithm has an option to set an object size. The object size is equal to a pixel and is in this case 25 centimetres. As concluded by Addink et al. (2007) it is quite difficult to find the optimal object size parameter. To find the optimal object size a trial and error method was used.

Figure 15 shows an area of interest with different sized natural objects. When we look at the number of segments, using an object size of 1, the number of segments is much higher than the object to be classified. It is important to find an object size where the natural objects are still detected and the number of segments is as low as possible. As can be seen in APPENDIX II finding the optimal object size is done by running the contrast split segmentation with different settings. Looking at all the graphs a minimal threshold of 10 is picked. It gave the best result on all areas of interest.

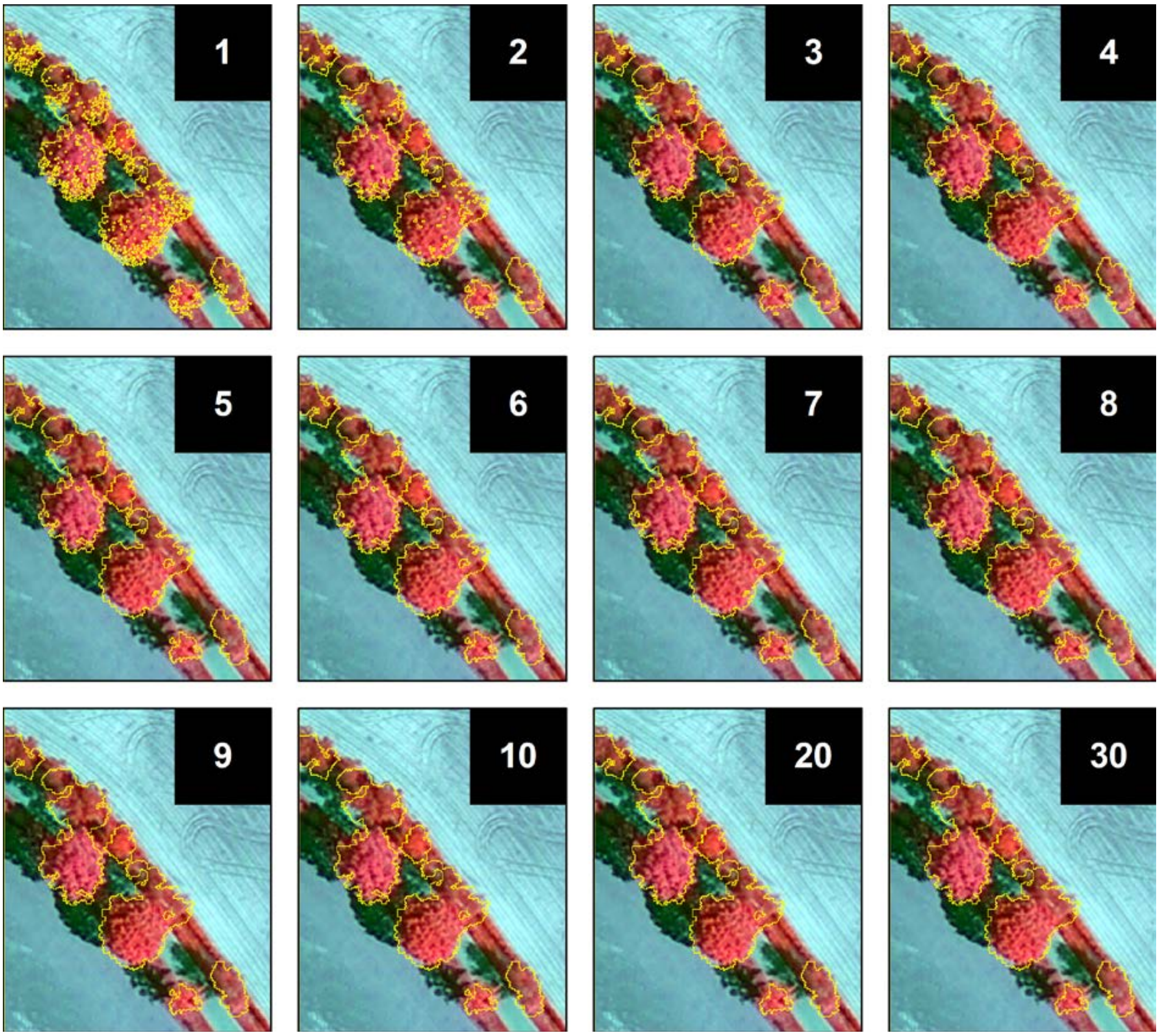


Figure 15: Example of contrast split segmentation with differen object sizes (indicated in the upper right corner) overlaid on a false colour image (NIR-R-B).

5.5 Discussion

In an ideal situation the power of LAStools and eCognition's deterministic approach are combined for a segmentation model. But because LiDAR is still not mainstream, the followed approach is good enough to answer my question. In the near future it is most likely that good LAS support will be built in to the major software packages. Packages from Esri are already showing support, but it is still under construction. Although LAStools is a very stable and powerful software suite, I sometimes had difficulty finding references for better understanding of the tools. In eCognition the wide variety of rule sets and options makes it hard to create a model. Because the goal is not to build the best model, but to have a working model for LiDAR and one for LiDAR in combination with false colour image, the combination of LAStools and eCognition satisfies.

6 Classification

6.1 Introduction

This chapter describes the parameters used for classifying the green small landscape elements. A total of ten areas of interest (AOI) are used. It will discuss what to use as a surface model and how to calculate this surface model. Analysis of the outcome is not described in this chapter and will be described in chapter 7.

6.2 Detecting natural objects with segmentation

Before a classification of green small landscape elements can be done, a few preprocessing steps on the LiDAR dataset needs to be done. As stated in paragraph 5.3 lasground is used to extract the bare earth and lasheight is used to compute the relative height. The computed height is also used to drop points above 60 metres. During the same preprocessing step of lasheight the z-value can be replaced with the computed relative height value. This is done to normalise the dataset. The same processing step is also made in eCognition so that it can be processed in one software package. After these steps the LiDAR dataset is ready to be classified, so that it can detect green small landscape elements and classify these elements. For segmentation there are several options. The contrast split segmentation is used to detect edges between low and high pixels. The contrast split segmentation algorithm segments an image or image object into dark and bright regions (Figure 18b and c). It is based on a threshold that maximizes the contrast between the resulting bright objects (consisting of pixels with pixel values above the threshold) and dark objects (consisting of pixels with pixel values below the threshold).

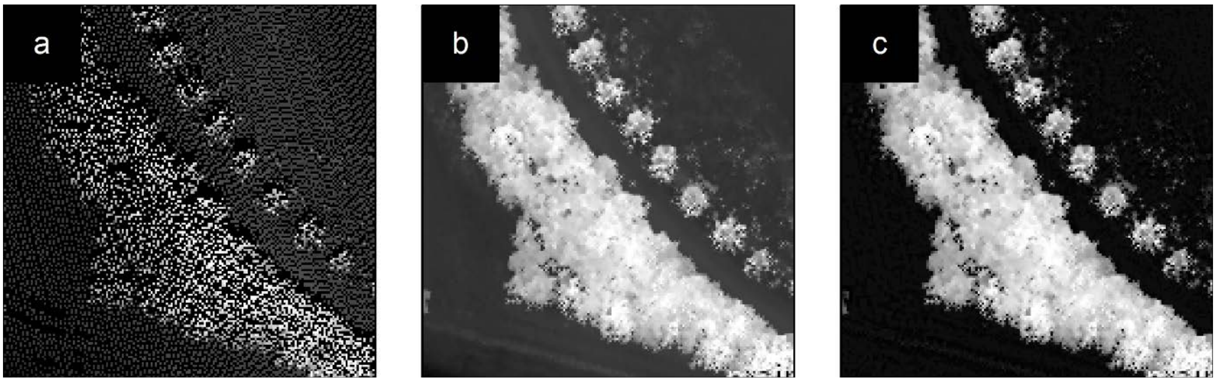


Figure 16: DSM: (a) DSM with cell size of 0,25m. (b) interpolated DSM (iDSM) with cell size of 0,25m. (c) normalised DSM (nDSM) with cell size of 0,25m.

In this case the bright values have a relative high elevation value and the dark values have a relative low elevation value. The high values are natural objects and the low values are bare earth. The algorithm uses the interpolated DSM (Figure 16b) with a cell size of 0,25m as input. By converting the LiDAR 1st return maximum elevation values a DSM is created (Figure 16a). Contrast split segmentation is tested on two different normalised digital surface models (nDSM).

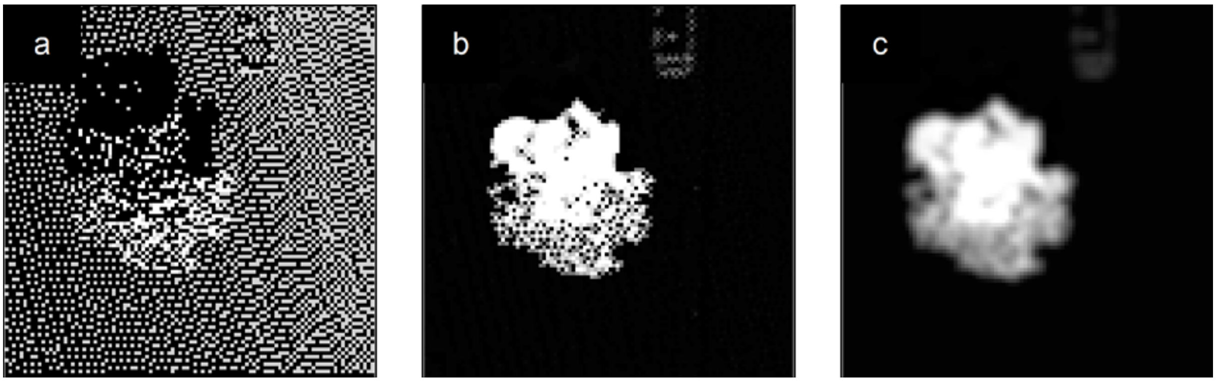


Figure 17: nDSM: (a) DSM with cell size of 0,25m. (b) nDSM. (c) smoothed nDSM.

The first nDSM (Figure 17b) is based on the following calculation; iDSM – iDEM_smooth5 = nDSM, the second calculation uses smoothing for both datasets; iDSM_smooth5 – iDEM_smooth5 = nDSM_smooth (c). In contrast to bare earth the surrounding of solitary trees is not a continuous surface.

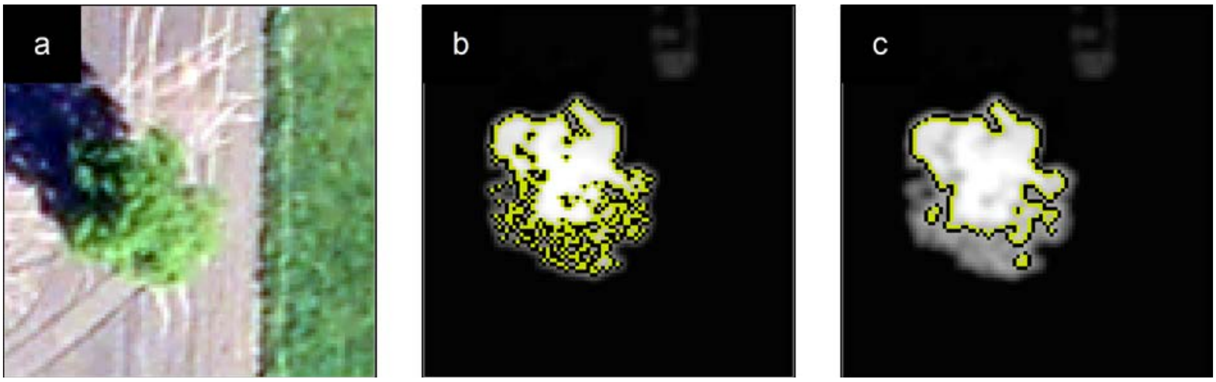


Figure 18: Contrast split segmentation: (a) true colour image. (b) contrast split segmentation on nDSM. (c) contrast split segmentation on smoothed nDSM.

The reason for not using the smoothed nDSM is because all the values at the edge of a tree crown are averaged with the bare earth. A comparison of the contrast split segmentation on both nDSM (Figure 18b and c) shows us that (b) gives us a more realistic outcome. Therefore it is clear that nDSM is the better one. During the processing of LiDAR a lot of small objects are created as can be seen in Figure 19a.

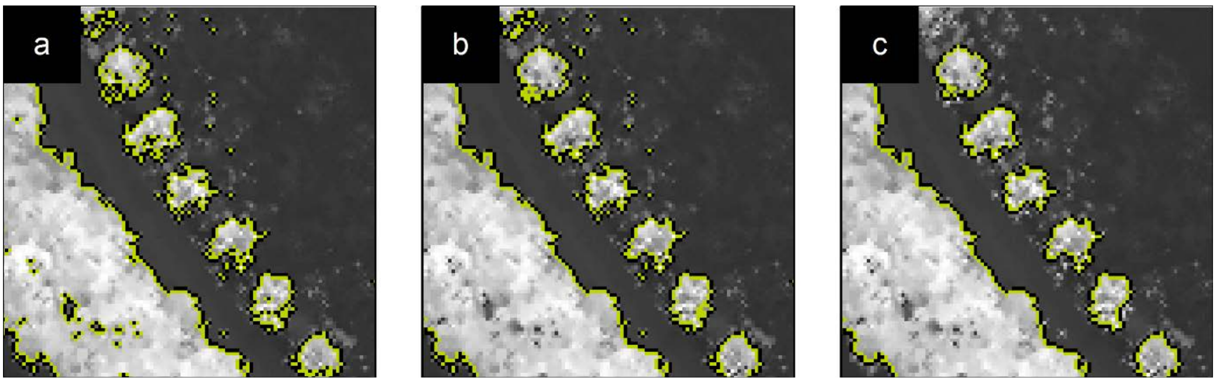


Figure 19: Remove and merge small objects: (a) interpolated DSM with cell size of 0,25m and showing contrast split segmentation boundary including small objects. (b) small objects within the natural objects are removed and merged. (c) small natural objects are removed and merged.

There are small unclassified objects within the natural objects (see Figure 19) and furthermore small natural objects that are too small. In the model the threshold for the smallest area is set to 3 m^2. These objects are cleaned up by removing the pixels based on area and merging these areas within the natural objects and unclassified objects (c).

6.2.1 Detecting solitary trees

Based on area and height solitary trees are separated from the natural objects and are classified. The area of the segment needs to be higher than 6 m and exceed 100 m^2. Figure 20 shows a classification of a solitary tree. In the upper right corner there is an object with a height below 6 metres and is therefore not classified.

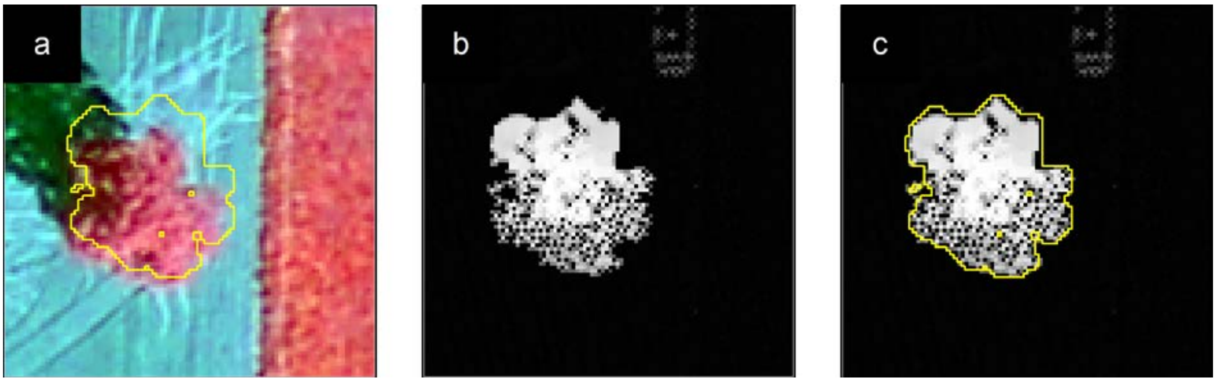


Figure 20: Classification of solitary tree (AOI 1)

In Figure 21a two trees standing next to each other with adjoining crowns are classified as one object. Because the object does not exceed the parameters of the object class solitary tree, these two trees are classified as a solitary tree. As can be seen in (b) and (c) it shows some surrounding vegetation with a height beneath 6 metres. The problem of this classification lies in the count of objects. This problem could be solved by using tree crown detection as described by Pouliot et al. (2002). For future research this technique could be added for better classification of trees with adjoining crowns.

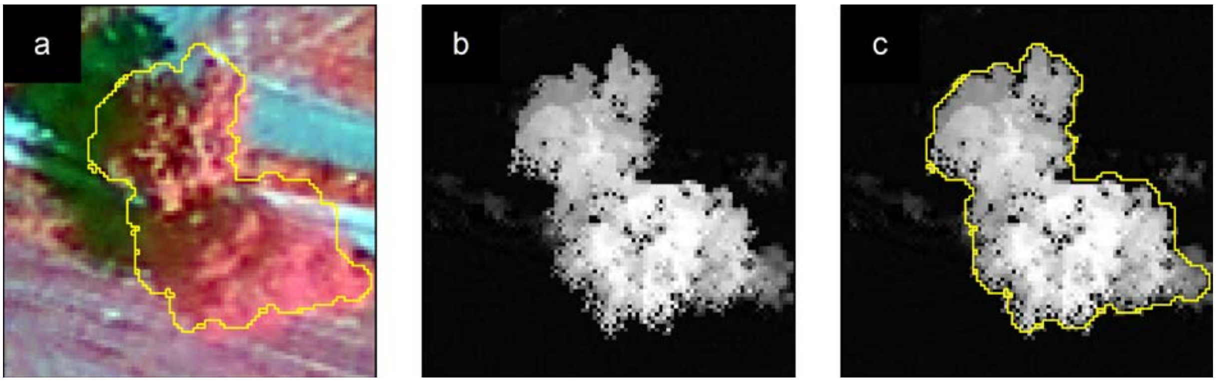


Figure 21: Classification of solitary tree (AOI 3)

Again two solitary trees are shown in Figure 22. Yet again they are classified as one object; solitary tree. In the lower left corner there are minor objects that are not relevant for detecting the solitary tree. These objects are not in the area of interest that is chosen.

