EXTRACTING CROSS SECTIONS AND WATER LEVELS OF VEGETATED DITCHES FROM LiDAR POINT CLOUDS

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ABSTRACT

The hydrologic response of a catchment is sensitive to the morphology of the drainage network. Dimensions of bigger channels are usually well known, however, geometrical data for man-made ditches is often missing as there are many and small. Aerial LiDAR data offers the possibility to extract these small geometrical features. Analysing the three-dimensional point clouds directly will maintain the highest degree of information. A longitudinal and cross-sectional buffer were used to extract the cross-sectional profile points from the LiDAR point cloud. The profile was represented by spline functions fitted through the minimum envelop of the extracted points. The cross-sectional ditch profiles were classified for the presence of water and vegetation based on the normalized difference water index and the spatial characteristics of the points along the profile. The normalized difference water index was created using the RGB and intensity data coupled to the LiDAR points. The mean vertical deviation of 0.14 m found between the extracted and reference cross sections could mainly be attributed to the occurrence of water and partly to vegetation on the banks. In contrast to the cross-sectional area, the extracted width was not influenced by the environment (coefficient of determination $R^2 = 0.87$). Water and vegetation influenced the extracted ditch characteristics, but the proposed method is still robust and therefore facilitates input data acquisition and improves accuracy of spatially explicit hydrological models.

Keywords: LiDAR; ditch; cross section; intensity; RGB

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1. Introduction

Process-based spatially explicit hydrological models are highly dependent on accurate information about the location and dimensions of drainage networks. However, such data are usually lacking for minor water courses such as agricultural drainage ditches and road ditches. These play a key role in reducing waterlogging and water erosion, purifying water, improving groundwater recharge and they support uncommon species such as temporary water invertebrates that are not recorded in any other water body types (Williams, 2004). Ditches vary greatly in type of shapes, materials and vegetation cover (D'Ambrosio et al., 2011; Peeters et al., 2014). Since recent studies have shown the high sensitivity of the hydrologic response of a catchment to the morphology of ditches cross sections, automated characterisation of ditches would be of significant benefit for hydrological modelling (Buchanan et al., 2013; Carluer and Marsily, 2004; Miller, 2003; Moussa et al., 2002).

Cross sections of water courses can be measured by several field survey techniques. Field surveys often require significant human resources and funding, and therefore result in a poor longitudinal resolution of the measurements along the water course (Dietterick et al., 2012). A promising alternative to ground-based measurement of cross sectional profiles are three-dimensional point clouds produced by airborne light detection and ranging (LiDAR or laser mapping) systems. LiDAR is an important and efficient technique for the acquisition of area-wide elevation data at sub-meter horizontal resolution (Bowen and Waltermire, 2002). LiDAR-derived datasets have already been used for detection of drainage channel networks (Bailly et al., 2008; Cazorzi et al., 2013; Hooshyar et al., 2015; Passalacqua et al., 2012), assessment of water levels (Hopkinson et al., 2011; Magirl et al., 2005) and water depths (Pan et al., 2015). To date, LiDAR technology allows describing some physical characteristics of stream channels, such as depth, width and area that are in close agreement with ground-surveyed features (Cazorzi et al., 2013; Dietterick et al., 2012; Faux et al., 2009; Miller et al.,

2004). This can be achieved for larger channels, but it is unclear whether equal accuracy can be obtained for smaller ditches.

Furthermore, current hydrological applications and assessments of cross-sections do not use the original LiDAR point cloud but rather start from rasterized digital elevation models (DEM) or Triangular Irregular Networks (TIN) derived from these point clouds (Caroti et al., 2014; Dietterick et al., 2012; Miller et al., 2004; Podhoranyi and Fedorcak, 2015; Roub et al., 2012). The reduced horizontal resolution of the DEM as compared to the original point cloud density can be an impediment to extract small elevation variations in the cross-sectional profiles. Höfle (2007) reported advances by directly analysing three-dimensional point clouds to maintain the highest degree of information without prior filtering and interpolating the discrete elevation measurements and applied it to observe glacier features and detect building and roof facets.

The objective of this paper is to propose and evaluate an automated approach to extract cross-sectional profiles of small vegetated drainage ditches and their characteristics such as cross-sectional area, width, presence of water and water level from original LiDAR point clouds. Furthermore, a method is proposed to classify the extracted cross-sectional profiles based on the presence of water and vegetation in the ditch. The approach was evaluated for a grassland area in the Flemish region of Belgium.

