LiDAR and Low vegetation: Extraction of structural characteristics and DTM error

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LiDAR and Low vegetation: Extraction of structural characteristics and DTM error

by

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Abstract

LiDAR has proved to an effective tool for mapping terrain and studying vegetation structural characteristics. Past researches have pursued studies related to low vegetation and its disturbing influence in determining the true elevation of the terrain using LiDAR. This study deals with extracting the vegetation structural characteristics of low vegetation and to determine the DTM error of the terrain using a new improved scanner which has a better vertical accuracy (1.5 cm) than the scanners that were used previously by other studies. This is so far have been challenging task because the range of low vegetation is well within the noise of the scanners. The scan angle for each plot is also determined to see if there is any influence of scan angle on the DTM error prediction and the vegetation structural characteristics estimation. The main methods involved in this study are hierarchic robust interpolation used for filtering the terrain points from the non terrain points. Second order spine interpolation has been used as a tool for interpolating two surfaces such as the DTM surface and all the points in order to find the height of the vegetation points above terrain. Vegetation density is found by employing the method of Vegetation Area Index. The scan angle and DTM error do not show any relationship with each other. The error check for the GPS used for field measurements was tested on a plot of asphalt and the error was found to be 0.9 cm. The field data about vegetation height and laser derived height of vegetation points showed good correlation for points above the height of 20cm. From the regression analysis performed between vegetation height and shift, there is a strong correlation seen for vegetation height data ranging from 3 to 7 cm. and shift values between 3 to 15cm. For vegetation height less than 6 cm, a mathematical relationship could be established with corresponding DTM error. Amongst other first order statistical measures that were found, only std deviation and 93^{rd} percentile found to have a strong correlation with vegetation height. Skewness and kurtosis proved poor correlation. For further research, It is recommended to use texture approach for extracting vegetation structural characteristics.

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1. Introduction

1.1. Background

With the development of geographical information systems (GIS), details regarding the earth elevation and its terrain have become important inputs for many studies. The earth's terrain is recorded as a continuous and smooth surface and represented as a model called Digital Terrain Models (DTM) (Podobnikar, 2002). They are used in many fields' viz., geomorphology, archeology, planning and hazard assessment. DTMs are also extensively used for hydrological applications where details about the bare Earth gives information about the water runoff, to determine runoff volume and to gauge ground water levels (B. Gorte et al., 2005).

Mapping topography and vegetation structure is one of the main parameters when dealing with vegetation studies. With the current issues on carbon cycle and climate change, vegetation structure and parameters related to vegetation have become an important criterion.Three-dimensional vegetation structure in floodplains are essential for ecological studies and hydrodynamic modeling of rivers (Straatsma and Middelkoop, 2006).

This study mainly deals with

1. extracting (low)vegetation structural characteristics using LiDAR and
2. to determine the true elevation of the terrain

1.2. A brief introduction to LiDAR

Out of the current methods that are used to map the terrain like RADAR and photogrammetry, LiDAR is an up-to-date technology that offers highest accuracy in terrain mapping. LiDAR is being used to generate DTMs for forest structure mapping as well as mapping low vegetation (Oude elberink et al., 2003). High frequency laser pulses in the near infra red region of the spectrum are fired towards the ground from an airborne platform (Bradbury et al., 2005), at discontinuous instances. The backscattered echoes from the targets are recorded as discrete returns. An aggregate of all the recorded echoes is referred to as point cloud.

Known as Light Detection And Ranging (or Airborne Laser Scanning), it is composed of 3 main components, a differential GPS – to locate the aircraft in space, an Inertial Navigation System (INS) which gives the orientation of the aircraft and the Laser Range Finder (LRF) that gives the distance between the aircraft and the target. The dGPS also has a base station on the ground which reduces the positioning error of the aircraft. Operationally used laser systems record discrete pulses. A discrete return LiDAR operates on a small footprint (20-80cm) diameter that records one to multiple returns.

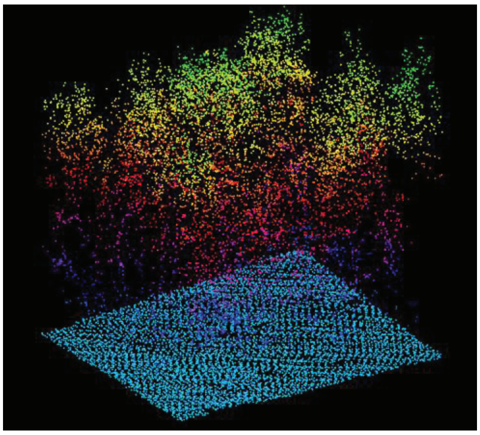

Figure 1-1: Point cloud of a forest

Figure1-2: Airborne laser scanning (John Chance Land Surveys, 2003)

Data from all three components are synchronized and combined to form a 3-D cloud of laser echoes of the target, usually the features below. The acquired data is then used to build high resolution LiDAR images of the ground or the forest canopy. The end product is almost always a high resolution DTM (Hopkinson et al., 2004). ALS data enables to perceive the terrain in a 3-dimensional environment thus making visualization easier and better, which is also why it is preferred over other conventional methods. LiDAR is helpful in fast data collection, little access to the site, and is less weather dependent compared to other survey systems. However, LiDAR is more expensive when it comes to data acquisition and needs complex algorithms for data handling and storage.

1.3. Problem statement

When LiDAR is used for terrain mapping, most of the pulses are backscattered from the topmost features in the terrain. In an urban or a forest scenario, it is usually buildings, poles or trees. These high lying points from buildings or trees can be easily discarded through filtering or using segmentation techniques. But when it comes to measuring a terrain that is covered with low vegetation(usually grassland/meadows with vegetation heights below 20 cm) (Gorte et al., 2005), they influence the accurate measurements of the terrain height since the pulses are reflected back from the top of the crop thus adding a small positive height to the true elevation of the terrain.(Gorte et al., 2005). This shift in height is termed as the DTM error.

Previous studies have shown that extracting the vegetation structural characteristics have proved to be efficient predictors in estimating this DTM error. Moreover the extraction of vegetation structural characteristics are not just used for determining the DTM error but also used as effective inputs for modeling floods in floodplains, especially in the Netherlands where floods occur during winter, when low vegetation consists of leafless stalks. Many studies have been undertaken in this regard. Related work has been more elaborately discussed in chapter 2.

This study will thus prove helpful to the flood modelers who will be benefited by extracting the structural characteristics of low vegetation to determine hydrodynamic roughness of the floodplain and country planners by getting a more reliable DTM. Below is a table explaining the previous researches done in this arena, the kind of data they used and the quality of results they obtained.

Reference	Footprint size (m)	Point density	No. of plots	Vegetation type	Height range (m)	Scanner Used
(Pfeifer, 2001)	0.2	10	24	Long grass, old willow forest and young forest	0.5 t o 1.8	FLIMAP II
(Straatsma and Middelkoop, 2007)	0.2	10 to 75	42	Herbaceous and grass	0.2-2	FLIMAP II
(Hopkinson et al., 2004)	Small	-	14	Acquatic veg, herbs, low shrubs	0-1.25	-
(Ahokas et al., 2003)	Small	7 to 8	8	Grass	0.03-0.25	Toposys I
(Hodgson and Bresnahan, 2004)	small	15	13	Low grass	< 0.8	Optech 1201
(Davenport et al., 2000)	0.15 – 0.23	-	18	Crops < 1m	0-0.9	
(Cobby et al., 2001)	0.24	7	55	Grassland and crops		Optech ALTM 1020

Table 1-1: Previous studies related to DTM error and vegetation height extraction

1.4. Innovation

This study advances one step forward in the field of extracting low vegetation characteristics using LiDAR. As seen in the table (1-1), previous studies have already been trying with varying scanner properties and using different point densities. The scanner that is used for this study is fugro’s FLIMAP 400 (Fast Laser Imaging and Mapping Airborne Platform).The innovation in Flimap 400 is the overall accuracy of the scanner. The absolute vertical accuracy of the scanner is quoted at 1-1.5 cm (1 sigma). Experiences has shown that a 3cm (1 sigma) is achievable for hard surfaces.(fugrowaterservices.com). Since the range of vegetation that this study deals with is less than 20cm, there is more opportunity that this study could arrive with predicting more accurate DTM errors and vegetation structure characteristics. More precisely, most of the plots that is considered for the study, range from heights 0.5cm to 3 cm, which even more stresses the need of a scanner with better accuracy.

1.5. Research Questions

Main research question

- What is the potential of a high accuracy airborne laser scanner in predicting vegetation structural characteristics and DTM error?

    - Are they helpful in the reliable estimation of the disturbing influence of low vegetation for the DTM generation process?

    - Is there any influence of scan angle on the terrain model?

    - Is Vegetation Area Index (VAI an effective method to extract the vegetation density using LiDAR data?

1.6. Research objectives

Main objective:

- Prediction of vegetation height and density using high accuracy LiDAR data

Sub objectives:

- To determine the DTM error based on the predicted vegetation height using LiDAR data
- To interpret the influence of scan angle on DTM error
- To extract vegetation density of the vegetation using VAI method

1.7. Study area

This study was tested using the data collected on two floodplains in the netherlands: 'Duursche Waarden' floodplain along the right bank of the River Ijssel and a floodplain in the province of noord brabant(as shown in fig). These floodplains are dominated by softwood forest and shrubs but mainly dominated by herbaceous vegetation. Herbaceous vegetation mainly consists of plant speices like sedge sedge (Carex hirta L.), sorrel (Rumex obtusifolius L.), nettle (Urtica dioica L.), thistle(Cirsium arvense L.) and clover (Trifolium repens L.) (Straatsma and Middelkoop, 2007)

Figure1-3: two of the plots from the study sites

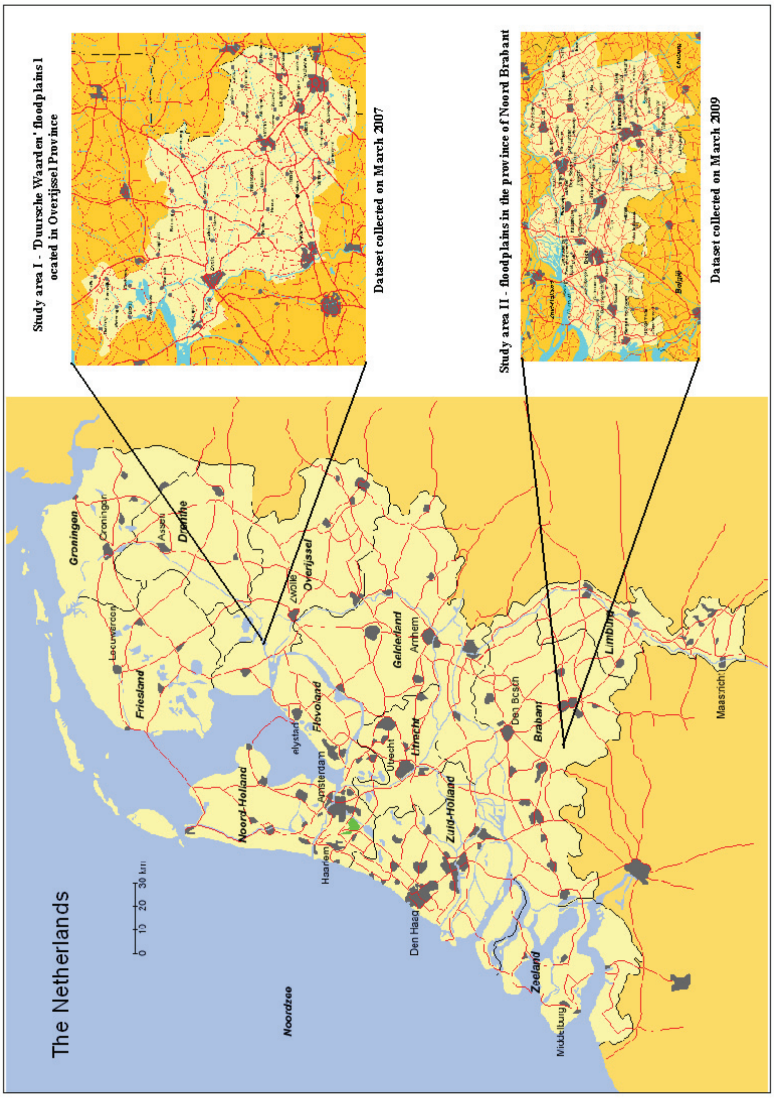

Figure:1-4 Study area

2. Literature review

2.1. Introduction

Airborne laser scanning is getting its recognition in the field of DTM extraction and in determining the structural characteristics of vegetation. Mainly used to find forest canopy heights, LIDAR is also being used in mapping floodplains and in extracting DTM. Mapping low vegetation and acquiring characteristics of the low vegetation with the use of an airborne laser scanner is a recent research arena. An overview of previous studies in this field is accounted for, in the following paragraphs. Sections 2.2 will give an overview of how airborne laser scanning have been used in effective DTM extraction through various filtering methods. Section 2.3 will discuss the previous studies done in the extraction of vegetation characteristics. Their subcategories deal more in detail about vegetation height and vegetation density respectively.

