

EXTRACTING STRUCTURAL CHARACTERISTICS OF DORMANT HERBACEOUS FLOODPLAIN VEGETATION FROM AIRBORNE LASER SCANNER DATA

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ABSTRACT:

To map spatial patterns of floodplain vegetation structure for hydrodynamic modelling, airborne laser scanning is a promising tool. In a test for the lower Rhine floodplain, vegetation height and density of herbaceous vegetation were measured in the field at 42 georeferenced plots of 200 m² each. Simultaneously, three airborne laser scanning (ALS) surveys were carried out in the same areas resulting in three high resolution, first pulse, small-footprint datasets. The laser data surveys differed in flying height, gain setting and laser diode age. Laser points were labelled as either vegetation or ground using three different methods: (1) a fixed threshold value, (2) a flexible threshold value based on the inflection point in the normalised height distribution, and (3) using a Gaussian distribution to separate noise in the ground surface points from vegetation. Twenty-one statistics were computed for each of the resulting point distributions, which were subsequently compared to field observations of vegetation height. Additionally, the Percentage Index (PI) was computed to relate density of vegetation points to hydrodynamic vegetation density. The vegetation height was best predicted by using the inflection method for labelling and the 95 percentile as a regressor ($R^2 = 0.74 - 0.88$). Vegetation density was best predicted using the threshold method for labelling and the PI as a predictor ($R^2 = 0.51$). The results of vegetation height prediction were found to depend on the combined effect of flying height, gain setting or laser diode age. We conclude that high resolution ALS data can be used to estimate vegetation height and density of herbaceous vegetation in winter condition, but field reference data remains necessary for calibration until a standard measure of sensitivity is supplied together with the laser data.

1. INTRODUCTION

In response to the increased awareness of the socio-economic importance of river flooding in the past decades, considerable effort has been undertaken in recent years in the development of hydrodynamic models of overbank flow to predict extreme flood water levels for the design of flood defence structures. Hydrodynamic roughness of the floodplain surface is one of the key parameters of these models, and depends to a large extent on vegetation height and density (Baptist, 2005). Vegetation density is the projected plant area in the direction of the flow per unit volume (m²/m³ or m⁻¹). For cylindrical vegetation, this equals the product of number of stems or stalks per unit area multiplied by the average stem diameter. Traditional methods to map vegetation patterns within the floodplain are based on classification of vegetation units or a uniform roughness is applied to the whole floodplain area. This leads to a considerable loss of within-class variation. There is thus a need for a fast and adequate approach to assess vegetation structure of floodplain surfaces.

Airborne laser scanning (ALS) provides information on the distribution of vegetation directly, and therefore has been used extensively in forestry surveys to estimate forest characteristics (Straatsma and Middelkoop, 2006; Lim et al., 2003). It has been used to map vegetation *height* in floodplains as well, but only in summer when vegetation was in leaf-on condition (Davenport et al., 2000; Cobby et al., 2001; Hopkinson et al., 2004; Mason et al., 2003). However, the portability of the established relations in these studies was low. Moreover, in the Netherlands most floods occur in winter and relations derived for summer vegetation may therefore be unrepresentative. No studies were found on the extraction of vegetation *density* of herbaceous vegetation. The main goal of this study was to estimate vegetation height and density of dormant herbaceous floodplain vegetation on a field plot level using ALS data and assess the

influence of flying height and amplification of the return signal at the receiver of the laser scanner.

2. MATERIALS AND METHODS

2.1 Study area and field measurements

This study is based on laser data collected in three floodplain sections of the distributaries of the River Rhine in The Netherlands: 'Duursche Waarden' floodplain (DW) along the right bank of the River IJssel, and the 'Afferdensche en Deestsche Waarden' (ADW) and the 'Gamerensche Waarden' (GW) floodplains along the left bank of the River Waal. Vegetation consisted of hardwood and softwood forest and shrubs, but is dominated by herbaceous vegetation. Vegetation is characterized by a heterogeneous pattern of vegetation types and structure. Herbaceous vegetation consists mostly of sedge [*Carex hirta* L.], sorrel [*Rumex obtusifolius* L.], nettle [*Urtica dioica* L.], thistle [*Cirsium arvense* L.] and clover [*Trifolium repens* L.].