2. Study area and available data

2.1. Study area

The study area is located in the alluvial valley of the river Dyle, ca 20 km east of Brussels in central Belgium. It is part of the nature reserve ‘de Doode Bemde’. The site has an extensive network of drainage ditches dating back to the 18th and 19th century and intended to turning the back swamps into meadows. The total length of the measured ditches in the study

area is approximately 3 km in an area of 10.3 ha (**Fig. 1**). Today the alluvial wetlands serve an important role in the watershed management by retaining and storing excess water and attenuating peak discharges in the river, thereby protecting downstream areas from flooding. To enhance its biodiversity and nature value, the alluvial land is being restored to an even wetter state (Joris, 2005) by abandoning the maintenance of the drainage network and allowing vegetation. Five piezometers are measured once every two weeks to monitor the groundwater level in the study area. The data are accessible through the ‘water in nature reserves’ (WATINA) database of the Flemish region (INBO, 2015).

Figure 1: Location and aerial photograph of the study area. The inset shows the study area bounded by a yellow polygon. The measured ditches and cross sections are represented with black and white lines respectively.

2.2. Reference data

Reference data were collected in the field in August 2015. The trajectories and cross sections of the ditches were measured with a real time kinematic (RTK) GPS device (Trimble 5800 model) with a horizontal accuracy of 0.01 m (RMSE_{xy}) and a vertical accuracy of 0.02 m (RMSE_z) (Trimble Navigation Limited, 2005). The real time correction was done using the reference stations network of the Flemish Positioning Service (FLEPOS). Since the ditches were man-made, they have a predominant linear layout so that a limited number of vertices sufficed to determine the course of the ditch. Perpendicularly to the banks of the ditch, 152 cross sections were measured manually approximately with a 10 meters interval (**Fig. 1**). Five to eleven points were captured per ditch profile, which had an average width of 3.6 m. Measurements were always taken for the left bank, left slope, centre, right slope and right bank. More points were measured depending on the shape complexity and width of the ditch. Also the water level, vegetation type, its relative cover and position of culverts were recorded.

2.3. Airborne LiDAR data

Between 2013 and 2015, an airborne LiDAR campaign was carried out for the entire Flemish region of Belgium (13,512 km²) commissioned by the Flemish Agency for Geographical Information (AGIV, *Agentschap Geografische Informatie Vlaanderen*). LiDAR point clouds and digital aerial RGB images with a spatial resolution of 10 centimetres were simultaneously collected during the winter seasons (15th November – 15th April) when foliage was minimal. To each LiDAR point the RGB colour values of the corresponding pixel in the aerial images were assigned. The points were further classified into three classes: ground, non-ground and water. The point density per flight strip was at least eight points per square meter but was higher in densely vegetated areas because of multiple LiDAR returns per pulse (AGIV, 2015; Vanderstraete, 2013). As the flight strips were overlapping for 50%, the final point cloud

was rather homogeneous with at least 16 points per square meter. The maximum planimetric distance between two points was 0.5 meters. The point cloud was subjected to a strict quality control, both planimetrically ($RMSE_{xy} = 0.10\text{m}$) and altimetrically ($RMSE_z = 0.05\text{m}$) (Vanderstraete, 2013). The elevation of the LiDAR points is expressed in meters above the standard Belgian geodetic datum (Tweede Algemene Waterpassing, TAW). The LiDAR Riegl LMS-Q680i laser scanning device was used for the study area. It had a laser beam in the near infrared (NIR) wavelength range at 1064 nm. NIR wavelengths are typically absorbed by the water surface. For each reflected echo signal, high-resolution information was provided for the intensity measurement. The instrument had a laser pulse repetition rate up to 400 kHz, a beam divergence smaller than or equal to 0.5 milliradians and a scan angle range of 60° (-30° to 30°) (Schechtner, 2012).

