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CANOPY DETECTION OVER ROADS USING MOBILE LIDAR DATA

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A high percentage of forest fires take place around roads. These infrastructures provide an escape route for the population in case of fire. Optimization of forest management in the surroundings of roads is a necessary task in terms of wildfires prevention and mitigation of their effects. Therefore, it is essential to avoid the horizontal continuity of vegetation across roads.

A methodology for the measurement of canopy area over roads is developed and based on mobile LiDAR point clouds. The acquisition of LiDAR data is done by Lynx Mobile Mapper System from University of Vigo. The methodology is automated using LiDAR data processing (M-estimator Sample Consensus and near neighbour algorithms) and image processing techniques (rasterization and binarization). The developed algorithms are tested on a study area, the DP-3606 road (Spain). Results are compared with ground truth data of the canopy projected on the road. The best obtained results present a mean geometric error of 2.82 % for 0.25 m resolution and 104.02 % for 2 m resolution. Furthermore, the higher the pixel size, the greater the error was obtained with a linear correlation value of 0.99.

Keywords: Canopy area, forest fire, mobile LiDAR, road management, forestry management, point cloud processing.

1 Introduction

Nowadays, the management of forest stands is a necessity for scientific, environmental and political studies. Prevention is one of the fundamental bases in the fight against forest fires (Xunta de Galicia 2012). In recent years, LiDAR technology has undergone great advances and show applicability to forest management. It has become a source of high precision geometric data with reduced human resources, which in many cases would be impossible to obtain by other techniques.

LiDAR systems used in surveys can be categorized into terrestrial laser scanning (TLS), mobile laser scanning (MLS) and airborne laser scanning (ALS), which collect data from different points-of-view, platforms and resolutions. The airborne Oceanographic Laser (AOL) was among the first LiDAR systems used for forestry applications, but was replaced by LiDAR systems developed specifically for terrestrial applications (Lim et al. 2003). In the early 1980s, it was demonstrated by Canadian Forestry Service the applicability of profiling LiDAR for the estimation of stand heights, crown cover density and ground elevation below the forest canopy (Lim et al. 2003). Dubayah and Drake (2000) studied the way of predicting forest attributes using empirical models from LiDAR data and characteristics such as canopy heights, stand volume, basal area and aboveground biomass were accurately estimated.

For the purpose of making forest inventories, Gorte et al. (2015) analysed laser data to estimate the number of trees, identify species, and estimate wood volumes. For large forest areas airborne laser scanning data were preferred as a data source, whereas for detailed studies at individual tree level TLS was preferred (Bienert et al. 2006).

In the last years Unmanned Aerial Vehicles (UAV) based studies are becoming more popular. Balsi et al. (2018) detected a single-tree in high density point clouds using a methodology focused on modelling the D-shape of the tree, which improves performance with respect to maxima-based models. UAV - LiDAR systems provide relevant information about treatment results and have the capability of providing a rich dataset, total tree height, crown diameter, height up to the last branch, length of the clear wood (Vepakomma and Cormier 2017). UAV usage reduces the cost of typical aerial LiDAR surveys, although decreases the coverage area.

Mobile laser scanning systems (MLS) integrate laser scanners and navigation sensors on ground vehicles to capture a rich dataset while moving. Navigation sensors typically include Global Navigation Satellite System (GNSS) for positioning and Inertial Measurement Unit (IMU) for attitude estimation. The quality of the point cloud is related to the precision and accuracy of the three components, as well as its synchronization (Bauwens et al. 2016; Puente et al. 2013; Ussyshkin 2009).

TLS has application in forest inventories but the occlusion effect limits the efficient processing to extract forest attributes. The use of MLS reduces this occlusion and allows for 3D structure acquisition on a larger scale and in a time-efficient manner (Bauwens et al. 2016).

Studies of MLS were conducted in forest environment before 2013 (Holopainen et al. 2013). There is a limitation in the use of MLS in forest areas probably caused by low GNSS signal detection under forest cover leading a low accuracy (Bauwens et al. 2016). There are known challenges in maintaining accurate positioning when GNSS signal is weak or even absent over long periods of time. The situation could be improved to a certain extent with higher performance IMUs, but increasing system costs make such approach unsustainable in general (Kukko et al. 2017).

MLS data sets are well suited to detect single trees and to model 3D trees in a highly automated manner. They preserve the outer shape of high vegetation objects, which represents the characteristics canopy shape and tree structure (Rutzinger et al. 2010; Saarinen et al. 2013). Gorte et al. (2015) tested three different approaches to tree segmentation: a 3D grid (voxel) approach, a 2D grid (probability matrix) and 3D vector connected components. Results show that 3D voxelization is suitable for segmentation in a tree-only dataset.

Liang et al.(2014) studied the detection of trees in a forest environment using MLS Sirmacek et al.(2015) studied an automated classification of trees from laser scanning point clouds by labelling each point to indicate whether it belongs to the tree class. A grid surface is filled with probability values which are calculated by checking the point density above the grid. The experimental results indicated the possible usage of the algorithm as an important step for tree growth observation, tree counting and similar applications. However, false detection of light poles, traffic signs and other objects close to trees cannot be avoided. Puttonen et al.(2011) also studied tree species classification

The installation of laser scanners on moving platforms has been studied as a convenient measurement method for forest mapping during several years. There are studies relating to the detection, classification and analysis of characteristics of single trees. However, there are not many studies relating to forest management as a whole.

On the other hand, municipalities and other authorities need to build spatial databases from the public space they manage. In this way there could be prevented possible irregularities in the forest management that could influence the propagation of a forest fire if continuity of the trees exists.

The aim of this work is to analyse the potential application of MLS to mapping crown projection areas over the roads, and developing a methodology to automatize the data processing. Firstly, the canopy points over the road are segmented and then classified in two groups: vegetation and non-vegetation points. Finally, the projection area of vegetation is calculated. In particular, the main contributions of this study are summarized as:

(1) Determination of points located inside and outside the edges of the road using a classification method.

(2) Development of a series of algorithms to automatically differentiate between vegetation points and non-vegetation points among the points inside the edges of the road.

(3) Design of a methodology to automatically calculate the projection area of vegetation points over the road.

(4) Determination of the accuracy of the used methodology by comparison with ground truth data.

2 Materials and Methods

2.1 Area of Study

The area of study is the road DP-3606 located in the municipality of Ferrol, northwest Spain (Figure 1). The section of road is located between the beaches of Vilar and Esmelle giving access to them. It is a tertiary type of road, with a double direction and a maximum speed of 50 km/h. Ferrol belongs to the Forest District I (Xunta de Galicia 2018) and should pay great attention to the prevention of forest fires. It is catalogued as a high risk area and it is also classified with a very high potential risk index (Xunta de Galicia 2015).