We measured vegetation height and density in 42 field plots of homogeneous vegetation: 12 plots in the DW and ADW floodplain in March 2001, and 30 plots in the GW floodplain in March 2003. Field measurements were carried out simultaneously with the ALS survey. The plots were geo-located using a Garmin GPS12 resulting in a horizontal accuracy of 5 meter.

2.2 Laser scanning data

The laser data were acquired by Fugro-Inpark using the FLI-MAP system. FLI-MAP, Fast Laser Imaging and Mapping Airborne Platform, is a first-pulse scanning laser range finder combined with a dGPS and an Inertial Navigation System for

Table 1. Metadata for the three laser scanning campaigns

Acquisition Time	Floodplain location	scan angle	no. of sensors	sensor age	Flying height	Gain	point density	Flight strips
March 2001	DWADW	$\pm 30^\circ$	1	old	80 m	100%	12 pts/m ²	Single
March 2003a	GWhigh	$\pm 30^\circ$	2	new	80 m	80%	75 pts/m ²	Double
March 2003b	GWlow	$\pm 30^\circ$	2	new	55 m	100%	60 pts/m ²	Single

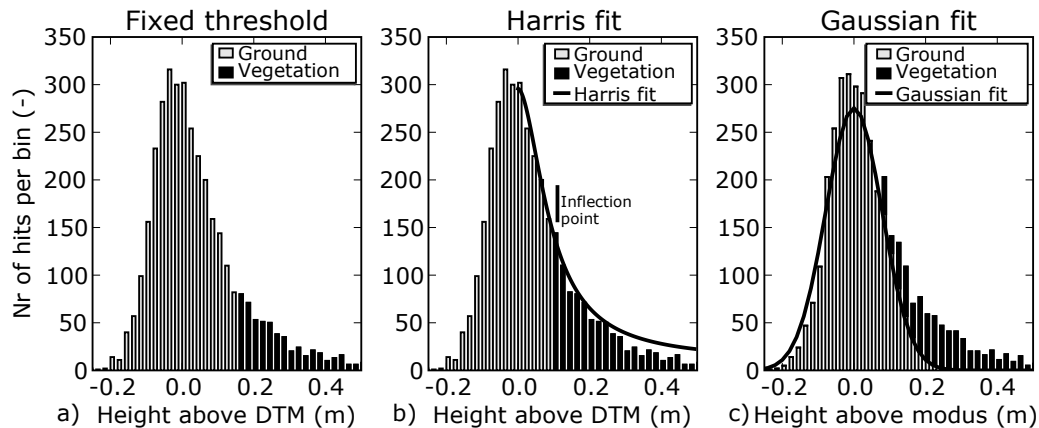


Figure 1. Labelling of vegetation point (black bars) and ground points (grey bars); a) threshold value of 0.15 m, b) inflection point, c) difference between Gaussian fit and point distribution.

positioning. FLI-MAP has an additional option to change the gain setting. The gain is the amount of amplification of the return signal before it is converted to a digital signal. Surveyors may increase the gain to compensate for the declining emission of energy due to ageing of the laser diode. Table 1 summarizes the characteristics of the three laser scanning campaigns carried out in three floodplain sections in the Rhine distributaries. The laser data collected in 2001 in the 'Duursche Waarden' and the 'Afferdensche en Deestse Waarden' floodplains is referred to as 'DWADW' dataset. Between 2001 and 2003, Fugro-Inpark added a second laser range finder to FLI-MAP, resulting in a doubling of the data collection rate and a re-orientation of the scanners. Instead of one nadir looking scanner, the two scanners were facing 7° forward and backwards to decrease the number of occlusions in built-up areas. With the new FLI-MAP configuration two datasets were collected in the 'Gamerensche Waard' floodplain in 2003. One was acquired from a height of about 80 m and with normal gain setting of the receiver, resulting in the 'GWhigh' dataset, the second from a minimum height of 55 m and with the maximum gain, called the 'GWlow' dataset. The GWhigh dataset covers the entire GW floodplain, while each flight line was flown twice to increase the point density resulting in a point density of 75 points/m². The GWlow dataset only covers 10 field plots. The three datasets enable the evaluation of the resulting regression equations to estimate vegetation height, which are influenced by the different flight parameters (table 1).