3. Methodology

3.1. Extracting cross-sectional profiles

As this study focuses on the topographic terrain, the first step consisted of removing the LiDAR-points classified as non-ground (i.e. large vegetation or man-made entities) from the point cloud (**Fig. 2 a-b**). Next, points that were located more than five meter away from the measured ditch centre line were excluded (**Fig. 2 b-c**). As very few points of interest are located exactly in the cross-sectional plane perpendicular to the ditch, LiDAR points within a predetermined cross-sectional buffer were considered to be a part of that cross section (**Fig. 2 d-e**). Different buffer widths were tried varying between 0.1 and 0.7 m with an incremental step of 0.1 m. The area for point extraction was determined by the intersection of the longitudinal and cross-sectional buffer (**Fig. 2 f-h**). Next, the selected points were horizontally projected on the cross-sectional plane (**Fig. 2 i-j**). Piecewise linear and cubic spline functions were fitted through the projected points by least squares optimization by means of the shape language

modelling (SLM) scripts optimized for Matlab by D'Errico (2014) (**Fig. 2j**). The SLM tools can build an infinite number of curve types from data and provide a prescription for a curve fit using a set of shape primitives. The SLM was set for modelling the minimum envelop of the data. For the linear model there were six knots and three for the cubic model (**Fig. 3**). The model with the lowest RMSE was chosen to represent the cross sectional profile at the location.

Figure 2: Procedure for LiDAR point selection for modelling a cross-sectional profile. (a) - (b) exclude non-ground objects; (b) - (h) select LiDAR points around cross section; (h) - (j) project LiDAR points onto vertical plane along the cross section.

Figure 3: Modelling of the cross-sectional profile based on the selected LiDAR points (black) using the SLM scripts for Matlab software. The black line shows the linear spline model with six free knots. The grey line shows the cubic spline model with three free knots (grey points).

3.2. Determining cross-sectional profile characteristics

Characteristics such as width, cross-sectional area and water level were calculated from the modelled cross-sectional profile. The left and right bank maxima were defined as the first local maximum either at the left or right from the centre of the ditch (**Fig. 4**). The potential maximum water level was set equal to the elevation of the lowest bank. The width of the ditch was calculated as the horizontal distance between the lower bank and the horizontal projection of this elevation on the higher bank (**Fig. 4**). The cross-sectional area was calculated as the area above the profiling curve with the maximum water level as the upper limit (**Fig. 4**).

Figure 4: Definition of width and cross-sectional area of the modelled cross-sectional profile.

3.3. Classification of ditch cross-sectional profiles

Correction of airborne LiDAR intensity values

The return strength of a LiDAR point, also called the intensity ($\lambda = 1064$ nm, NIR) is partially determined by the reflectivity of the object struck by the laser pulse and were found to be broadly representative of the NIR reflectance such as in optical remote sensing ($\lambda = 700$ nm - 1500 nm) (Boyd and Hill, 2007). However, the values need to be corrected or calibrated on an individual flight strip basis in order to increase the usability of the intensity information across flight strips (Ahokas et al., 2006; Boyd and Hill, 2007). The model used for this correction has been proposed by Ahokas et al. (2006) and Kaasalainen et al. (2011):

$$I_{corrected} = I_{original} \cdot \frac{R_i^2}{R_{ref}^2} \cdot \frac{1}{\cos \alpha} \cdot \frac{1}{T^2} \cdot \frac{E_{Tref}}{E_{Tj}} \quad (1)$$

where $I_{original}$ is the original intensity value (-), R_i is the distance (range) from the sensor to the measuring point on the ground (m), R_{ref} is the chosen reference distance (m), α is the incidence angle ($^\circ$), T is the total atmospheric transmittance (-), E_{Tj} (J) is the pulse energy value in a current flight line and E_{Tref} (J) is the chosen reference pulse energy (Kaasalainen et al., 2011).

The flight strips for the study area were surveyed in one single day (2nd of March 2014) with the same settings for the instrument. The transmittance (T) and pulse energy term (E_{Tref}/E_{Tj}) were therefore set to 1 as they did not affect the intensity values between flight strips. The scan angle α is the same as the incidence angle for horizontal surfaces (**Fig. 5**) and was available for each LiDAR point. To calculate the distance R_i between the point and the aircraft, the exact position (X, Y, Z) of the aircraft had to be reconstructed for every scan line measured along the flight strip.

Determining the scan lines was done by sorting the points in time using the GPS time stamp. The logical ‘end of flight line’ variable stated if the point was the last point of that scan line. The planimetric position of the aircraft was calculated as the mean of the X and Y coordinates of the points along the line with a scan angle of 0° (**Fig. 5**). The lines going through the points of the scan line with their corresponding scan angle as slope, intersect at the altitude of the aircraft (Z) (**Fig. 5**). Points along the scan line with a scan angle smaller than 5° were ignored as small errors in their scan angle lead to large differences in the altitude of the intersection. The range R_i for each point on the scan line was then calculated as the Euclidean distance between the point and the aircraft. The reference range R_{ref} was chosen as the average altitude of the aircraft.