2.2. DTM extraction and filtering of low vegetation sites

All laser point clouds represent the ground whose continuity is broken by objects like buildings, vegetation and electric lines. Segmenting the laser points according to the feature from which they were scattered back is known as filtering. This is useful to reconstruct the objects in a 3D environment or to construct a faithful representation of the topography of the scene. There are two types of filtering methods a) point based filtering b) segment based filtering. In point based filtering, each point is considered individually and classified as terrain or non terrain analyzing slope between the adjacent points. The second type of filters deal with points in segments, that show some homogeneity. These types of filters consider the smoothness of a surface or the height difference between neighbouring segments and accordingly classify the points. (Tóvári and Pfeifer, 2005)

Filtering methods are usually employed to separate terrain and non terrain points using geometry of the neighbourhoods such as slope and height differences (Geopfert and Soergel, 2007). The main motive in this study is to remove the high lying laser pulses from vegetation. These filtering methods serve different purpose but most of them aim to improve DTM accuracy. However in the case of low vegetation, filtering methods usually fail to produce convincing results since low vegetation points are not substantially higher than the surrounding terrain. This may also be a potential problem when the vegetation is too dense for the laser pulses to hit the ground.

Most filtering algorithms work by searching for the lowest point in the scene and treating these as terrain points, e.g. morphological filters (Kilian et al., 1996); (Vosselman, 2000) (Roggero, 2001) as cited by (Sithole and Vosselman, 2004). Some robust filters find points that is closest to a fitting surface and treat that as bare earth as explained in (Kraus and Pfeifer, 1998). (Brovelli, 2002) came about with another approach by treating small cluster of point clouds as objects (Sithole and Vosselman, 2004). (Axelsson, 1999,2000,2001) created a filtering algorithm mainly suitable for urban areas. He used the lowest points to form a TIN as the first set of ground points. For each triangle an additional unclassified ground point is added based on investigating the angles between the triangle face and the distance to the nearby facet nodes. Hence, if a point is below the threshold value it is classified as ground point and moves to the next triangle, the triangulation getting dense progressively.

2.2.1. Robust interpolation Method

A novel approach was developed by Pfeifer and Briese (2001) by combining filtering and interpolation procedures in a hierarchical approach. In this algorithm, a polynomial surface that roughly matches the terrain is constructed first. Points lying above and below this surface are given a weight depending on the distances between the surface and the point (Fig 2-1). The surface is then adjusted considering the weights of the points. A point with a high weight will attract the surface and similarly point with lower weight will have less influence towards the surface. After each iteration, if the distance is above a certain threshold, the point is classified as non terrain and discarded from the process. This is repeated until all non terrain points are eliminated or a certain number of iterations is exceeded. This technique has been applied in areas of dense high vegetation as used by (Wagner, 2006) for their research on retrieving DTM of a forested terrain.

2.2.2. Repetitive interpolation (REIN)

Recent research on filtering methods have been done by (Kobler et al., 2007) which is called Repetitive interpolation (REIN). This has many advantages over other methods since this can be applied on steep forested areas where other algorithms have problem differentiating terrain and non terrain points. Though, this study does not deal with forested areas, this filtering method would give better results because of its expertise and innovative approach.

This filter works as a two stage process. As the first stage, already existing filtering techniques are employed to discard negative and positive outliers (most of them, not all) that are non terrain points. In the next stage, REIN is introduced to estimate individual DTM points by interpolating from the neighbouring terrain points. These elevation estimates are produced from multiple individual samples taken from the previously filtered point samples. REIN can be applied both in a vector grid as well in a TIN (Triangular Irregular Network).

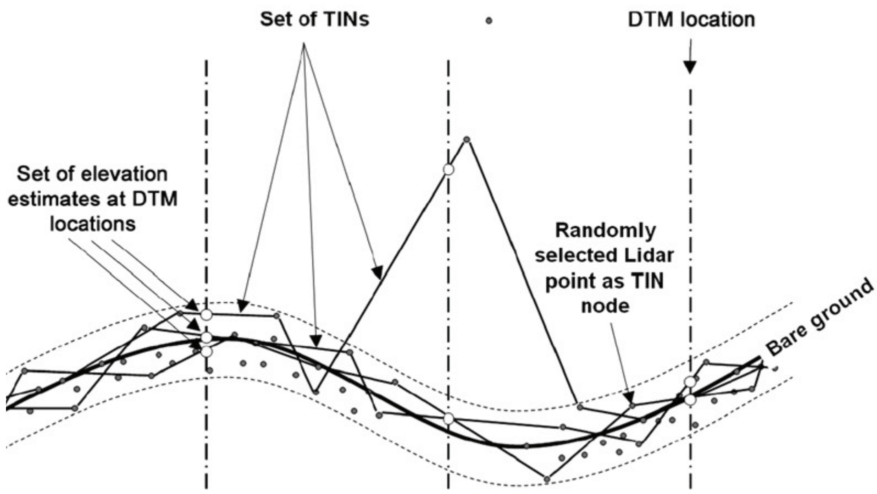

Figure2-1 : repeated random selection of laser points used to build a set of TINs, out of which sets of elevation estimates are interpolated at the locations of DTM grid points. The remaining unfiltered vegetation points may become TIN nodes. (Kobler et al., 2007)

2.3. Structural characteristics of low vegetation

2.3.1. Vegetation Height

LiDAR have been widely used in extracting vegetation height in previous years. Initially profiling scanners were used but the returning signals were almost always from the top of the canopy. (Krabill, 1984) took into account the second return signal to find the topography while (Ritchie, 1996) used frequent and consistent returns from the ground for the same purpose. However when later saw tooth pattern or type of scanners were used, they not only gave rise to lower spatial sampling rates but also lower probability of receiving signals from the ground since most of the signals would be intercepted by vegetation. Both conditions would therefore make measuring topography of the ground difficult to achieve.

(Davenport et al., 2000) found ALS to be a useful tool to predict crop height which proved to be an important indicator of bird species population. Their research could achieve a height accuracy of better than 10 cm. Only pulses that were returned from within the crop were taken into account rather than those reflected from the canopy or the ground. After detrending the heights for topography, an algorithm to measure the variation in returned heights was developed. Thus, a relation between the mean crop height and the standard deviation of detrended return heights was used to derive the crop height of the field.

The delay time between the first and the last returns of each signal were considered to represent vegetation canopy and ground respectively however, in densely populated areas, the last returns might not necessarily represent ground and hence this method is not a reliable one. In order to avoid exaggeration in vegetation height due to high slope areas, adequate filtering method was used. Te bilinear interpolation technique was employed to remove first order height trends. For a certain size of a plot across the field, spot heights are detrended and their distribution is plotted. Narrower distribution is obtained from a non-vegetated region and the broader spread obtained from a 92 cm high crop. The spread is measured by calculating the standard deviation($\sigma_{d)}$ of the detrended height. A simple relationship between this standard deviation and the surveyed height of the crops was established using a simple linear regression which resulted as follows with an r^2 of 0.892.

$$\text{Manually surveyed height} = 8.0559 \times \sigma_d - 0.3513$$

This produces estimates of the crop height with a mean error of 8.3 cm. Their research further concludes that the accuracy of this technique could be improved by giving more detail at the varying laser incidence angle and scan angle of the laser beam. A similar research was also carried out by (Cobby et al., 2001) who demonstrated that crop vegetation of upto 1.2 m in height could be predicted from the standard deviation of the detrended laser pulse returns.

As an extension to this research (Hopkinson et al., 2004) worked on vegetation that ranged from wetland grass to plantation forests. He observed that for forest vegetation the pulse distribution was often bimodal whereas low vegetation tends not to display a bimodal distribution and this is accounted by the following reasons i) homogenous vegetation structure from canopy to ground (Cobby et al., 2001), ii) limitations in segregating first and last pulse for ranges below 1.5m (As per recent advancements). Moreover for low vegetation, it is highly likely that the scanner might associate some noise with the resulting data. As a conclusion, Hopkinson's research proved the fact that a simple multiplication factor (M) could be applicable in vegetation height extraction studies where a M of 2.7 was suitable for low vegetation height extraction. The only potential limitation of M being when applying for low vegetation, the standard deviation of detrended pulses tends to increase with increasing slope irrespective of vegetation height resulting in positional inaccuracy (Hodgson and Bresnahan, 2004)

2.3.2. The Contrast Texture Approach

Pfiefer et al, in 2004 formulated a method where texture was used as a criterion to investigate any shift in height of the low vegetation. Two different approaches were experimented and among that, control point based approach yielded positive results. According to (Oude Elberink and Maas, 2000), texture is qualitatively and quantitatively defined by height. Hence this justifies as one of the parameters that can be exploited to find the height of the vegetation.

Texture in an image(in a raster form) is commonly defined as a regular repetition of a pattern in spatial phenomena (Pfeifer et al., 2004). But rasterization of the laser dataset would lead to loss in detail hence it is advisable to adhere to vector domain. Hence texture of a point (here) is always considered as a neighbourhood than a single point in order to get a hold of one complete pattern. Usually they are seen as local variability of grey levels varying spatially and thus reveal information regarding the object structure. Best known method to deal with textural feature extraction algorithm is Grey level occurrence matrix (GLCM) or Grey tone spatial dependency matrix. (Haralick, 1979) did extensive studies about this algorithm to deal with statistical and structural approaches to texture. In simple terms, he defines GLCM as, "characterizes texture by the co-occurence of its grey tone". Coarse textures are those for which there is only slight variation of distribution with distance and those of finer texture are characterized in which there is rapid change in distribution with distance. The GLCM can be computed as matrix format of relative frequencies F_{ij} with which 2 neighboring pixels (in this case points) situated apart by a distance d each of them with a grey level 'i' and 'j' respectively (Haralick, 1979).

Its elements are expressed by

$$p(i,j) = \frac{P(i,j)}{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P(i,j)}$$

Where	p (i, j)	-	elements of the matrix
	P (i, j)	-	Relative frequencies
	i,j	-	Grey level (0-255)
	N_g	-	Total number of grey levels

(Ruiz et al., 2004)

The main advantage of GLCM being it can characterize the spatial interrelationships of the grey tones in a textural pattern but cannot significantly derive the shape aspects of the tonal patterns.