2.3 DTM extraction and labelling

For the determination of the vegetation height, the effect of the undulations of the terrain was eliminated. We constructed a Digital Terrain Model (DTM) for each plot using iterative residual analysis based on a simplified version of the method of

Kraus and Pfeifer (1998). In each step, a surface was computed as a local second order trend surface in a moving window. The window radius was 1.5 m to ensure enough points are available for a robust fit. The residual distance to this surface was computed for each point. Points with positive residuals are likely to be vegetation points. Since the range of values for an unvegetated, flat surface was computed and proved to be approximately 30 cm, a simple weight function was applied to compute the surface in the next iteration: points with a residual value of more than 15 cm were excluded from further analysis in the DTM processing. With the remaining points a new DTM surface was computed. Iterations were continued until all points had residuals less than 15 cm. The final DTM was a smooth surface running through the middle of these ground points. Heights relative to the DTM were used in subsequent computations.

In a second step, a detailed study was carried out to decide which points should be labelled as vegetation. Three different methods were evaluated: (1) a threshold method, (2) an inflection method, and (3) a Gaussian method. The first method is based on a fixed threshold value above the DTM, the other two are based on histogram analysis of normalised heights. For the threshold method, we used 15 cm above the DTM as a threshold (figure 1a), similar to the DTM filtering setting. For the second and third method laser points were binned in 2 cm vertical bins. Narrower bin intervals led to very spiky histograms, wider intervals to a loss of detail. The vertical point distribution was considered as a combination of a noise distribution of ground points and a uniform distribution of vegetation points. The inflection method finds the point of maximum concave-up curvature in the upper limb of the histogram, the so-called inflection point. The rationale behind the selection of this point as a threshold value is that the sum of

a noise distribution of the ground points and the uniform distribution of the vegetation points gives a strong concave up curvature. Any point that lies above the inflection point value is labelled as a vegetation point, all points below are ground points. To find the inflection point, a Harris function was fitted through the upper part of the histogram for each field plot (figure 1b). The Harris function is defined as:

$$y(h) = (a + b \cdot h^c)^{-1} \quad (1)$$

where $y(h)$ is the frequency of occurrence in a bin at height h . Parameters a , b and c are estimated from a least squares fit using a minimum of 15 bins to ensure stability of the fit. The inflection point was obtained by determining the height at which the second derivative of the Harris function reaches the maximum value. The height of the inflection point in the example is 0.09 m (figure 1b). The Gaussian method fits a Gaussian curve to the histogram. The Gauss curve is defined as:

$$p(h) = (2\pi\sigma^2)^{-0.5} \exp\left(-\frac{1}{2}\left(\frac{h-\mu}{\sigma}\right)^2\right) \quad (2)$$

where $p(h)$ is the frequency of noise occurrence at height h , μ is the mean, σ is the standard deviation. Fitting the Gauss curve boils down to finding the mean and standard deviation of the ground points. The mean of all points in the plot however also considers the vegetation points. Therefore, we used the mode of the distribution instead of the mean to estimate μ . The disadvantage of the mode is that the data have to be binned which introduces a dependence on the choice of the bin boundaries. Moreover, the mode can be undetermined. To counteract this effect we used the weighted mode, the average of the seven most frequent values in the point distribution, weighed by frequency. The standard deviation was based on the points lower than the weighted mode. The Gauss curve was then scaled by the product of twice the number observations below the weighted mode and the bin width (figure 1c). The difference between the histogram values and the fitted Gauss curve in the range above one standard deviation above the mode provided the number of points per bin that were assumed to represent vegetation. In each bin, points were labelled randomly as vegetation up to the predicted number of vegetation points. This ensured a spatially random distribution of the vegetation points.