There are areas of high potential risk of forest fire (HRZ) where the application of defence measures is recognised as a priority due to the risk of fires, its virulence or the importance of threatened values. In addition, the study area belongs to Natura 2000 Network and it is catalogued as a Place of Community Interest (Xunta de Galicia 2014).The main tree species in the study area are formed by *Eucalyptus globulus* and *Pinus pinaster* but also there are the presence of leafy species like *Alnus glutinosa, Salix alba, Sambucus nigra, Betula alba, Laurus nobilis* and *Quercus robur.* These species formed the typical riparian forest in Galicia.

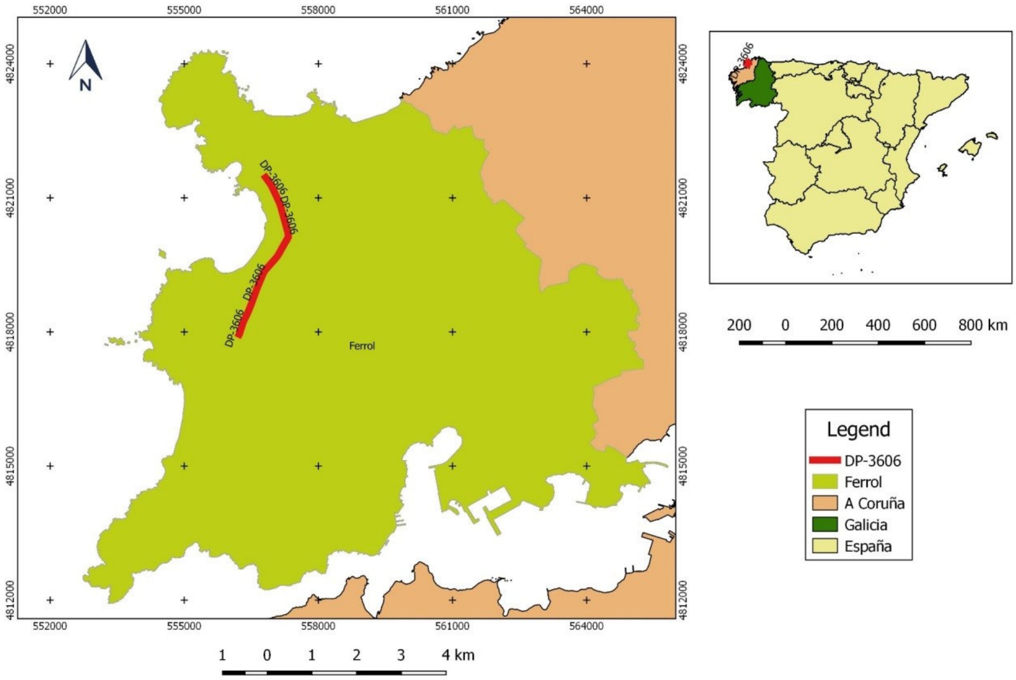

Figure 1 Location of DP-3606 road.

2.2 Mobile LiDAR system

The experimental data for this work were collected using the Lynx Mobile Mapper (Figure 2) by OPTECH (Optech 2011). This system was previously used in many road management studies (Wang et al. 2014; Iglesias et al. 2015; Riveiro et al. 2015; Puente et al. 2014; Martínez et al. 2014; González et al. 2013; González-Jorge et al. 2016; González-Jorge et al. 2016; Soilán et al. 2016).

The Lynx Mobile Mapper generates rich survey-grade LiDAR and image data. The system is composed of two LiDAR sensor heads with 500.000 measurements per second and a field of view (FOV) of 360°. The angle between their rotational axes is 90° and they have an angle of 45° with respect to the trajectory of the vehicle. The navigation system integrates an Inertial Measurement Unit (IMU) with a two GNSS antenna heading measurement systems (GAMS). Furthermore, imagery data is registered by four 5-MPx JAI cameras that are synchronized by the Lynx Survey software.

The positioning system was designed by APPLANIX (POS LV 520) and the GNSS receivers belong to TRIMBLE. The system control software enables to select the camera image frame size for highly efficient image capture (Puente et al. 2011).

Figure 2. Mobile LiDAR System used for the survey.

Figure 3 shows two examples of the point cloud data from the area of study obtained using the Lynx Mobile Mapper. The dataset is divided in five sections to make it easier to handle. Length of the sections is as next described: section 1 (421 m), section 2 (522 m), section 3 (499 m), section 4 (417 m), and section 5 (462 m).