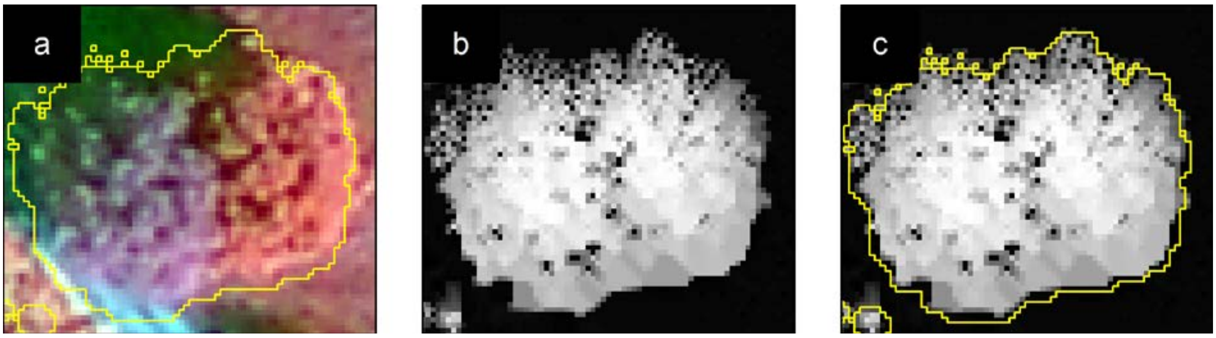


Figure 22: Classification of solitary tree (AOI 6)

Figure 23 shows one solitary tree at the border of the area of interest. The object is classified correctly.

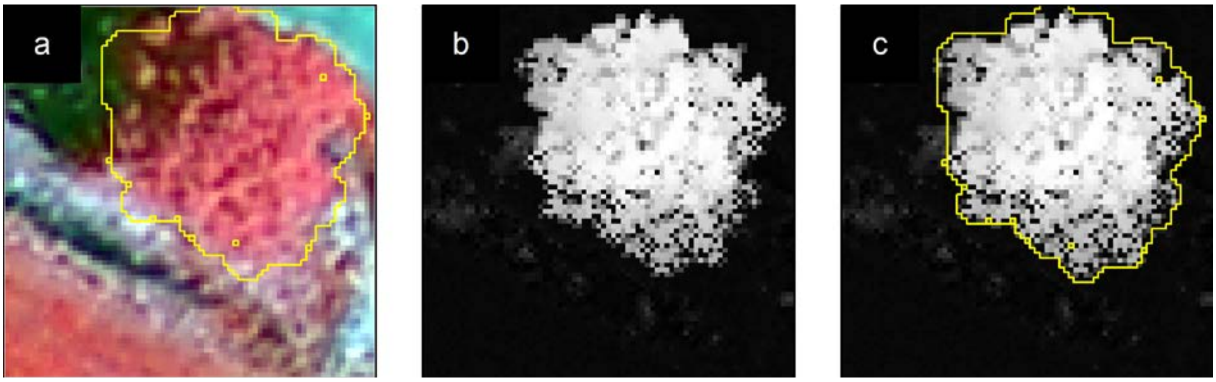


Figure 23: Classification of solitary tree (AOI 10)

The last area of interest with a solitary tree is shown in Figure 24. A small part of the crown of a tree is visible in the lower left corner. This tree is outside the area of interest. Because it almost touches with the solitary tree, they are classified as one object.

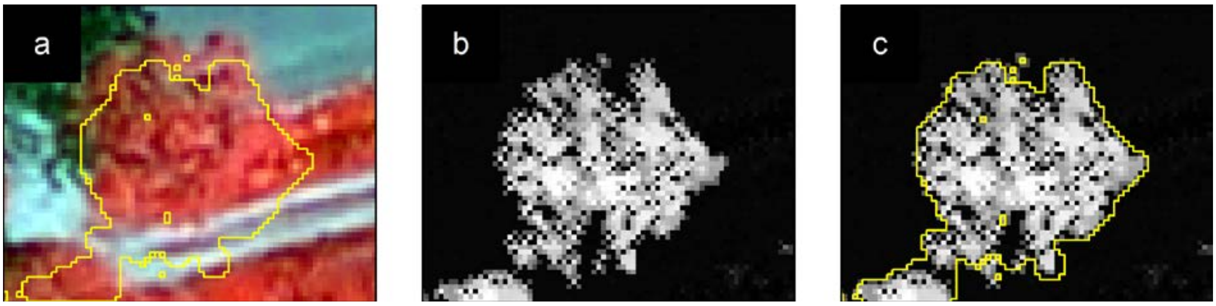


Figure 24: Classification of solitary tree (AOI 19)

6.2.2 Detecting tree row

A tree row can spatially be described as multiple solitary trees that stand in a line. The trees can be separated, but can also have touched boundaries. Therefore two different rules were created. There must be at least 8 trees per 100 m. It can have one row at most. If there is more than one row the object is seen as a lane. The line of trees will be digitised with a width of one metre. The first rule is for separated trees that form a tree row. The boundaries of the trees are not allowed to exceed 5 m and the number of solitary trees is greater than 8 individual trees.

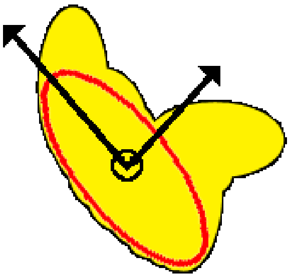


Figure 25: Radius of largest enclosed ellipse

The second rule is for a tree row where the tree crowns touch each other. In such cases the area should be larger than 500 m^2 and the object needs to be wider than 10 m. During processing it became clear that another value needs to be taken into account for better discrimination between a tree row and a group of trees. This is done by setting a threshold for the radius of the largest enclosed ellipse (Figure 25). It uses the following expression for calculating the ratio of the radius: $\varepsilon v(xo, yo)$. Figure 26 shows a tree row where the boundaries of the tree crowns touch each other, visually it shows us a line of trees.

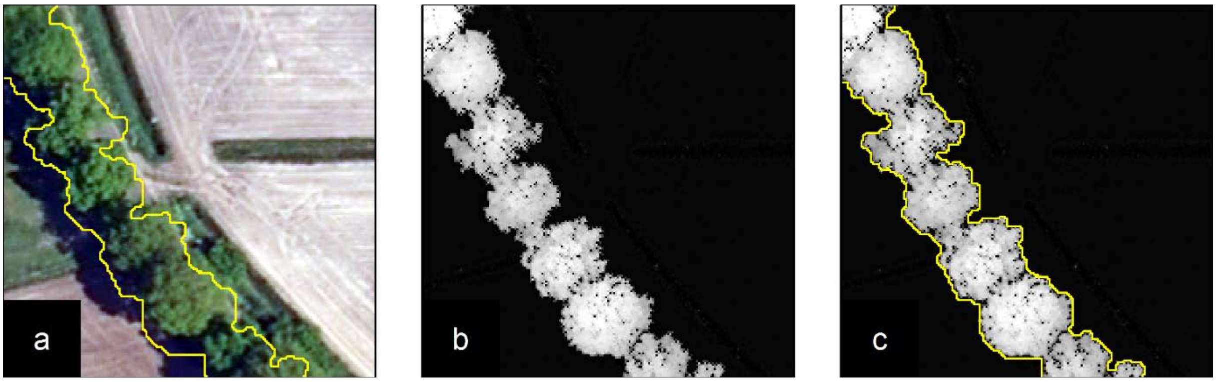


Figure 26: Classification of tree row (AOI 14)

The tree row in Figure 27 looks somewhat detached. But according to several methodologies it is a tree row. This can be difficult to classify in larger areas.

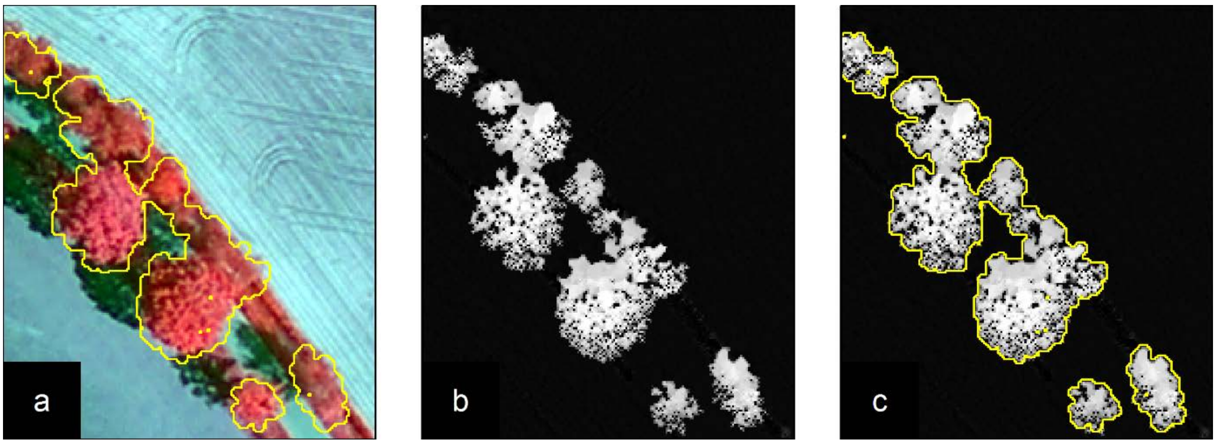


Figure 27: Classification of tree row (AOI 24)

In the last area of interest three trees in line are visible. Following SNL methodology as described by Braat (2009) it would not be considered as a tree row. This is due to geometric parameters as can be seen in Table 6. Trees are only classified as a tree row when the length has a minimum of 100 metres, a height above 6 metre and a minimum of 8 trees. In the Chaam dataset there were no areas of interest for tree rows that met the SNL criteria. Therefore, the number of trees parameter was adjusted from

8 to a minimum of 4 trees in the model. By adjusting the length parameter in the model it was classified as a tree row.

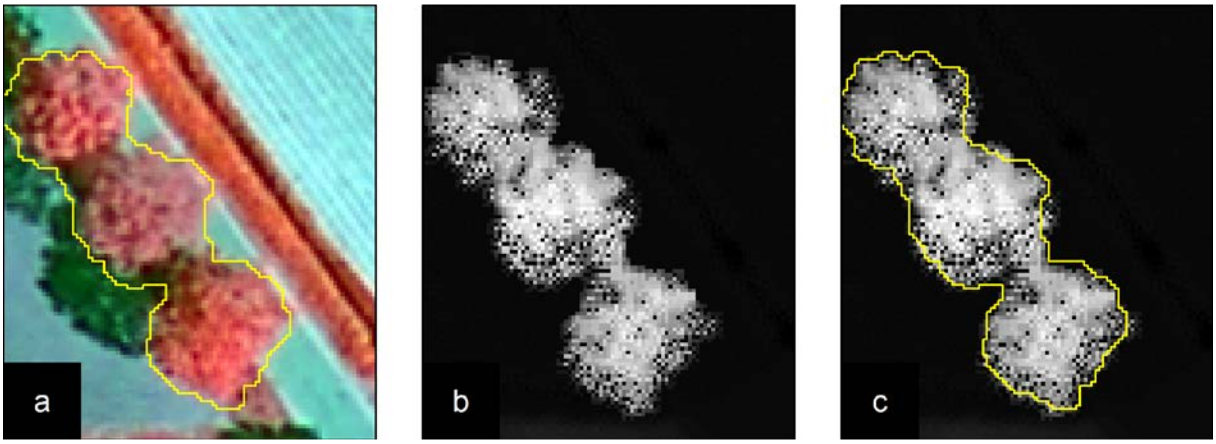


Figure 28: Classification of tree row (AOI 25)

6.2.3 Detecting lane

A lane consists of multiple tree rows. A lane has a tree row at each side of a road. It can be a driving road, but also a footpath is possible.

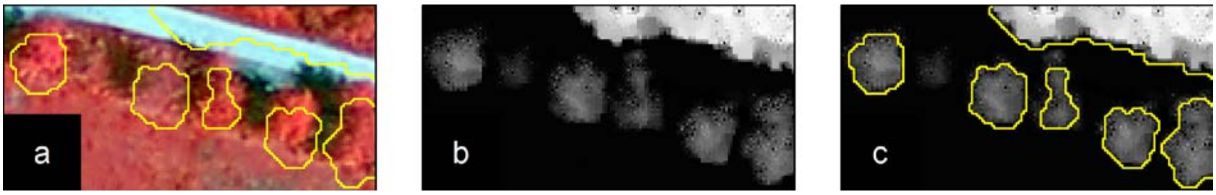


Figure 29: Classification of lane (AOI 12)

The model classified the objects in Figure 29 as a tree row. Two tree rows on each side of the road is the condition for the classification of a lane. The road which is clearly visible in the false colour image is not visible in the nDSM. By adding topographic information from top10nl the roads can be made visible. This is likely an important attribute for the classification of a lane. Due to time shortage it was not possible to improve the model for better results. Therefore, the class is dropped. Ideally it would look something like Figure 30.


Figure 30: Examples of a lane

6.2.4 Detecting group of trees

As described in paragraph 6.2.2 a radius of the largest enclosed ellipse is used to discriminate between a tree row and a group of trees. Combined with a minimum area threshold of 500 m^2 and a width of 20 m group of trees are detected.

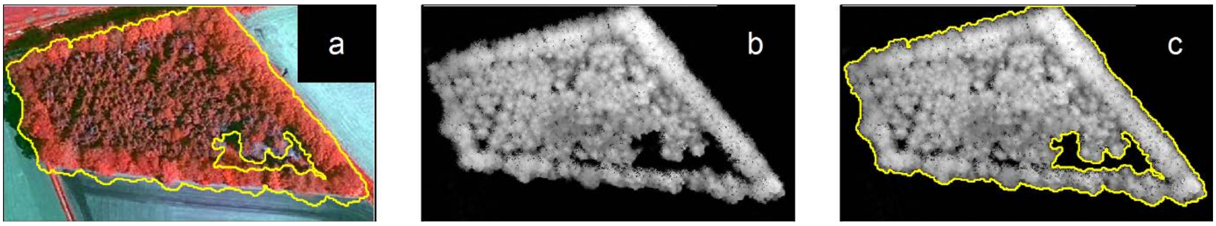


Figure 31: Classification of a group of trees (AOI 18)

Figure 31 shows a group of trees with an open spot in the lower left area. Around the group of trees there seem to be a deciduous tree row. This was not anticipated for in the model.

6.3 Detecting natural objects with LiDAR combined with a false colour image

For detecting natural objects with LiDAR combined with a normalised difference vegetation index (NDVI), the same model as for LiDAR only is used, but adding an extra rule that the average NDVI of the object should be positive. NDVI is derived from a false colour image and uses the near infrared and red band. The NDVI is calculated as follows:

$$NDVI = \frac{nir - red}{nir + red}$$

NDVI is used to identify vegetated areas and their "condition", and it remains the most well-known and used index to detect live green plants. The NDVI value is added for distinguishing natural objects from man-made objects. In APPENDIX III the results can be seen. The NDVI does not have an added value in areas where there are only natural objects compared to LiDAR, but it is very useful in areas where there are man-made objects, such as buildings as can be seen in the Wageningen dataset.

What can be learned from the two different models is that with LiDAR combined with NDVI some shifting appears within some of the AOI's. This has to do with orthorectification and the viewing angle of the sensor.

6.4 Discussion

With LiDAR it is quite easy to separate the dataset on a vertical level. As seen with areas of interest of Chaam it gives us a nice first outcome. The borders of the natural objects follow nicely the distinction between a natural object and bare earth. When we look at the usage of LiDAR combined with NDVI of the Chaam area we see little difference in outcome as shown in APPENDIX III. There are a few AOI's that show a small displacement between LiDAR and NDVI. There are two reasons that can explain this: first the false colour image is not orthorectified and second there is a difference of a year between the two datasets. For the Wageningen UR area a bigger difference is expected because of the presence of man-made objects.

7 Results and validation

7.1 Introduction

In this chapter the outcome of the results from the classification of LiDAR and LiDAR combined with NDVI is discussed. The classified LiDAR dataset of Chaam is compared with field measurements done by an expert using a laser distance meter. A visual comparison of the LiDAR combined with NDVI is conducted. And lastly a validation of the model is conducted. This is done by making use of a different location. The location that is used for validation lies around the Wageningen UR, see Figure 2. The outcome of the classification of green small landscape elements is validated by using an error matrix. From the matrix it is possible to calculate user, producer and overall accuracy as described by Congalton (1991).

7.2 Results Chaam – LiDAR

A regression analysis is done to see whether the calculated maximum height of trees from the LiDAR dataset have a correlation with measurements done in the field. This is needed because the height is an important parameter in the model and therefore we must see whether it is valid to use or not.