2.4 Normalized point height distribution and comparison with field data

The three methods, described in the previous section, result in three height distributions of vegetation points for each plot. With respect to predicting the vegetation height, each point distribution was described by 21 different statistics:

- Central tendency: mean, median, mode
- Variability: standard deviation and variance
- Shape: skewness and kurtosis
- Percentiles: D_{10} , D_{20} , ..., D_{100} + D_{95} , D_{96} , D_{97} , D_{98} , D_{99}

The observed vegetation heights in the field were subsequently compared to these statistics using correlation as an indicator of the strength of the relation. Forward stepwise linear regression was subsequently carried out to determine the strongest predictors (Wonnacott and Wonnacott, 1990). The effects of gain setting and flying height were tested using two statistical tests; a t-test on differences in means and a paired sample t-test of the D_{95} percentiles of the GWhigh and GWlow data set. Samples could be paired for the GW datasets since the same reference plots were used. To gain insight in the effect of laser

diode age and the flight parameters, the slopes of the regression models for vegetation height were compared using three Student's t-tests.

Vegetation density was predicted using the Percentage Index (PI), which computes the percentage of laser hits that fall within the height range of the vegetation (h_1 to h_2):

$$PI_{h_1-h_2} = \frac{1}{h_2 - h_1} * \frac{N_{h_1-h_2}}{N_{tot}} \quad (3)$$

in which $N_{h_1-h_2}$ is the number of vegetation points between height 1 and 2 above the ground surface, N_{tot} is the total number of points in the field plot including vegetation points and ground surface points. The height interval for PI is equal to the height of the vegetation. The first term in the equation is added, because higher vegetation would increase $N_{h_1-h_2}$, but does not necessarily increase the vegetation density. Ideally, h_1 should be set to zero, and h_2 to the maximum height of the vegetation. However, h_1 should not include noise of the ground surface. Therefore we chose the lower limit of the vegetation point height distribution as a minimum value.

3. RESULTS

3.1 Vegetation height and density

Vegetation height in the 42 sample plots ranged from 0.26 to 1.66 m. Vegetation density varied between 0.0003 and 0.72 m^{-1} . For each plot, three different labelling methods were applied and 21 laser-derived statistics were computed. The correlations between the field vegetation heights and the laser statistics were shown in figure 2. The following parameters showed the highest correlations: (1) D_{30} for the threshold method ($r = 0.72$), (2) D_{90} to D_{98} plus the standard deviation and variance for the inflection method ($r > 0.85$), and (3) D_{70} for the Gaussian fit ($r = 0.70$).

The parameter with the highest correlation was chosen for vegetation height prediction for each labelling method. For the inflection method, a few parameters showed a high correlation. The 95 percentile was selected to maintain congruency in predictors even though the standard deviation and the variance showed a marginally better correlation coefficient. Figure 3 shows nine scatter plots depicting the measured vegetation heights versus the predicted heights based on the selected laser percentiles. Forward stepwise regression was carried out to select the best regression model, starting with the selected percentile (D_{30} , D_{95} , and D_{70} for the threshold, inflection and Gaussian method respectively). This did not result in the selection of any additional parameters for any of the regression models, due to multicollinearity constrictions. Table 2 summarizes the regressions. Results of the prediction of vegetation density using the Percentage Index (PI) are shown as scatter plots (figure 4). The threshold and Gaussian method show a positive relation with vegetation density ($R^2 = 0.51$ and 0.49 respectively). Conversely, prediction based on the inflection labelling shows a weak negative relation ($R^2 = 0.09$). Table 3 summarizes the equations.

3.2 Effect of flying altitude and gain setting

The GWhigh and GWlow laser datasets share 10 field plots, which allowed to compare the combined effect of lower flying altitude and increased the gain setting (cf. table 1). The following tests were performed using the inflection labelling method and the D_{95} percentile:

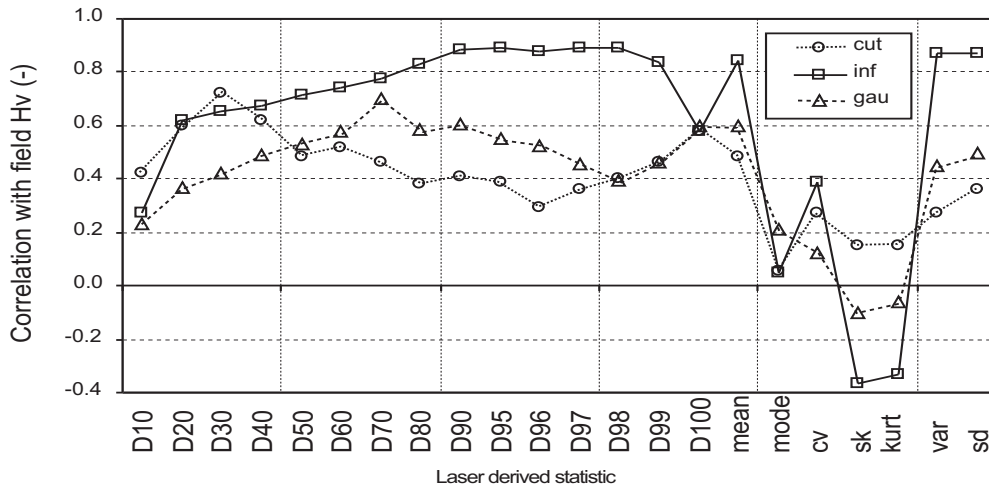


Figure 2. Effect of point labelling methods on the strength of correlation between laser-derived statistics and field vegetation heights. Dx = X percentile of the vegetation points, cv = coefficient of variation, sk = skewness, kurt = kurtosis, var = variance, sd = standard deviation

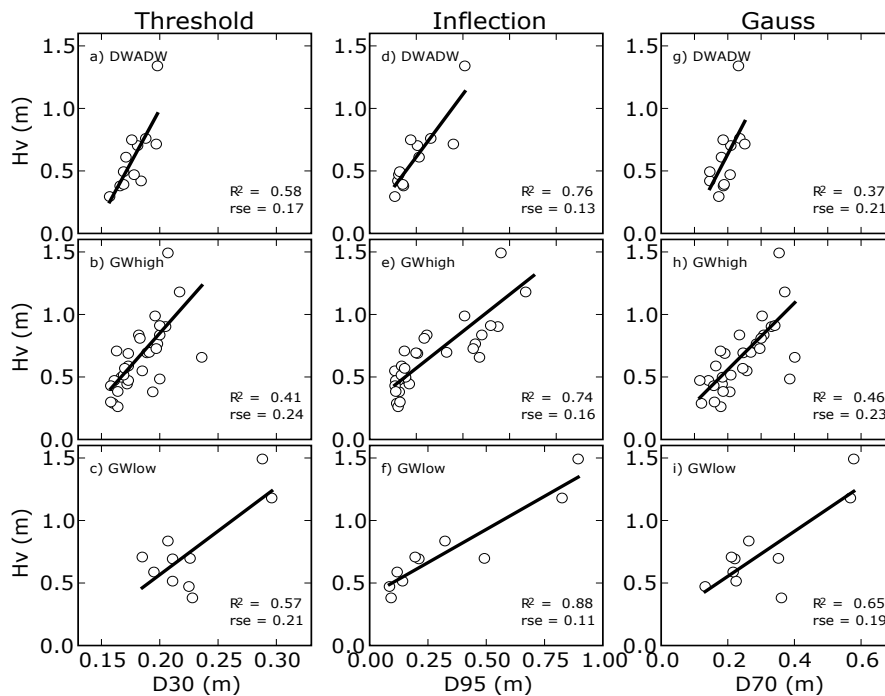


Figure 3. Scatter plots of predictions of vegetation height per dataset using three different point labelling methods: a), b), and c) threshold method, d), e) and f) inflection method, g), h) and i) Gaussian method

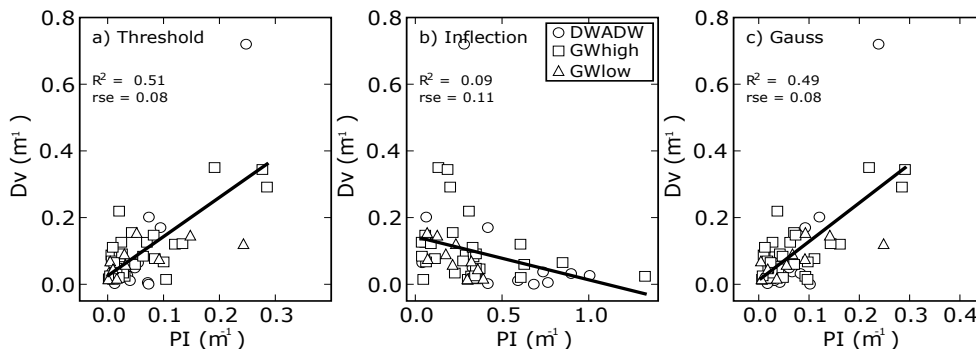


Figure 4. Scatter plots of predictions of vegetation density per dataset using three different point labelling methods: a) threshold method, b) inflection method and c) Gaussian method

