EXTRACTING DRAINAGE NETWORKS AND THEIR CONNECTIVITY USING LIDAR DATA

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ABSTRACT

Policies, measures and models geared towards flood prevention and managing surface waters benefit from high quality data on the presence and characteristics of drainage ditches. As a cost and labour effective alternative for acquiring such data through field surveys, we propose a method (i) to extract vector data representing ditch drainage networks based on local morphologic features derived from high resolution digital elevation models, and (ii) to identify possible (dis)connections in the ditch network by calculating a probability of the connectivity using a logistic regression where the predictor variables are characteristics of the ditch centre lines or derived from the DEM.

Using LiDAR derived DEMs with a 1 m resolution, the method was developed and tested for a mixed agricultural residential area in north-eastern Belgium. The derived ditch segments had an error of omission of 8% and an error of commission of 5%. The original positional accuracy of the centre lines of the extracted ditches was 0.6 m and could be improved to 0.4 m by shifting each vertex to the position of the lowest LiDAR point located within a radius equal to the spatial resolution of the used DEM. 69% of the false disconnections in the network were identified and corrected leading to a reduction of the unconnected parts of the ditch network by 71%. The extracted and connected network approximated the reference ditch network fairly well.

Keywords: LiDAR; DEM; ditch; water course; connectivity; network

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1 Introduction

Agricultural lowlands under humid climates are frequently drained by means of artificial ditch networks to improve biophysical production conditions (Bailly et al., 2008, 2011). This is also true for urban and suburban areas where artificial ditches are implemented to modify the natural drainage system to avoid excess water (Jankowsky et al., 2013). Ditches are distinguishable from larger water courses by the high edge to volume ratio, and hence by a more intense exchange of matter and organisms with the surrounding land (Herzon and Helenius, 2008). In the lowlands of Western Europe, the density of open artificial drainage networks can reach 200-300 m/ha and their presence and characteristics have been found to influence the catchment's hydrological regime in terms of water quantity but also water quality (Levavasseur et al., 2014; Roelens et al., 2016). Ditches tend to reduce the risk of excess water and local flooding of the upstream areas of a catchment by collecting and conveying runoff to downstream surface water bodies (Buchanan et al., 2013; Moussa et al., 2002). However, as the evacuation of excess water is accelerated (Moussa et al., 2002), downstream areas may become more prone to flooding. Ditches require maintenance to ensure efficient functioning, else they degrade, collapse or get blocked, increasing the risk of flooding (Herzon and Helenius, 2008; Paavilainen and Päivänen, 1995). Knowledge about the functioning of ditch networks is critical in planning interventions for flood mitigation and water quality preservation (Dadson et al., 2017). Hence policies, models and measures geared towards flood prevention and surface water quality management benefit from high quality data about the presence and characteristics of ditches. This information, however, is often incomplete or even lacking (Andersson et al., 2015; Carluer and Marsily, 2004; Cavalli, 2013; Cazorzi et al., 2013; Moussa et al., 2002).

For the region of Flanders in northern Belgium, georeferenced information on water courses is stored in the Flemish Hydrographic Atlas (*Vlaamse Hydrografische Atlas*, VHA). Apart from data from field surveys conducted in some communes, hydrographic bodies were

digitized from topographic maps derived from aerial photographs older than 1992, and published at a 1:10,000 scale (Integraal Waterbeleid, 2014). The positional quality of this dataset is imperfect due to resolution limitations of the source imagery and the cartographic scale while small hydrographic elements are missing. Completing such a dataset through field surveys is tedious and prohibitively expensive.

High resolution airborne laser scanning (ALS) – also termed airborne LiDAR – provides an alternative to field surveys for the efficient acquisition of high resolution topographic data (Bowen and Waltermire, 2002; Höfle and Rutzinger, 2011; Tarolli, 2014). Most commonly applied methods to derive drainage networks, as well as other landscape features, rely on rasterized elevation and surface models (DEM/DSM) rather than on the original LiDAR point cloud data (Bailly et al., 2008; Cazorzi et al., 2013; Hooshyar et al., 2015; Lindsay and Dhun, 2015; Passalacqua et al., 2012; Schwanghart et al., 2013; Seibert and McGlynn, 2007; Sofia et al., 2014b).

Traditional hydrological flow path algorithms applied to rasterized DEMs perform poorly when extracting artificial ditch networks as the course of ditches is not only determined by the surface topography, but also by the spatial configuration of road networks and agricultural parcels (Bailly et al., 2008; Cazorzi et al., 2013; Duke et al., 2006). Hydrological approaches for drainage network extraction are even more problematic in flat areas because of the weak topographic gradient leading to low accuracies with which the flow direction can be determined (Cazorzi et al., 2013; Passalacqua et al., 2012). Additionally the presence of piped connections complicate the extraction of ditches from surface data (Jankowsky et al., 2013).

Methods that draw on morphologic rather than on hydrologic characteristics are therefore recommended to detect drainage networks in flat areas. They are particularly useful for the detection of linear structures in all kinds of spatial data coverages (Bai et al., 2015; Bailly et al., 2008; Cazorzi et al., 2013; Heijmans, 1995; Mason et al., 2006; Passalacqua et al.,

2010, 2012; Rapinel et al., 2015; Sofia et al., 2014a). Detecting artificial drainage networks from rasterized DEMs using morphological methods has however two main disadvantages: (i) they provide an incomplete view of the network by producing sets of unconnected segments so that hydrological connectivity is not accounted for (Bailly et al., 2011; Cazorzi et al., 2013; Tarolli, 2014) and (ii) the vectorised extracted lines will often not connect the lowest-lying LiDAR-points as these were obscured in the interpolated and rasterised DEM.

The objective of this study was to investigate how high resolution LiDAR point clouds and derived rasterized elevation products can be used to update existing hydrographic vector data. A procedure is proposed to extract ditch segments and their connectivity in three steps: (i) adapting the morphological procedure of Cazorzi (2013) to extract a preliminary version of the ditch network as a binary raster from the DEM, (ii) vectorising the binary raster into a line network and improving the positional accuracy of the ditch centre lines by shifting these towards the lowest LiDAR-points, and (iii) connecting the network segments based on a connection probability model. Every step of this procedure and its parameters are developed, validated and discussed for a case study area in northern Belgium.

2 Study area and data

2.1 Study area

The study area (*ca.* 150 ha) is located in the alluvial valley of the Demer river in north-eastern Belgium (**Figure 1**) with an elevation ranging between 30.0 and 39.6 m asl. The area is characterised by an extensive network of drainage ditches dating back to the 18th century, created mainly for improving agricultural production at that time. A small part of the drainage network was dug to provide water to fishing ponds. In the 20th century the ditches were deepened for lowering the groundwater table even more and turning marshes, moorlands and meadows into land suitable for mechanised agriculture (Agentschap Onroerend Erfgoed, 2013).