The corrected intensity values were used as a proxy for NIR-reflectance. Akohas et al. (2006) concluded that the corrected intensity values had a strong positive linear relation with the target reflectance values at the 1064 nm (NIR) wavelength defined from laboratory measurements (coefficient of determination $R^2 > 0.99$). The corrected intensity values were linearly rescaled to match the range of the RGB colour values (0 - 1) that were already calibrated and linked to the LiDAR points (section 2.3).

Figure 5: Points along the scan line with their corresponding scan angles (α). The X,Y-coordinates of the aircraft are defined as the mean X and Y values of the points along the scan line for which the scan angle equals 0° . The lines that go through the points of the scan line with their corresponding scan angle intersect at the altitude of the aircraft (Z).

Water and vegetation index

To differentiate vegetated from water LiDAR points, the spectral indices Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI) were calculated. The NDWI was calculated for each point according to McFeeters (1996):

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (2)$$

This index with values in the range $[-1,1]$ was designed to yield a maximum value for water targets. The higher reflection of green wavelengths is contrasting with the lower reflection of NIR by water surfaces. In contrast to water surfaces, soil and vegetation have high reflections in the NIR. As a consequence, water features have positive NDWI values, while vegetated and soil targets have zero or negative values (McFeeters, 1996; Xu, 2006).

The Normalized Difference Vegetation Index (NDVI) is based on the red and near-infrared bands of the electromagnetic spectrum (Rouse et al., 1973):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (3)$$

Alike NDWI, NDVI values are in the range [-1,1]. Extreme negative values are known to be associated with water while values between -0.1 and 0.2 typically represent bare soil and values between 0.5 and 0.8 dense green vegetation (Carlson et al., 1990). However, only the NDWI values were further used as it turned out that the two spectral indices were highly correlated (-0.99 on average).

Classification of LiDAR ditch cross-sectional profiles and extraction of water level

The ditch profiles were classified based on the LiDAR-derived spectral indices, the length of the data ‘gap’ along the profile and the variance of elevation in the centre of the ditch profile. There were four classes: dry vegetated ditch, wet ditch with clear water, partially vegetated wet ditch and densely vegetated wet ditch. Dry non-vegetated ditch did not occur in the study area (**Fig. 6**).

LiDAR intensity values of water surfaces are generally low due to the strong absorption of near-infrared light. When the intensity of the point is below the detection limit, the point ‘disappears’ (Höfle et al., 2009). This leads to a reduction of the point density on water surfaces (Hooshyar et al., 2015). As a result, a wet ditch with no vegetation will appear as a gap in the point cloud along the profile. The maximum planimetric distance between two points for the point cloud was 0.5 m. This value was defined as G_t . Profiles with a gap greater than G_t along the profile were classified as ‘wet ditch with clear water’ (**Fig. 6a**).

The first step to classify the remaining vegetated profiles was to distinguish bank and centre points along the ditch profile. Points along the profile closer to the bank than to the centre were classified as ‘bank’. The other points were classified as ‘centre’. The spectral indices of the bank and centre points were compared using a one-sided t-test. Profiles with significantly smaller NDWI values for the centre points ($p\text{-value} < 0.1$) were classified as ‘partially vegetated

wet ditch' (**Fig. 6b**). In case there is more vegetation in the ditch, the difference between NDWI values of the centre and bank points is expected to be not significant.

In dry vegetated ditches, there is no water level that obstructs the reflectance of vegetation or other materials in the ditch. In the presence of vegetation, the elevation of the centre points is typically more variable. Therefore, the variance in elevation of the centre points was calculated. As variance and mean square error (MSE) have the same units of measurement, a threshold of two times the MSE_z of the LiDAR point cloud ($= 2 \times 0.0025 \text{ m}^2$) was set for the variance to separate dry vegetated ditches and densely vegetated wet ditches. This threshold was defined as V_t . Profiles with a larger variance than V_t were classified as 'dry vegetated ditch' (**Fig. 6d**). The remaining ditch profiles were classified as 'densely vegetated wet ditch' (**Fig. 6c**). The water level in the cross-sectional profiles classified as 'wet ditch' was determined as the elevation of the lowest LiDAR point.