Table 2. Regression equations for vegetation height

Labelling method / dataset	Regression equation	R ²	RSE (m) ^a
Threshold			
DWADW	Hv = 17.20D ₃₀ - 2.45	0.58	0.17
GWhigh	Hv = 10.57D ₃₀ - 1.26	0.41	0.24
GWlow	Hv = 6.98D ₃₀ - 0.83	0.57	0.21
Inflection			
DWADW	Hv = 2.51D ₉₅ + 0.11	0.76	0.13
GWhigh	Hv = 1.47D ₉₅ + 0.28	0.74	0.16
GWlow	Hv = 1.06D ₉₅ + 0.40	0.88	0.11
Gaussian			
DWADW	Hv = 5.13D ₇₀ - 0.39	0.37	0.21
GWhigh	Hv = 2.67D ₇₀ + 0.02	0.46	0.23
GWlow	Hv = 1.80D ₇₀ + 0.19	0.65	0.19

^a Residual Standard Error

Table 3. Regression equations for vegetation density using three different methods

	Regression equation	R ²	RSE (m ⁻¹) ^a
Threshold	Dv = 1.18PI + 0.03	0.51	0.08
Inflection	Dv = -0.13PI + 0.14	0.09	0.11
Gaussian	Dv = 1.16PI + 0.01	0.49	0.08

^a Residual Standard Error

A paired sample t-test revealed significant differences between the height of the D₉₅ percentile of the GWhigh and GWlow datasets ($\alpha = 90\%$, $p = 0.08$). These results indicate that a low flying height, combined with a high gain improves detection of the top of the vegetation.

The slope of the regression lines between laser data and observed vegetation height also indicates the ability of the laser signal to detect the top of the vegetation. A steeper slope indicates a poorer detection of the vegetation top. Figure 3 shows the regression lines for the DWADW, GWhigh and the GWlow data sets. The slope of the DWADW is steepest, and the slope of the GWlow dataset is mildest. Based on three Student's t-tests, all differences in slope were significant at the 95 % level of confidence.

4. DISCUSSION

4.1 Vegetation height and density estimation

Vegetation height of herbaceous floodplain vegetation can be predicted reliably at the plot level using high-density first-pulse airborne laser scanning data ($R^2 = 0.74$ to 0.88 using the inflection labelling method), while estimation of vegetation density is less accurate ($R^2 = 0.51$ using the threshold method). The inflection method shows the best predictions of vegetation height for all three datasets (figure 3). The threshold and the Gaussian method in general selected fewer points, and are therefore more sensitive to outliers in the height distribution. Conversely, vegetation density was predicted better by the threshold and Gaussian method (figure 4). The PI relates point density of vegetation points to hydrodynamic vegetation density. The inflection method labels more points as vegetation than the two other methods, but the PI values did not correlate well with field reference values, and are even negatively correlated. This could be caused by the height at which the vegetation density

was measured in the field, which was at least at 13 cm above the ground surface (half the minimum vegetation height). This is well above a typical inflection height of 5 cm. The threshold method performed marginally better than the Gaussian method. The inverse dependence of PI on h_2 minus h_1 (eq. 3) could lead to unrealistic values in case h_2 nears or equals h_1 . This should not be a problem for vegetation higher than 25 cm as in this study.

The quality of prediction of vegetation height in this study is similar to the results obtained in regression models for forests: Means et al. (1999), Naesset and Bjercknes (2001), and Naesset (2002) reported regression models explaining 74 to 95 percent of the variance in the field reference data of vegetation height. Similar to our study, forestry studies obtained better results for vegetation height than for parameters related to vegetation density. Given the small range in height of herbaceous floodplain vegetation, it is remarkable that the results obtained in our study are of similar quality as those obtained in forestry surveys.