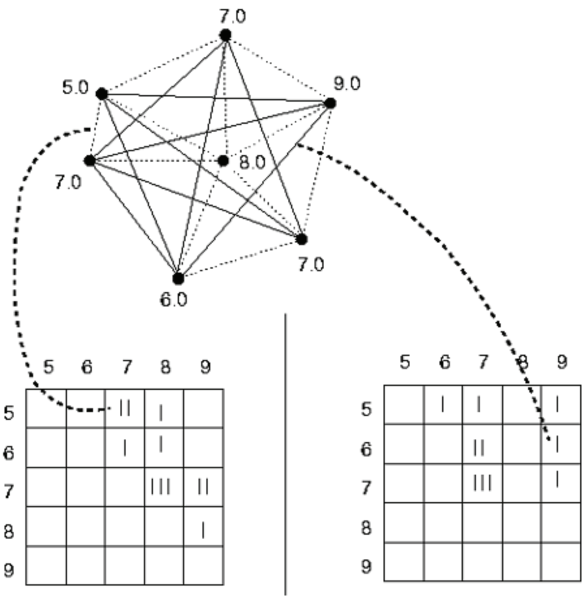

Fig 2-2: GLCM on a point cloud texture Source: (Pfeifer et al., 2004)

Now proceeding to the control point based approach, this is one of way devised by (Pfeifer et al., 2004) to evaluate how the heights of the control points relate to the laser point texture. Hence first, the accurate 'z' measurements of control points are obtained from fieldwork (type of vegetation is also noted down for future use). If the heights are to be obtained from the laser data, the average height of the k-nearest laser points are calculated but this would always mean a positive shift upwards in comparison to field measurements.

2.3.3. Vegetation density

Hydrodynamic vegetation density (*Dv*) is defined as the sum of the frontal areas of all plant elements (*A*) in the direction of the water flow (*F*) per unit volume. Mathematically defined as

$$D_v = \frac{\sum A_i}{AXl}$$

where A_i is the projected area of a vegetation element (m^2), *A* is the surface area of the plot in side view (m^2) and *L* is the length of the plot in the flow direction (*m*). The unit is m^{-1}

Vegetation density can be predicted using methods like percentage index (PI), parallel photography and vegetation area index (VAI). Among these, the vegetation area index gives better results in terms of floodplain vegetation. VAI was proposed by (Macarthur and Horn, 1969) also compensates for occlusion which was later verified by (Aber, 1979) . VAI was later used by (Lefsky et al., 1999) to measure canopy height profiles of foliage as well as the woody vegetation of trees.

Hence this results in not just a leaf area index but a vegetation area index. In VAI, it calculates the number of laser hits that fall within a height range of h_1 to h_2 that could be inundated with water. It is mathematically described as

$$VAI_{h1-h2} = \frac{1}{h2-h1} * \ln\left(\frac{N_{h2}}{N_{h1}}\right)$$

Where N_{h1} and N_{h2} are the number of vegetation points below height 1 and height 2. The first section of the formula is to make the VAI independent of the height interval. This method holds good considering the following assumptions, i) that laser pulses hit the surface parallel to each other, ii) that the horizontal distribution of the floodplain vegetation is random, iii) and that all vegetation elements are hit at an equal angle, which strictly speaking, is not the case (Straatsma, 2005).

2.3.4. Summary of Literature review

Few researches have been done in investigating the disturbing influences of low vegetation and DTM extraction. Previous studies made by Pfiefer et al and Straatsma and Middelkoop show considerable work in trying to estimate the disturbing influence of low vegetation using statistical measures and texture measures and thus to produce a DTM that is not influenced by low vegetation.

(Pfeifer et al., 2001) performed studies in an urban area, DTM accuracy was obtained as following after removing random errors during modeling. Around 816 check points spread over a test area of 2.5 km^2 were used and the results were as following, in a street without cars: +1.0 cm, street with parking cars: +3.7 cm, in an open area: +4.5 cm, park with light stock of trees: +7.8 cm, park with dense trees: +11.1 cm. there is also a systematic shift of the laser points above the check points exhibiting similar behavior as in the accuracies.

In 2003, (Ahokas et al., 2003) investigated various land cover including asphalt, grass, forest ground and gravel from a flying height ranging from 400 – 550 m using roughly 3500 points, obtained results as ±10 cm, ±11 cm, ±4 cm, and ±17 cm respectively. However there was not any consistent shift observed between the laser points and the check points.

(Hodgson and Bresnahan, 2004) found that the accuracy values ranged from a low of 17 to 19 cm (pavement, low grass, high grass, bush and evergreen forests) to a high of 26 cm (deciduous forests) investigated over a laser dataset containing 654 checkpoints using an airborne system which flew over a height of 1207 meters. Statistical tests revealed that on an average, pavement elevations were over predicted (+6.0 cm) and high grass, bush, low trees and evergreen forests were under predicted (-3.8 to -6.0 cm).

Later, (Pfeifer et al., 2004) chooses 10 points/$m^{2,}$ which is very dense laser data compared to the previous study. The height shift was observed to be +11.6 for old willow forest, +9.4 cm for young forests and +7.3 for long dense grass.

(Straatsma and Middelkoop, 2007) analyzed ALS data obtained with varying point densities (10 and 75 points/m^2) over 42 plots spreading 200 m^2 each. Twenty one statistics were computed for each vegetation point and was compared with the available field data of vegetation height. Labeling of the laser data points was done using 3 methods and best results were found when using inflection method with an R^2 ranging from 0.74 to 0.88.

(Hopkinson et al., 2004) approaches the problem by detrending the first and last pulse with the terrain model. Then the standard deviations of the heights were calculated and were compared to average height per field. On testing it on 14 plots of low vegetation (from heights 0.2m to 1.3m) They found a rough estimate of vegetation height as vegetation height = 2.7 X standard deviation of the detrended heights, assuming that this relationship will hold good for all types of low vegetation.(Cobby et al., 2001) and (Davenport et al., 2000) adopt a similar approach as that of Hopkinson et al regarding detrending and deriving standard deviations. They also try out bilinear interpolation techniques in texture measures and to extract the DTM. However such a method remains a crude estimation. (Hopkinson et al., 2004) figured out that there is a positive correlation between this height shift and texture measures. This relationship is thus exploited instead of using standard deviation for low vegetation (<0.2 m).

3. Methodology

3.1. Field data

In both the study areas, a number of parameters were measured. For around 35 different plots of various vegetation types covering an area of 15mx15m, vegetation height and density were measured. These were measured at 25-30 dGPS checkpoints and later averaged to get vegetation height and density per plot. The field plots in Duursche Waarden were mainly grasslands and brushwood while field plots in Brabant were meadows and herbaceous vegetation. the type of DGPS used was LEICA 1200. The dGPS were then converted to the Dutch projection system. All processing was done with spatial data being projected to RDnew projection system. From the Brabant area, one plot was measured on an asphalt area (open parking space) to validate the accuracy of the GPS. Another plot was measured along a road to check the effect of scan angle. In each plot, the diameter 'd' of 'N' number of stems per m^2 were measured. Vegetation density was then computed as a product of N and d (Straatsma, 2005)

3.2. LiDAR data

Flight was flown on the study area resulting in many flight strips. Laser pulses are recorded along the flight path. LiDAR data is usually provided in LAS (Log Ascii) format that makes it compatible with many processing tools and storage friendly. Below is a figure that shows flight strips covering many plots with their corresponding GPS checkpoints Each of the flight strip contains millions of laser point data with not just XYZ attributes but also RGB, intensity, point id and return of the pulse.

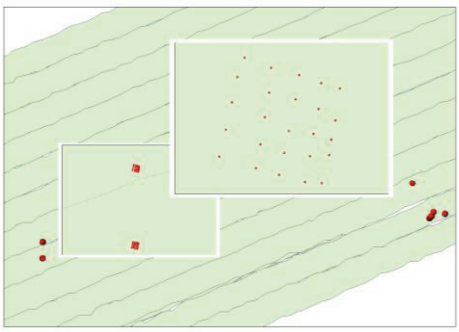

Figure3-1: Flight strips and GPS checkpoints

3.3. Pre-processing

Raw LiDAR points as given by the data provider have to undergo a series of preprocessing in order to be useful for further analysis. The raw LiDAR data given by the data provider is huge in data size, which is inconvenient for computing since it demands a high processing speed and memory storage. Moreover the field data is available only for a small plot. Therefore the LiDAR is clipped into bounding boxes covering the area for which field data is available. This bounding box is even more accurately clipped using point in polygon operation done using python.

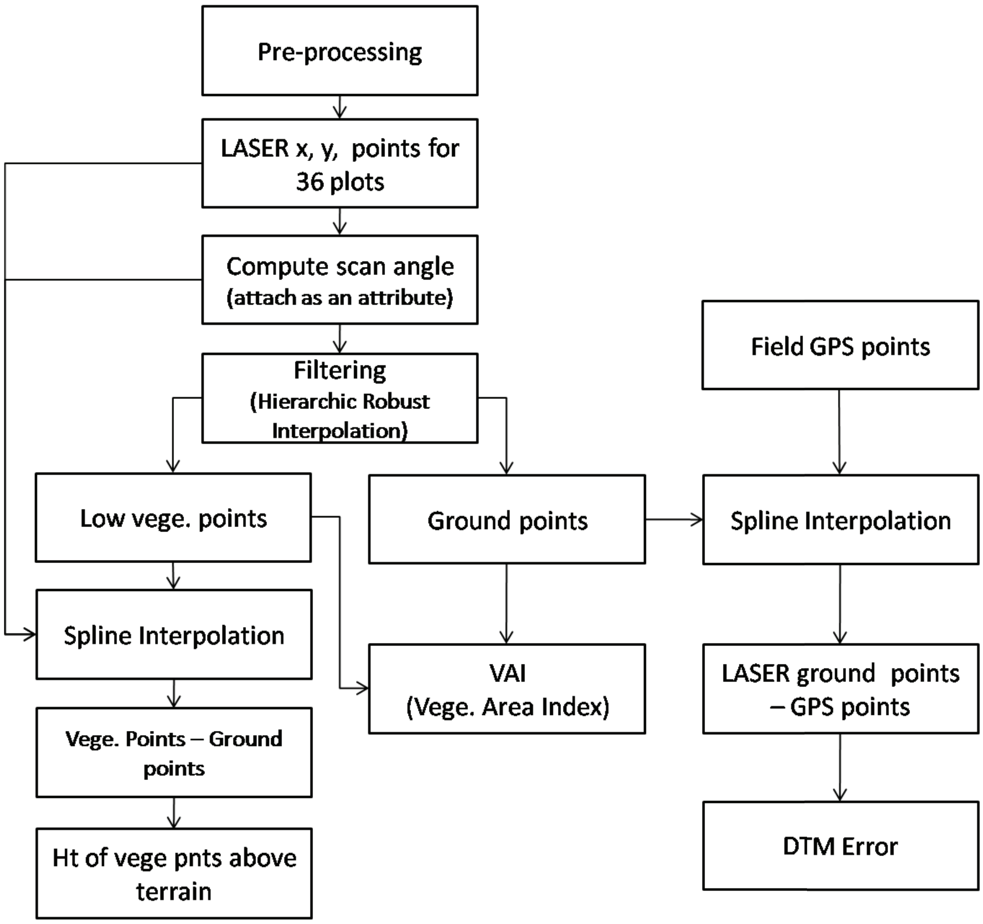

Figure3-2: General workflow

3.4. Scan angle

The scan angle is the angle subtended between the vertical and the direction in which the laser pulse was fired. The importance of studying the effect of scan angle on vegetation structure is because, scan angle is expected to influence the prediction of vegetation structural characteristics, since vegetation is more easily detected when viewed from an angle. Not many researches have been done on the effect of scan angle and vegetation. To calculate the scan angle it is important to know the flight scanner position in time while it was deployed. Since the time stamps of the scanner are taken from the start of the week, while the time stamps of the laser data starts from the start of the day, both these time stamps have to be brought to the same baseline. Once this is done, the xyz of the scanner is sorted and subtracted from the nearest laser pulses xyz. The obtained differences in x,y,z are subjected to the following equation:

$$\alpha = \arccos(\sqrt{(dz)^2} / \sqrt{(dx)^2 + (dy)^2 + (dz)^2})$$

where ..,

α	-	Scan angle (degrees)
dz	-	difference in height (m)
dx	-	difference in latitude (m)
dy	-	difference in longitude (m)