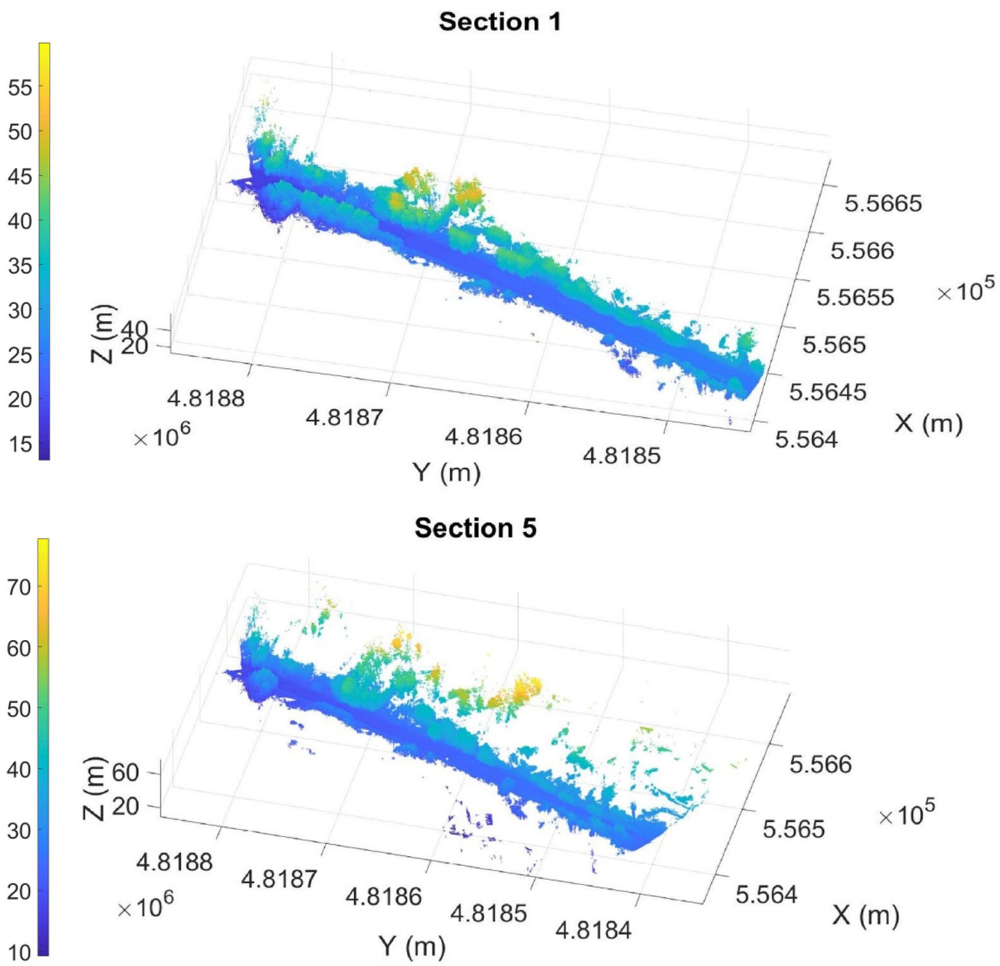

Figure 3. Point Cloud of sections 1 and 5 from the road DP-3606 used in this study.

2.3 Data Processing

The sequence of algorithms and data processing is described in Figure 4. MATLAB software (MATLAB 2018) is used for data processing. The computer on which the data processing was carried out is a MSI GP72 LEOPARD PRO, with the following technical characteristics:

- Processor: Inter(R) Core (TM) i7-7700HQ CPU @ 2.80GHz.
- Installed RAM: 16.0 GB.

System type: 64-bit operating system, x64-based processor.

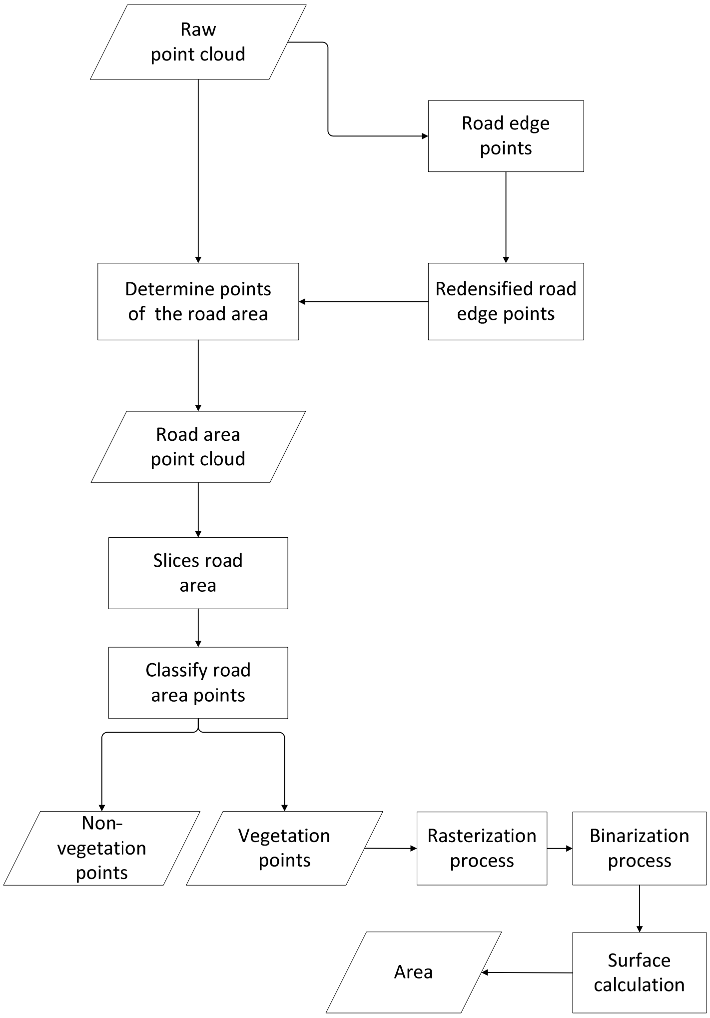

Figure 4. Workflow of the methodology to detect canopy area over the road.

Data processing begins limiting the edges of the road (Figure 5). Edge of the road is obtained from Cloud Compare software by point picking. This is the only manual part of the data processing. No effort has been made to automate this part, since the geometry of the road edges is usually known from project draws or geometric as-built road inventories.

In a following step, an algorithm is implemented in MATLAB to increase the density of points of edges of the road. This algorithm is based on a linear interpolation (Sanmiquel Pera 2003). The first part of the algorithm consists of the calculation of the geometric distance and azimuth between each two neighbour points from the previously obtained road edge points. Then, this information is used to calculate the coordinates xyz of the new re-densified points with a distance step previously defined. In this study the distance between points was 10 meters.

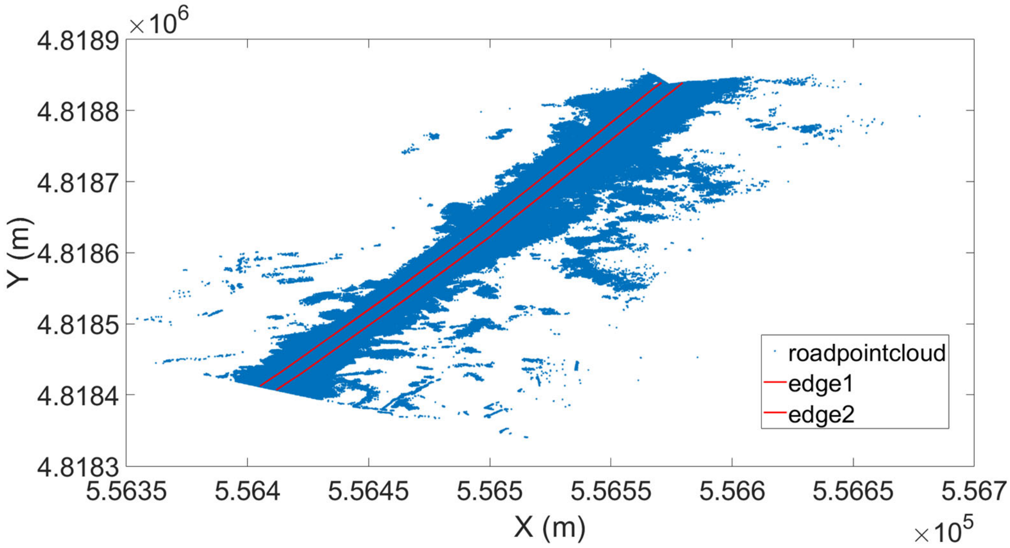

Figure 5. Edges of the road (red) in section 1.