Davenport et al. (2000), Cobby et al. (2001) and Hopkinson et al. (2004) studied vegetation height of low vegetation in leaf-on condition. Conversely, in our study, we predicted vegetation height of dormant herbs. This means that the vegetation signal is much weaker, due to the smaller plant surface. Still, the predictive quality of vegetation height found in this study is comparable to the studies on low vegetation in leaf-on condition. The differences found in the regression equations from this study and previous studies (Davenport et al., 2000; Cobby et al., 2001; Hopkinson et al., 2004) demonstrate that portability of the derived relations is low. It points to the need for future field reference data. A standardized empirical measure of sensitivity could be provided together with the laser data by laser scanning of artificial objects with varying reflectivity as suggested by (Wotruba et al., 2005). Further improvements are expected from a decrease in laser point accuracy. Our data showed a 4 cm standard deviation, but present day scanners show standard deviations down to 1.5 to 2 cm, which might allow mapping vegetation heights of meadows.

4.2 Effects of flight parameters; flying height, laser diode age and gain setting

The DWADW and GWhigh data sets yielded different slopes of the regression models to estimate vegetation height, which was significant at the 99.9 confidence level. The reason for this difference might be the age of the laser diode age, the calibration settings or the larger average incidence angle in the GWhigh dataset, due to the reorientation of the laser scanners between 2001 and 2003. The slope of the GWlow dataset was significantly steeper than for the GWhigh dataset. The paired sample t-test also showed significant differences between the GWhigh and GWlow datasets. Remarkably, the increase in the regression slope of the GWhigh and GWlow dataset was significant even though the field and laser data were collected on the same day. The reason for the difference in slope and 95 percentile must therefore be the combination of the reduced flying height and increased gain setting for the GWlow dataset. Together these effects result in a larger amount of energy reaching the analogue to digital converter in the laser scanner from an equally reflective object. Consequently, small objects are detected better, and the regression slopes are lower. Naesset (2004) concluded for spruce and pine forest that the effect of flying altitude is marginal and that the flying altitude can be increased by 60 % without any serious effect on the estimated stand properties. These conclusions for forests are contrary to our conclusions for herbaceous floodplain vegetation. The reason for this difference might lie in the shape and structural properties of the vegetation involved. Trees are larger and Naesset's data were collected in leaf-on conditions, which make

detectability of trees better than thin floodplain herbs, which seem at the edge of detectability. With these datasets, it is impossible to assess the influence of the individual parameters. However, as long as the parameters influencing the regression equations are unclear, field reference data will remain necessary to establish the regressions.

5. CONCLUSIONS

Laser scanning provides detailed and accurate estimates of vegetation height and to a lesser extent of vegetation density. Three different vegetation labelling methods were evaluated (threshold, inflection and Gaussian). Vegetation height estimation was most successful using the inflection method for point labelling. The 95 percentile proved the best predictor, ($R^2 = 0.74$ to 0.88). However, regression models differed significantly for datasets that were acquired with different flying height, gain, and laser diode age. The validity range for vegetation height is the height range order of 0.2 to 2 m. Vegetation density was predicted using the Percentage Index (PI), which relates vegetation point density to hydrodynamic vegetation density. The PI based on the threshold ($R^2 = 0.51$) and Gaussian ($R^2 = 0.49$) labelling method proved better estimators of vegetation density than the PI based on the inflection method ($R^2 = 0.09$). This might be caused by difference in reference heights between field and laser data. The validity range for vegetation density is in the order of 0.001 to 0.7 m^{-1} .

Because these herbs in winter are low and thin, height estimation is sensitive to the combined effect of flying height, gain setting and age of the laser diode. The common factor in these parameters is that they influence the amount of energy at the receiving end of the laser scanner. With increasing energy, the vegetation detection increases too. We conclude that airborne laser scanning data can be used to map vegetation height and density of dormant floodplain vegetation for floodplain roughness parameterization. Field observations of vegetation structure remain, however, necessary to calibrate the regression models until a standard measure of laser sensitivity is supplied together with the laser data.

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