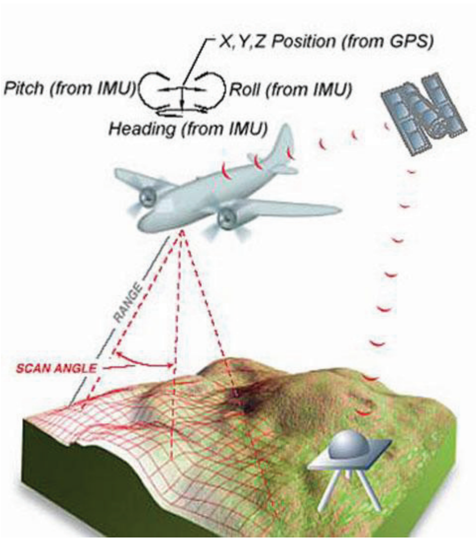

Figure3-3: Range and scan angle
(Source: http://spinternetdev.dot.state.oh.us)

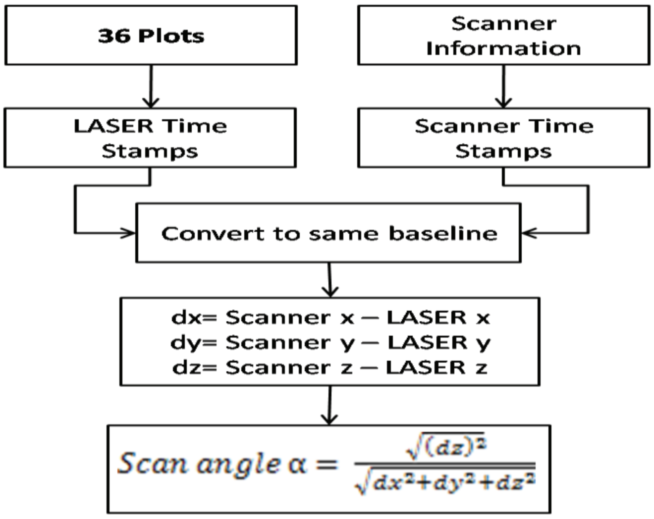

Figure 3-4: Scan angle workflow

3.5. Filtering

As discussed in the previous chapter, filtering plays a very crucial role in this study. For this study, Hierarchic robust filtering method was used. This technique is inbuilt in the software SCOP++ developed by Inpho. For filtering, there is a series of process that is done, which has input from the preceding process and the output is fed to the next process. This is often called filtering strategy (Scop++ manual). The steps involved are mentioned briefly.

- Eliminate buildings: in Eliminate buildings step, the original input data is fed, separating building points(if any) from other points.

- Thin out: In this step, the input set of points is reduced in details, is thinned out. This step is helpful in making sure that a good mixture of blunders and ground points are delivered.

- Sortout: In a sortout step points are compared to a DTM, and the residuals are calculated. If the residuals are beyond a certain threshold, they are rejected.

- Filter: this step deals with the set of points that contains gross errors. These gross errors are categorized as 'off-terrain' points and the aim is to build a DTM with the remaining set of ground points. The output is the points with gross errors, a DTM and good points.

- Interpolate: interpolate step derives a model using linear prediction, where identifying of gross errors is not possible, unlike filter step. The output is a DTM.

- Classify: classify forms a useful extension to the sort out step. Points are compared to the DTM but are given more height difference. The output is classified as buildings, high vegetation, medium vegetation, low vegetation, ground points and below ground. Height intervals and outputs depend on user preference.

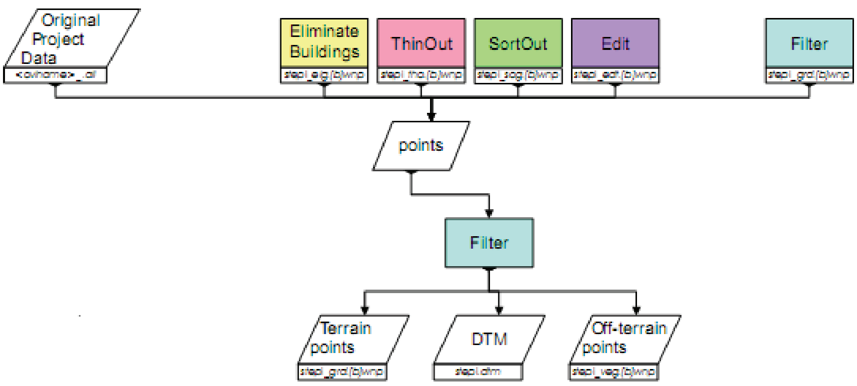

Figure 3-5: Filter strategy in Scop++
(Source: Scop++ manual, inpho.de)

For filtering of low vegetation plots, LIDAR DTM default (Fig 3-4), an inbuilt readymade parameter settings were made use of with some minor changes in grid width and mean accuracy. The classify step was adjusted to suit the height interval that is to be categorized as low vegetation and ground points. Low vegetation was given a height interval from 2 cm to 20cm, medium vegetation from 20 cm to 60 cm and 60 cm and above would be classified as high vegetation. But since most of the plots are only low vegetation and medium vegetation, other categories need not be given much attention.

3.6. Normalisation

LiDAR points show a digital surface model (DSM) that also contains echoes from trees, buildings apart from the ground points. Whereas a digital terrain model (DTM) describes only the ground. A normalized DSM or the nDSM is a difference between the DSM and the DTM(Oude Elberink and Maas, 2000).

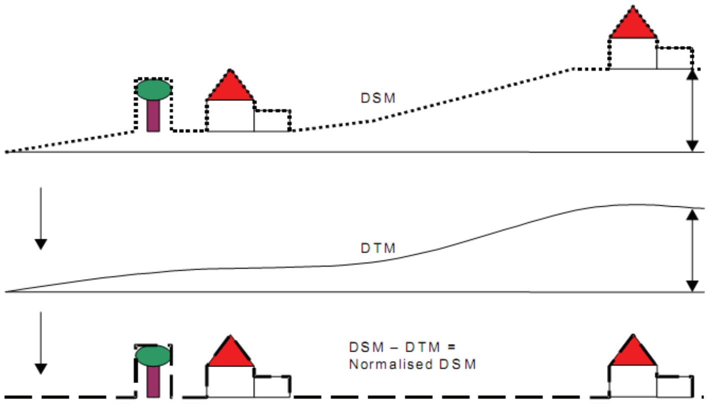

Figure 3-6: Steps to build an nDSM (Source: (Oude Elberink and Maas, 2000)

This process is often done as the first step before trying to quantify anything since the models until they are normalized do not give the exact local height above the terrain (Haala, 1999). It means that all the features are placed on a height above terrain. The ground points and low vegetation points obtained from the filtering process are then normalized.

For normalization in this study, the ground points obtained from filtering are made into a DTM surface. All points, including the low vegetation, ground and other points (if any) were fed as the surface model. Using second order spline interpolation method, a corresponding point in DSM for every point in DTM was interpolated. This was done by feeding the DSM (all points of the point cloud) and the DTM (only the ground points) in GSTAT. A second order polynomial was fit to the DSM with a search radius of 1(Euclidean distance). The heights of new interpolated points from the DSM are then subtracted from the corresponding DTM (ground) points to find the local height above terrain. This height above terrain was added as an attribute to each point.

3.7. DTM Error

In chapter 2, there is a description about the positive height shift due to the disturbing influences of low vegetation in deriving a DTM. Below is a method to check if this DTM error is dependent on the vegetation structure and scan angle. Before computing the DTM error, it was essential to check the accuracy of the dGPS used. In order to compute the accuracy of the dGPS, the asphalt (flat) plot is taken into account. Asphalt plot is filtered to remove of any high lying pulses like car (since it is a parking area) or poles. The laser ground points after they are filtered, are then interpolated over the gps checkpoints using second order spline interpolation. The difference between each of the gps point with its corresponding laser ground point gives the error in the dGPS.

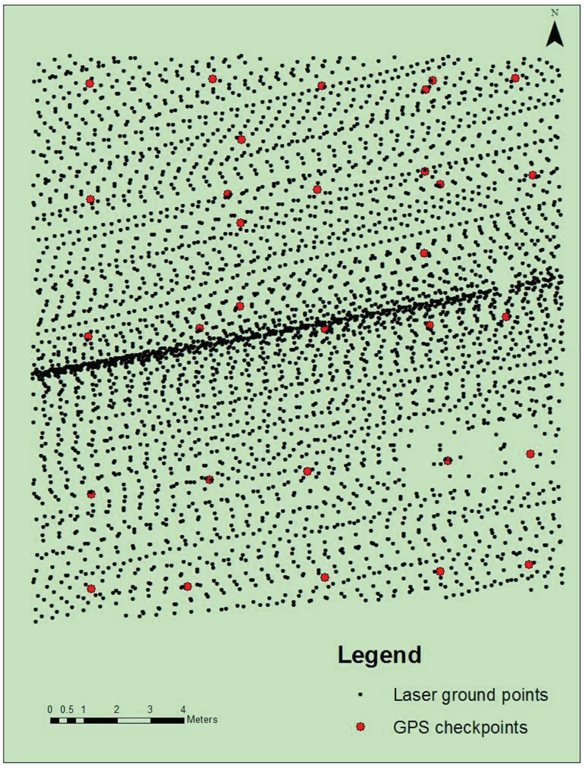

Figure3-7: dGPS checkpoints and laser derived ground points of the asphalt plot

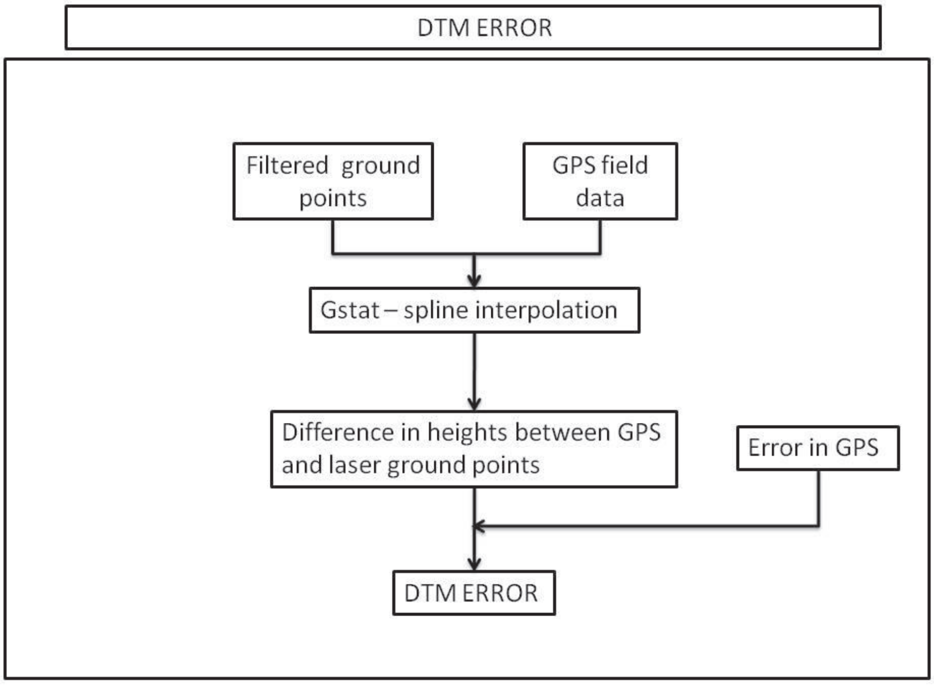

Figure 3-8: Flowchart showing the process of finding DTM error

Now the same procedure is repeated for other herbaceous plots to predict the DTM error in that particular terrain due to low vegetation. Mean DTM error is then subtracted from the GPS accuracy to find accurate DTM error per plot.