Once the density of points of the edges was increased, polygonal regions are defined every two points of each edge. Thus, points are classified depending on whether they lie within the limits of the polygon or not. As a result, the point cloud is segmented in two classes: points from the road area (includes pavement and canopy over the road) and points not belonging to the road area (Figure 6).

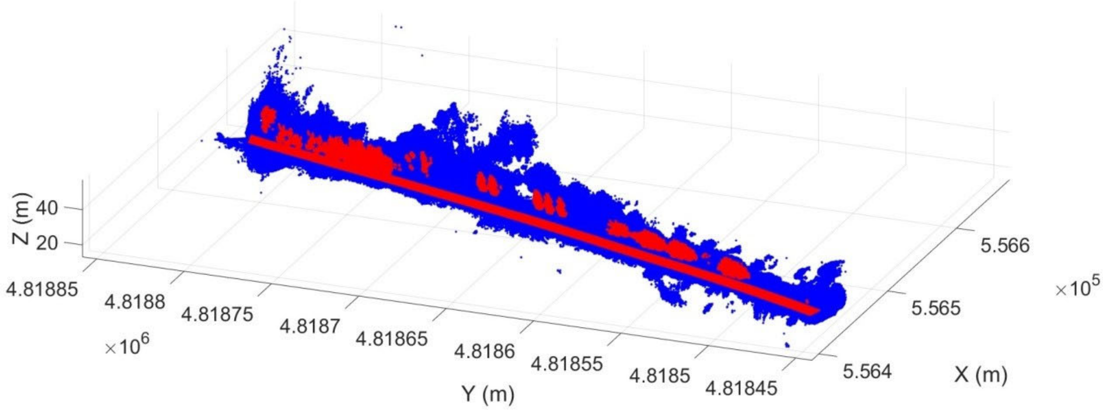

Figure 6. Point cloud classification of section 1. Road area points (red) and non-road area points (blue).

Once the study points are grouped, the road is divided into 10 m slices according to direction of the vehicle driving (Figure 7). Thus, data are easier to handle and slope effect of the road cloud be avoided.

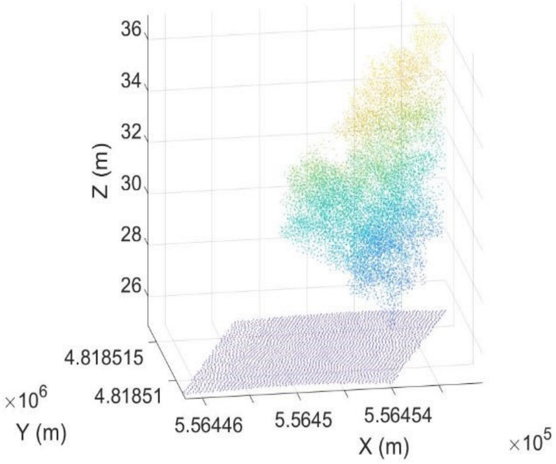

Figure 7. Slice example of 10 meters of length of section 1. Canopy over the road can be easily identified.

Next step is focused on the classification between vegetation points and non-vegetation points (pavement). A M-estimator Sample Consensus (MSAC), a variant of the Random Sample Consensus (RANSAC) algorithm (Fischler and Bolles 1981), is used to fit a plane to the pavement sections (Torr and Zisserman 2000). MSAC improves the performance of RANSAC by modifying its cost function, but it also requires a user-specified error tolerance (Wang, Mirota and Hager 2010). Results are shown in Figure 8.

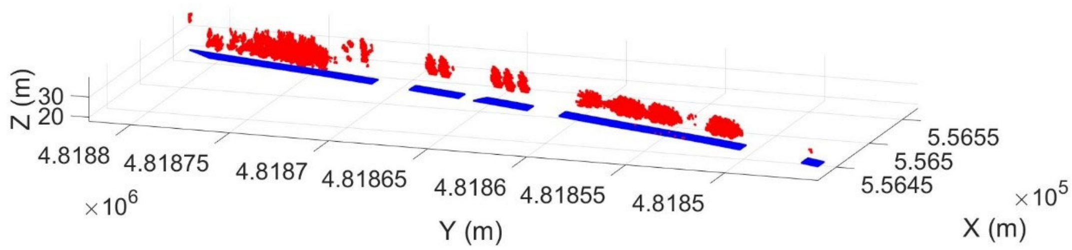

Figure 8. Slices of section 1 which contains vegetation points (red) and non-vegetation points / pavement (blue). Areas without vegetation over the road are not represented.

The rasterization process is a widely used procedure for point cloud processing. First, because this process allows a simplification in the volume of data to be processed without significantly affecting the precision of the results. Moreover, and from the point of view of interoperability, the rasterization process enables the application of digital image processing techniques to dense 3D point clouds. The 3D points are converted to 2D space and the pixel value is related with the z coordinate from the point cloud (Mitchell et al. 2011; Streutker and Glenn 2006; El-Ashmawy and Shaker 2014; Bienert et al. 2007). Different spatial resolutions are used for testing the methodology (0.25 m, 0.5 m, 1 m, and 2 m).

After rasterization, the image is binarized. This process requires the introduction of a threshold to convert raster images to a binary image (Figure 9). The threshold is relative to the signal levels possible for the class and is automatically obtained following the Otsu method (Otsu 1979). It chooses the threshold that minimizes the intraclass variance of the black and white pixels.