While the drainage network is dominated by open drainage ditches, some are blocked or have been replaced by culverts or underground pipes to allow vehicles and agricultural machineries to pass.

Figure 1: Location and aerial photograph of the study area. The white lines on the photograph show the ditches measured in the field, while the black lines represent the rivers as indicated in the Flemish Hydrographic Atlas.

2.2 Reference data

Ground truth data was collected in September and October 2016 (**Figure 1**). The trajectories of the ditches were recorded using a hand-held Trimble Geo-Explorer XT GNSS and differentially corrected to obtain a sub-meter horizontal accuracy. Road side ditches (**Figure 2A & 2B**), ditches between and within agricultural fields (**Figure 2C & 2E**), and ditches separating agricultural fields from non-agricultural parcels (**Figure 2D**) were mapped. Also their width, which varied between 0.30 and 2.20 m, and the location, length and width of culverts were measured. An example of a culvert is given in **Figure 2F**. The total length of the measured ditches in the study area was *ca.*18.1 km of which 1.7 km (9%) was underground.

The length of the true disconnections (no culvert) or apparent disconnections (culvert present) due to ditch burial varied between 1.6 m and 20.6 m. Apparent disconnections with a length between 46.5 and 231.5 m occurred as well coinciding with series of connected driveways along roads.

Figure 2: The drainage network in the study area consists of road side ditches (A, B), ditches between and inside agricultural fields (C, E), and ditches between agricultural fields and non-agricultural parcels (D). Some of these ditches contain culverts (F).

2.3 Airborne LiDAR data and derived DEM

Between 2013 and 2015, an airborne LiDAR campaign was carried out for the entire region of Flanders (13,512 km²) commissioned by the Flemish Agency for Geographical Information (AGIV, www.agiv.be). LiDAR point clouds with a density of at least 16 points per square meter and digital RGB images with a spatial resolution of 0.10 m were simultaneously acquired during the winter months (15th November – 15th April) when foliage was minimal. The point cloud was subjected to a strict geometric quality control, both planimetrically

(RMSE_{xy} = 0.10 m) and altimetrically (RMSE_z = 0.05 m) and the points were classified as ‘ground’, ‘non-ground’ or ‘water’. The maximum planimetric distance between two points was 0.5 meters (Vanderstraete, 2013). The laser scanning device was a LiteMapper 6800, based on the RIEGL LMS-Q680i, with a laser beam in the NIR wavelength range (at 1064 nm). For each reflected echo signal, a 16-bit intensity measurement was available. The instrument had a laser pulse repetition rate up to 400 000 Hz, a beam divergence smaller or equal to 0.3 milliradians and a scan angle range of 60 ° (-30° to 30°) (Petrie, 2011; Schechtner, 2012). Raster DEMs with a spatial resolution of 1 m and 0.5 m were derived using the Delaunay triangulation grid interpolation algorithm of the LAStools (Isenburg et al., 2006; Petermans, 2013) and OPALS software (Mandlbürger et al., 2009) respectively. The LiDAR data of the case study area were recorded on the 11th of March 2015.

3 Methodology

The procedure for extracting the ditch network from the high resolution LiDAR-DEM and the underlying point cloud, consisted of three steps: (i) preliminary extraction of ditch segments, (ii) vectorisation and improvement of the positional accuracy, and (iii) correction of connectivity. Python scripts and user information for all the steps described below can be found on <https://github.com/JenniferRoelens/DitchDetConn>.

3.1 Extracting the preliminary ditch network

Ditches are characterized by a high edge to volume ratio as revealed by negative transitions in the landscape surface, especially in areas where the slope gradient is relatively low (Cazorzi et al., 2013; Herzon and Helenius, 2008). Accordingly, the method proposed by Cazorzi et al. (2013) was used to extract a preliminary ditch network. This method allows extracting local small, low-relief features from DEMs and eliminate as far as possible large

landscape forms. The latter are identified by applying a low-pass filter to the DEM. The landscape is then detrended by subtracting the original DEM from the smoothed DEM so that only small-scale topographic features are preserved. Every pixel of the resulting surface is characterised by a Relative Elevation Attribute (REA) expressed as (Carturan et al., 2009; Cazorzi et al., 2013):

$$REA = \bar{E}_r - E_{DEM} \quad (1)$$

where $\bar{E}_r$ is the average elevation of cells within a circular or squared area with radius r (in meters) around the grid cell with elevation E_{DEM} . To reduce errors of omission (better detection of the actual ditch pixels) and errors of commission (decreasing false detections), areas with a presumed low occurrence of ditches or with high levels of noise, such as urban areas and dense forests, were masked using an updated land cover map with a 1 m spatial resolution (AGIV, 2012).

To ensure that the method is as generic as possible and spatially transferrable to other study areas, the automated Otsu image threshold selection method (Otsu, 1979) was used to label pixels with REA peak values as ‘ditch’. Otsu’s algorithm finds the threshold value which minimizes the within-class variance and maximizes the between-class variance of the REA values. The result is a binary map with the ditch pixels represented as ‘1’ and the landscape as ‘0’.

Small irregularities in the DEM, inherent to noise in the data, get ‘wrongly’ identified as ditch pixels in the binary map (Sofia et al., 2011). To remove this noise, the binary data was post-processed by evaluating the length of clusters of ‘ditch pixels’. The length of a cluster was defined as the ratio between the area, expressed as the number of pixels, and its width. The width of a cluster was calculated as twice the maximal Euclidean distance between a ‘ditch pixel’ of the cluster and the nearest ‘landscape pixel’ (Cazorzi et al., 2013; Sofia et al., 2014a). Clusters of ‘ditch pixels’ consisting of just one pixel were discarded right away. Subsequently

a threshold was set for retaining the longest clusters:

$$Length > Q_3 + 1.5 IQR \quad (2)$$

where the interquartile range (IQR) is the difference between the third quartile (Q_3) and first quartile (Q_1).

3.2 Vectorisation of ditch pixel clusters

The resulting post-processed ditch pixel clusters were thinned to a width of one raster cell according to the approach of Zhan (1993) and vectorised using the Douglas-Peucker algorithm (Douglas and Peucker, 1973) to match the format of the of Flemish Hydrographic Atlas. The initially extracted vector lines were still cell-shaped and not always located in the exact centre of the ditches, and so did not meet the required geospatial standards.