3.8. Vegetation Height extraction

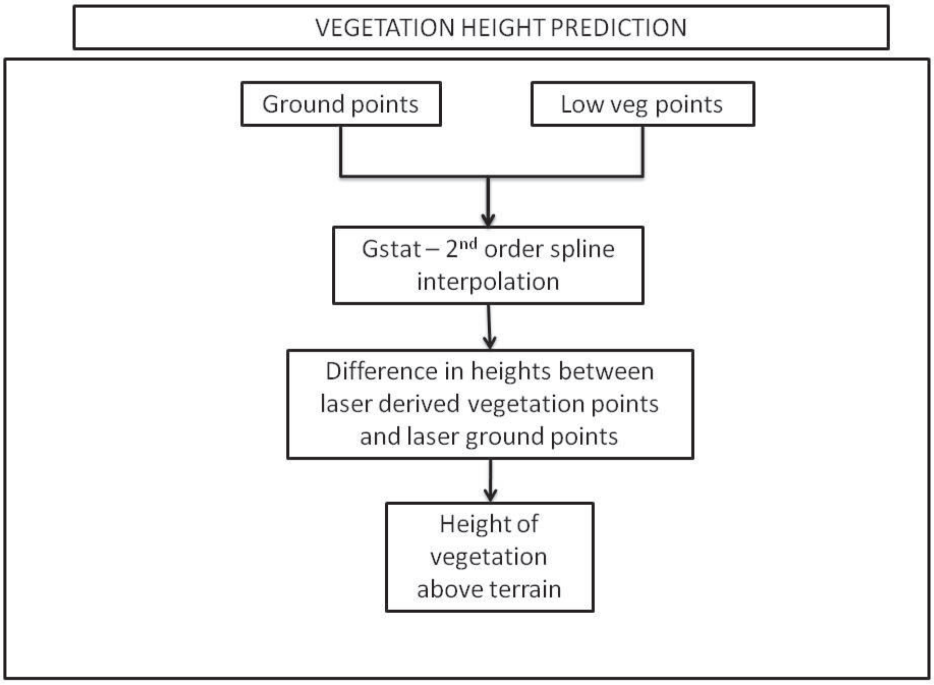

Figure 3-9: Flowchart showing the process of finding vegetation height

Terrain points and vegetation points are fed as inputs to the GSTAT processing in order to undergo a second order spline interpolation. After interpolation, the heights of the vegetation point for every ground point are subtracted. This gives the height of a vegetation point above a terrain. These normalized heights were then used to compute statistics against DTM error and field data. Correlation and regression analysis was performed to check if there was any relationship that existed between the DTM error of the terrain and the height of the vegetation points above the terrain. The same procedure were done for both the datasets.

3.9. Vegetation density extraction

In this study, vegetation area index (VAI) is made use to predict the vegetation density. As described in chapter 2, VAI is mathematically described as

$$VAI_{h1-h2} = \frac{1}{h2-h1} * \ln\left(\frac{N_{h2}}{N_{h1}}\right)$$

Where ..,

h_1 – 25 percentile of the laser extracted height of the vegetation point above terrain
h_2 – 75 percentile of the laser extracted height of the vegetation point above terrain
Nh_1 – no. of points that lie below the height of h_1
Nh_2 – no. of points that lie below the height of h_2

Since h2 and h2(h2>h1) indicates the level of inundation of water, it was decided to consider h2 and h1 as the 75th and 25th percentile of the predicted vegetation height respectively. Thus the numbers of points that fall below both these heights were calculated and the vegetation density for each plot was found using the above equation.

4. Results

4.1. Scan angle

The scan angle for herbaceous plots in Brabant floodplain was computed using the method described in chapter 3. Below is an illustration of the flight path and the subsequent laser pulses and how the scan angle changes with the flight path.
The scan angle was computed for around 13 herbaceous plots in both the datasets. The scan angle varied from 6 degrees to 25 degrees.

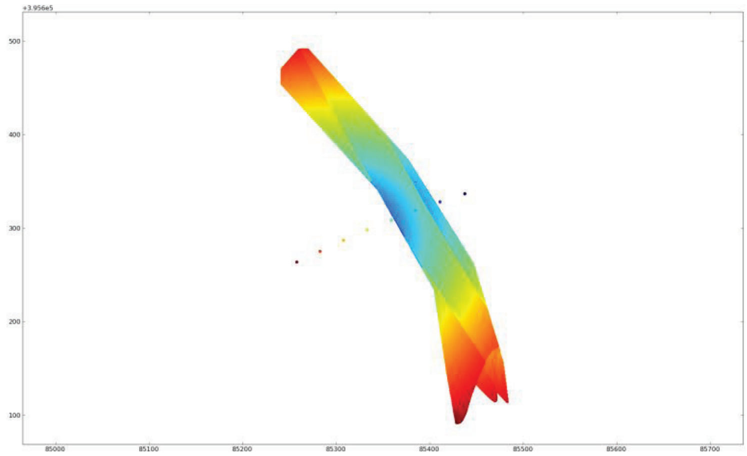

Figure4-1: Flight path(dots) and laser echoes of a road showing variation in scan angle along with the flight path

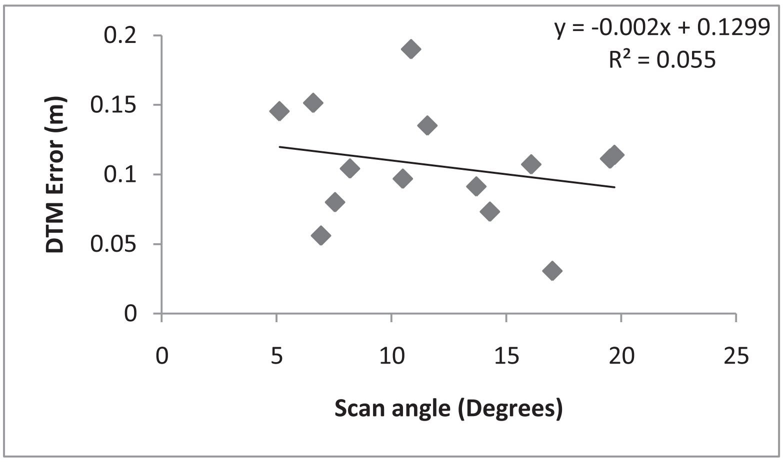

Figure 4-2: Mean scan angle Vs mean DTM error

4.2. DTM Error

The DTM error for the Brabant floodplain for meadows and herbaceous plots was found to be as below (Table 2) Mean DTM error being 10.61 cm with a standard deviation of ±4.1 cm for meadows and herbaceous plots. The DTM error for Duursche Waarden was not able to be computed since there was no GPS data available. The GPS error check was done using the asphalt plot. The error in GPS was found to be 0.9 cm. The table regarding the GPS error calculation is attached in the appendix I.

PLOT NR	Mean DTM ERROR
1	7.32
2	8
6	9.13
9	11.13
10	11.4
15	5.6
17	10.72
18	9.69
19	15.14
20	19
27	13.51
28	10.42
29	14.54
32	3.06

Table 4-1: DTM error for low vegetation plots in Brabant

4.3. Vegetation Height statistics

As a predictor of vegetation height, many statistical measures were computed and correlation was used to see if there is a strong correlation found between vegetation height and any of the statistics.

4.3.1. Mean and Standard deviation per plot

plot no.	plot type	mean	stddev
1	meadow	0.035	0.012
2	meadow	0.037	0.012
6	herbaceous	0.054	0.03
7	herbaceous	0.051	0.026
9	herbaceous	0.122	0.112
10	herbaceous	0.094	0.084
15	meadow	0.045	0.007
17	herbaceous	0.061	0.018
18	herbaceous	0.056	0.029
19	herbaceous	0.104	0.057
20	herbaceous	0.16	0.148
27	herbaceous	0.063	0.019
28	herbaceous	0.052	0.022
29	herbaceous	0.059	0.029
32	meadow	0.034	0.011