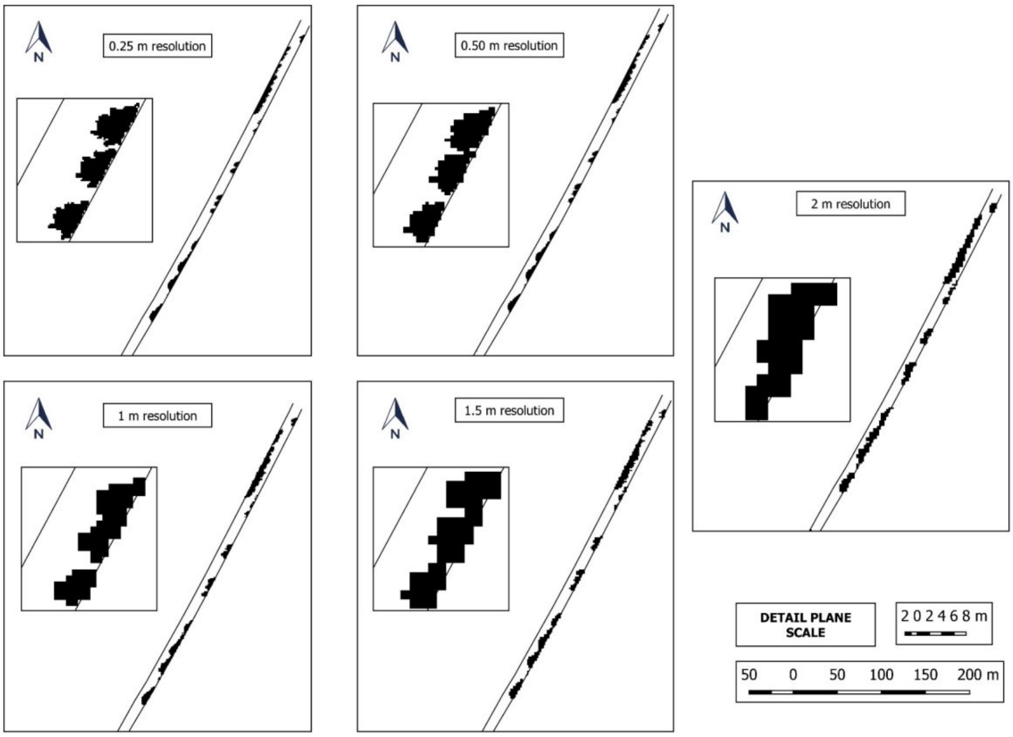

Figure 9. Binary image presentation of resolutions used of section 1. Black pixels represent vegetation and white pixels represent pavement area inside the edges of the road (parallel lines in North-East orientation).

The last step is to calculate the area occupied by selected vegetation in previous steps. For this purpose, the binary image is used and the area is calculated based on the histogram of the image and the pixel area.

3 Results and Discussion

Figures 10 - 14 show the results of the canopy area over the road sections under study. Results are obtained using the automated procedure developed for this work with a focus on the different resolution values between 0.25 m and 2 m.

Figure 15 shows the geometric error of the method described for all studied sections. The error (equation 1) is obtained by comparing the canopy area over the road, A_C, automatically obtained with the methodology developed for this work, and the area manually calculated by an experienced surveyor, A_{GT}. The surveyor uses the same input point cloud and estimates the contour and area by manual drawing.

$$\text{error (\%)} = \left|\frac{A_C - A_{GT}}{A_{GT}}\right| \cdot 100 \qquad \text{(Equation 1)}$$

Figure 16 shows the elapsed time of the method described for all studied sections. The highest resolution (0.25 m) exhibits the most accurate results with a mean error of 2.82 % and limited in all cases by 4 %. On the other hand, the lowest resolution (2 m) shows a mean error of 104,02 %. This error reached 72 % in the best case. As expected, resolution and error correlate, with a value of correlation coefficient of 0.99 for a linear function. Elapsed time for algorithm computation is also depicted. It increases with the increasing of grid resolution.

Future research could follow the line of current legislation. It would be interesting to know the distance from the vegetation to the road and be able to determine vegetation of road areas that does not keep to with the minimum distance specified in the law. Comparison with high resolution satellite remote sensing could be also interesting for example to the classification the tree species over the road.

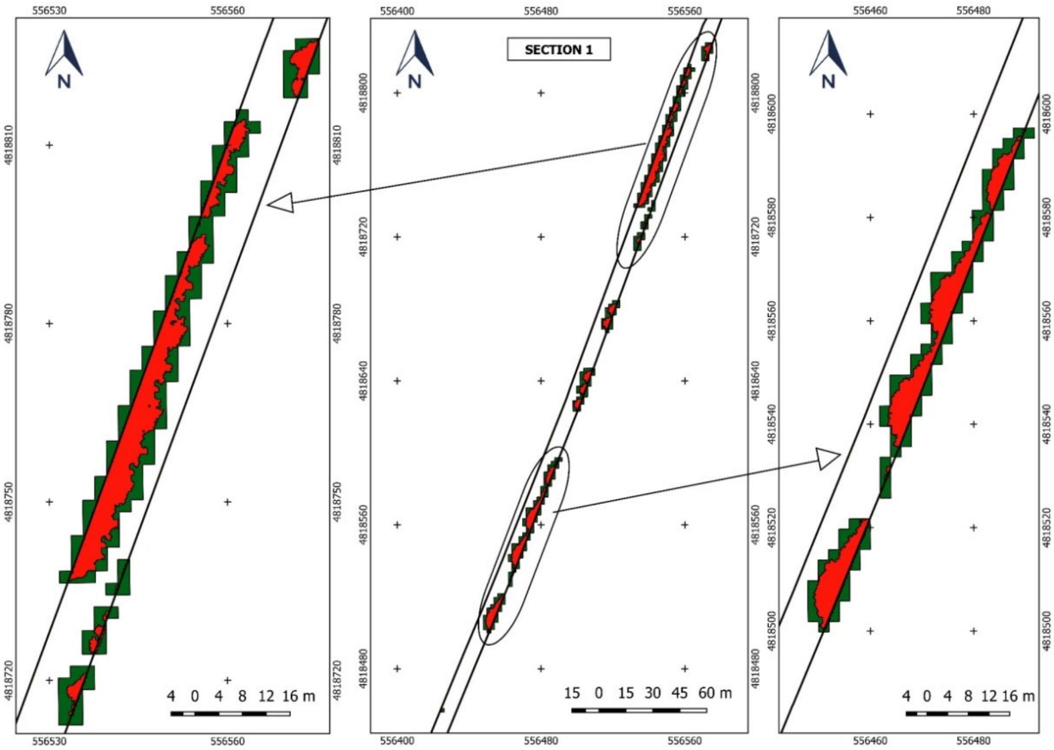

Figure 10. Detail of two vegetation stretches of section 1. Resolution of 0.25 m (red) and 2 m (green).