The positional accuracy of the derived ditch centre lines was subsequently improved by referring back to the original LiDAR point cloud. First, the detected preliminary segments were discretised at vertices, and in-between the vertices at a 20 m interval. The position of the centre lines was improved by shifting each vertex to the position of the lowest LiDAR point located within a radius equal to the spatial resolution of the used DEM.

3.3 Connection probability model

The previous steps resulted into a vector drainage network that contains true and false disconnections. False disconnections, or missing connections, occur where culverts, overpassing driveways, or shallowness of segments prohibit their detection. To add these missing connections to the network, a connection probability model was developed. The parameterisation and application of the model consisted of 5 steps (**Figure 3**): (i) spatially merging of the preliminary ditch network with the watercourse lines available in the Flemish Hydrographic Atlas, and determining the flow direction of the segments of the merged network;

(ii) upstream tracing of the resulting network starting at the potential outlets and determining the dead ends; (iii) identifying possible connecting segments and retrieving their characteristics; (iv) using these characteristics as predictor variables to calibrate and implement a logistic regression model for the connection probability, and (v) iteratively adding the most probable connecting segments while tracing the resulting network, letting the network grow in each iteration. These steps, together with the previous ones, are schematically represented in **Figure 3**.

Figure 3: Schematic representation of the methodology for extracting and connecting drainage network segments from LiDAR data and LiDAR-derived DEM.

3.3.1 Constructing geometric networks

First, the extracted ditch network was spatially merged with the existing digitized watercourses of the Flemish Hydrographic Atlas (**Figure 1**). As the latter have at best a positional accuracy of 2.5 m, prior to the merging, the discretized watercourses were shifted using the LiDAR points, but not for more than 2.5 m (section 3.2). Where there were no segments of the Flemish Hydrographic Atlas in the immediate neighbourhood, this merging was not done. Improving the positional accuracy resulted in a network that consisted of short

straight ditch segments that were connected or unconnected to other ditch segments. A ditch was then defined as a set of ditch segments connected at a planimetric angle of less than 45° (**Figure 4A**). The threshold of 45° was chosen given that ditches are often designed to follow rectangular parcels and hence join at near perpendicular angles.

After defining the ditches, their flow directions were derived from the LiDAR elevation of their start and end points. The flow direction of each ditch was confirmed when the elevation difference between the start and endpoint was at least 0.1 m ($2 \times \text{RMSE}_z$). If the difference was smaller, an indeterminate flow direction was assigned to the ditch. The orientated ditches were then integrated into a geometric network structure fitting the ArcGIS-format.

3.3.2 Detecting possible connecting segments

End points of ditches having a confirmed flow direction were considered as potential outlets of the network. Starting at these potential outlets, the network was traced upstream until a dead end was reached. If during the tracing, a ditch with an indeterminate flow direction was encountered, the ditch was treated as an upstream ditch. To identify possible connecting segments from the reached dead ends, the following conditions were set: (i) the dead end cannot connect to an already traced vertex, (ii) the dead end can only connect to one of the five closest vertices within a search radius set to 100 m, (iii) the dead end may connect to a ditch only once, (iv) the dead end can only connect to a vertex with a relative elevation difference of less than 0.1 m ($2 \times \text{RMSE}_z$) and, (v) the possible connecting segment cannot cross other ditches. All the identified possible connecting segments were then classified either as a true disconnecting segment or as a missing connecting segment based on the field data and were then used to calibrate the connection model.

3.3.3 Calibrating the connection probability model

A logistic regression model was used to calculate the probability of possible connecting segments being true connections. The predictor variables that were used for the logistic regression model and a justification for their selection are listed in **Table 1**. The list encompasses both characteristics specific to the possible connecting segment and characteristics computed from the DEM for a 2 meter buffer zone around the segment (**Figure 4**). The variables computed for the buffer zones were characterized by their mean value, standard deviation, variance and range using a zonal statistics algorithm that takes overlapping polygons into account.

Figure 4: A graphical representation of characteristics specific to the possible connecting segment (grey line) in the planimetric [A] and altimetric plane [B]. The buffer zone used for calculating the zonal characteristics is depicted in [A] in grey.

To reduce the set of 27 candidate predictor variables, a 'random forest recursive feature elimination' (RF-RFE) was applied. The algorithm starts from the complete set and then eliminates the least relevant variables one after the other based on a variable importance ranking produced by fitting random forests (Guyon et al., 2002; Zhou et al., 2014). A logistic regression model was then calibrated using the retained variables and the possible connecting segments

from section 3.3.2 that were classified based on field data. The model was set up to assess the probability of a possible connecting segment to be a true connection. The probabilities were calculated as:

$$\text{Connection probability} = \frac{e^{f(\text{predictor variables})}}{1 - e^{f(\text{predictor variables})}} \quad (3)$$

The continuous probabilities (0-1) were then transformed into 0 or 1 based on a cut-off value defined as the proportion of the number of true missing connecting segments over the total number of possible connecting segments of the calibration data set. The calibrated connection model was then cross-validated (section 3.4.2).

3.3.4 Implementing the connection probability model

The calibrated connection model was implemented for the entire network by iteratively tracing the network as described below. Starting from the initial topological network as described in section 3.3.1, the connected segments of the network were traced upstream starting at the end point of the lowest-lying segment, taken as the lowest outlet. At every dead end, possible connecting segments were identified and their characteristics calculated. A connecting segment was added to the network if its probability, using the calibrated logistic model presented in section 3.3.3, was higher than the cut-off value. If there was more than one possible connecting segment at a dead end, the segment with the highest probability was chosen. The procedure was then repeated with the segment added to the network and iterated until all segments having a high enough probability to be connected were processed. A new outlet was then defined as the end point of the next lowest ditch that was not traced yet. This procedure was iterated over all the following outlets and resulted in different connected parts of the network each having its own outlet.