Figure 6: Classification of ditch profiles as (a) wet ditch with clear water, (b) partially vegetated wet ditch, (c) densely vegetated wet ditch, (d) dry vegetated ditch and (e) dry non-vegetated ditch where $G_t = 0.5 \text{ m}$ and $V_t = 0.005 \text{ m}^2$.

3.4. Validation

The modelled cross-sectional profiles were validated with the reference measurements using two different error measures: (i) the mean vertical deviation between the reference profile points and the projection of these points on the fitted LiDAR profile (**Fig. 7a**) and (ii) the (dimensionless) relative difference between the areas of the measured and the modelled cross-sectional profiles, expressed as

$$\text{Relative Area Difference} = \frac{\text{Area LiDAR profile} - \text{Area reference profile}}{\text{Area reference profile}} \quad (4)$$

To calculate the area of the reference profile, the measured points were connected by linear segments (**Fig. 7b**). The calculated width of the LiDAR profile was compared with the field measured width, while the ditch water level extracted from the LiDAR profile was compared with the water level of the closest piezometer.

Figure 7: (a) The vertical deviation and (b) relative area difference. In both graphs, the blank points represent the LiDAR points with the full line as the modelled cross-sectional profile. Similarly, the black points represent the reference points with the dashed line as the measured reference profile.

The validity of the classification in absence of reference observations at the time of the LiDAR data acquisition was determined by visually comparing the modelled LiDAR profiles

with the measured profiles. The comparison was necessary to make a distinction between the wet and dry vegetated ditches as this was important for determining the water level.

4. Results

4.1. Ditch profile characteristics

Sensitivity analysis cross-sectional areas

The number of extracted LiDAR points increased linearly with increasing cross-sectional buffer distance (**Fig. 8a**). The mean vertical deviation decreased or remained stable until a cross-sectional buffer width of 0.6 m was reached (**Fig. 8b**). The median of the relative area differences was negative, meaning that the LiDAR cross-sectional area was smaller than the area of the reference profile. The relative area difference increased until the cross-sectional buffer width of 0.4 m was reached (**Fig. 8c**). Based on these results, the cross-sectional width, water level and classification of the ditch were determined using a cross-sectional buffer of 0.4 m. Using this cross-sectional buffer, only 15 cross sections (10 %) were modelled by cubic spline functions, the rest was modelled by linear piecewise spline functions.

Figure 8: (a) Number of extracted LiDAR profile points, (b) mean vertical deviation and (c) relative area difference of the extracted LiDAR profiles as a function of the width of the cross-sectional buffer.

Spatial distribution of errors

The spatial distribution of the mean vertical deviation between the cross-sectional profiles for the ditches throughout the study area is visualized in **Fig. 9**. The coloured classes for the error values are similar along the ditch and thus spatially auto-correlated.

Figure 9: Spatial distribution of the mean vertical deviation (from light to dark: $\circ$ -0.20 m to -0.10 m, $\circ$ -0.10 m to 0 m, $\circ$ 0 m to 0.10 m, $\bullet$ 0.10 m to 0.20 m, $\bullet$ > 0.20 m. The background shows the hillshaded digital terrain model.

Ditch width

The comparison of the ditch width between the LiDAR ditch profile and the one observed in the field is displayed in **Fig. 10**. Most of the observations are around the 1:1 line. The coefficient of determination (R^2) was 0.87 and the mean error -0.15 m.

Figure 10: Modelled versus measured ditch width ($R^2 = 0.87$, mean error = -0.15 m)

4.2. Classification of ditch cross-sectional profiles

Intensity correction

The effect of the intensity correction is demonstrated in **Fig. 11**. The cumulative distribution function (CDF) for the intensity values for three overlapping flight strips was extracted for a homogeneous patch of grassland. **Fig. 11a** shows the original intensity values CDFs for each of the flight strips separately. **Fig. 11b** shows that the distributions are in much better mutual agreement after correcting the intensities. The corrected intensity was used to calculate the NDWI.

Figure 11: Cumulative distribution of the original (left) and the corrected intensity values (right) for a homogeneous patch of grassland for three different flight lines (black = flight line 32098, dotted = flight line 32099, grey = flight line 32100).