Table 4-2:mean and std deviation for Brabant plots

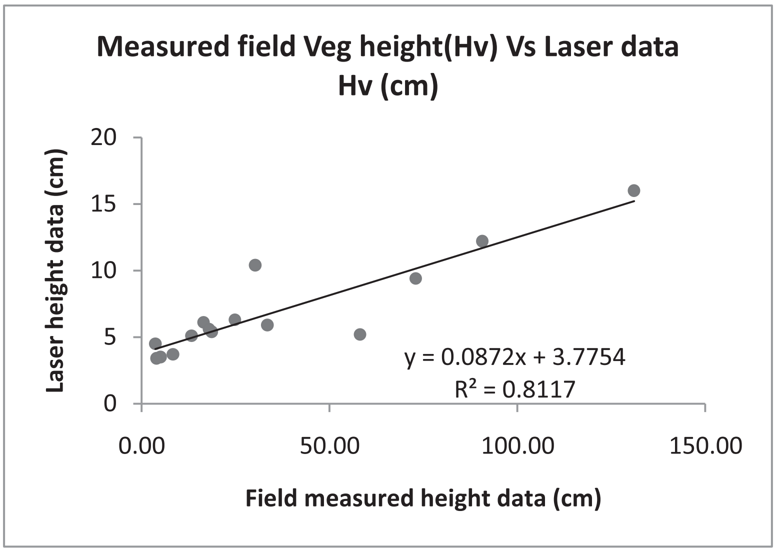

Figure 4-3: Plot between field veg height and laser veg height

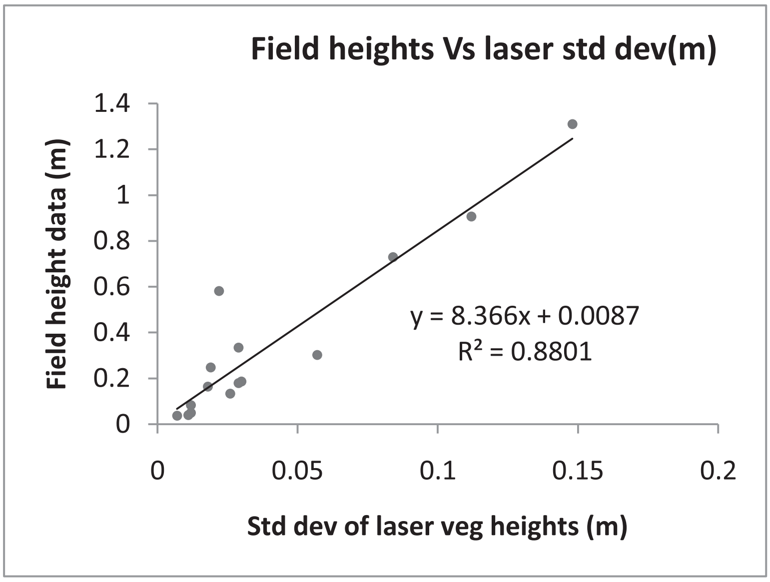

Figure 4-4: Plot between field veg height and laser veg height

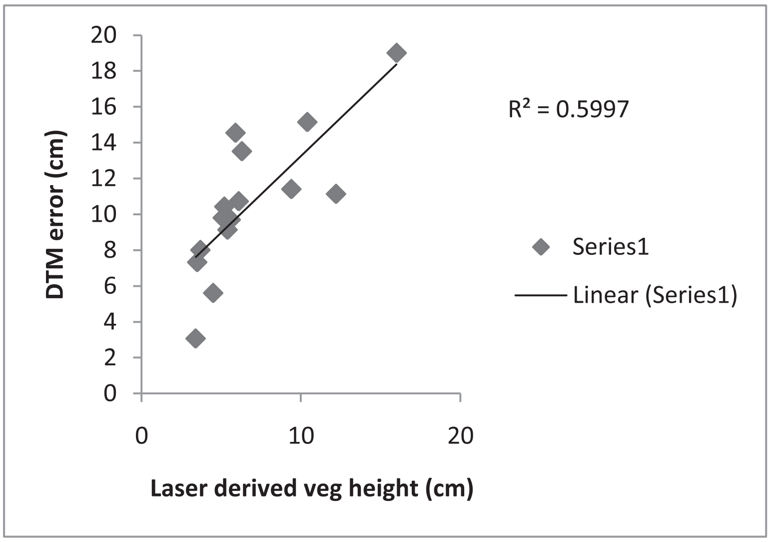

Figure 4-5: Plot between laser veg height and DTM error

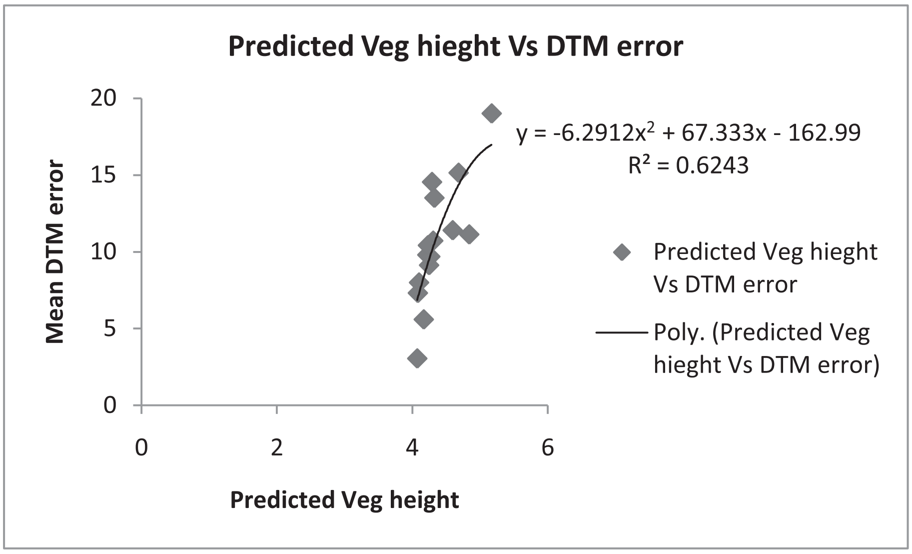

Figure 4-6: Plot shown between predicted vegetation height using regression equation and DTM error

4.4. Vegetation density statistics

As discussed in the previous chapter, vegetation area index is a measure of estimating vegetation density. Vegetation density obtained from field and VAI calculated were correlated and the obtained results are as below.

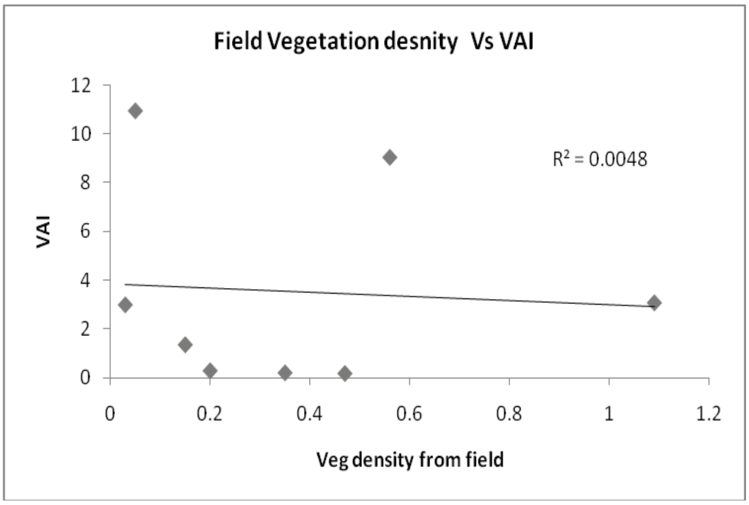

Figure 4-7: Plot drawn between field measured vegetation density and VAI

Unfortunately vegetation density computed using VAI shows meagre correlation with vegetation density measured in the field.

A multiple regression analysis was done between laser derived vegetation height, VAI and DTM error. Regression coefficient R^2 for this study was found to be 0.74 with an rmse value of 2.2 cm.

5. Discussion

5.1. Scan angle

The objective of devising the scan angle was to see if there is any correlation found between scan angle and the DTM error found in the calculation. . With the change in scan angle, the pattern of laser echoes changes(Lohani, 2008). It was assumed that the lower scan angle would offer contribute less to the DTM error than higher scan angles, since lower scan angles have a higher chance of hitting the ground.

The scatter plot(Fig 4-2) shows that there is not notable relationship between DTM error and scan angle. This is again limited to other parameters such as the flying height, point density and pulse frequency. With the given dataset, that has a point density of 10 points/m^2 and a flying height of 400 ft, such a result is obtained. It would be interesting to test this by varying the above parameters. Unfortunately it was not possible to test this in the Duursche-waarden floodplain since there were no GPS measurements taken in order to find the DTM error.

- Some plots could fall between 2 overlying flight strips.
- GPS time stamps and Laser time stamps should match
- Important to consider the projection systems of the scanner GPS and the system in which laser data is projected.
- A good validation technique for scan angle and DTM error relationship was to check this on a plot of asphalt. Due to technical problems faced in filtering of the plot in SCOP++, unfortunately the results could not be found. This is recommended for the future researches.

5.2. DTM error

State of art accuracy reached in computing the DTM error has been done by many researches before. For the same point density of 10points/m^2, (B. Gorte et al., 2005) found a positive shift of ±7.3 cm in long dense grass, ±9.4 cm in a ground of young forest and ±11.6 cm in an old willow forest. The method they employed to find the shift was using grey level co occurrence matrix (GLCM) method that primarily uses texture as a parameter to find the DTM error. Various other researches and their findings are tabulated as below.

Research group	Findings on low vegetation	Notable parameters
(Pfeifer et al., 2001)	±4.5cm	800 terrestrial check points
(Ahokas et al., 2003)	±11cm	Flying height - 550 m, 3500 ground points
(Bollweg and de Lange,2003)	±14cm	-
(Crombaghs et al., 2002)	±15cm	-
(Hodgson and Bresnahan, 2004)	±6cm	650 checkpoints

Table 5-1: Comparative study of the results obtained in previous studies regarding DTM error using airborne laser scannning
(As cited in AGI rijkswaterstad, Dutch ministry of public works report, 2005)

Interpolation method that is deployed for finding the DTM error is very crucial. Inverse distance weighting that is used in this study as well the AGI rijkswaterstad report of 2005, remarks that averaging over a large area(in this case 25 m^2) considers only few points into account. Since the point nearest to the centre gets the highest weight, it might be the case that the point is either a ground point or a vegetation point which is very difficult to judge in the case of low vegetation. Quantifying this kind of stochastic nature in low vegetation is still a challenge. The GPS that is used for calibrating DTM error had to be converted from ellipsoid model to the geoid model.

5.3 V**egetation Height characteristics**

As seen in fig 4-3 and 4-4, there seems a good relationship between height data from laser and field measurements. Similar correlation was done by (Cobby et al., 2001) and (Davenport et al., 2000) though they used low resolution(1 points 9m^2). Since the density of crops was high, they were not able to efficiently demarcate ground surface which led them to use detrended laser heights as predictors of vegetation height. Another research done by (Hopkinson et al., 2004) predicted vegetation height of aquatic marshland. Similar to the studies done previously, they used standard deviations of laser heights corrected for local terrain undulations as a predictor of vegetation height.

A comparative study of the above studies is tabulated as below.

RESEARCH GROUP	TYPE OF VEGETATION	R^2	MAPPING CONDITIONS
(Cobby et al., 2001)	Grass and cereal crops	0.80 (log)	Low point density, leaf on condition
(Davenport et al., 2000)	Farmland	0.89	Low point density, leaf on condition
(Hopkinson et al., 2004)	Aquatic marshland, grassland and herbs	0.77	Point density 3/m^2
This study	Meadow and herbaceous	0.88	10 points/m^2, Winter, leaf off

Table 5-2: Comparative study showing results obtained in predicting vegetation height

However, it is important to note that the previous studies were done in a dense vegetation area with leaf on conditions, were there is meager chance of the laser pulses getting reflected from the top of the canopy. This might add more bias to the shift in terrain height. With this study It was interesting to see how the relationship is established in winter season leaf off conditions. Results show that point density plays a positive role in the establishment of a strong correlation observed between both the quantities. A regression analysis was performed between various statistical measures of laser derived vegetation height and field measured vegetation height.

- Regression between field measured mean vegetation height with laser derived mean vegetation height
- Multiple regression between laser derived, field measured vegetation height and scan angle
- Using the first regression equation, vegetation height per plot is predicted. This is used to find any correlation with mean DTM error per plot.

Reg	Field height data (cm)	DTM error (cm)
Laser Veg height (cm)	R^2: 0.81 Stderr: 1.62 Reg eq: Laser veg h = 0.08*Fieldheight + 3.77	R^2 = 0.62 DTM error = $-6.2912x^2 + 67.333x - 162.99$ where x = predicted laser hveg height
Laser Veg height and scan angle	R^2: 0.81, Stderr: 1.68, Reg eq: Laser veg h = 0.08*fieldheight - 0.02*scanangle+3.99	

Table 5-3: Regression results with predicting vegetation height with various parameters

Correlation with field vegetation height and laser derived statistics:

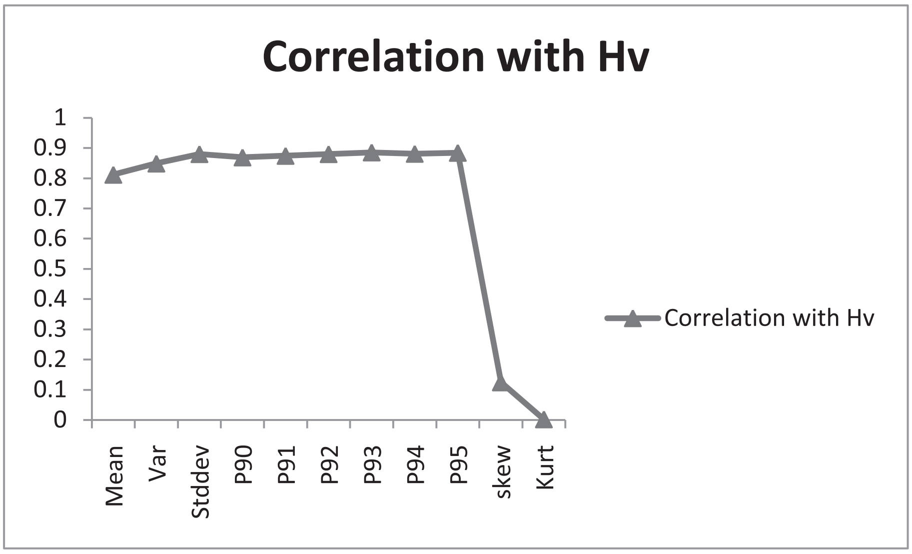

Figure 5-1: graph showing strength of correlation between laser height data and various statistical measures

As seen in the figure, the statistical measures, standard deviation and 93 percentile show highest correlation with the laser derived vegetation height however skewness and kurtosis show a negligible correlation.

Type of filtering method used, grid width, interpolation method, height interval specified for classification of points play a key role. Two major challenges of this study being, the height of low vegetation is well within the noise levels of the laser scanner and the filtering algorithms might need justified parameters to filter low vegetation points from the ground points, which is still ambiguous.