296 *Table 1: Characteristics of the possible connecting segments used as candidate predictor variables and*
 297 *justification for their consideration.*

Predictor variable	Shape	Justification
Slope	Line	Higher slopes will more likely drain water.
Length	Line	Short blockages and culverts of ditches frequently occur in the study area to allow access to adjacent agricultural fields.
Planimetric angular difference	Line	Connecting segments with small planimetric angular differences are more likely to belong to the same ditch.
Profile curvature	Buffer	The profile curvature identifies steep slopes in the transition from the top of the possible connection to the surface of the ditch (Carlson and Danner, 2010). The buffer around a true connection segment will contain raster cells with large profile curvature values and will yield a higher average value.
Tangential curvature	Buffer	The tangential curvature can identify the smoothness of the edges of possible connections (Carlson and Danner, 2010). Edges of natural overpasses are less 'smooth' than for example, edges of asphalted surfaces.
Fill	Buffer	Using local flow accumulation values, false disconnections in the DEM will result in blockages of large volumes of water (Carlson and Danner, 2010). Therefore, large fill values are expected upstream of possible connections. The buffer around a true connection segment will contain raster cells with large fill values and will yield a higher fill average.
Residual topography	Buffer	It was observed in the field that the ground surface over culverts was often higher than the surrounding terrain. These would then be represented by a negative residual elevation attribute.
LiDAR intensity	Buffer	Surface moisture conditions influence LiDAR intensity returns (Garroway et al., 2011). Shallower soils covering culverts are expected to have a higher intensity signal due to lower moisture storage capacity.
Multispectral RGB image	Buffer	There is a negative correlation between the values of the red, green and blue bands and soil moisture, indicating that the soils become lighter with lower surface moisture (Santos et al., 2016). Shallower soils covering culverts are expected to have a higher RGB reflectance due to lower moisture storage capacity.

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3.4 Validation

3.4.1 Validation of the geometry of the corrected ditch trajectories

The validity of the extracted ditch network was tested using the method of Broersen et al. (2017) that is based on the equally-distributed-sample-points (EDSP) method (Hölbling et al., 2008). The detected network segments were discretized by representing them with points uniformly positioned along the segments, with a point distance equal to the resolution of the underlying DEM. For each point the shortest Euclidean distance to the ditch centre lines in the reference dataset was determined. The positional accuracy was then calculated as the mean absolute error of these Euclidean distances with a threshold value of 2 m. Points at a distance larger than this threshold, were considered as part of the error of commission. Furthermore, the reference network was also discretised and the shortest Euclidean distances were calculated to the extracted network. Points at a distance larger than the threshold of 2 m, were considered as part of the error of omission.

3.4.2 Validation of the connection probability model

To validate the calibrated connection probability model, based on the possible connections described in section 3.3.2, a 10-fold cross validation was used to determine the percentage of true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN). True positives were defined as true connections that were missed in the extracted network, whereas true negatives were defined as true disconnections. The accuracy, omission error and commission error for possible connections were calculated as follows (Fawcett, 2006):

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$error\ of\ omission = \frac{FN}{FN + TP} \quad (5)$$

$$error\ of\ commission = \frac{FP}{FP + TN} \quad (6)$$

After implementing the calibrated logistic model on the network, the added connections (section 3.3.4) were compared to the (dis)connections in the reference network and vice versa to determine the error of commission and error of omission.

4 Results

4.1 Vectorised preliminary ditch network

The errors of commission and omission of the extracted vectorised preliminary networks for different combinations of DEM resolution, DEM smoothing, window size and window shape are presented in **Figure 5**. Overall, using the 0.5 m DEM resulted in a higher error of commission (**Figure 5A**) but in a lower error of omission (**Figure 5B**) than the 1 m DEM, with larger differences for the error of commission. The error of commission for both DEMs was not different between the squared and circular smoothing window (**Figure 5A**), but with a squared window the error of omission for both DEMs increased with an increasing smoothing window when the radius exceeded 2 m (**Figure 5B**). From **Figure 5**, the effect of the smoothing window size can also be seen. In general, the error of omission reaches an ‘optimum’ when the smoothing window is small and increases when the smoothing window is larger. For the errors of commission, it is more difficult to find a trend. An ‘optimal’ smoothing window could be chosen by primarily evaluating the error of omission and secondly the error of commission. Finally it was decided to proceed with a circular window of 3 m for the 1 m DEM and of 2.5 m for the 0.5 m DEM.

Table 2 contains more detailed results for the selected extracted networks before and after using the original LiDAR point cloud to improve the positional accuracy of the network. The table shows that the positional accuracy was significantly better for the shifted ditch centre lines in the network. Also the length of the extracted network decreased slightly after improving

the positional accuracy. Using the 0.5 m DEM led to a longer network of shorter ditches. The number and total length of ditches in the reference network length is higher than the ones in the 1 m DEM derived network and lower than the one in the 0.5 m DEM derived network (Table 2), but the 1 m DEM comes closer.

Figure 5: Error of omission [A] and error of commission [B] for the spatially shifted extracted ditch networks plotted against the smoothing window radius. The full lines represent the results using the 1m DEM and the dashed lines represent the results using the 0.5m DEM. The shape of the smoothing window (square and circular) is reflected in the shape of the markers.

Table 2: Positional accuracy, network length, number of ditches and average ditch length for the extracted ditch networks using a 0.5 m DEM (2.5 m circular window) and 1 m DEM (3 m circular window), before and after implementing a spatial shift. A comparison is made with the reference ditch network as measured in the field.

	Spatial shift	1 m DEM	0.5 m DEM	Field
Positional accuracy (m)	without	0.57	0.43	-
	with	0.39	0.37	-
Network length (m)	without	15,637	18,251	-
	with	15,293	17,530	16,391
Number of ditches	with	244	610	164
Average ditch length (m)	with	62.68	28.74	99.95

4.2 Calibrating the connection probability model

Given the lower error of commission, the connection model was calibrated and implemented using the results of the 1 m DEM with a circular smoothing window radius of 3 m. After tracing the 51 potential outlets upstream, 68 possible connecting segments were identified (section 3.3.2). Comparing them to the ground data revealed that 23 of the 68 were truly connecting. Three predictor variables were selected with the RF-RFE method and resulted in a statistically significant logistic model ($p < 0.001$) (**Table 3**). The negative logistic regression coefficient for the angular difference indicated that the higher the angular difference is – and thus the less straight the ditch is – the lower the probability that a potential connecting segment is a true connection. Furthermore, in line with the expected correlation in **Table 1**, high fill values lead to a higher connection probability, which is also the case for higher profile curvatures of steep slopes in the transition from the top of the possible connecting segment to the bottom of the ditch.

Connecting segments with a probability higher than the cut-off value of 0.33 (23/68) were classified as ‘true’. The values for accuracy, error of omission and error of commission for the calibrated model, after 10-fold cross-validation, are presented in **Table 4**.

Table 3: Retained coefficients of the selected logistic regression model after RF-RFE with their p-value

Predictor variable	Coefficient	p-value
Planimetric angular difference	-0.27	< 0.01
Average[profile curvature]	0.44	< 0.05
Average[fill]	28.57	< 0.01

Table 4: Accuracy, error of omission and error of commission for the calibrated logistic regression model and after its implementation.