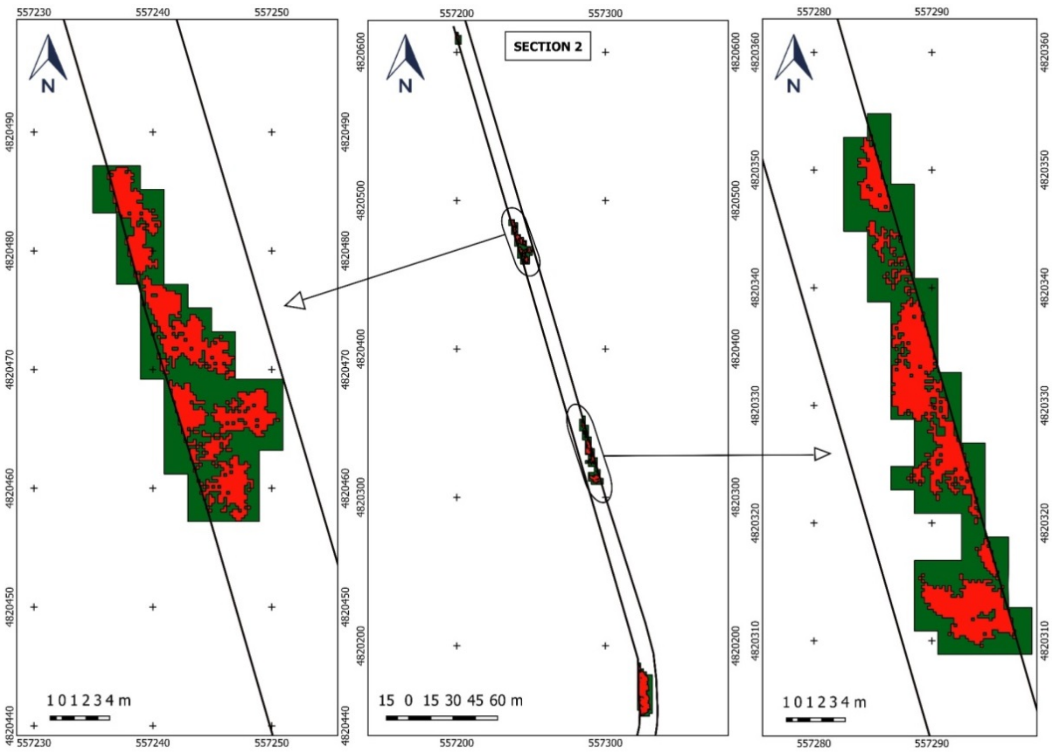

Figure 11. Detail of two vegetation stretches of section 2. Resolution of 0.25 m (red) and 2 m (green).

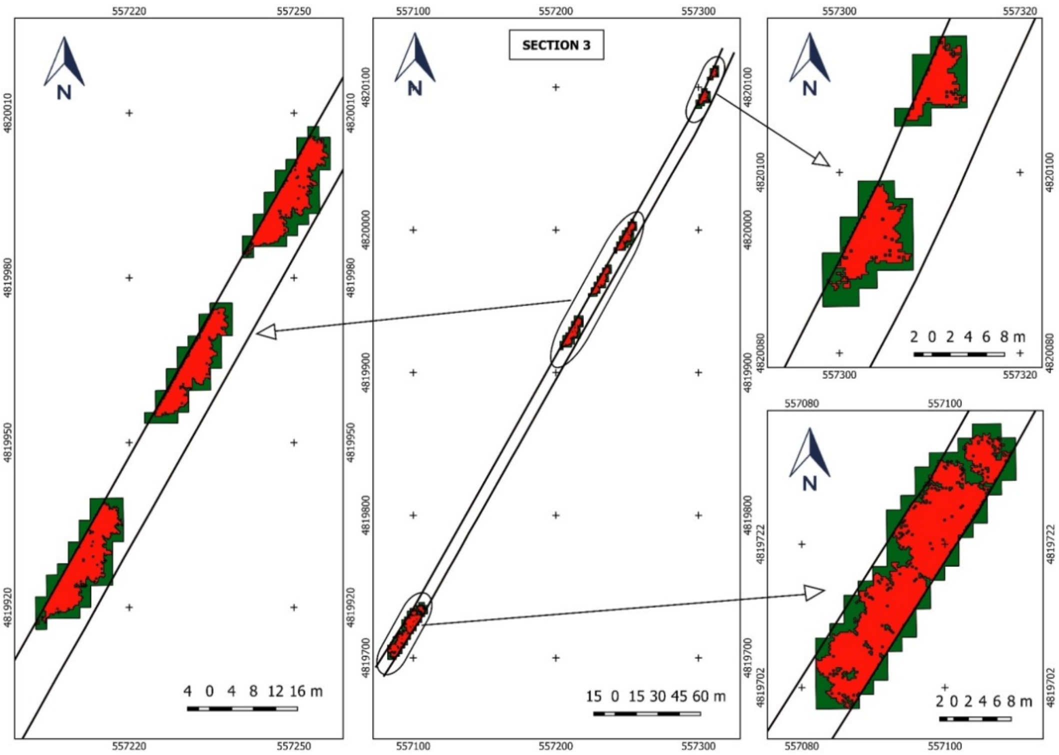

Figure 12. Detail of two vegetation stretches of section 3. Resolution of 0.25 m (red) and 2 m (green).

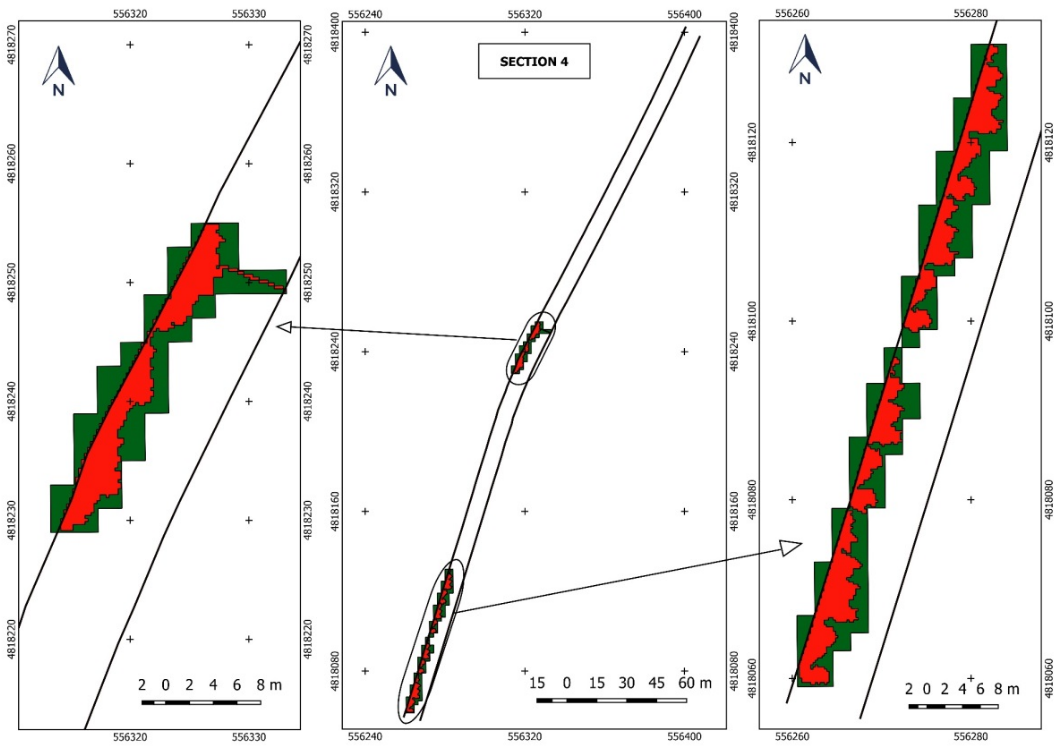

Figure 13. Detail of two vegetation stretches of section 4. Resolution of 0.25 m (red) and 2 m (green).