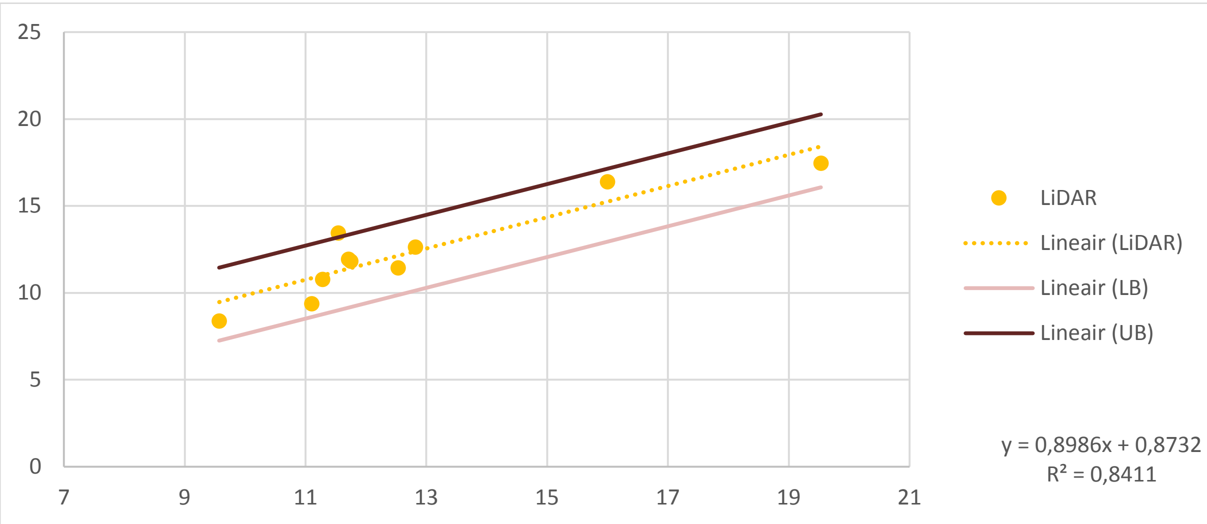


Figure 32: Linear regression

Figure 32 shows a R^2 of 0,84 and when we look at the 95 % of the data it is clear that there is one major outlier. This concerns AOI 03, see APPENDIX I. The fact that the R^2 is not closer to 1 is due to the fact that the LiDAR data was gathered in early spring when no leaves are present (Mücher et al. 2010). Also field measurements are more error-prone because it is difficult to maintain the exact same method for measuring objects that have a difference in height. Now that the LiDAR is checked with field measurements and the correlation looks good, classification based on height is reliable.

7.3 Results Chaam – LiDAR combined with NDVI

Anticipating on the fact that when the model is used for detecting green small landscape elements on a smaller scale, it is assumed that there are man-made objects. These need to be taken into account when running the model. To do this a normalized difference vegetation index (NDVI) derived from a false colour image is used. The NDVI is a simple numerical indicator that can be used to analyse remote sensing measurements, and assess whether the target observed contains live green vegetation or not. Live green plant appear relatively bright in the near infrared (Krause et al. 2010). Looking at the ten areas of interest of Chaam little difference on object level is noted between a LiDAR only model and a LiDAR combined with a NDVI model. This is because there are no man-made objects in the areas of interest. A comparison of the outcome of the models can be found in APPENDIX III

7.4 Comparison of results

Looking at the ten areas of interest (AOI) that were also used for the LiDAR only model some differences in size and area are visible. Especially for AOI 01 and 19 there is a 21,7 % and 15,7 % of change respectively. The number of objects and classes of the objects were maintained. The reason that there is a discrepancy between LiDAR and NDVI is due to the fact that the false colour image that is used for calculating the NDVI is not orthorectified. Especially for the areas that have a wider angle. An orthorectified image refers to an aerial or satellite image that has been corrected for terrain and/or satellite viewing perspective (Tucker et al. 2004). Figure 33 gives an example of the misplacement due to the angle. The same accounts for the false colour images that are used for Chaam and Wageningen UR area.

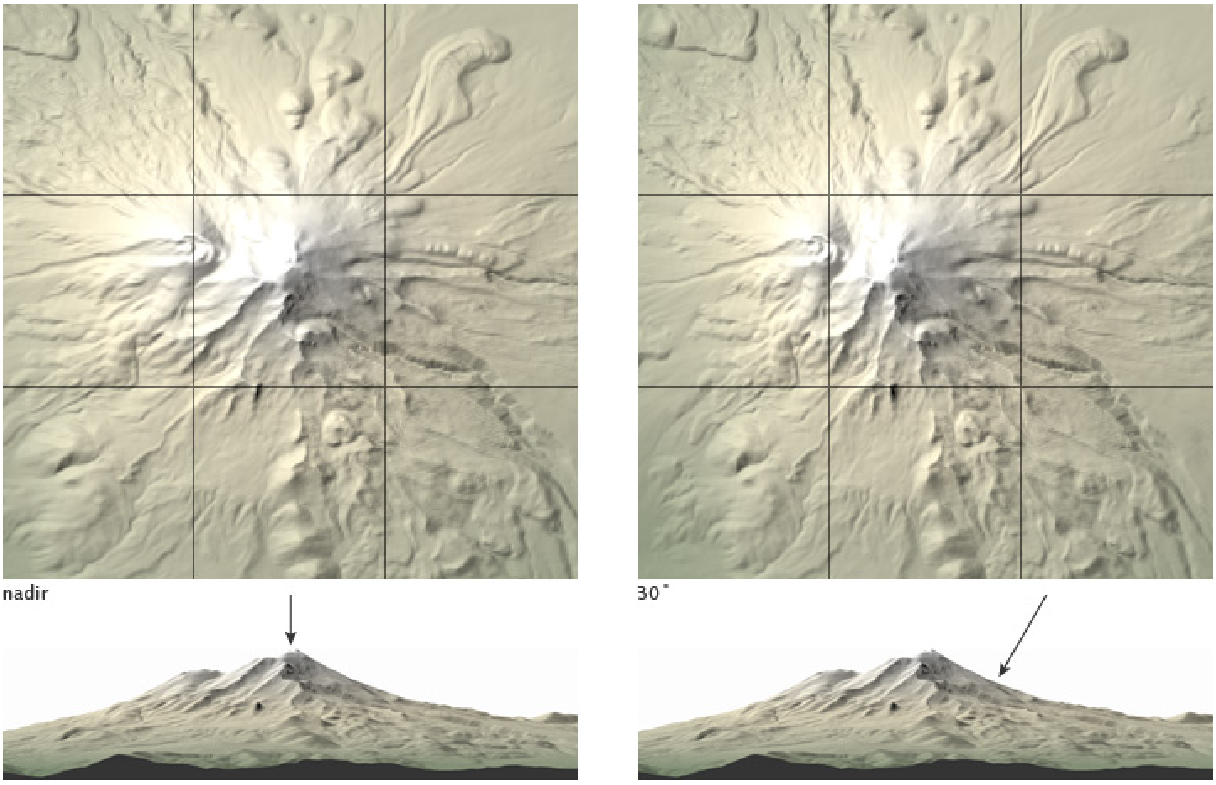


Figure 33: Example of an image before (right) and after (left) orthorectification (NASA Earth Observatory images by Robert Simmon, based on the USGS National Elevation Dataset).

7.5 Validation with Wageningen dataset

To validate the model a different area with small green landscape elements is used, this is the area around Wageningen UR. At forehand I made a classification of this area into the three accounted classes. To classify the image information the false colour image was combined with the normalised digital service model. This way it was possible to filter out the trees with a minimal height of 6 metres. From the classified objects a random selection was made for calculating the accuracy. A minimal of five objects per class was chosen and where possible more objects within the class were selected. See Table 7 for the number of objects per class. To validate the model, the user, producer and overall accuracy is calculated for the three classes. Table 7 shows the calculated accuracies.

Table 7: User, producer and overall accuracy of LiDAR model

	solitary tree	tree row	group of trees	**SUM**
solitary tree	21	3	0	**24**
tree row	1	1	0	**2**
group of trees	0	2	5	**7**
SUM	**22**	**6**	**5**	**33**
producer accuracy	95,45%	16,67%	100,00%	
user accuracy	87,50%	50,00%	71,43%	
overall accuracy	81,82%			

As can be seen in the table above, the solitary trees have a high producer and user accuracy as expected. Almost all random selected trees are recognised. This is because the solitary tree usually stands alone and does not have interference from other man made and/or other natural objects. This is also the reason for a wrong classification of one of the solitary trees, as can be seen in Figure 34. This solitary tree was classified as a group of trees because the tree crown touches the boundary of the surrounding natural objects.

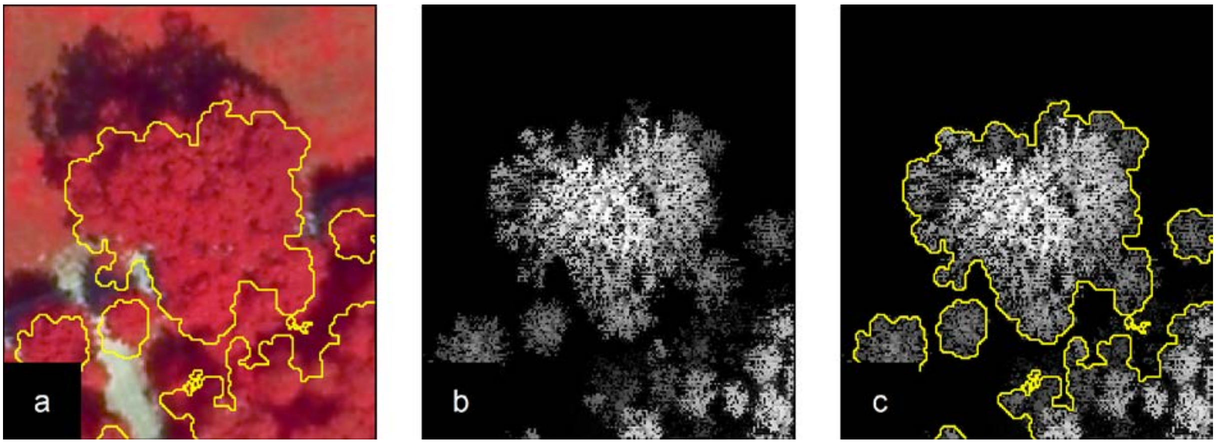


Figure 34: Misclassification of a solitary tree due to touching tree crowns

At this moment the classification of a tree row is the most difficult class to classify. This is due to two reasons. The first reason is that multiple objects in line are not connected and therefore they are not seen as a tree row. They are classified as solitary trees. And the second reason is when the boundaries of the trees touch each other and especially when they are connected to a group of trees the tree row is seen as an element of that class. The tree row is then classified as a group of trees. In the Chaam dataset this problem did not arise because the areas of interest were carefully chosen with a minimal of neighbouring objects.

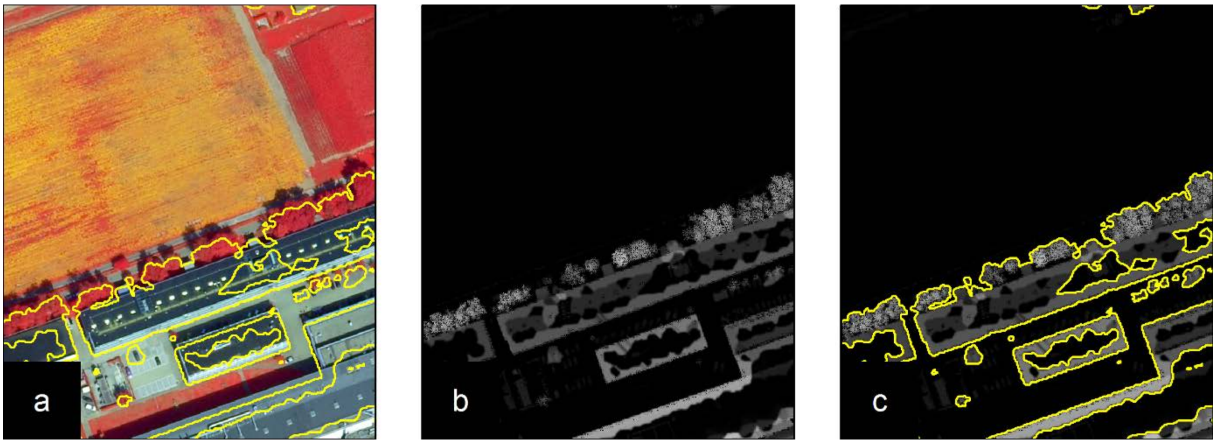


Figure 35: Misclassification of a tree row due to man-made object and unconnected objects

Figure 35 shows a tree row alongside a man-made object. First of all the man-made object is wrongly classified as a natural object and therefore everything is classified as a group of trees. It is clear that the outcome of a LiDAR only model has too many errors with man-made objects as can be seen in Figure 36. With the classification of group of trees there were also problems with the man-made objects. Because height and area is importantfor the classification of group of trees the man-made objects are falsly classified as group of trees because they meet the criteria in the model. In the error matrix the outcome looks good, this is because the group of trees are classified together with man-made objects. Therefore, another model was made were NDVI derived from a false colour image is taken into account and filters out the man-made objects.

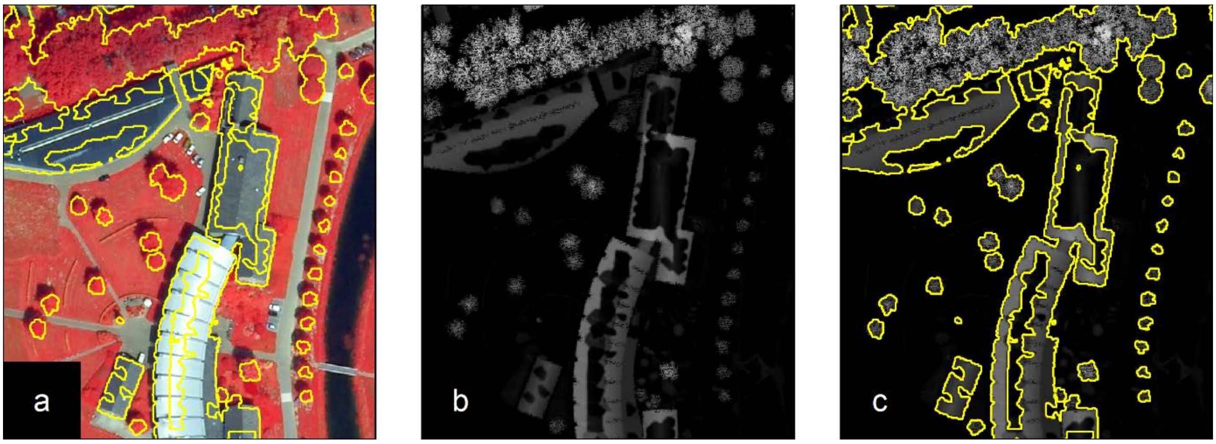


Figure 36: LiDAR only model had difficulties with man-made objects and classifies them as natural objects

Table 7 shows the variance in number of objects per class. Therefore a normalized error matrix is made. An iterative proportional fitting procedure is used, which forces each row and column in the matrices to sum to one. In this way the classes are more balanced (Congalton 1991).

Table 8: Normalised accuracy of LiDAR model

	solitary tree	tree row	group of trees	**SUM**
solitary tree	0,7508	0,2491	0,0000	**1,0000**
tree row	0,3010	0,6991	0,0000	**1,0000**
group of trees	0,0000	0,0856	0,9144	**1,0000**
SUM	**1,0000**	**1,0000**	**1,0000**	**3,0000**
normalised accuracy	78,81%			

As said before a normalised accuracy of 78,81% looks very nice, but after visual inspection it shows us that the man-made objects are seen as natural objects. This needs to be addressed because the man-made objects need to be filtered out. So that the results are more realistic and credible. This is why a second model is made where NDVI is taken into account. Figure 37 shows a part of the classified area where we can see how the NDVI filters out the man-made object. When we compare this to Figure 36 a big difference in classification is seen.

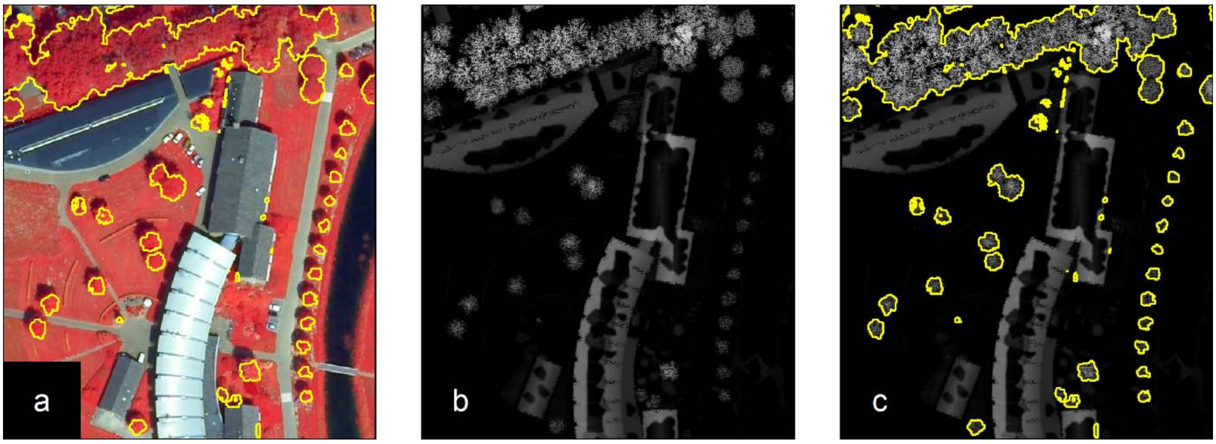


Figure 37: LiDAR combined with NDVI has a much better classification of the objects, it filters out the man-made objects.

When we compare the results of classification of green small landscape elements in both models there is little difference on object level. However, Figure 38 shows that there is a big improvement on filtering out the man-made objects and therefore the calculated accuracies have more value. Due to the low amount of objects in the area there is no difference to be found between the control dataset and the results of the model. The error matrix for the model combined with NDVI shows that there is on object level no difference with the LiDAR only erorr matrix and has no influence on the outcome. And therefore, it is not shown.