Classification

The classification of the ditch profiles into four classes is presented in **Table 1**. **Fig. 12** shows examples of the different ditch profile classes: **(a)** ‘wet ditch with clear water’, **(b)** ‘partially vegetated wet ditch’, **(c)** ‘densely vegetated wet ditch’ and **(d)** ‘dry vegetated ditch’. Only three out of the 152 modelled LiDAR profiles were classified as ‘dry vegetated ditch’. Comparison with the reference data revealed that two of them were included in the right class. The other one was classified as a densely vegetated wet ditch.

Figure 12: Modelled profiles classified as (a) wet ditch with clear water, (b) partially vegetated wet ditch, (c) densely vegetated wet ditch and (d) dry vegetated ditch compared to the corresponding measured profile. The latter is presented as a hatched line while the modelled profile is presented as a full line. The points are symbolised according to their NDWI value.

Table 1: Classification of the profiles over the four different classes and their frequencies

Class	Number of profiles
Wet ditch with clear water	45
Partially vegetated wet ditch	61
Densely vegetated wet ditch	43
Dry vegetated ditch	3
Total	152

4.3. Presence of water and water level

Water is assumed to be present in profiles of the first three classes (**Fig. 12, Table 1**). The mean vertical deviation for these profiles was calculated for the centre and the bank points separately (**Fig. 13**). The mean vertical deviation was significantly larger for the centre points ($p\text{-value} < 0.001$) due to the presence of water.

Figure 13: Mean vertical deviation between measured and corresponding LiDAR points for bank and centre points of wet ditch profiles.

To evaluate the LiDAR-derived water levels in the ditches, the closest cross-sectional profile to each of the five available piezometers was selected. The results of the comparison of the piezometer levels and extracted water levels are given in **Table 2**. The closest date for the piezometer measurements was four days before the LiDAR survey. The difference in water

level ranged from -0.54 to 0.70 m, with the border values corresponding to the piezometers furthest located of the ditch. Furthermore, the spatial distribution of the extracted water levels were in line with the flow direction and configuration of the ditches in the study area.

Table 2: Comparison of piezometer values from the WATINA database with water levels calculated from the LiDAR profiles.

Point WATINA	Date WATINA	Level piezometer (m TAW)	Date LiDAR	Water level LiDAR (m TAW)	Distance to piezometer (m)	Difference water level (m)
DYLP085	02/03/2014	26.91	02/03/2014	26.67	0.40	- 0.24
DYLP087	26/02/2014	26.72	02/03/2014	26.64	7.55	- 0.08
DYLB065	26/02/2014	27.04	02/03/2014	26.67	6.66	- 0.37
DYLP086	26/02/2014	27.08	02/03/2014	26.54	27.18	- 0.54
DYLP047	26/02/2014	26.07	02/03/2014	26.77	16.86	0.70

5. Discussion

5.1. Ditch cross-sectional profiles and their characteristics

The proposed methodology is accurate and robust for the size of cross-sectional buffer to extract cross-sectional profiles of small vegetated drainage ditches using LiDAR point data. Though the number of extracted LiDAR points increased linearly for increasing width, the errors remained stable. Due to the use of the minimum envelope for modelling the cross-sectional profile, with each incremental step for the cross-sectional buffer, the number of the extracted ‘lowest’ elevation points remained stable. Spline functions allowed for the flexibility needed to approximate a profile of any form (D’Errico, 2014), but when points disappeared in the profile due to spectral absorption, a data gap was present along the profile and caused difficulties for modelling the centre of the profile resulting in outliers in our validation set (**Fig. 8 - Fig. 10**).

The mean vertical deviation between the extracted LiDAR cross sections and reference

observations was 0.14 m for a cross-sectional buffer of 0.4 m (**Fig. 8**). The vertical deviation for the centre points of the wet profiles was significantly larger than the one for the banks due to the high water level that leads to an absorption of LiDAR pulses at 1064 nm (**Fig. 13**). The presence of water in the ditch leads to an underestimation of the depth (Rapinel et al., 2013). The mean vertical deviation of the bank points was also positive due to the reflections of the signal by the vegetation on the banks. Likewise, the relative area difference between the LiDAR cross-sectional area and reference area was high (-0.48) (**Fig. 8**). This result was slightly lower than reported by Podhoranyi and Fedorcak (2015) for the Olza River in the Czech Republic using a rasterized DEM with a resolution of 0.2 m. The width-depth ratio of the water course was larger than the ones of the ditches studied here. When there is standing water in the ditch, the cross-sectional profile under the water level could not be measured and was also not estimated in this study. Methods for this can be found in the studies of Mersel et al. (2013), Nathanson et al. (2012) and Roub et al. (2012).