	Calibration	Implementation
Accuracy	0.91	-
Error of omission	0.03	0.31
Error of commission	0.18	0.15

4.3 Implementing the connection probability model

While re-tracing the network iteratively and implementing the calibrated logistic regression model (**Table 3**), out of the 175 possible connecting segments, 52 segments were added to the network. The number of network fragments decreased from 261 to 57 and their average length increased from 64 m to 240 m. The total length of the network increased with 1700 m (**Table 5**). The results were further compared to the reference network (**Table 5**). The errors of the implemented connection model are presented in **Table 4**. The added connections were compared to the (dis)connections in the reference network and vice versa. The error of commission of the logistic regression model was similar at calibration and implementation. In contrast, the error of omission increased from 0.03 at calibration to 0.31 at implementation. In **Figure 6**, the ditches and their connections are shown in a part of the study area after the implementation of the connection model. Of the false disconnections (green lines) 69% were identified, corrected and mapped. Many of the connecting segments that were missed (black lines) were long connections with many of them situated along houses where the drainage is routed underneath the driveways. Furthermore, 15% of the mapped connections were wrongly

mapped as true connections (red lines) (**Table 4, Figure 6**).

Table 5: Total network length, number of network fragments and average network fragment length before and after implementation of the connection model. A comparison is made with the measured ditch network in the field.

	Before connection	After connection	Field
Total network length (m)	16,766	18,466	20,441
Number of network fragments	261	77	29
Average network fragment length (m)	64.24	239.82	704.86

Figure 6: Detail of the Relative Elevation Attribute (REA) map with the extracted ditch network represented by white lines and the correctly identified connections by green lines. The omitted segments are represented by black and the committed segments by red lines. Grey rectangles are building footprints.

5 Discussion

5.1 General discussion

The case study shows that it is possible to derive a vectorised extracted network from a 1 m DEM and a 3 m circular window to calculate residual relief, with a high positional accuracy and low errors of omission and commission (**Table 2, Figure 5**). The errors of omission are mainly due to the land cover mask that contained almost 2% of the measured ditches and by buried possible connections in the network, such as culverts. Furthermore, relative high water levels influence the error of omission as negative transitions in the landscape are less pronounced for water-filled ditches given that water absorbs NIR waves. Where no laser signals return from water surfaces, ‘gaps’ appear in the point cloud and translate into ‘flat areas’ in the raster DEM. The errors of commission occur along former borders between land parcels or along big furrows in ploughed agricultural fields. Another source of errors may be the time lag of 17 months between the LiDAR aerial survey and the field survey.

Implementing a connection model based on the planimetric angular difference between the ditch and the possible connecting segment, and taking into account the average fill and profile curvature values of a 2 m buffer around possible connecting segments, allows to reduce the already low error of omission even more. Using this connection model, 69% of the false disconnections in the network could be identified and corrected (**Table 4**) and the number of network fragments was reduced by 71% (**Table 5**), approximating the reference ditch network fairly well. A set of true connecting segments were missed mainly because they were not part of the set of possible connecting segments as (i) some of the connections in the network did not fit the ‘logical’ framework, such as underground pipes undercrossing streets and (ii) the searching distance of 100 m, that was already quite high, was too low to connect ditches that were separated by series of connected driveways of buildings along a street (**Figure 6**). Furthermore, there was a number of false connecting segments because of blockages in the

ditches that look like culverts, but do not contain a subsurface pipe, inhibiting the water to flow in the network.

As the methodology is spatially and data generic, it should be applicable to other LiDAR surveyed areas. The parameters used for the extraction and connection of the drainage network were chosen independently from the area and only chosen based on the data properties of the used DEM and LiDAR point cloud. These parameters include the REA threshold (Otsu), the length threshold (upper outliers), the distance for the spatial shift (DEM resolution) and the threshold for confirming the flow direction ($2 \times \text{RMSEz}$).

5.2 Preliminary ditch network extraction and vectorisation

The parameter influencing the preliminary ditch extraction most was the resolution of the DEM whereby there is a trade-off between the error of omission and commission depending on the resolution of the DEM. The error of omission was furthermore influenced by the window size and shape, with an increasing error at the lower and higher edge pointing to an optimum at 3 m. A circular window shape was preferred over a squared since the error of commission was lower.

To extract the provisional network, the calculated and thresholded REA raster was post-processed based on the length of the clustered pixel fragments. The method of Sofia et al. (2014a) was originally used to post-process binary images of scarps and levees which alike ditches are elongated elements. However, using the original threshold yielded a negative value as ditches are less wide than the target features in the study of Sofia et al. (2014a). The threshold was adapted as there were many more small irregularities that were classified as a ditch pixel, favouring the upper outliers that were the largest connected ditch pixel clusters.

The classified raster was vectorised to match the data format of the Flemish Hydrographic Atlas as this is required for many applications in the Flemish region of Belgium, e.g. ArcNEMO (Van Opstal et al., 2014). A new element in this research was that the spatial

shifting of the ditch network using the underlying LiDAR point cloud lead to an improvement of the positional accuracy to a level which would allow for extracting ditch properties, such as the water level, ditch width and cross-sectional area (Roelens et al., 2016). Most of the common errors that occur in skeletonization procedures like the creation of loops or neckings were cancelled out by shifting the network. However a fraction of these errors were persistent and are difficult to resolve through automatic procedures so that they require manual intervention (Sofia et al., 2014a). Still, these errors did not break the ‘connectivity’ of the ditch segments.

5.3 Connection probability model

The method we used involved several new elements. First, in contrast to the model developed by Bailly et al. (2011), the connection probability model we propose allows to identify the occurrence of ditches, and their connecting segments, independently of plot boundaries. Secondly, using the original LiDAR point cloud to determine the flow direction, and not the interpolated DEM, leads to a more accurate determination of the flow direction. Thirdly, calculating connection probabilities with a logistic regression model (**Table 3**) allows classifying connecting segments using a threshold of 0.33 pointing to a true connection. Traditionally, for a binary classification, the default threshold is 0.5. However, a threshold value of 0.5 does not always lead to the best classification results where unbalanced class sizes need to be classified (Calabrese, 2014). In this study, there were multiple possible connections per dead end, while in reality there will be almost always only one or no connection. A threshold value of 0.5 strongly favours the majority class of disconnections and leads to a very low detection of the missing connections. Since the optimal cut-off value is related to the event rate of true missing connections in the dataset, the cut-off value was defined as the proportion of true missing connections over the possible connections used of the calibration set.