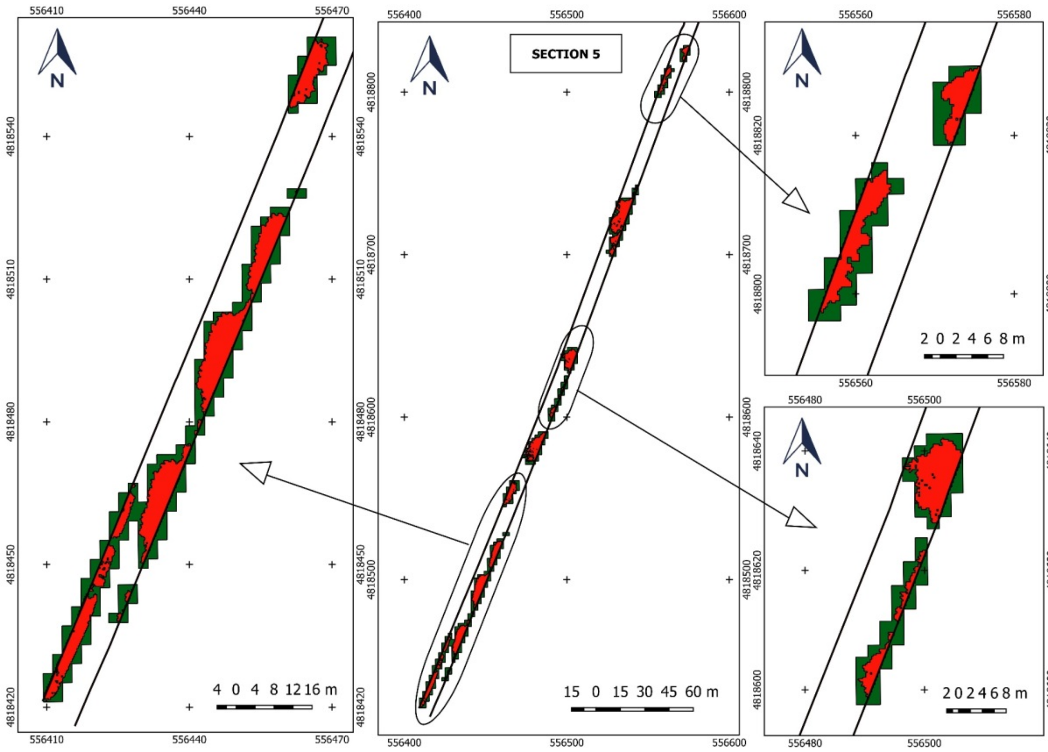

Figure 14. Detail of two vegetation stretches of section 5. Resolution of 0.25 m (red) and 2 m (green).

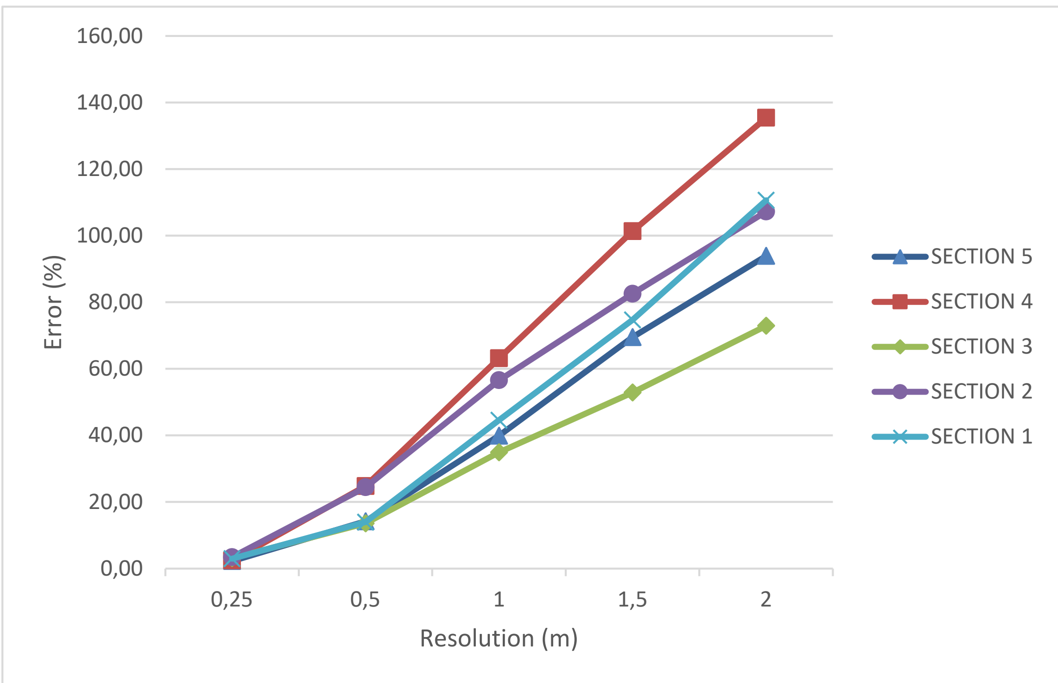

Figure 15. Error of the algorithms for each section studied.