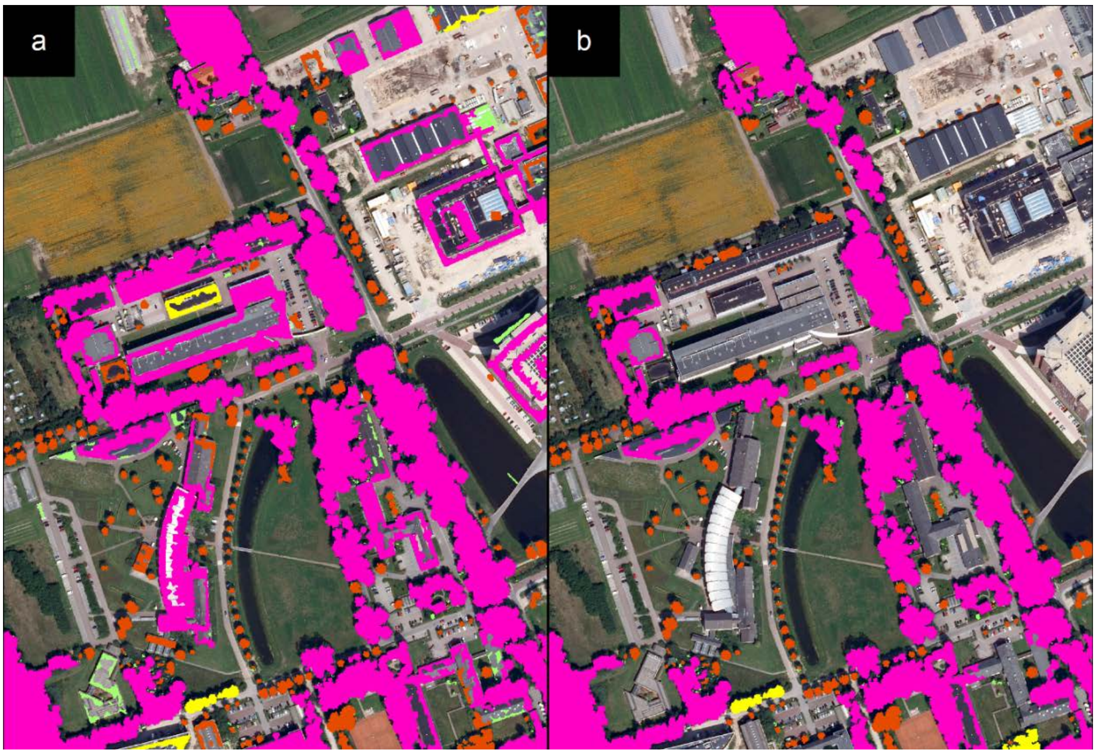


Figure 38: Classification results: (a) LiDAR model. (b) LiDAR combined with NDVI

7.6 Discussion

It is clear that NDVI has an added value to the classification accuracy of green small landscape elements. This is because when the image has man-made and natural objects, it is possible to use NDVI for filtering out the objects that are man-made. The accuracy of the classification of solitary trees and especially the classification of group of trees becomes higher with NDVI. Tree rows are still difficult to classify correctly. With the use of NDVI there is a small amount of error in filtering out man-made objects. I suspect this is due to natural objects (e.g. moss) growing on the roofs of buildings which led the NDVI classify the buildings as natural objects. Furthermore, it was quite clear that the used false colour image for calculating the NDVI was not orthorectified it still had an added value when working on the Wageningen UR area.

Validating the model with the Wageningen UR area also showed the impact of the datasets that were at my disposal. It showed that classification becomes more difficult when the area for classification is bigger and has many more neighbouring objects. Because of the carefully picked areas of interest in the Chaam dataset the problem with neighbouring objects was less of a problem.

8 Conclusion and future work

8.1 Conclusion

In this thesis the following research question was formulated:

Is it possible to automate a classification model for green small landscape elements with an object-based approach on LiDAR data, making use of segmentation?

To answer the research question three sub-questions were stated, namely:

1. Can segmentation techniques be used to classify green small landscape elements?
2. How accurate is the model?
3. Is the accuracy improved when combining a NDVI derived from a false colour image with LiDAR data?

Firstly, the sub-questions will be discussed and after that the main research question will be answered. Secondly, the results of this research will be discussed and compared to other research that studies object-based image analysis by making use of segmentation. Lastly, some directions for future research will be given.

Can segmentation techniques be used to classify green small landscape elements? As is shown in chapter 5 and 6 segmentation techniques form an essential part in the model to classify green small landscape elements. By using contrast split segmentation, multiresolution segmentation and a merge algorithm important steps were made in identifying green small landscape elements. So yes, segmentation techniques can be used to classify green small landscape elements. But it needs to be combined with other techniques to maximise its potential. It is an on-going process to determine what combination of techniques and rulesets is needed to classify a certain object. Compared to a pixel based classification where no segmentation is used, it shows that the information retrieved with an object-based image analysis approach is able to take into account numerous datasets of different types. This shows that segmentation technique is more powerful and has better potential on classifying objects.

How accurate is the model? And is the accuracy improved when the LiDAR data is combined with NDVI? As shown in Table 8 the normalised accuracy of the LiDAR data model is 78,81%. The accuracy is improved when NDVI is added to the model, because the NDVI filters out man-made objects as can be seen in Figure 38. Unfortunately the result of the LiDAR only model is biased due to man-made objects seen as natural objects. The error matrix of the models did not show a difference (therefore the second error matrix of LiDAR combined with NDVI was not shown), this is probably due to the fact that the man-made objects are not taken into account in the error matrix. For future work this needs to be included so that the accuracy is more representative.

With the results of the research I conclude that it is possible to automate a classification model for green small landscape elements, but that there are still problems that need to be solved. The model shows promising outcomes. At this moment it is not yet possible to create a national dataset, but the steps that were made in this research are a good starting point.

The results of this research show that LiDAR is a very promising technique for classifying green small landscape elements. It is very accurate and therefore ideal for classification on a high level of detail. Combined with a NDVI image the accuracy is much improved, especially for areas with man-made objects, as shown with the Wageningen UR area. Detecting solitary elements is also easy. As shown in Table 7 the LiDAR only model classifies 21 of the 22 solitary trees correctly. Combined with the NDVI the accuracy on object level stays the same. Group of trees are also 100% correctly classified. The model has however problems with classifying tree rows where the tree crowns do not touch each other. To solve this an extra rule has to be added to the model that helps with linking objects that lie in near proximity of each other. The solution lies with the detection of tree crowns and object linking.

Tree crown detection is very useful for counting objects. By counting objects the rules that oblige for tree rows can be set narrower. There are also tree rows that need to be linked, so that the number of links can be taken into account and used as a parameter for classification.

Other research shows promising results in the detection of tree crowns. For example, the research of Tiede et al. (2006) about single tree crown delineation. A core element of Tiede's approach is the possibility to break down regions to pixel sized objects. After the break down a new supervised build-up of objects can be performed. Tiede et al. (2006) developed specific rule-sets to do this. In these rule-sets a region growing segmentation algorithm is programmed using a continuity constraint starting from tree tops (local maxima) as seed points.

The techniques that Tiede et al. (2006) used, could help to better identify tree rows (and lanes) because it helps in linking objects together. Unfortunately, this research came to my attention in the final process of this thesis. Therefore, it was not possible to add a region growing algorithm to the model.

8.2 Future work

For an improved model with better outcomes and more classes for detection, more research needs to be done on object linking. This should tackle the problem that came up for detecting tree rows and solitary trees. It is also clear that more research on crown detection is necessary. Already in a few areas of interest it became clear that the model classifies an object as one solitary tree when it actually consists of two trees with adjoining crowns. By making use of the tree crowns this can be avoided.

For every object that needs to be classified a different rule-set and correct parameters needs to be defined through a process of trial and error. Considering this, it could be possible to build up a sort of library in which the different rule-sets/algorithms are stored. For every new dataset it would be possible to select out of the library the best fitting rule-set/algorithm, this is also described by Tiede et al. (2006)

More research is needed on topographic layers and see how they can help in classifying green small landscape elements. It is already clear that with a lane there is a link with a road. So when a dataset is incorporated into the model with roads it can help in detecting lanes.

From the results of my research it became clear that the use of orthorectified false colour images gives the best results when NDVI is added to the model. A better fitting of the tree crowns with LiDAR is then possible.

References

Addink, E.A., de Jong, S.M., & Pebesma, E.J. (2007). The importance of scale in object-based mapping of vegetation parameters with hyperspectral imagery. *Photogrammetric Engineering and Remote Sensing, 73*, 905-912

Baas, H., Mobach, B., & Renes, H. (2005). *Leestekens van het landschap*. Utrecht: Landschapsbeheer Nederland

Baret, F., Clevers, J.G.P.W., & Steven, M.D. (1995). The robustness of canopy gap fraction estimates from red and near-infrared reflectances: A comparison of approaches. *Remote Sensing of Environment, 54*, 141-151

Blaschke, T. (2010). Object based image analysis for remote sensing. *Isprs Journal of Photogrammetry and Remote Sensing, 65*, 2-16

Braat, C. (2009). Index Natuur en Landschap. In M.v. LNV (Ed.)

Bradbury, R.B., Hill, R.A., Mason, D.C., Hinsley, S.A., Wilson, J.D., Balzter, H., Anderson, G.Q.A., Whittingham, M.J., Davenport, I.J., & Bellamy, P.E. (2005). Modelling relationships between birds and vegetation structure using airborne LiDAR data: a review with case studies from agricultural and woodland environments. *Ibis, 147*, 443-452

Bunce, R.G.H., Metzger, M.J., Jongman, R.H.G., Brandt, J., De Blust, G., Elena-Rossello, R., Groom, G.B., Halada, L., Hofer, G., Howard, D.C., Kovar, P., Mucher, C.A., Padoa-Schioppa, E., Paelinx, D., Palo, A., Perez-Soba, M., Ramos, I.L., Roche, P., Skanes, H., & Wrbka, T. (2008). A standardized procedure for surveillance and monitoring European habitats and provision of spatial data. *Landscape Ecology, 23*, 11-25

Burrough, P.A., & McDonnell, R.A. (1998). *Principles of geographical information systems*. New York: Oxford University Press Oxford

Carson, W.W., Andersen, H.E., Reutebuch, S.E., & McGaughey, R.J. (2004). LiDAR Applications in Forestry – An Overview. In

Congalton, R.G. (1991). A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sensing of Environment, 37*, 35-46

Fernandez-Juricic, E., & Jokimäki, J. (2001). A habitat island approach to conserving birds in urban landscapes: case studies from southern and northern Europe. *Biodiversity and Conservation, 10*, 2023-2043

Flood, M. (2001). Laser altimetry: From science to commercial lidar mapping. *Photogrammetric Engineering and Remote Sensing, 67*, 1209-1218

Graf, R.F., Mathys, L., & Bollmann, K. (2009). Habitat assessment for forest dwelling species using LiDAR remote sensing: Capercaillie in the Alps. *Forest Ecology and Management, 257*, 160-167

Hill, R.A., Smith, G.M., Fuller, R.M., & Veitch, N. (2002). Landscape modelling using integrated airborne multi-spectral and laser scanning data. *International Journal of Remote Sensing, 23*, 2327-2334

Isenburg, M. (2013). LAStools - efficient tools for LiDAR processing. Version 130213, http://lastools.org. In

Korpela, I., Koskinen, M., Vasander, H., Holopainen, M., & Minkkinen, K. (2009). Airborne small-footprint discrete-return LiDAR data in the assessment of boreal mire surface patterns, vegetation, and habitats. *Forest Ecology and Management, 258*, 1549-1566

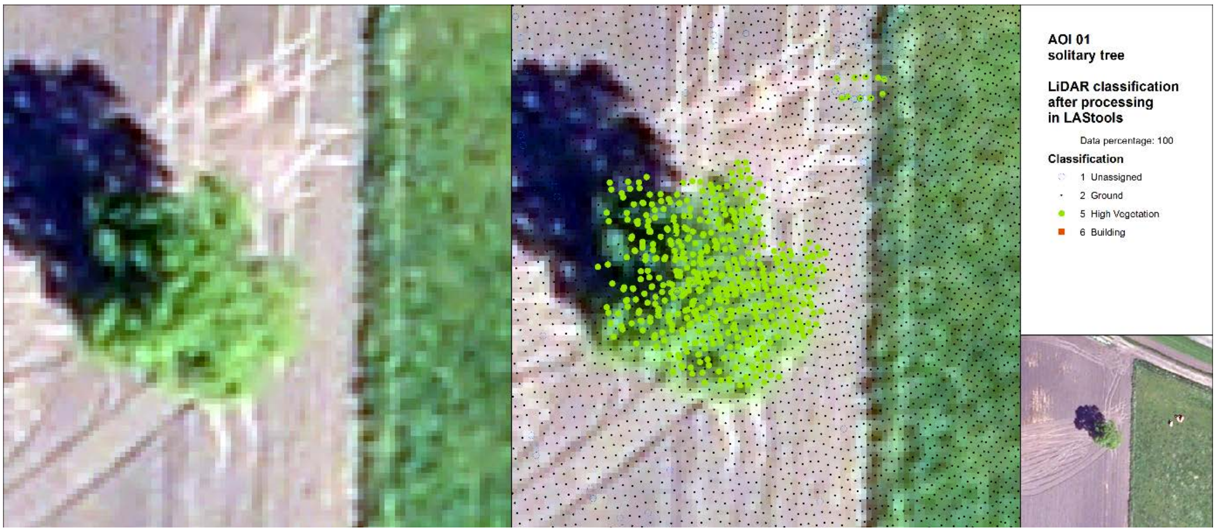
Krause, A.U.M., Danes, M.H.G.I., Janssen, H., Kramer, H., & Rip, F.I. (2010). Recording small landscape features with object recognition; Possibilities and limitations of automated procedures to support monitoring in the of the GeoCAP. In (p. 86). Wageningen: Alterra

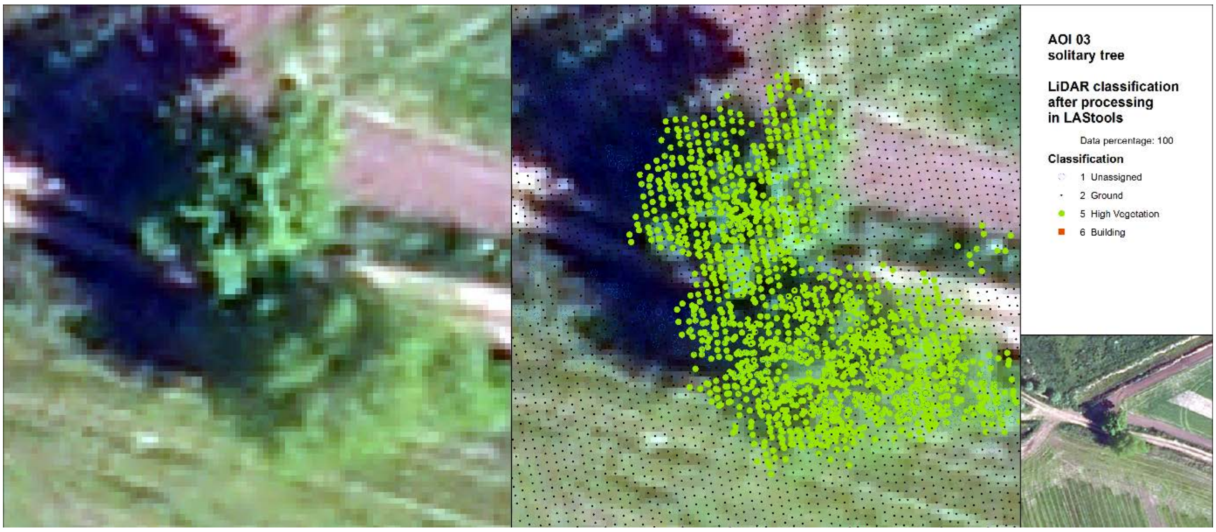
Lefsky, M.A., Cohen, W.B., Parker, G.G., & Harding, D.J. (2002). Lidar remote sensing for ecosystem studies. *Bioscience, 52*, 19-30

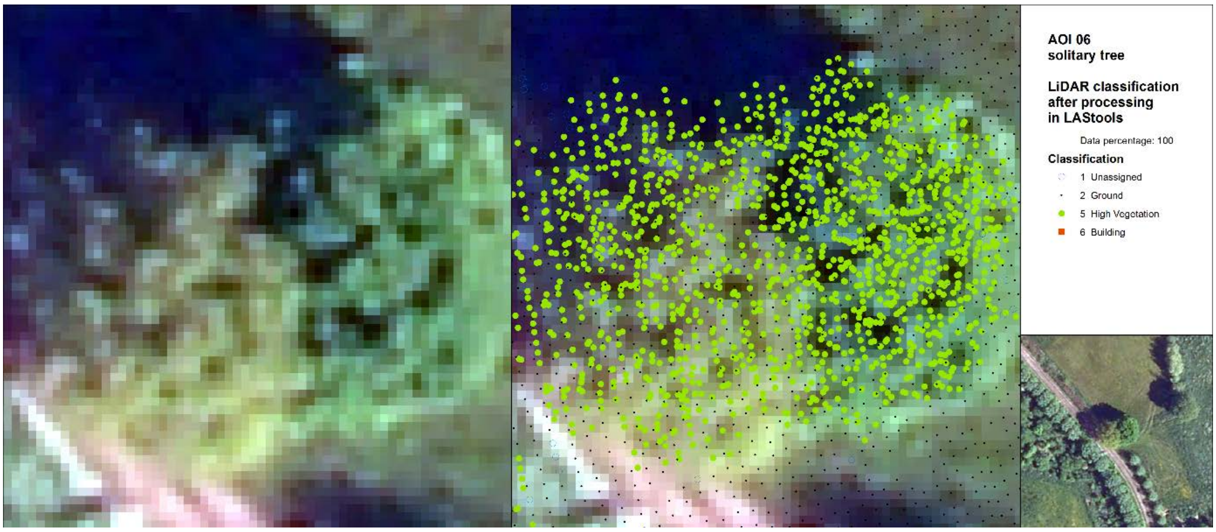
Lillesand, T.M., & Kiefer, R.W. (2000). *Remote sensing and image intepretation*. (4th edition ed.). New York, NY: John Wiley and Sons Inc.