5.4 Validation

The method of Broersen et al. (2017) was chosen for validating the vectorised preliminary networks as it can take the different lengths of the reference and extracted networks into account. Nevertheless, a drawback of the validation method of Broersen et al. (2017) is that the validation is dependent on the correctly mapped length and not the number of mapped objects. One ditch is represented by a certain number of points at a fixed distance from each other and changing this distance leads to different omission and commission errors. That is why it was recommended here to set the distance equal to the spatial resolution of the used DEM as an pragmatic standard.

5.5 Practical implications

Having complete hydrographic inventories with a high positional accuracy facilitate the automatic extraction of ditch characteristics such as the water level, presence of vegetation and ditch width using LiDAR point clouds (Roelens et al., 2016). Knowledge on the position, characteristics and connectivity of drainage networks is essential for planning future interventions for mitigation of floods, strengthening of biodiversity and protection of water quality (Dadson et al., 2017). For example, upland ditches may increase or decrease downstream flood peaks at the local scale depending on the layout of the drains, topography, management of the connectivity (e.g. ditch blocking) and flood peak synchronization in the main channel (Dadson et al., 2017; Lane and Milledge, 2013; Ramchunder et al., 2009). These effects can be tested in hydrological models such as variable source area hydrological models (Bracken and Croke, 2007) or in distributed models like MIKE-SHE (Refsgaard and Storm, 1995) or ArcNEMO (Van Opstal et al., 2014). Information on ditch networks are particularly of interest when using a coupled hydrological/hydraulic model like the MIKE SHE/MIKE 11 system that was e.g. used by Thompson et al. (2004) to model the hydrology of a wetland where

ditches play an important role in the hydrology. The results of our study can also be indirectly implemented in hydrological models that parameterize drainage processes by using the drainage density or the distance to open drains.

With future LiDAR campaigns, it will be possible to keep these hydrographic datasets and the derivation of its characteristics up to date.

5.6 Future research

To further decrease the errors in the extracted network, use could be made of both DEM's (0.5 m and 1 m) by dynamic multiresolution thresholding (Song et al., 1990). Furthermore, as the accuracy of the generated DEM's is subject to the correctness of the classification of ground points (Thenkabail, 2016), more recent LiDAR point classification methods can help further improving the results. To further reduce the errors of commission in the connected extracted ditch network, segments in the ditch network that are unconnected and shorter than a certain length could be removed. Furthermore, the logistic regression model can be improved by expanding the list of predictor variables in **Table 1** by combining the variables, such as the intensity and RGB values, creating vegetation and water indices (Roelens et al., 2016). Although the overall procedure was made as generic as possible by using parameters based on the data properties derived from the DEM and LiDAR point cloud, calibrating the logistic regression model was still dependent on a subset of the field data.

6 Conclusion

In this paper, a method was proposed and applied to extract ditches and their connectivity from a LiDAR-derived high resolution raster DEM in combination with the original LiDAR point cloud dataset. Ditch segments could be successfully extracted from the 1 m DEM with omission errors limited to 8% and commission errors to 5%. The positional accuracy of the ditch centre lines and their flow direction were improved by using the underlying point cloud as the reference. The omission errors of the extracted ditch network were lowered by implementing a logistic regression model for calculating the probability of candidate network segments to be true connecting segments. These connecting segments can connect the extracted ditches to the known water courses and to each other where necessary. Predictor variables in the logistic regression model were characteristics of the ditch centre lines, such as the planimetric angular difference, or derived from the DEM, such as the profile curvature and fill values. To implement the proposed method only LiDAR-derived variables are required without the need for incorporating ancillary variables like RGB. The applicability of the method is in completing existing hydrographic inventories for the smaller unmapped entities and, with future LiDAR campaigns, keeping such datasets up to date. Furthermore, availability of more accurate ditch centre lines, will facilitate the determination of geometric ditch characteristics like width, cross-sectional shape and area and water level. Altogether, the method is believed to contribute to the improvement of the explanatory and predictive performance of water and nutrient discharge models.