5.3. Vegetation density

Height intervals h_1 and h_2 are crucial while deciding to compute VAI. It is important that h_1 does not fall under the noise that's mixed with the ground points. In field, density was measured taking half of the average vegetation height into account.

Also dependent on the accuracy of filtering method employed to classify points. VAI is very sensitive to the number of ground points. With decreasing number of ground points, VAI is overestimated (Straatsma, 2005). One probable reason for VAI to fail in predicting vegetation density could be the occlusion factor that VAI takes into account. This model proves more suitable for leaf off forest canopy where ground points could be better segregated than for low vegetation.

6. Conclusion

- This paper discussed few aspects of extracting structural characteristics of low vegetation in Dutch floodplains using advanced airborne laser scanning data.

- This study also effectively discussed about the DTM error in low vegetation areas while using LiDAR as a tool.

- From the regression analysis performed between vegetation height and shift, there is a strong correlation seen for vegetation height data ranging from 3 to 7 cm. and shift values between 3 to 15cm.

- For vegetation height less than 6 cm, a mathematical relationship could be established with corresponding DTM error.

- Standard deviation of vegetation height in 15 herbaceous plots were measured which expand to an area of 5m x 5m.
  Standard deviations in a range below 5 cm, there is a strong correlation between field data and laser derived std deviation of vegetation height.

- Effect of scan angle on vegetation height and DTM error was also studied. No strong correlation was found to exist.

- Amongst other first order statistical measures that were found, only std deviation and 93rd percentile found to have a strong correlation with vegetation height. Skewness and kurtosis proved poor correlation.

- Vegetation density of all the plots was computed using VAI, an index that's comparable with vegetation density. When comparing with field data, VAI did not prove a strong predictor of vegetation density.

For further research

- Exploring into other tools like texture measures, spatial auto correlation could also be explored to predict vegetation height and DTM error.

- A major venture into this study would be to improve on the filtering methods and deduce a segmentation method that's built specially for segregating low vegetation and ground points.

7. References:

ABER, J. D. 1979. A method for estimating foliage height profiles in broad leaved forests. *Ecology,* 67**,** 35-40.

AHOKAS, E., KAARTINEN, H. & HYYPPÄ, J. 2003. a quality assessment of airborne laser scanner data. *International Archives of Photogrammetry and Remote Sensing,* 34**,** 13-18.

AXELSSON, P. 1999,2000,2001. Processing of Laser Scanner data – Algorithms and Applications. *ISPRS Journal of Photogrammety and Remote Sensing, ,* Vol.54,**,** 138-147.

B. GORTE, PFEIFER, N., AND & OUDE ELBERINK, S. Year. Height texture of low vegetation in airborne laser scanner data and its potential for DTM correction. *In:* ISPRS Journal of Photogrammetry and Remote Sensing, 2005 Enschede. ISPRS

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.

BROVELLI, M., A., CANNATA, M., AND LONGONI, U .M. Year. Managing and processing LIDAR data within GRASS. *In:* GRASS Users Conference, 2002 University of Trento, Italy 29 pp.

COBBY, D. M., MASON, D. C. & DAVENPORT, I. J. 2001. Image processing of airborne scanning laser altimetry data for improved river flood modelling. *ISPRS Journal of Photogrammetry and Remote Sensing,* 56**,** 121-138.

CROMBAGHS, M., OUDE ELBERINK, S., BRUGELMANN, R. & DE MIN, E. 2002. Assessing height precision of laser altimetry DEMs. Delft, The Netherlands: Ministry of transport. Public works and water management.

DAVENPORT, I. J., BRADBURY, R. B., ANDERSON, G. Q. A., HAYMAN, G. R. F., KREBS, J. R., MASON, D. C., WILSON, J. D. A. & VECK, N. J. 2000. Improving bird population models using airborne remote sensing. *International Journal of Remote Sensing,* 21**,** 2705-2717.

GEOPFERT, J., AND & SOERGEL, U. 2007. Estimation of the LIDAR Height offset in coastal vegetated areas. *ISPRS Workshop on Laser Scanning and Silvilaser* Espoo, Finland.

GORTE, B., PFEIFER, N., AND & OUDE ELBERINK, S. Year. Height texture of low vegetation in airborne laser scanner data and its potential for DTM correction. *In:* ISPRS Journal of Photogrammetry and Remote Sensing, 2005 Enschede. ISPRS

HAALA, N. A. W., V., 1999. Automatic classification of urban environments for database revision using LiDAR and colour aerial imagery. *International Archives of Photogrammetry and Remote Sensing,,* Vol. 32, .

HARALICK, R. M. 1979. Statistical and Structural approach to texture. *Proceedings of the IEEE,* 67**,** 786-804.

HODGSON, M. E. A. & BRESNAHAN, P. 2004. Accuracy of Airborne Lidar-Derived Elevation: Empirical Assessment and Error Budget. . *Photogrammetric Engineering & Remote Sensing***,** 331-339.

HOPKINSON, C., K. , LIM, L. E., CHASMER, P., TREITZ, I. F., CREED, A. & GYANN, C. 2004. Wetland grass to plantation forest – estimating vegetation height from the standard deviation of lidar frequency distributions. *International Archives of Photogrammetry and Remote Sensing,* 34.

JOHN CHANCE LAND SURVEYS, I. 2003. *FLI-MAP* [Online]. Available: http://www.flimap.com/site47.php [Accessed 11th Jan 2010].

KILIAN, J., HAALA, N., AND & ENGLICH, M. 1996. Capture and evaluation of airborne laser data. *International Archives of Photogrammetry and Remote Sensing,* 31**,** 383-388.

KOBLER, A., PFEIFER, N., OGRINC, P., TODOROVSKI, L., OSTIR, K. & DZEROSKI, S. 2007. Repetitive interpolation: A robust algorithm for DTM generation from Aerial Laser Scanner Data in forested terrain. *Remote Sensing of Environment,* 108**,** 9-23.

KRABILL, W. B., COLLINS, J. G., LINK, L. E., SWIFT, R. N., AND BUTLER, M. L., 1984. Airborne laser topographic mapping results. . *Photogrammetric Engineering and Remote Sensing,* 50**,** 685–694.

KRAUS, K. & PFEIFER, N. 1998. Determination of terrain models in wooded areas with airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing,* 53**,** 193-203.

LEFSKY, M. A., HARDING, D., COHEN, W. B., PARKER, G., AND & SHUGART, H. H. 1999. Surface LiDAR remote sensing of Basal area and biomass in Deciduous Forests of Eastern Maryland, USA. *Remote Sensing of Environment,* 67**,** 83-98.

LOHANI, B., AND SINGH, R., 2008. Effect of data density, scan angle, and flying height on the accuracy of building extraction using LiDAR data *Geocarto International,* Volume 23**,** 81-94.

MACARTHUR, R. H., AND & HORN, H. S. 1969. Foliage profile by vertical measurements. *Ecology,* 50**,** 594-598.

OUDE ELBERINK, S., AND, G. B. & BRUGGELMANN, R. Year. 3-D construction from airborne laser scanner and InSAR data. *In:* MAAS, H. G., VOSSELMAN, G. & A., S., eds. Proceedings of the ISPRS working group III/3 workshop, 2003 Dresden, Germnay.

OUDE ELBERINK, S. A. & MAAS, H. G. 2000. The use of Anisotropic Height Texture Measures for the Segmentation of Airborne Laser Scanner Data
International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, , 33-part 3B.

PFEIFER, N., AND BRIESE, C. Year. Airborne laser scanning and derivation of digital terrain models. *In:* Fifth Conference on Optical 3-D Measurement Techniques, , 2001 Vienna, Austria.

PFEIFER, N., B. GORTE, A. & ELBERINK, S. O. 2004. Influences of vegetation on laser altimetry – analysis and correction approaches. *International Archives of Photogrammetry and Remote Sensing,* 36.

PFEIFER, N., P. STADLER, A. & BRIESE, C. Year. Derivation of digital terrain models in the SCOP++ environment. *In:* OEEPE Workshop on Airborne Laserscanning and Interferometric SAR for Detailed Digital Terrain Models, 2001 Stockholm, Sweden.

PODOBNIKAR, T. Year. Various data sources of different quality for DTM production. *In:* 5th AGILE conference on Goegraphical Information Science, April 25th - 27th 2002 Palma, Spain.

RITCHIE, J. C., MENENTI, M., AND WELTZ, M. A., 1996. Measurements of land surface features using an airborne laser altimeter: the HAPEX-Sahel experiment. . *International Journal of Remote Sensing, ,* 17**,** 3705–3724.

ROGGERO, M. 2001. Airborne laser scanner-clustering in raw data. *International Archives of Photogrammetry and Remote Sensing,* 34**,** 227–232.

RUIZ, L. A., FDEZ-SARRÍA, A. & RECIO, J. A. 2004. Texture feature extraction for classification of remote sensing data using wavelet decomposition: a comparative study. *20th ISPRS Congress.*

SITHOLE, G. & VOSSELMAN, G. 2004. Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing,* 59**,** 85-101.

STRAATSMA, M. W. 2005. Quantitative mapping of hydrodynamic vegetation density of floodplain forests using airborne laser scanning. *ISPRS Workshop.* Enschede.

STRAATSMA, M. W., AND & MIDDELKOOP, H. 2006. Airborne laser scanning as a tool for lowland floodplain vegetation monitoring

Hydrobiologia, 565**,** 87-103.

STRAATSMA, M. W., AND & MIDDELKOOP, H. 2007. Extracting structural characteristics of herbaceous floodplain vegetation under leaf-off conditions using airborne laser scanner data. *International Journal of Remote Sensing*

28**,** 2447-2467.

TÓVÁRI, D. & PFEIFER, N. Year. Segmentation based robust interpolation – a new approach to laser data filtering

In: Proceedings of Laserscanning 2005, 2005 Enschede, The Netherlands. IAPRS pp.79-84.

VOSSELMAN, G. 2000. Slope based filtering of laser altimetry data. *International Archives of Photogrammetry and Remote Sensing,* 33**,** 935-942.

WAGNER, W., ULLRICH, A., DUCIC, V., MELZER, T., & STUDNICKA, N. 2006. Gaussian decomposition and calibration of a novel small-footprint fullwaveform digitising airborne laser scanner,. *ISPRS Journal of Photogrammetry and Remote Sensing* 60**,** 100-112.