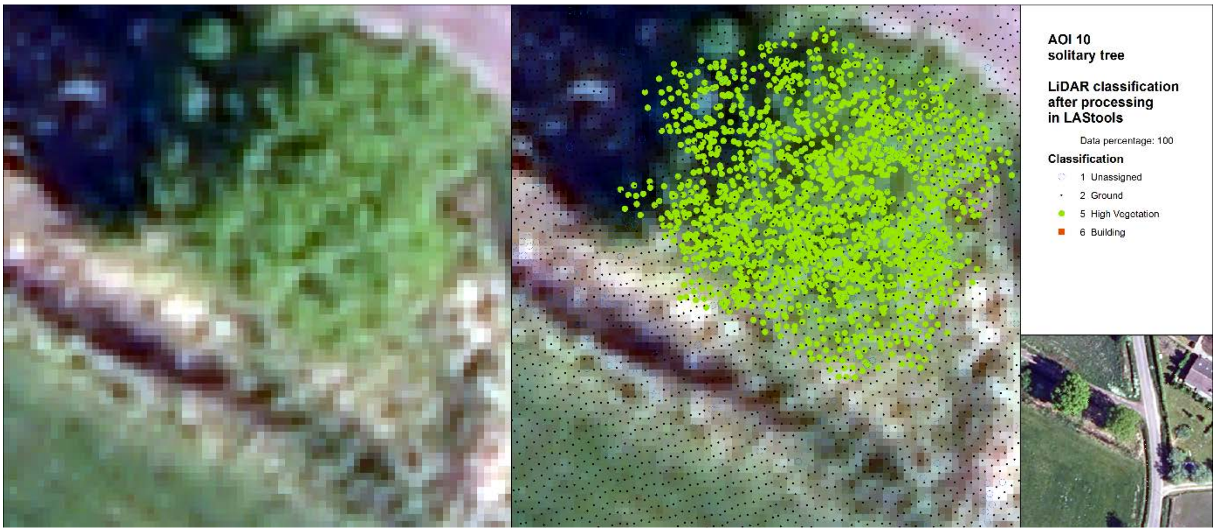
Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography, 27*, 88-106
Lubberink, E. (2011). Subsidiestelsel Natuur- en Landschapsbeheer. In D. Regelingen (Ed.): Ministerie van Economische Zaken
Mallet, C., & Bretar, F. (2009). Full-waveform topographic lidar: State-of-the-art. *Isprs Journal of Photogrammetry and Remote Sensing, 64*, 1-16
Mücher, C.A., Roupioz, L., Kramer, H., & Griffioen, A. (2010). Use of LiDAR to map and monitor habitats
Norman, P. (1999). Putting iterative proportional fitting on the researcher's desk
Oosterbaan, A., Berg, C.A., van den van Blitterswijk, H., Griffioen, A.J., Frissel, J.Y., Baas, H.G., & Pels, M.S. (2004). Meetnet Kleine Landschapselementen. Studie naar methodiek, haalbaarheid en kosten aan de hand van proefinventarisaties. In (p. 54). Wageningen: Alterra
Oosterbaan, A., & Pels, M. (2007). Monitoring of small landscape elements in the Netherlands. *Landscape Research, 32*, 95-102
Pouliot, D.A., King, D.J., Bell, F.W., & Pitt, D.G. (2002). Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. *Remote Sensing of Environment, 82*, 322-334
Roth, R.B., & Thompson, J. (2008). PRACTICAL APPLICATION OF MULTIPLE PULSE IN AIR (MPIA) LIDAR IN LARGE-AREA SURVEYS. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVII– B*, 183-188
Ryan, C. (2013). Using LiDAR survey for land use classification. In, *Floodplain Management Association National Conference*. Coffs Harbour, Australia
Schenk, T., & Csatho, B. (2006). Fusion of lidar data and aerial imagery for a more complete surface description. *Commission III, Working Group 5 Report*
Sithole, G. (2005). Segmentation and classification of airborne laser scanner data. In (p. 184). The Netherlands: Technical University of Delft
Suarez, J.C., Ontiveros, C., Smith, S., & Snape, S. (2005). Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. *Computers & Geosciences, 31*, 253-262
Tiede, D., Lang, S., & Hoffmann, C. (2006). Supervised and forest type-specific multi-scale segmentation for a one-level-representation of single trees. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36*, 4
Trimble (2011). eCognition Developer 8.7. In, *User Guide*. München, Germany: Trimble Germany GmbH
Tucker, C.J., Grant, D.M., & Dykstra, J.D. (2004). NASA's global orthorectified landsat data set. *Photogrammetric Engineering and Remote Sensing, 70*, 313-322
Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., & Steininger, M. (2003). Remote sensing for biodiversity science and conservation. *Trends in Ecology & Evolution, 18*, 306-314
van der Sande, C., Soudarissanane, S., & Khoshelham, K. (2010). Assessment of Relative Accuracy of AHN-2 Laser Scanning Data Using Planar Features. *Sensors, 10*, 8198-8214
Wehr, A., & Lohr, U. (1999). Airborne laser scanning - an introduction and overview. *Isprs Journal of Photogrammetry and Remote Sensing, 54*, 68-82
Wilhelm, W., Ruwe, K., & Schlemmer, M.R. (2000). Comparison of three leaf area index meters in a corn canopy
Yan, G. (2003). Pixel based and object oriented image analysis for coal fire research. In, *Enschede, Netherlands*

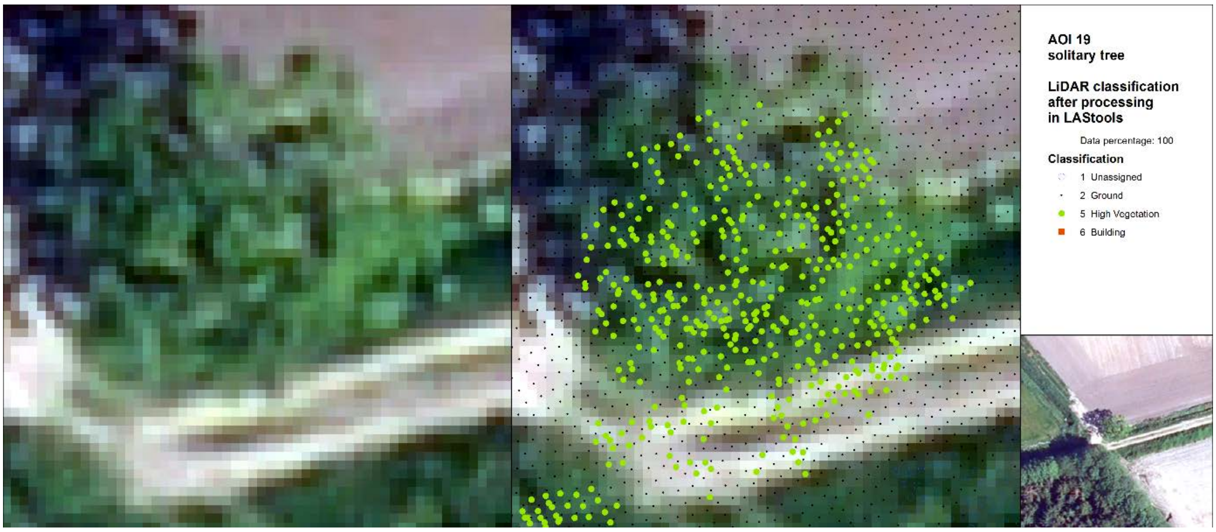
APPENDIX I – preprocessing LiDAR with LAStools