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- Agentschap Onroerend Erfgoed, 2013. Vijvergebied tussen Laambek en Slangebek [WWW Document]. Inventar. Onroer. Erfgoed. URL <https://id.erfgoed.net/erfgoedobjecten/300246>
- AGIV, 2012. Bodembedekkingskaart (BBK), 1m resolutie, opname 2012.
- Andersson, J.C.M., Pechlivanidis, I.G., Gustafsson, D., Donnelly, C., Arheimer, B., 2015. Key factors for improving large-scale hydrological model performance 77–88.
- Bai, R., Li, T., Huang, Y., Li, J., Wang, G., 2015. An efficient and comprehensive method for drainage network extraction from DEM with billions of pixels using a size-balanced binary search tree. *Geomorphology* 238, 56–67. <https://doi.org/10.1016/j.geomorph.2015.02.028>
- Bailly, J.S., Lagacherie, P., Millier, C., Puech, C., Kosuth, P., 2008. Agrarian landscapes linear features detection from LiDAR: application to artificial drainage networks. *Int. J. Remote Sens.* 29, 3489–3508. <https://doi.org/10.1080/01431160701469057>
- Bailly, J.S., Levavasseur, F., Lagacherie, P., 2011. A spatial stochastic algorithm to reconstruct artificial drainage networks from incomplete network delineations. *Int. J. Appl. Earth Obs. Geoinformation* 13, 853–862. <https://doi.org/10.1016/j.jag.2011.06.001>
- Bowen, Z.H., Waltermire, R.G., 2002. Evaluation of light detection and ranging (LiDAR) for measuring river corridor topography. *J. Am. Water Resour. Assoc.* 38, 33–41. <https://doi.org/10.1111/j.1752-1688.2002.tb01532.x>
- Bracken, L.J., Croke, J., 2007. The concept of hydrological connectivity and its contribution to understanding runoff-dominated geomorphic systems. *Hydrol. Process.* 21, 1749–1763. <https://doi.org/10.1002/hyp.6313>
- Broersen, T., Peters, R., Ledoux, H., 2017. Automatic identification of watercourses in flat and engineered landscapes by computing the skeleton of a LiDAR point cloud. *Comput. Geosci.* 106, 171–180. <https://doi.org/10.1016/j.cageo.2017.06.003>
- Buchanan, B., Easton, Z.M., Schneider, R.L., Walter, M.T., 2013. Modeling the hydrologic effects of roadside ditch networks on receiving waters. *J. Hydrol.* 486, 293–305. <https://doi.org/10.1016/j.jhydrol.2013.01.040>
- Calabrese, R., 2014. Optimal cut-off for rare events and unbalanced misclassification costs. *J. Appl. Stat.* 41, 1678–1693. <https://doi.org/10.1080/02664763.2014.888542>
- Carlson, R., Danner, A., 2010. Bridge detection in grid terrains and improved drainage enforcement, in: *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems, GIS '10*. ACM, New York, NY, USA, pp. 250–259. <https://doi.org/10.1145/1869790.1869827>
- Carluer, N., Marsily, G.D., 2004. Assessment and modelling of the influence of man-made networks on the hydrology of a small watershed: implications for fast flow components, water quality and landscape management. *J. Hydrol.* 285, 76–95. <https://doi.org/10.1016/j.jhydrol.2003.08.008>
- Carturan, L., Cazorzi, F., Dalla Fontana, G., 2009. Enhanced estimation of glacier mass balance in unsampled areas by means of topographic data. *Ann. Glaciol.* 50, 37–46.
- Cavalli, M., 2013. Semi-automatic derivation of channel network from a high-resolution DTM: the example of an Italian alpine region. *Eur. J. Remote Sens.* 152–174. <https://doi.org/10.5721/EuJRS20134609>
- Cazorzi, F., Fontana, G.D., Luca, A.D., Sofia, G., Tarolli, P., 2013. Drainage network detection and assessment of network storage capacity in agrarian landscape. *Hydrol. Process.* 27, 541–553. <https://doi.org/10.1002/hyp.9224>
- Dadson, S.J., Hall, J.W., Murgatroyd, A., Acreman, M., Bates, P., Beven, K., Heathwaite, L., Holden, J., Holman, I.P., Lane, S.N., O'Connell, E., Penning-Rowsell, E., Reynard, N., Sear, D., Thorne, C., Wilby, R., 2017. A restatement of the natural science evidence concerning catchment-based 'natural' flood management in the UK. *Proc. R. Soc. Math. Phys. Eng. Sci.* 473, 20160706. <https://doi.org/10.1098/rspa.2016.0706>
- Douglas, D.H., Peucker, T.K., 1973. Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. *Cartogr. Int. J. Geogr. Inf. Geovisualization* 10, 112–122. <https://doi.org/10.3138/FM57-6770-U75U-7727>
- Duke, G.D., Kienzie, S.W., Johnson, D.L., Byrne, J.M., 2006. Incorporating ancillary data to refine anthropogenically modified overland flow paths. *Hydrol. Process.* 20, 1827–1843. <https://doi.org/10.1002/hyp.5964>
- Fawcett, T., 2006. An introduction to ROC analysis. *Pattern Recognit. Lett., ROC Analysis in Pattern Recognition* 27, 861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>
- Garroway, K., Hopkinson, C., Jamieson, R., 2011. Surface moisture and vegetation influences on lidar intensity data in an agricultural watershed. *Can. J. Remote Sens.* 37, 275–284. <https://doi.org/10.5589/m11-036>
- Guyon, I., Weston, J., Barnhill, S., Vapnik, V., 2002. Gene Selection for Cancer Classification using Support Vector Machines. *Mach. Learn.* 46, 389–422. <https://doi.org/10.1023/A:1012487302797>
- Heijmans, H., 1995. *Mathematical Morphology: A Modern Approach in Image Processing Based on Algebra and*

- Geometry. *SIAM Rev.* 37, 1–36. <https://doi.org/10.1137/1037001>
- Heipke, C., Mayer, H., Wiedemann, C., Jamet, O., 1997. Evaluation of automatic road extraction. *Int. Arch. Photogramm. Remote Sens.* 32, 151–160.
- Herzon, I., Helenius, J., 2008. Agricultural drainage ditches, their biological importance and functioning. *Biol. Conserv.* 141, 1171–1183. <https://doi.org/10.1016/j.biocon.2008.03.005>
- Höfle, B., Rutzinger, M., 2011. Topographic airborne LiDAR in geomorphology: A technological perspective. *Z. Fr Geomorphol. Suppl. Issues* 55, 1–29. <https://doi.org/10.1127/0372-8854/2011/0055S2-0043>
- Hölbling, D., Pernkof, M.L., Jekel, T., Albrecht, F., 2008. An Exploratory Comparison of Metrics for Line Error Measurement, in: Car, A., Griesebner G. & Strobl, J., *GI-Crossroads@ GI-Forum*. Heidelberg: Wichmann. pp. 134–139.
- Hooshyar, M., Kim, S., Wang, D., Medeiros, S.C., 2015. Wet channel network extraction by integrating LiDAR intensity and elevation data. *Water Resour. Res.* 10029–10046. <https://doi.org/10.1002/2015WR018021>
- Integraal Waterbeleid, 2014. Toelichting bij de Vlaamse Hydrografische Atlas ten behoeve van de Watertoets.
- Isenburg, M., Liu, Y., Shewchuk, J., Snoeyink, J., Thirion, T., 2006. Generating raster DEM from mass points via TIN streaming, in: *International Conference on Geographic Information Science*. Springer, pp. 186–198.
- Jankowsky, S., Branger, F., Braud, I., Gironás, J., Rodriguez, F., 2013. Comparison of catchment and network delineation approaches in complex suburban environments: application to the Chaudanne catchment, France. *Hydrol. Process.* 27, 3747–3761. <https://doi.org/10.1002/hyp.9506>
- Lane, S.N., Milledge, D.G., 2013. Impacts of upland open drains upon runoff generation: a numerical assessment of catchment-scale impacts. *Hydrol. Process.* 27, 1701–1726. <https://doi.org/10.1002/hyp.9285>
- Levavasseur, F., Lagacherie, P., Bailly, J.S., Biarnès, A., Colin, F., 2014. Spatial modeling of man-made drainage density of agricultural landscapes. *J. Land Use Sci.* 1–21. <https://doi.org/10.1080/1747423X.2014.884644>
- Lindsay, J.B., Dhun, K., 2015. Modelling surface drainage patterns in altered landscapes using LiDAR. *Int. J. Geogr. Inf. Sci.* 29, 397–411. <https://doi.org/10.1080/13658816.2014.975715>
- Mandlbürger, G., Otepka, J., Karel, W., Wagner, W., Pfeifer, N., 2009. Orientation and processing of airborne laser scanning data (OPALS)—Concept and first results of a comprehensive ALS software. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* 38, 55–60.
- Mason, D.C., Scott, T.R., Wang, H.-J., 2006. Extraction of tidal channel networks from airborne scanning laser altimetry. *ISPRS J. Photogramm. Remote Sens.* 61, 67–83. <https://doi.org/10.1016/j.isprsjprs.2006.08.003>
- Moussa, R., Voltz, M., Andrieux, P., 2002. Effects of the spatial organization of agricultural management on the hydrological behaviour of a farmed catchment during flood events. *Hydrol. Process.* 16, 393–412. <https://doi.org/10.1002/hyp.333>
- Otsu, N., 1979. A threshold selection method from gray-level histograms. *IEEE Trans. Syst. Man Cybern.* 9, 62–66. <https://doi.org/10.1109/TSMC.1979.4310076>
- Paavilainen, E., Päivänen, J., 1995. *Peatland Forestry: ecology and principles*, Ecological Studies. Springer Berlin Heidelberg, Berlin, Heidelberg. <https://doi.org/10.1007/978-3-662-03125-4>
- Passalacqua, P., Belmont, P., Foufoula-Georgiou, E., 2012. Automatic geomorphic feature extraction from lidar in flat and engineered landscapes: feature extraction in engineered landscapes. *Water Resour. Res.* 48, n/a–n/a. <https://doi.org/10.1029/2011WR010958>
- Passalacqua, P., Tarolli, P., Foufoula-Georgiou, E., 2010. Testing space-scale methodologies for automatic geomorphic feature extraction from lidar in a complex mountainous landscape. *Water Resour. Res.* 46, n/a–n/a. <https://doi.org/10.1029/2009WR008812>
- Petermans, T., 2013. Een technisch inzicht adhv LiDAR testdata Geraardsbergen.
- Petrie, G., 2011. Airborne Topographic Laser Scanners [WWW Document]. URL http://petriefied.info/Petrie_Airborne_Topographic_Laser_Scanners_GEO_1_2011.pdf (accessed 8.21.17).
- Ramchunder, S.J., Brown, L.E., Holden, J., 2009. Environmental effects of drainage, drain-blocking and prescribed vegetation burning in UK upland peatlands. *Prog. Phys. Geogr.* 33, 49–79. <https://doi.org/10.1177/0309133309105245>
- Rapinel, S., Hubert-Moy, L., Clément, B., Nabucet, J., Cudennec, C., 2015. Ditch network extraction and hydrogeomorphological characterization using LiDAR-derived DTM in wetlands. *Hydrol. Res.* 46, 276. <https://doi.org/10.2166/nh.2013.121>
- Refsgaard, J., Storm, B., 1995. MIKE SHE, in: Singh, V.P., (Ed.), *Computer Models of Watershed Hydrology*. Water Resources Publications, Colorado, USA, pp. 809–846.
- Roelens, J., Dondeyne, S., Van Orshoven, J., Diels, J., 2016. Extracting cross sections and water levels of vegetated ditches from LiDAR point clouds. *Int. J. Appl. Earth Obs. Geoinformation* 53, 64–75. <https://doi.org/10.1016/j.jag.2016.08.003>
- Santos, J.F.C. dos, Silva, H.R.F., Pinto, F.A.C., Assis, I.R. de, 2016. Use of digital images to estimate soil moisture.