Appendices

Appendix 1.1 Field data – Duursce waarden Floodplains

Klasse	Puntnummer	datum	Resolutie	Zoom	Sluitert	Diafragm	Plotdpt mtr	Cam-scherm mtr	Hgt cam cm	Afst fot cm	# foto's
Forest	1	27-Mar-07	2272x1704	4x	P	P	20	20	135	15	40
Forest	2	27-Mar-07					n.v.t.				
Forest	3	27-Mar-07					n.v.t.				
Forest	4	27-Mar-07	2272x1704	4x	P	P	15.5	15.5	135	15	44
Hedge	5	27-Mar-07	2272x1704	4x	P	P	4.7	9.1	135	15	80
Grasl/Rubbish dumps	6	27-Mar-07	2272x1704	4x	P	P	15	15	20	15	80
Grasland	7	27-Mar-07					n.v.t.				
Forest	8	02-Apr-07	2272x1704	4x	P	P	14.65	14.65	135	15	40
Forest	9	04-Apr-07					n.v.t.				
Forest	10	02-Apr-07	2272x1704	4x	P	P	12.2	12.2	135	15	40
Forest	11	02-Apr-07	2272x1704	4x	P	P	11.4	11.4	135	15	40
Forest	12	02-Apr-07	2272x1704	4x	P	P	16.5	16.5	135	15	40
Forest	13	04-Apr-07	2272x1704	4x	P	P	13.5	13.5	135	15	40
Forest	14	04-Apr-07	2272x1704	4x	P	P	13	13	135	15	40
Forest	16	04-Apr-07	2272x1704	4x	P	P	10	10	135	15	40
Grasl/Rubbish dumps	17	29-Mar-07	2272x1704	4x	P	P	13.55	13.55	40	15	40
Rubbish dumps	18	29-Mar-07	2272x1704	4x	P	P	8.2	8.2	80	15	
Grasland	19	29-Mar-07					n.v.t.				
Grasland	20	29-Mar-07					n.v.t.				
Grasland	21	29-Mar-07					n.v.t.				
Grasland	22	29-Mar-07					n.v.t.				
Grasland	23	29-Mar-07					n.v.t.				
Grasland	24	29-Mar-07					n.v.t.				
Brushwood	25	29-Mar-07	2272x1704	4x	P	P	9,4 - 3,5	9.4	135	15	40
Brushwood	26	29-Mar-07	2272x1704	4x	P	P	3	6.5	135	15	40
Grasland	27	02-Apr-07					n.v.t.				
Brushwood	28	02-Apr-07	2272x1704	4x	P	P	10.8	12.7	135	15	40
hedge	29	02-Apr-07	2272x1704	4x	P	P	4.6	10.1	135	15	40
Rubbish dumps	30	02-Apr-07	2272x1704	4x	P	P	17.8	17.8	80	15	40
Grasl/Rubbish dumps	31	04-Apr-07					n.v.t.				
Hedge	32	04-Apr-07	2272x1704	4x	P	P	3.2	10	135	15	40
Reed	33	04-Apr-07	2272x1704	4x	P	P	2.8	3	135	15	40
Brushwood	34	04-Apr-07	2272x1704	4x	P	P	8.1	10	135	15	40
Reed	35	04-Apr-07	2272x1704	4x	P	P	2.2	2.2	135	15	40
Brushwood	36	04-Apr-07	2272x1704	4x	P	P	5	5	135	15	40

Appendix 1.2 Field data – Duursce waarden Floodplains continued

piket 1		piket 2		piket 3		piket 4			
X	Y	X	Y	X	Y	X	Y	Xaverage	Yaverage
202560.607	486544.236	202576.553	486540.281	202580.964	486558.746	202562.424	486565.155	202570.137	486552.105
202476.327	486490.510	202458.912	486495.592	202472.361	486520.775	202486.380	486513.106	202473.495	486504.996
202301.323	486591.608	202305.395	486614.668	202284.851	486619.075	202278.871	486596.743	202292.610	486605.523
202242.476	486645.950	202244.970	486629.905	202223.614	486628.112	202220.904	486645.160	202232.991	486637.281
203449.877	487402.91	203449.236	487397.421	203462.167	487396.471	203462.965	487401.451	203456.061	487399.563
203903.086	487615.228	203912.439	487610.064	203906.603	487596.117	203894.259	487603.518	203904.097	487606.232
203751.017	487666.757	203748.909	487677.44	203729.166	487670.67	203732.174	487661.434	203740.317	487669.075
202192.623	486678.635	202173.106	486688.046	202177.324	486707.111	202195.959	486699.384	202184.753	486693.294
202223.722	486726.485	202211.286	486740.317	202223.702	486754.595	202236.658	486744.868	202223.842	486741.566
202141.631	486851.628	202160.168	486851.695	202142.212	486874.043	202160.327	486870.020	202151.084	486861.847
202169.768	486991.683	202183.273	486998.158	202185.122	486983.292	202172.980	486979.591	202177.786	486988.181
202238.972	487133.874	202254.497	487119.693	202265.155	487129.331	202256.856	487143.423	202253.870	487131.580
202374.840	487150.045	202383.154	487134.663	202374.099	487125.096	202361.125	487139.098	202373.305	487137.226
202478.675	486981.918	202484.811	486966.275	202471.566	486960.612	202463.120	486971.184	202474.543	486969.997
202543.017	486666.144	202543.074	486679.312	202526.843	486686.903	202525.386	486672.512	202534.580	486676.218
202973.616	487105.379	202987.1	487108.479	202981.242	487125.786	202969.177	487122.256	202977.784	487115.475
203000.636	487119.576	202999.214	487130.733	202986.322	487128.674	202988.971	487116.388	202993.786	487123.843
202750.847	487313.699	202768.484	487323.199	202757.64	487339.549	202742.062	487327.081	202754.758	487325.882
202674.718	487317.674	202665.011	487332.576	202650.394	487322.68	202661.843	487308.027	202662.992	487320.239
202540.938	487351.652	202553.122	487337.858	202561.007	487343.467	202549.465	487356.908	202551.133	487347.471
202513.993	487348.314	202525.895	487331.763	202544.052	487340.352	202532.263	487355.039	202529.051	487343.867
202465.765	487334.9	202448.908	487325.603	202455.781	487311.509	202474.9	487318.009	202461.339	487322.505
202485.31	487304.99	202469.576	487297.934	202476.61	487281.324	202494.468	487288.777	202481.491	487293.256
203023.452	487205.274	203015.363	487207.279	203011.787	487198.751	203026.771	487196.43	203019.343	487201.934
203040.619	487311.868	203047.434	487311.148	203048.586	487317.717	203041.424	487319.479	203044.516	487315.053
202215.928	486389.556	202200.159	486395.249	202191.833	486380.131	202207.768	486372.894	202203.922	486384.458
203899.246	486969.515	203891.492	486973.095	203895.847	486987.502	203903.282	486984.523	203897.467	486978.659
203943.523	486979.473	203931.799	486974.333	203938.514	486964.91	203945.757	486968.138	203939.898	486971.714
203720.661	486913.266	203715.593	486902.105	203698.924	486905.061	203703.065	486915.772	203709.561	486909.051
203722.567	486938.127	203733.927	486954.912	203713.855	486963.144	203705.457	486946.646	203718.952	486950.707
203608.178	486770.895	203603.432	486774.702	203609.701	486782.491	203614.823	486778.655	203609.034	486776.686
201866.117	486414.943	201869.242	486415.02	201868.688	486421.288	201865.67	486421.297	201867.429	486418.137
201807.274	486689.718	201806.986	486696.024	201817.06	486697.37	201817.369	486689.392	201812.172	486693.126
201812.657	486712.084	201814.86	486711.647	201813.616	486718.135	201815.855	486718.126	201814.247	486714.998
201854.848	486257.409	201849.953	486256.092	201851.434	486250.157	201856.553	486251.062	201853.197	486253.680

Appendix 1.3 Field data – Duursce waarden Floodplains continued

opmerkingen	Veldplot Nummer	Veldwaarn ondergrens	Veldwaarn bovengren:	Veldwaarn HOOGTE (	Veldwaarneming DICHTHEID
tachimeter	1	0.2	2.5		0.0484
tachimeter	2	0.5	2.5		0.0099
tachimeter	3	0.5	2.5		0.0122
tachimeter	4	0.4	2.2		0.0358
NETPOS	5	0.6	2.4		0.1636
NETPOS				33.2	0.003
NETPOS				3	
tachimeter	8	0.2	2.6		0.0308
tachimeter	9	0.5	2.5		0.0137
tachimeter	10	0.4	2		0.035
tachimeter	11	0.5	2.2		0.0789
tachimeter	12	0.5	2.2		0.0263
tachimeter	13	0.5	2.5		0.075
tachimeter	14	0.3	2.3		0.05
tachimeter	16	0.5	2.3		0.0672
NETPOS	17	0.25	0.7	67	0.0527
NETPOS	18	0.25	1.5	142.7	0.0966
NETPOS	19			4.7	
NETPOS	20			8.8	
NETPOS	21			8.9	
NETPOS	22			16.4	
NETPOS	23			16	
NETPOS	24			12.8	
NETPOS	25	0.5	2.2		0.2608
NETPOS	26	0.9	2.1		0.3535
NETPOS	27			6.2	
‹ NETPOS, maa	28	0.7	2.5		0.0545
NETPOS	29	0.5	2.5		0.2374
NETPOS	30	0.2	2.2	134.5	0.0391
NETPOS	31			22.9	
NETPOS	32	0.4	2.4		0.4201
NETPOS	33	1.2	1.6		0.3077
NETPOS	34	1.2	2.7		0.1605
NETPOS	35	1.4	1.8		0.3686
NETPOS	36	1	2		0.1572

Appendix II Field data – Brabant Floodplains

					Manual Measurement		Parallel Photography			
X	Y	Plot	Date	Vegetation type	Hv (cm)	Dv (m^-1)	Plot depth (m)	Distance camera-screen (m)	Camera height (m)	Spacing (m)
134632.1	412795	1	19-02-2009	Meadow	5.02					
134686.8	412802.5	2	19-02-2009	Meadow	8.33					
134659.7	412892.4	3	19-02-2009	Maize stubs	11.56	0.15				
134628.8	412993.1	4	19-02-2009	Maize stubs	11.50	0.16				
134486.5	412947.6	5	19-02-2009	Unvegetated	0.00					
134155.9	412197.3	6	19-02-2009	Herbaceous	18.64	3.08				
134174.8	412240.9	7	19-02-2009	Herbaceous	13.28	2.22				
134192.1	412109.3	8	19-02-2009	Maize stubs	35.07	0.12				
132976.4	412315.9	9	19-02-2009	Herbaceous	90.67	0.15				
132982.9	412292.5	10	19-02-2009	Herbaceous	72.93	0.05				
135039.9	405611.9	11	20-02-2009	Heatthland	33.77	0.82				
135014	405749.3	12	20-02-2009	Heatthland	50.67	1.03				
135310.7	405895.5	13	20-02-2009	Unvegetated	0.00	0.00				
135816.2	405177.9	14	20-02-2009	Unvegetated	0.00	0.00				
135721.1	405255.3	15	20-02-2009	Meadow	3.63					
135803.9	411220.6	16	20-02-2009	Leak	34.30	0.49				
132633.3	413159.9	17	20-02-2009	Herbaceous	16.45	1.09				
132591.1	413419.9	18	20-02-2009	Herbaceous	17.90	1.73				
72206.53	404460.4	19	28-2-2009	Herbaceous	30.22	0.47	2.75	2.75	0.14	0.1
72427.03	404790	20	28-2-2009	Herbaceous	131.03	0.20	5.2	5.2	0.6	0.1
72266.02	405751.8	21	28-2-2009	Tidal	35.93	0.75	0.8	1	0.25	0.1
72240.85	405799.2	22	28-2-2009	Tidal	60.13	1.04	0.72	1.05	0.26	0.1
72302.15	405829	23	28-2-2009	Unvegetated	0.00	0.00				
78782.89	399973.6	24	28-2-2009	Agriculture, stubs	13.07	0.17				
78780.08	399788.1	25	28-2-2009	Agriculture, stubs	16.47	0.22				
83000.48	400644.8	26	28-2-2009	Step edge						
83194.77	400244.4	27	1-3-2009\	Herbaceous	24.80	0.35	1	1	0.2	0.1
83218.21	400270.1	28	1-3-2009\	Herbaceous	58.13	0.03	8.3	8.3	0.31	0.1
83241.54	400318.8	29	1-3-2009\	Herbaceous	33.47	0.56				
83373.05	400295.1	30	1-3-2009\	Reedland	150.75	0.15	4.1	4.1	0.72	0.1
84779.29	397345.7	31	1-3-2009\	Agriculture, aggr	0.00	0.00				
84781.1	397432.5	32	1-3-2009\	Meadow	3.96					
84645.91	397316.8	33	1-3-2009\	Agriculture, ploug	0.00	0.00				
85405.56	395835.3	34	1-3-2009\	Roadline for scar	0.00	0.00				
86999.84	403639.9	35	1-3-2009\	Grassland for sc	9.84	0.00				
87785.57	403286.5									