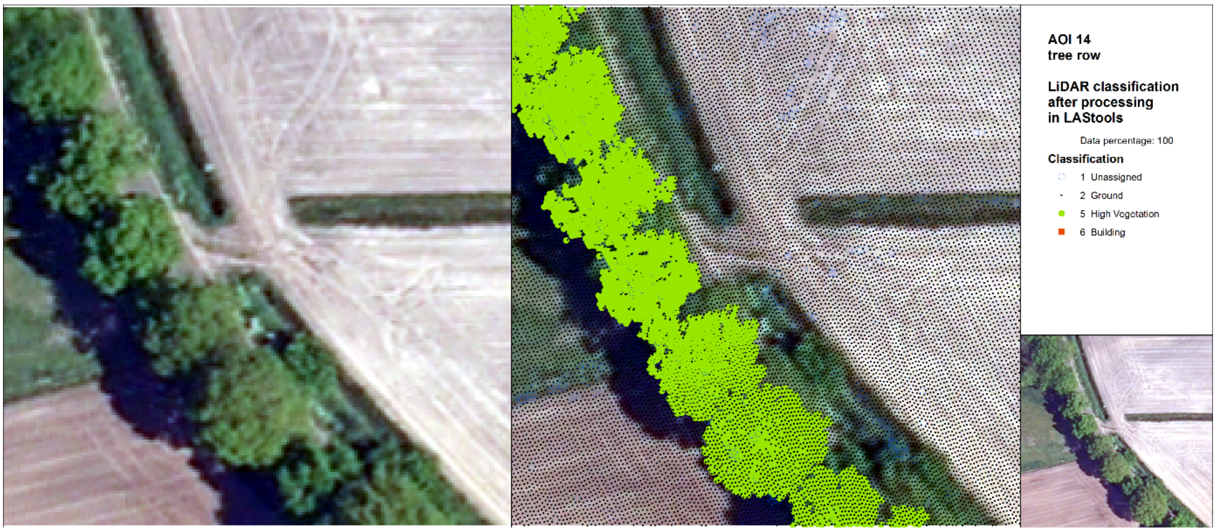

AOI 01
solitary tree
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

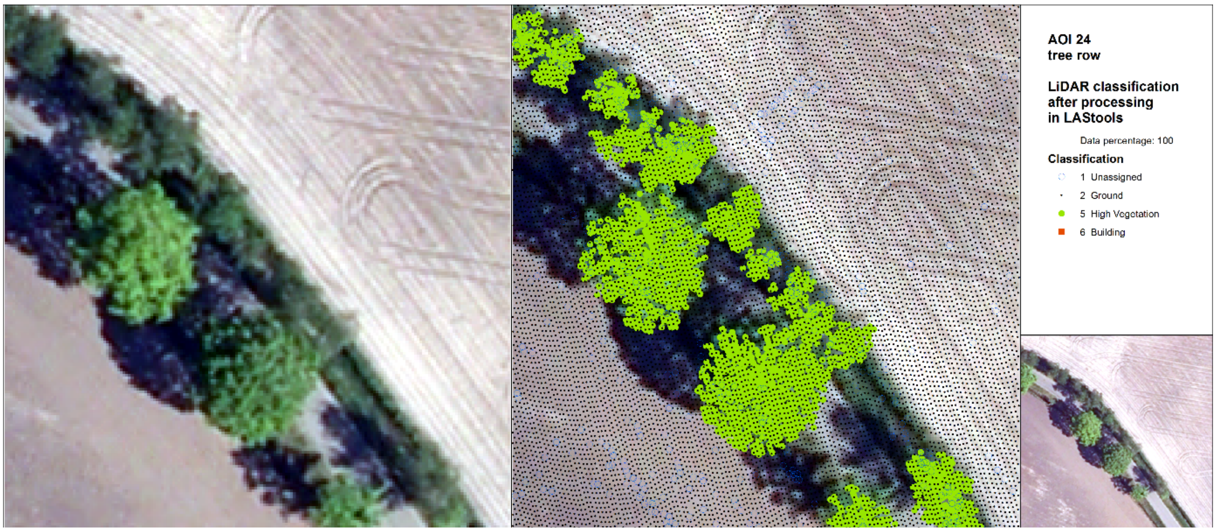

AOI 03
solitary tree
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

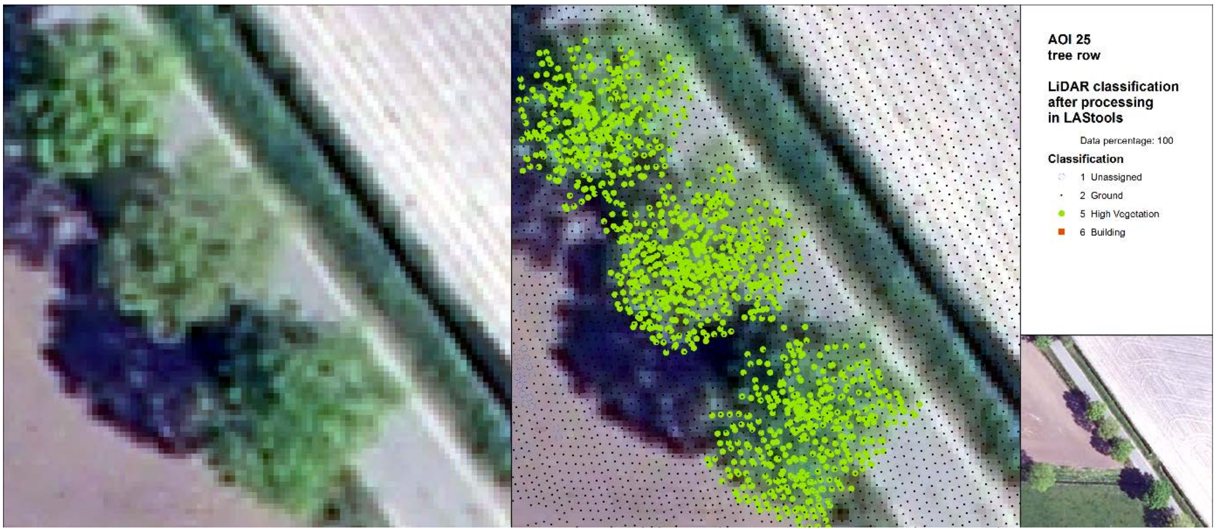

AOI 06
solitary tree
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

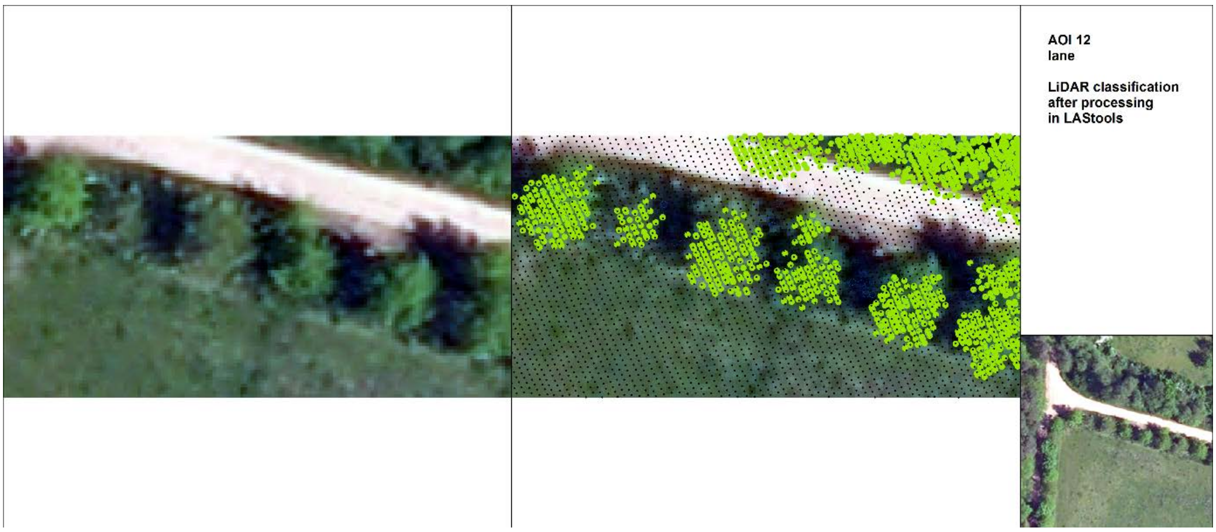

AOI 10
solitary tree
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

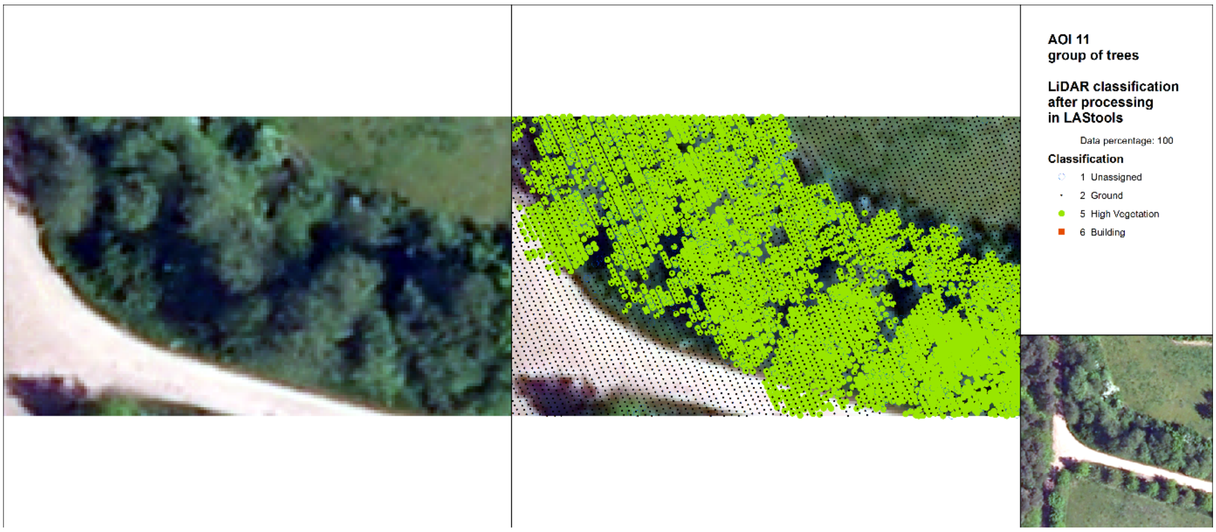

AOI 19
solitary tree
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

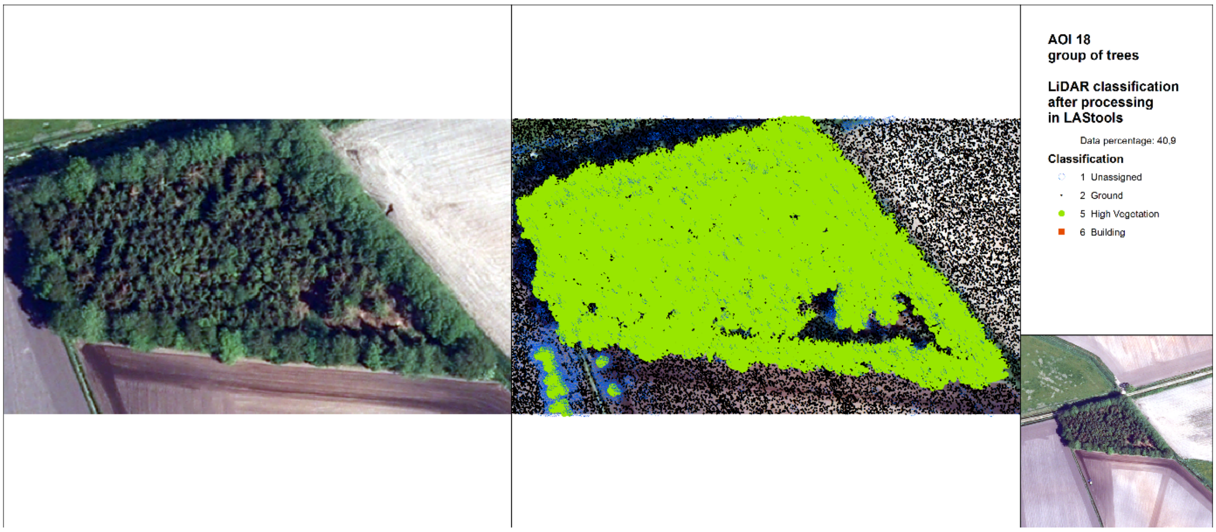

AOI 14
tree row
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building


AOI 24
tree row
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

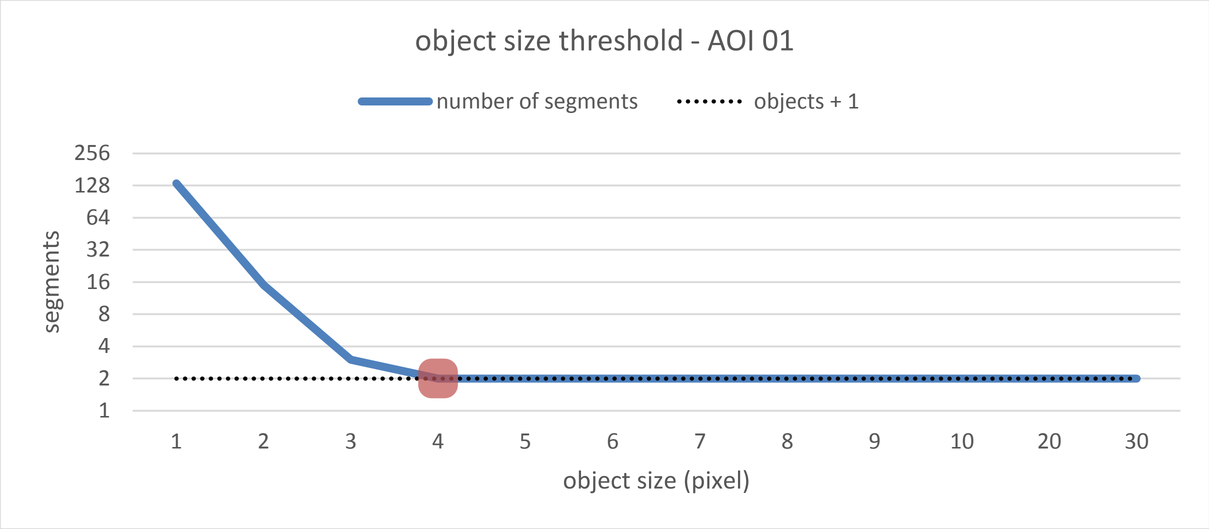

AOI 25
tree row
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

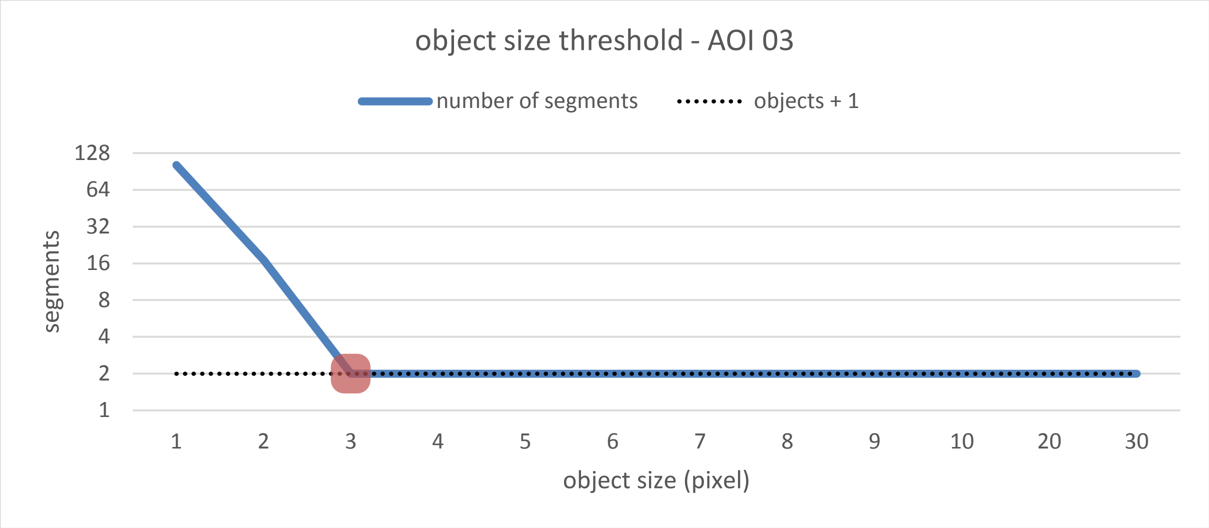

AOI 12
lane
LiDAR classification
after processing
in LAStools

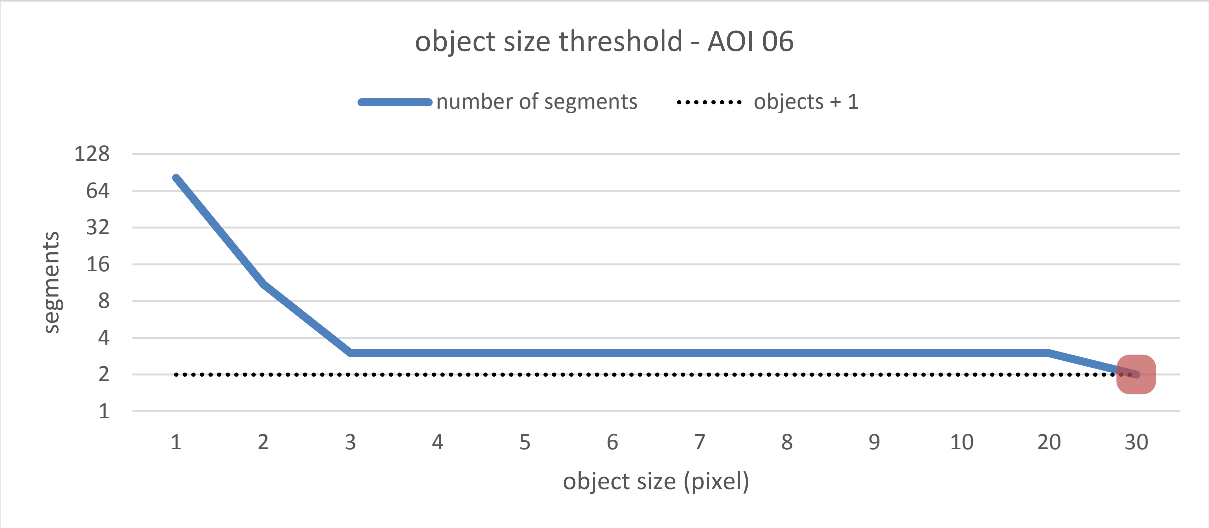

AOI 11
group of trees
LiDAR classification
after processing
in LAStools
Data percentage: 100
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

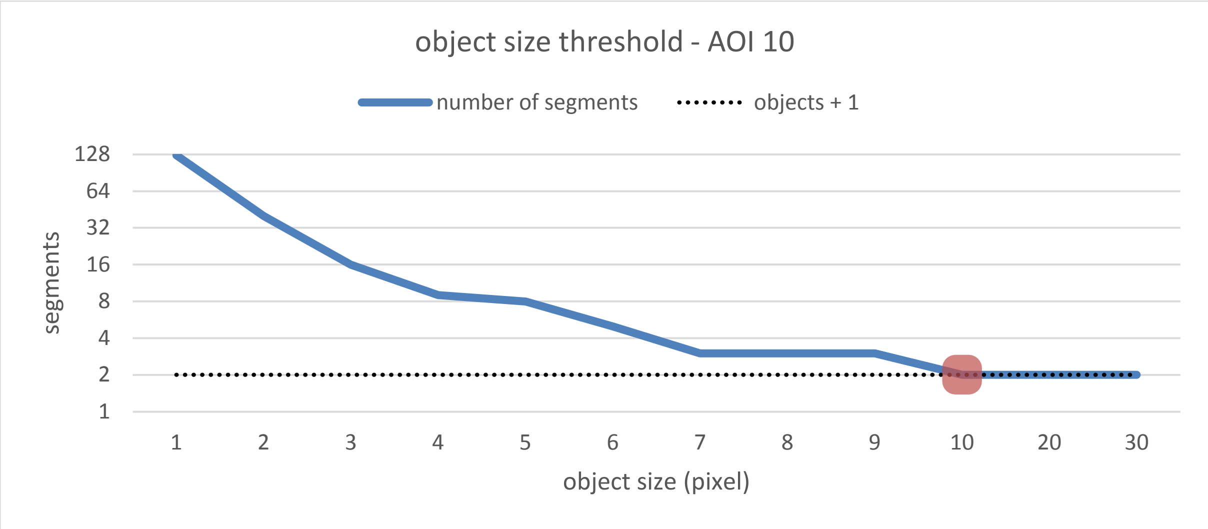

AOI 18
group of trees
LiDAR classification
after processing
in LAStools
Data percentage: 40,9
Classification
1 Unassigned
2 Ground
5 High Vegetation
6 Building

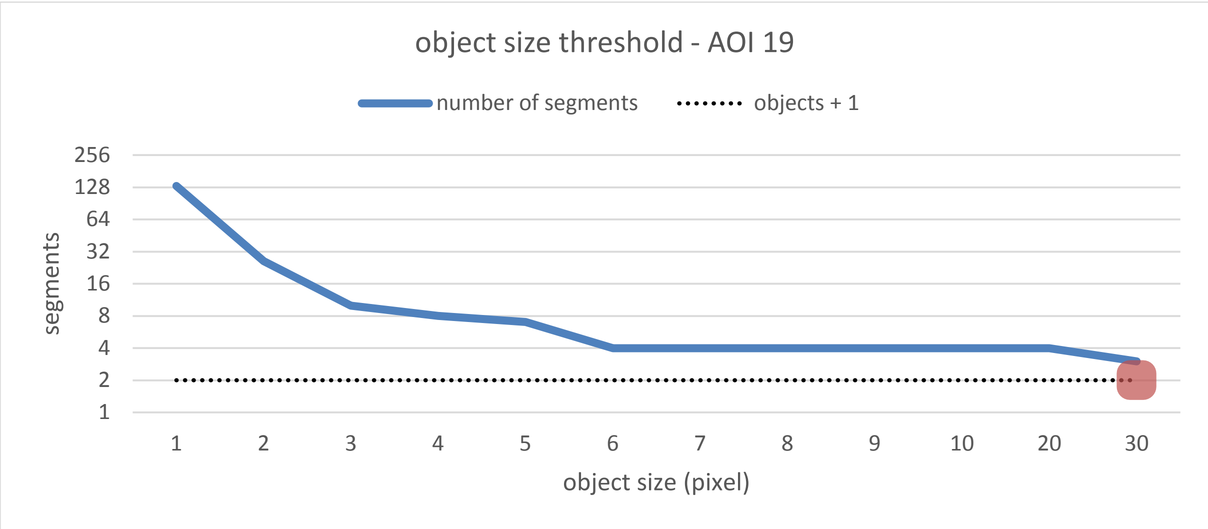
APPENDIX II – object size threshold for segmentation

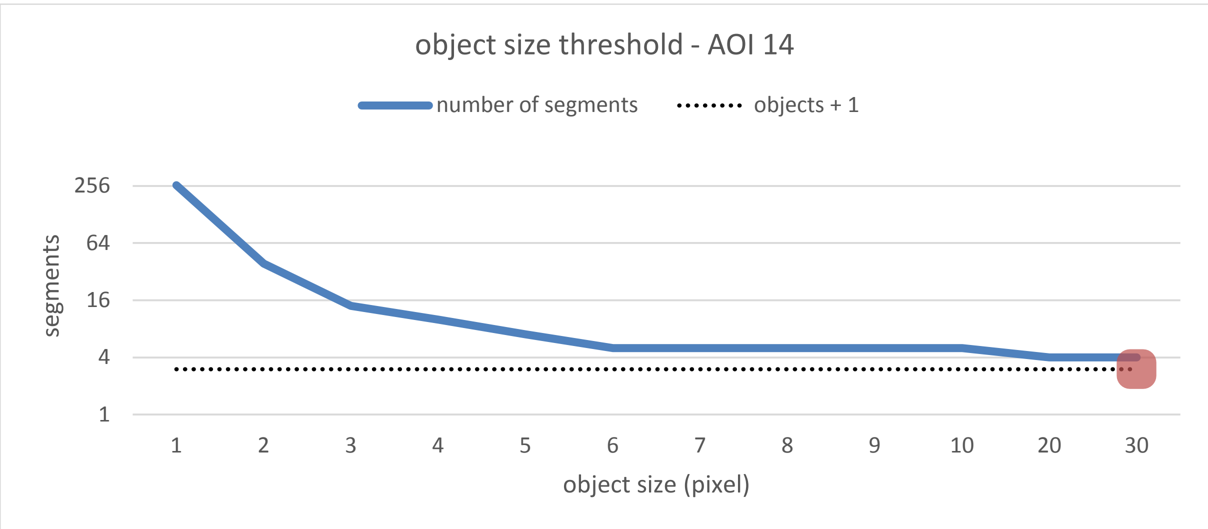

object size threshold - AOI 01
number of segments
objects + 1
256
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)

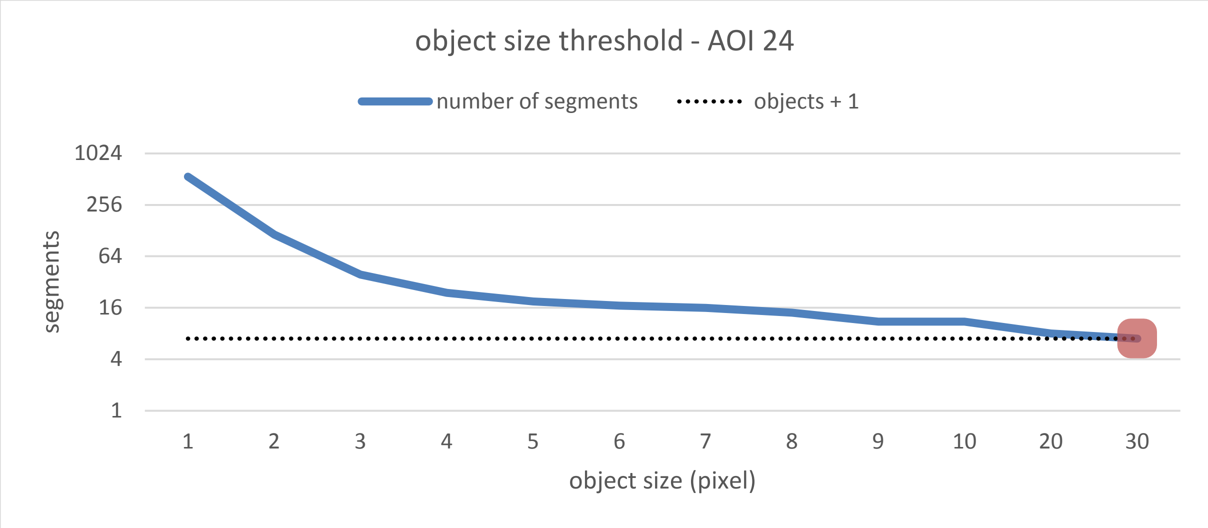

object size threshold - AOI 03
number of segments
objects + 1
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)