- Rev. Bras. Eng. Agríc. E Ambient. 20, 1051–1056. <https://doi.org/10.1590/1807-1929/agriambi.v20n12p1051-1056>
- Schechtner, D., 2012. Long-Range Airborne Laser Scanner for Full Waveform Analysis LMS-Q680i.
- Schwanghart, W., Groom, G., Kuhn, N.J., Heckrath, G., 2013. Flow network derivation from a high resolution DEM in a low relief, agrarian landscape. *Earth Surf. Process. Landf.* 38, 1576–1586. <https://doi.org/10.1002/esp.3452>
- Seibert, J., McGlynn, B.L., 2007. A new triangular multiple flow direction algorithm for computing upslope areas from gridded digital elevation models. *Water Resour. Res.* 43, n/a–n/a. <https://doi.org/10.1029/2006WR005128>
- Sofia, G., Fontana, G.D., Tarolli, P., 2014a. High-resolution topography and anthropogenic feature extraction: testing geomorphometric parameters in floodplains: LiDAR dtms and anthropogenic feature extraction. *Hydrol. Process.* 28, 2046–2061. <https://doi.org/10.1002/hyp.9727>
- Sofia, G., Prosdocimi, M., Dalla Fontana, G., Tarolli, P., 2014b. Modification of artificial drainage networks during the past half-century: Evidence and effects in a reclamation area in the Veneto floodplain (Italy). *Anthropocene* 6, 48–62. <https://doi.org/10.1016/j.ancene.2014.06.005>
- Sofia, G., Tarolli, P., Cazorzi, F., Dalla Fontana, G., 2011. An objective approach for feature extraction: distribution analysis and statistical descriptors for scale choice and channel network identification. *Hydrol. Earth Syst. Sci.* 15, 1387–1402. <https://doi.org/10.5194/hess-15-1387-2011>
- Song, S., Liao, M., Qin, J., 1990. Multiresolution image dynamic thresholding. *Mach. Vis. Appl.* 3, 13–16. <https://doi.org/10.1007/BF01211448>
- Tarolli, P., 2014. High-resolution topography for understanding Earth surface processes: Opportunities and challenges. *Geomorphology* 216, 295–312. <https://doi.org/10.1016/j.geomorph.2014.03.008>
- Thenkabail, P.S. (Ed.), 2016. Remotely sensed data characterization, classification, and accuracies, *Remote Sensing Handbook*. Taylor & Francis, Boca Raton, FL.
- Thompson, J.R., Sørensen, H.R., Gavin, H., Refsgaard, A., 2004. Application of the coupled MIKE SHE/MIKE 11 modelling system to a lowland wet grassland in southeast England. *J. Hydrol.* 293, 151–179. <https://doi.org/10.1016/j.jhydrol.2004.01.017>
- Van Opstal, M., Tits, M., Beckers, V., Batelaan, O., Van Orshoven, J., Elsen, A., Diels, J., D’heygere, T., Van Hoof, K., 2014. ArcNEMO, a spatially distributed nutrient emission model developed in Python to quantify losses of nitrogen and phosphorous from agriculture to surface waters, in: *EGU General Assembly Conference Abstracts*. p. 11652.
- Vanderstraete, T., 2013. Vlaanderen in 3D: digitaal hoogtemodel Vlaanderen II inwinningsproces en producten.
- Zhan, C., 1993. A Hybrid Line Thinning Approach, in: *Proceedings Auto-Carto 11*. Minneapolis, pp. 396–405.
- Zhou, Q., Zhou, H., Zhou, Q., Yang, F., Luo, L., 2014. Structure damage detection based on random forest recursive feature elimination. *Mech. Syst. Signal Process.* 46, 82–90. <https://doi.org/10.1016/j.ymssp.2013.12.013>