The modelled cross-sectional profile's width was highly correlated ($R^2 = 0.87$) with a mean error of -0.15 m with the reference measurements (**Fig. 10**). Given the high correlation, determining the width of the ditch was not affected by the vegetation on banks and in the profile. The correlation was slightly higher than in the study of Dietterick et al. (2012) ($R^2 = 0.81$) using a TIN to determine the bank full widths of channels. The errors of the extracted cross-sectional profiles were continuous along the course of the ditch, which gives another indication for the robustness of the proposed method.

5.2. Classification of ditch cross sectional profiles

The size of the absorption gap in the LiDAR point cloud along the profile and the NDWI values of the points provided us with strong criteria to make a distinction between the classes 'wet ditch with clear water', 'partially vegetated ditch' and 'densely vegetated ditch' (**Fig.12**,

Table 1). The corrected intensities of the LiDAR points, which are active NIR reflection measurements, were combined with the multispectral (RGB) data to calculate the NDWI values. For the grassland in this study area, the number of returns was limited and the RGB values corresponded with the extracted LiDAR cross-sectional profile points. However, when there are more returns for the LiDAR point, the spectral characteristics of the first return should be taken into account.

The vegetation in ‘densely vegetated ditch’ and in ‘dry vegetated ditch’ profiles made it more difficult to distinguish these types. The variance of the elevation in the centre points was used for this. The thresholds for classification were selected rather arbitrary, but are flexible and still based on the characteristics of the Flemish LiDAR dataset.

5.3. Extracting water levels

Water level measurements on the day of the LiDAR recordings are indispensable to more accurately evaluate the extracted water levels. For this research, the data of the closest piezometers and corresponding timing were used (**Table 2**). For one of the piezometers, the water level was available for the day of the LiDAR recordings. For the other piezometers, the water level was taken four days before the LiDAR survey. This was justified because water levels varied very little in this period: In the next two weeks the levels did not differ by more than 0.01m (piezometer DYLP086) and 0.08m (piezometer DYLP087) from the observation used for validation. The greater the distance between piezometer and ditch, the greater the difference between the extracted and measured water levels. Hopkinson et al. (2011) validated LiDAR extracted water levels with gauge measurements for river deltas and obtained mean offsets from -0.22 m to +0.04 m, which are in the same order of magnitude as the results represented in **Table 2**. These observations indicate that this method is suitable for the proposed model. Furthermore, the spatial distribution of the extracted water levels were in line with the

flow direction and configuration of the ditches in the study area.

The proposed approach in this paper should now be further tested in other areas. The present study area is dominated by land which was converted from arable land to extensive pasture. The water table is high, which causes a high water level in the ditches and hence complexity for the extraction of cross sections. As the groundwater table is high, most ditches had standing water hampering the extraction of cross section with LiDAR points.

6. Conclusion

An objective of this study was to propose and evaluate an automated methodology for extracting the geometrical properties of vegetated ditches from LiDAR point clouds. The results indicate that the presence of water and partially the presence of vegetation influence the vertical deviation and cross-sectional area between the extracted LiDAR cross sections and reference observations. The extracted ditch width was highly correlated to the reference observations and not influenced by the vegetation on the banks. The independence of the errors to the cross-sectional buffer and the similarity of the errors along the different ditches indicate the robustness of the proposed method.

This work also proposed a procedure for classifying the extracted ditch profiles depending on the occurrence of water and vegetation. The corrected intensity values and multispectral information (RGB) could be used to assign a water index value to each LiDAR-point along the profile. This index and the spatial configuration of the points along the cross-sectional profile could be used to classify the profiles and determine if there was water present.

These results support the proposed methodology to remotely sense and extract the morphology of ditches from LiDAR point clouds in an automated way. This facilitates the input data acquirement for spatially explicit hydrological models by avoiding field surveys that require significant human resources and funding. This data input can improve the accuracy of

spatially explicit hydrological models and the catchments hydrologic response.

Acknowledgments

This research was funded by KU Leuven. The LiDAR data was made available by Agentschap Informatie Vlaanderen (AIV) (former AGIV). We like to thank Vrienden van Heverleebos en Meerdaalwoud (VHM) for authorizing us to work in ‘de Doode Bemde’ and a special word of thanks to Piet Debecker for his cooperation. Another word of thanks to Mike Alonzo for introducing us to the SLM toolbox.

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