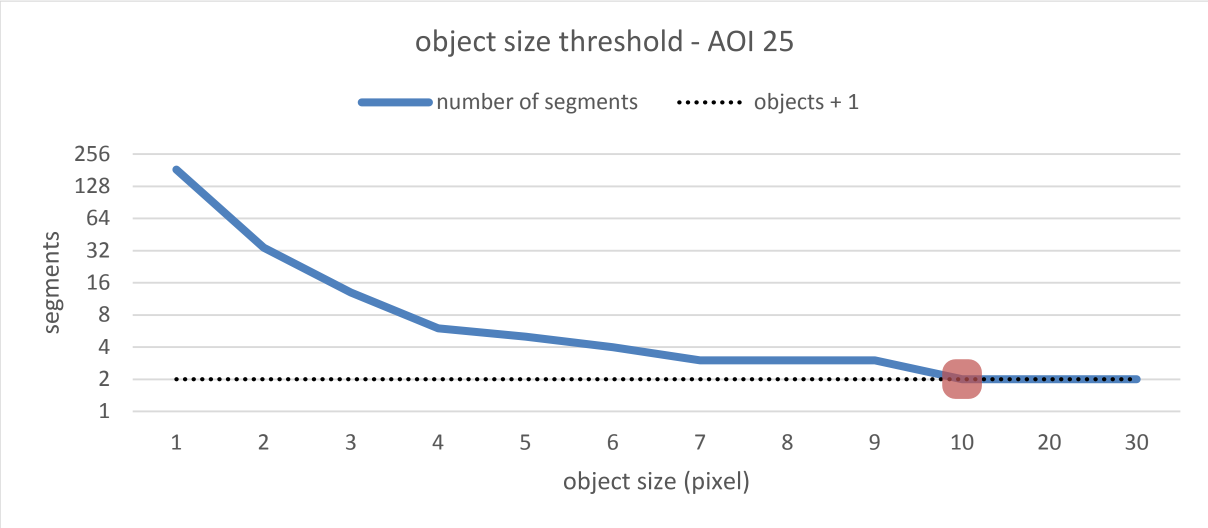

object size threshold - AOI 06
number of segments
objects + 1
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)

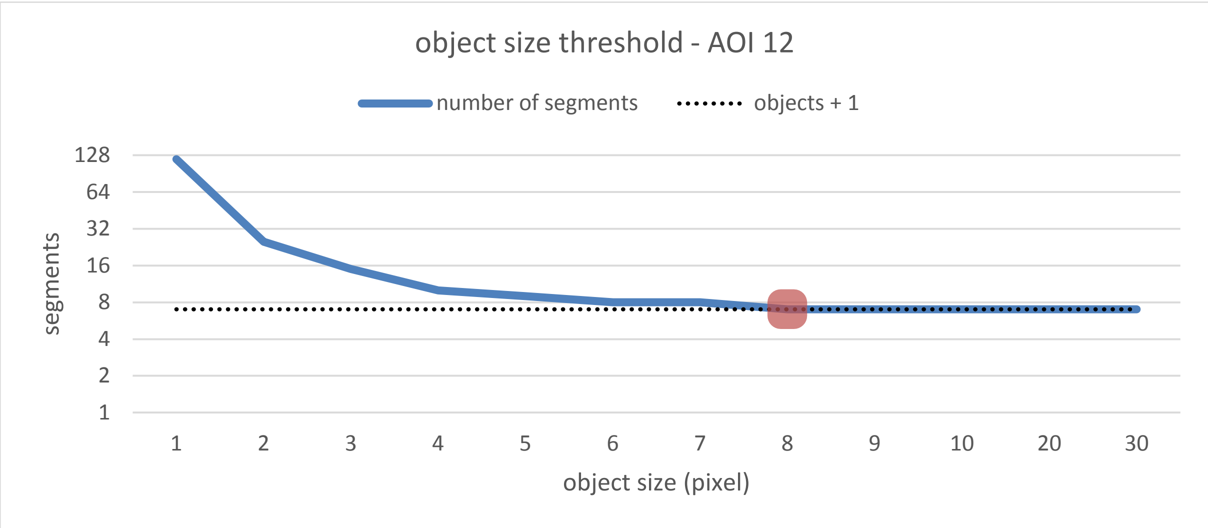

object size threshold - AOI 10
number of segments
objects + 1
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)

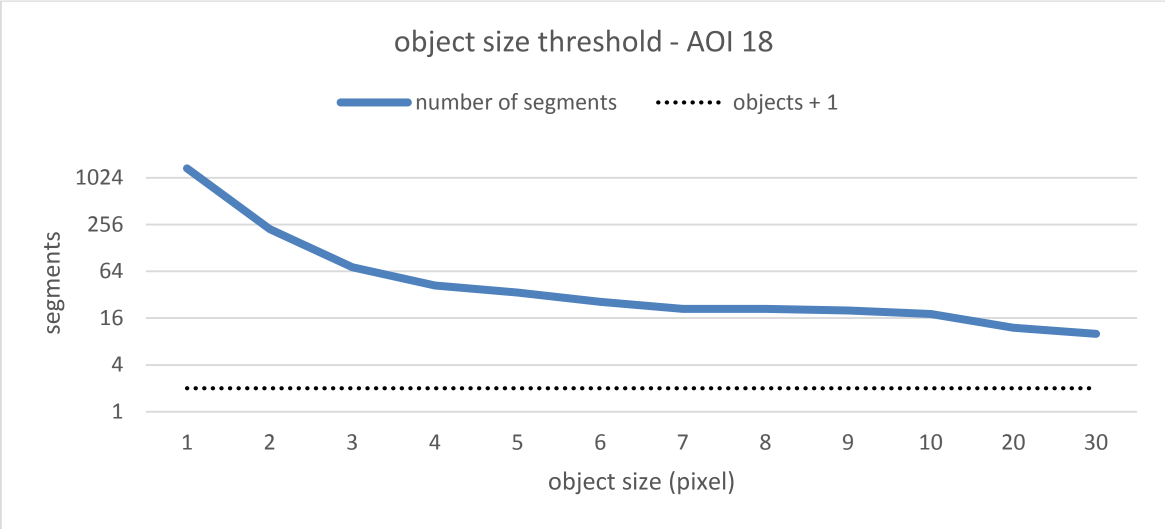

object size threshold - AOI 19
number of segments
objects + 1
256
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)


object size threshold - AOI 14
number of segments
objects + 1
256
64
16
4
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)


object size threshold - AOI 24
number of segments
objects + 1
1024
256
64
16
4
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)

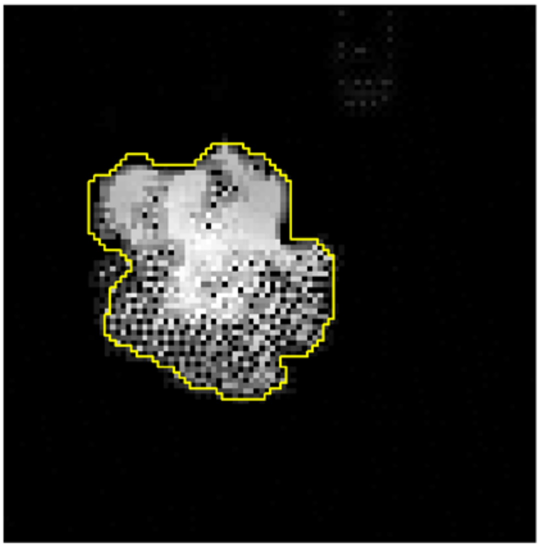

object size threshold - AOI 25
number of segments
objects + 1
256
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)


object size threshold - AOI 12
number of segments
objects + 1
128
64
32
16
8
4
2
1
segments
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)


object size threshold - AOI 18
number of segments
objects + 1
segments
1024
256
64
16
4
1
1
2
3
4
5
6
7
8
9
10
20
30
object size (pixel)

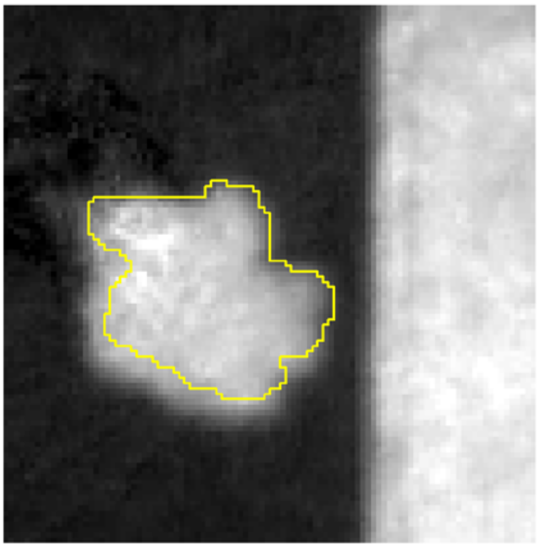
APPENDIX III – results from model on AOI's Chaam

AOI 01



LiDAR (1)

Area: 99 m2
Height: 11,93 m



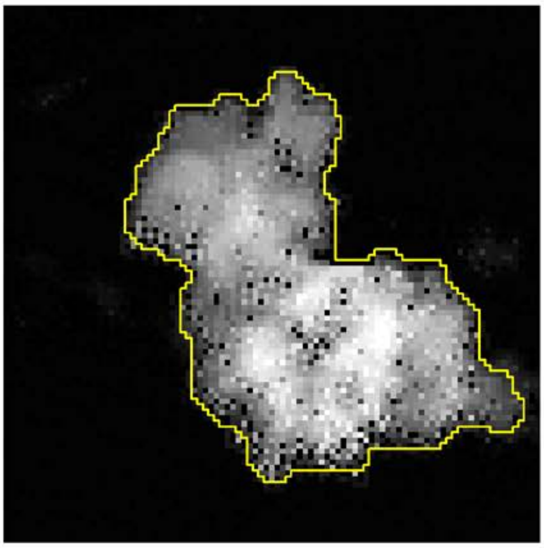
LiDAR + NDVI (2)

Area: 77,56 m2
Height: 11,93 m

Comparison of 1 & 2

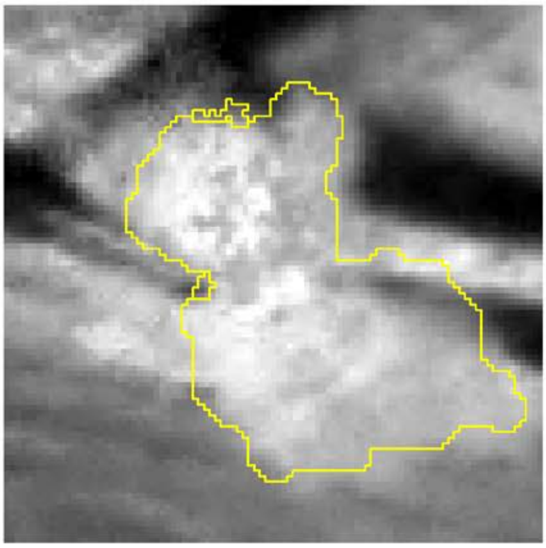
Difference
Area: 21,44 m2 21,7 %
Height: 0 m 0 %

AOI 03



LiDAR (1)

Area: 179,75 m2
Height: 13,42 m



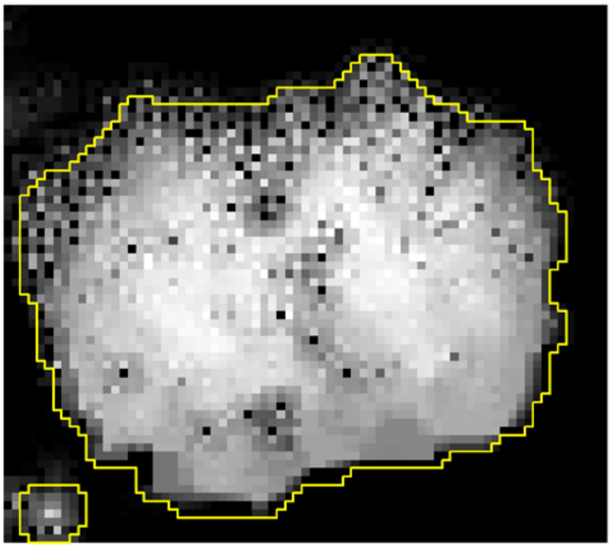
LiDAR + NDVI (2)

Area: 173,44 m2
Height: 13,42 m

Comparison of 1 & 2

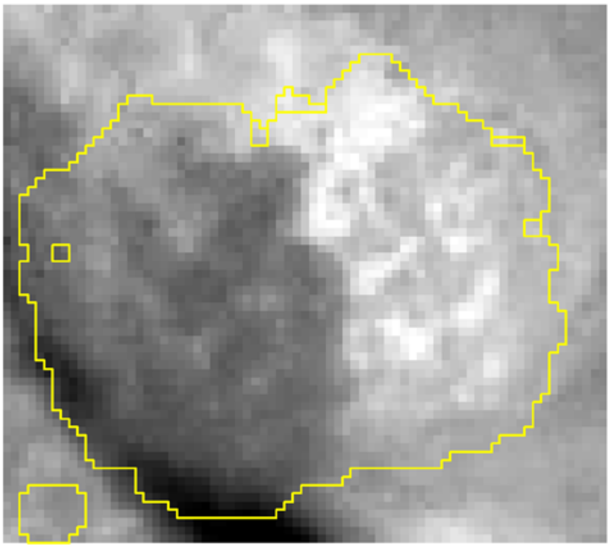
Difference		
Area:	6,31 m2	3,5 %
Height:	0 m	0 %

AOI 06



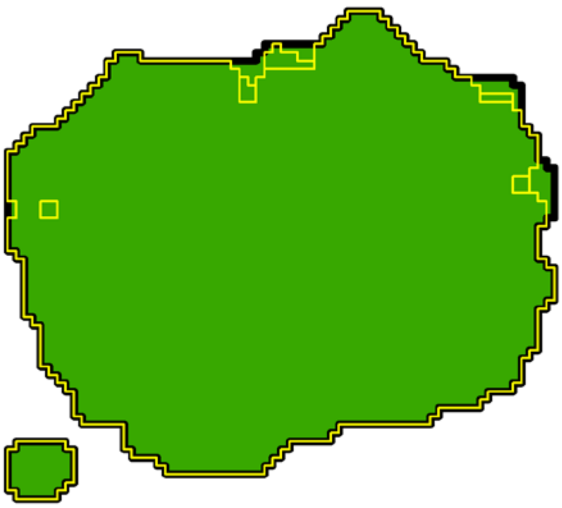
LiDAR (1)

Area: 173,19 m2
Height: 11,41 m



LiDAR + NDVI (2)

Area: 168,69 m2
Height: 11,41 m

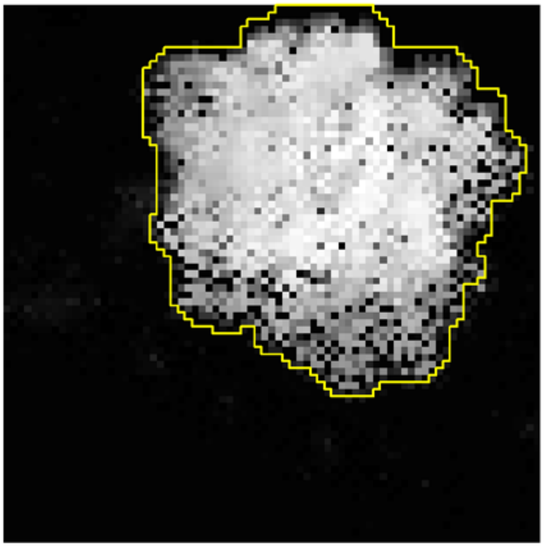


Comparison of 1 & 2

Difference

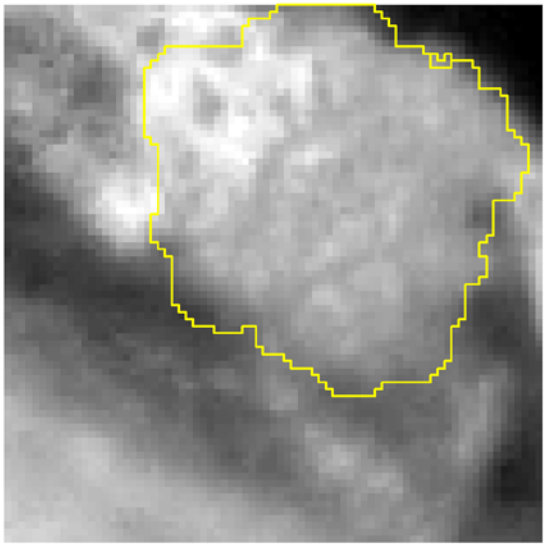
Area:	4,5 m2	2,6 %
Height:	0 m	0 %

AOI 10



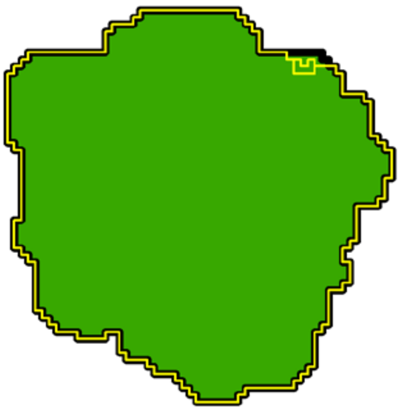
LiDAR (1)

Area: 140,19 m2
Height: 17,40 m



LiDAR + NDVI (2)

Area: 139,38 m2
Height: 17,40 m

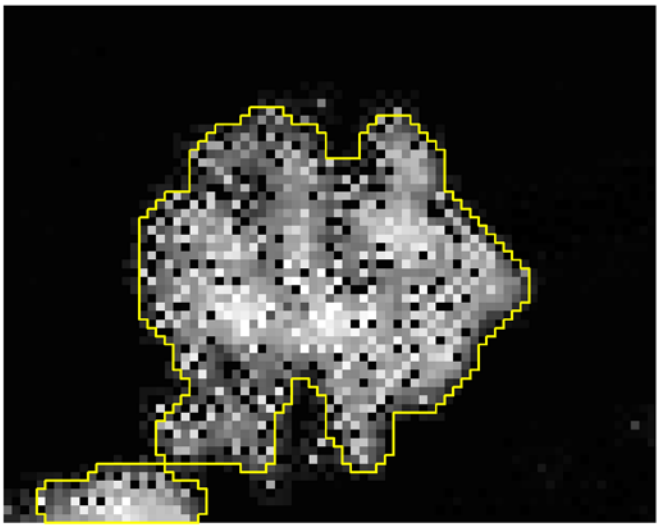


Comparison of 1 & 2

Difference

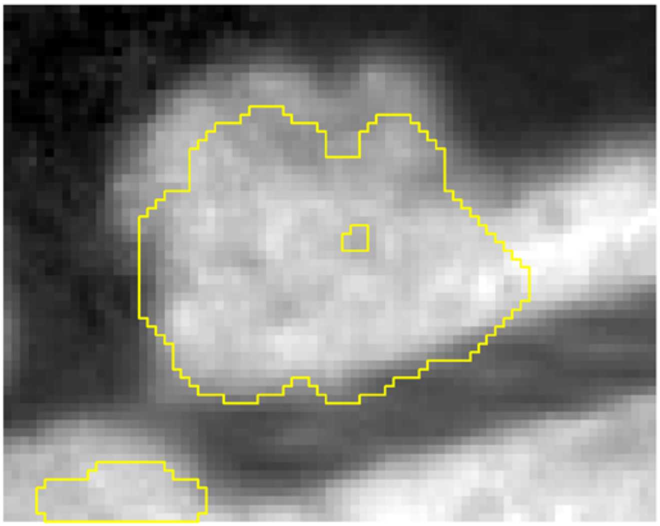
Area:	0,81 m2	0,6 %
Height:	0 m	0 %

AOI 19



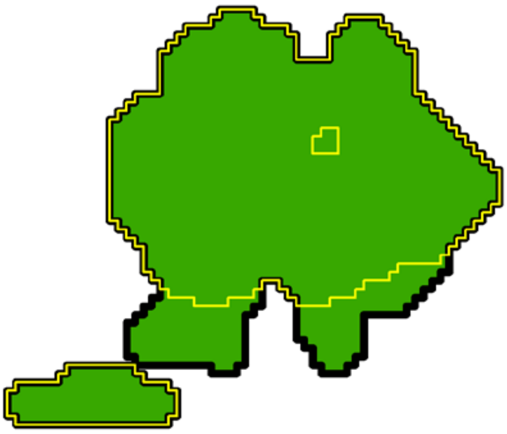
LiDAR (1)

Area: 85,19 m2
Height: 10,38 m



LiDAR + NDVI (2)

Area: 71,81 m2
Height: 10,38 m

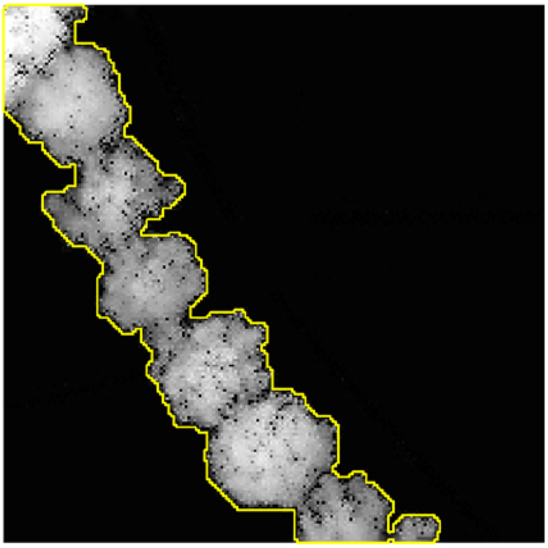


Comparison of 1 & 2

Difference

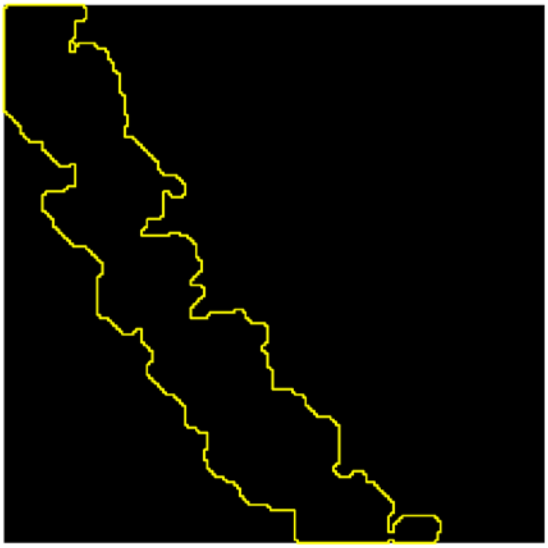
Area:	13,38 m2	15,7 %
Height:	0 m	0 %

AOI 14



LiDAR (1)

Area: 85,19 m2
Height: 10,38 m



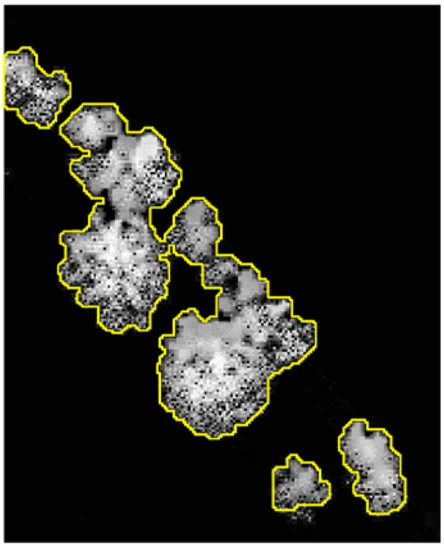
LiDAR + NDVI (2)

Area: 71,81 m2
Height: 10,38 m

Comparison of 1 & 2

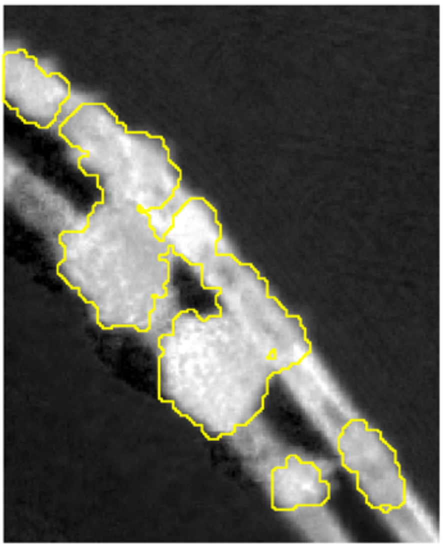
Difference
Area: 13,38 m2 15,7 %
Height: 0 m 0 %

AOI 24



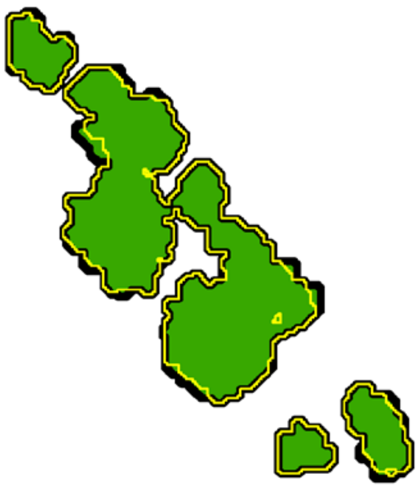
LiDAR (1)

Area: 541,25 m2
Height: 8,48 m



LiDAR + NDVI (2)

Area: 512,63 m2
Height: 8,48 m

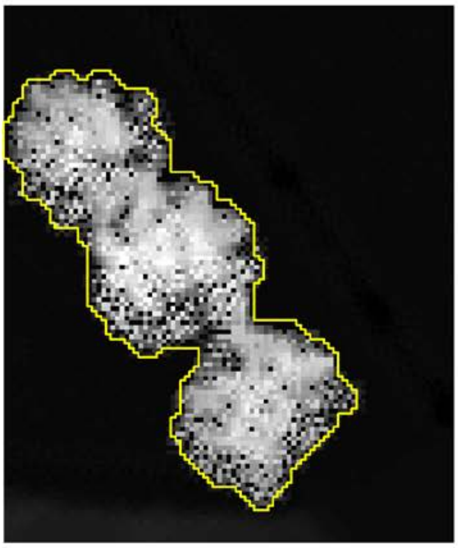


Comparison of 1 & 2

Difference

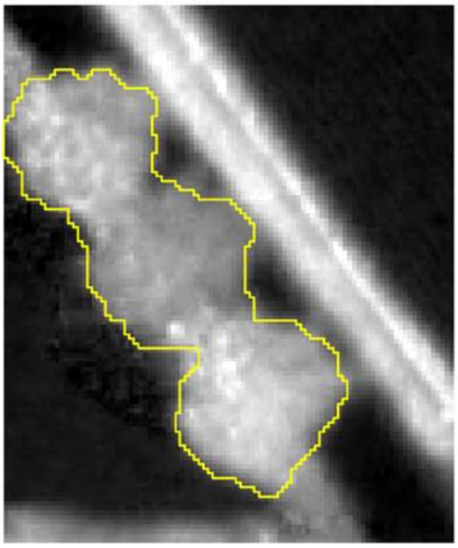
Area:	28,62 m2	5,3 %
Height:	0 m	0 %

AOI 25



LiDAR (1)

Area: 193,06 m2
Height: 12,64 m



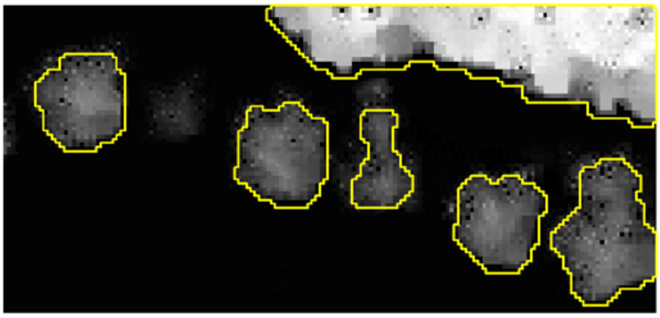
LiDAR + NDVI (2)

Area: 177,94 m2
Height: 12,64 m

Comparison of 1 & 2

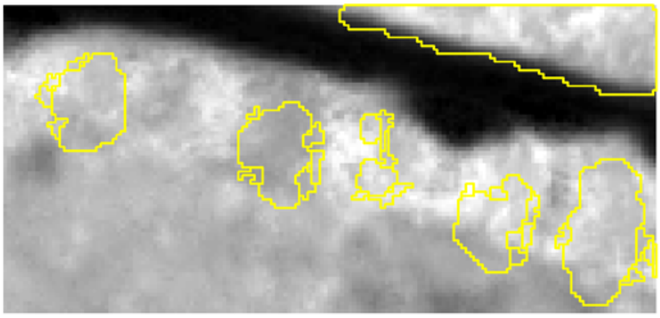
Difference		
Area:	15,12 m2	7,8 %
Height:	0 m	0 %

AOI 12



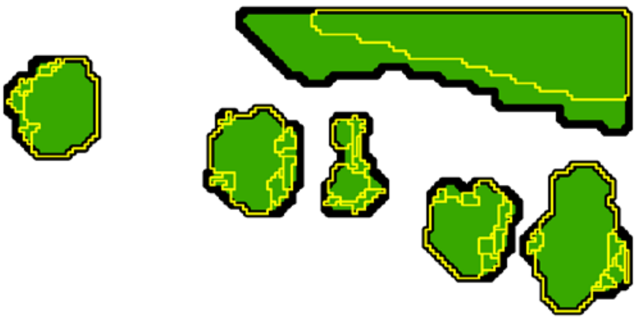
LiDAR (1)

Area: 252,81 m2
Height: 9,93 m



LiDAR + NDVI (2)

Area: 186,44 m2
Height: 9,93 m

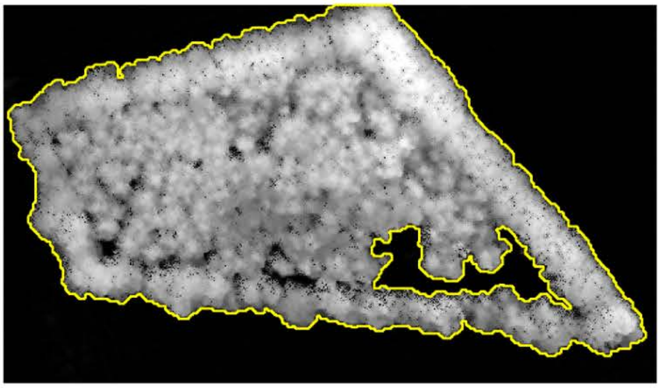


Comparison of 1 & 2

Difference

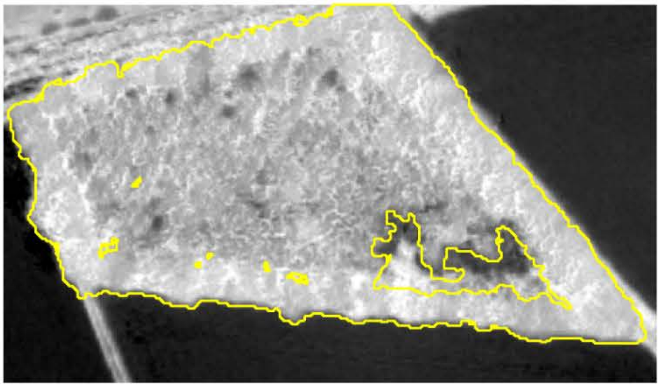
Area:	66,73 m2	26,4 %
Height:	0 m	0 %

AOI 18



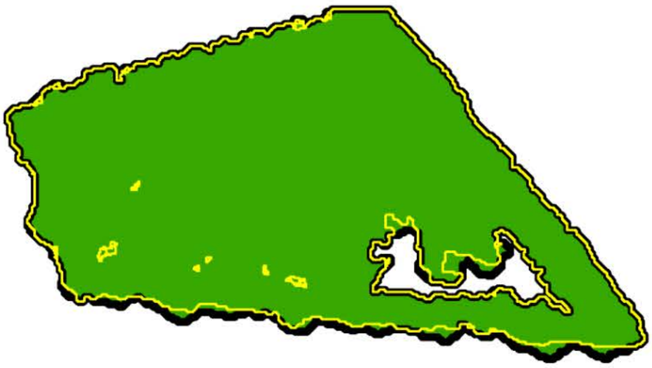
LiDAR (1)

Area: 5464,06 m2
Height: 9,36 m



LiDAR + NDVI (2)

Area: 5236 m2
Height: 9,55 m



Comparison of 1 & 2

Difference
Area: 228,06 m2 4,2 %
Height: 0,19 m 2 %

APPENDIX IV – software packages

For modelling, analysing and presenting the following software packages will be used.

- **ArcGIS for Desktop Advanced 10.1**
  - for making maps
- **eCognition Developer 8.7.0 (Build 1905 x64)**
  - for objectbased processing
  - used for analysing
- **ERDAS IMAGINE 2011**
  - used for viewing datasets, especially aerial images
- **FugroViewer**
  - viewer for raw LiDAR datasets
- **LAStools (version 6 May 2013)**
  - used for modelling within ArcGIS for desktop
  - calculate bare earth

APPENDIX V – specifications of Fugro FLI-MAP 400

Manufacturer	Fugro
Type/name of Lidar sensor	FLI-MAP 400
Date of introduction/last update	Q1-2006
Dimensions	
- weight [kg] & size [cm] of laser system	30kg, 50 x 30 x 30cm
- weight [kg] & size [cm] of total system	~100kg
- power requirements	24V /30W
Laser Pulse Characteristics	
- wavelength [mm]	1,500nm
- pulse length [ns]	4ns
- beam divergence (across/along tr.) [mrad]	0.45 mrad (radial)
- type/class laser	Fiber / Class 1 M
- eyesafe range [m]	0.3m
Recording Methodology	
- scanning method [1]	Rotating mirror
- rotation speed of mirror [2]	150Hz
- pulse frequency (min-max) [Hz]	250,000Hz
- max. scan angle [deg]	60 deg
- max. # of recorded echoes/pulse	4
- pulse sampling frequency [3]	0.025 ps
- pulse detection method [4]	Threshold
- dynamic range of intensity signal [bits]	11 bits
Positioning System	
- GPS system [5]	2x Trimble DB950 L1/L2, 10 Hz
- GPS precision planimetric/height (2 sigma) [cm]	5 / 10cm (2 sigma)
- INS system[6]	Applanix PosAV 410, 200 Hz
- INS precision (roll/pitch/heading) [deg]	0.008 / 0.008 / 0.015 deg
- GPS/INS postprocessing software	GrafNav/PosProc
Precision and Resolution	
- Pointing precision (roll/pitch/heading) [deg]	0.008 / 0.008 / 0.015 deg
- Range precision (2 sigma) [cm]	2-3 cm
- Elevation precision at 1km (2 sigma) [cm]	Depending on network quality
- Overall planimetric precision (2 sigma) [cm]	Depending on network quality
- Range precision (2 sigma) [cm]	2-3 cm (2 sigma)
- Max. # of points/m2	175 points (first return) altitude and speed-dependent
- Along-track point spacing [m] [7]	0.27m @ 150km/h
- Across-track point spacing [m] [8]	0.46m @ 400m AGL
Other System Parts	
- Cameras [9]	Forward and downward-looking 11Mpix still and video
- Data Storage Facilities [10]	Removable hard disks, 80 GB
- Power equipment	Aircraft power 24V
Operation Characteristics	
- typical platform	Helicopter/fixed wing
- flying heights (min/typical/max) [m]	50 - 400m
- max. acquisition duration [hrs]	3 - 6hrs
- air temperature (min-max) [°C]	-10 to 50 °C
- air humidity (min-max) [%]	99% non-condensing
- mission-planning software	FLIP7
- postprocessing software	FLIP7
- proven applications	Corridor mapping, DTM/DSM
Remarks	

[1] E.g. rotating mirror, oscillating mirror etc.
[2] Also called scan frequency.
[3] Also called sample interval per pulse.
[4] Describe here which part of the reflected pulse is recorded.
[5] Brand, number of channels, single or dual frequency, update frequency [Hz].
[6] Brand, update frequency [Hz].
[7] Number referred to flight altitude 1000m.
[8] Number referred to a typical flying speed of 150 km/h, or other appropriate speed.
[9] Types of camera standard to system.
[10] Type of storage facilities (tape, disk, etc.), storage [GB], removable or not.