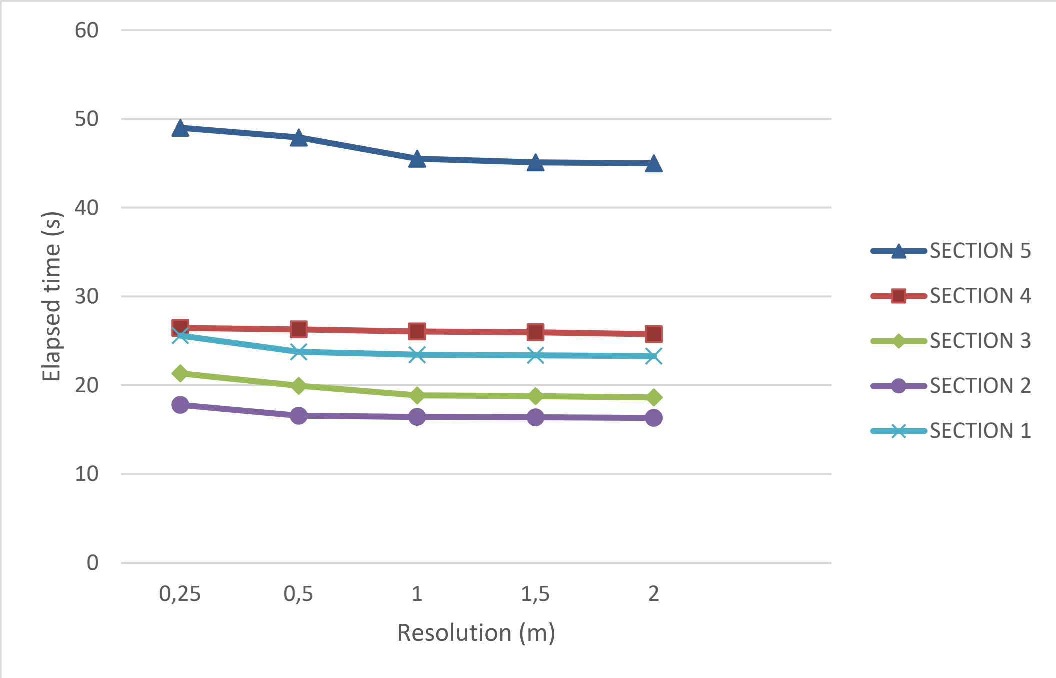

Figure 16. Elapsed time of the algorithms for each section studied.

4 Conclusions

An automated methodology for evaluation of canopy area projected on the road limits was developed. It is based on the combination of point cloud and image processing algorithms implemented in MATLAB software.

The methodology is automated in a way that could provide a vegetation condition on roads, which is difficult to measure by human methods. However, there is a first manual part focused on determining the road edges by clicking points on the PC. The geometric information from road limits is provided in the project data, thus this manual part is not very detrimental for the automation strategy.

The methodology to calculate projection area of canopy over road is analysed and compared with ground truth data from manual drawing. The mean geometric error for the maximum resolution of 0.25 m is 2.82%. The resolutions studied suggest that the limit of admissible resolution would be 1 m with an average error of 47.81 %. The smaller the pixel size, the more accurate the area evaluation and higher the elapsed time to run the algorithms. The computational time is typically not higher than 50 s for the road sections under study.

The method will be improved in future works, specially related to the classification method. In the current approximation, objects appear on the road, that are classified as canopy (i.e. power lines). The effect is not very strong in the case of 0.25 m grid, but significantly increases with the grid size.

The results of this study are of special interest for forest management, in particular to know the condition of horizontal continuity of vegetation on roads being able to spread a forest fire.

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5 References

Balsi, M, S Esposito, P Fallavollita, and C Nardinocchi. 2018. “Single-Tree Detection in High-Density LiDAR Data from UAV-Based Survey.” *European Journal of Remote Sensing* 51 (1): 679–692. doi:10.1080/22797254.2018.1474722.

Bauwens, S, H Bartholomeus, K Calders, and P Lejeune. 2016. “Forest Inventory with Terrestrial LiDAR: A Comparison of Static and Hand-Held Mobile Laser Scanning.” *Forests* 7 (6). doi:10.3390/f7060127.

Bienert, A, S Scheller, E Keane, F Mohan, and C Nugent. 2007. “Tree Detection and Diameter Estimations by Analysis of Forest Terrestrial Laserscanner Point Clouds.” In *ISPRS Workshop on Laser Scanning*, 2007:50–55.

Bienert, A, S Scheller, E Keane, G Mullooly, and F Mohan. 2006. “Application of Terrestrial Laser Scanners for the Determination of Forest Inventory Parametrs.” In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*. Vol. 36. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84979512974&partnerID=40&md5=54c38bb5173da83d1cea91d06df0aa26.

Dubayah, Ralph O, and Jason B Drake. 2000. “Lidar Remote Sensing for Forestry.” *Journal of Forestry* 98 (6): 44–46. doi:10.1093/jof/98.6.44.

El-Ashmawy, N, and A Shaker. 2014. “Raster Vs. Point Cloud LiDAR Data Classification.” *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XL-7: 79–83. doi:10.5194/isprsarchives-XL-7-79-2014.

Fischler, Martin A, and Robert C Bolles. 1981. “RANSAC1981.Pdf” 24 (6). doi:10.1145/358669.358692.

González-Jorge, H, L Díaz-Vilariño, H Lorenzo, and P Arias. 2016. “Evaluation of Driver Visibility from Mobile Lidar Data and Weather Conditions.” *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences* 41.

2016. “Automatic Registration of Mobile LiDAR Data Using High-Reflectivity Traffic Signs.” *Journal of Construction Engineering and Management* 142 (8). American Society of Civil Engineers: 4016022.

González, M Varela, H González Jorge, B Riveiro Rodríguez, P Arias Sánchez, and Escuela Superior de Ingenieros de Minas. 2013. "Software Para La Explotación de Datos LiDAR En Carreteras."

"IQPC 2015 Track: Tree Separation and Classification in Mobile Mapping Lidar Data." In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 40:607–612. doi:10.5194/isprsarchives-XL-3-W3-607-2015.

Holopainen, Markus, Ville Kankare, Mikko Vastaranta, Xinlian Liang, Yi Lin, Matti Vaaja, Xiaowei Yu, Juha Hyyppä, Hannu Hyyppä, and Harri Kaartinen. 2013. "Tree Mapping Using Airborne, Terrestrial and Mobile Laser Scanning–A Case Study in a Heterogeneous Urban Forest."

2015. "Diagnóstico de Visibilidad En Carreteras Con Nubes de Puntos Obtenidas Mediante Sistemas LiDAR."

Kukko, A, R Kaijaluoto, H Kaartinen, V V Lehtola, A Jaakkola, and J Hyyppä. 2017. "Graph SLAM Correction for Single Scanner MLS Forest Data under Boreal Forest Canopy." *ISPRS Journal of Photogrammetry and Remote Sensing* 132: 199–209. doi:10.1016/j.isprsjprs.2017.09.006.

Liang, Xinlian, Juha Hyyppä, Antero Kukko, Harri Kaartinen, Anttoni Jaakkola, and Xiaowei Yu. 2014. "The Use of a Mobile Laser Scanning System for Mapping Large Forest Plots." *IEEE Geoscience and Remote Sensing Letters* 11 (9). IEEE: 1504–1508.

Lim, Kevin, Paul Treitz, Michael Wulder, Benoît St-Onge, and Martin Flood. 2003. "LiDAR Remote Sensing of Forest Structure." *Progress in Physical Geography: Earth and Environment* 27 (1).

2014. "La Conservación de Las Carreteras En El Siglo XXI. Proyecto'SITEGI': Una Aproximación a Las Nuevas Técnicas de Inspección de Infraestructuras." In *II Congreso Virtual Sobre Historia de Las Vías de Comunicación*, 193–214. Asociación Orden de la Caminería.

MATLAB. 2018. "Matlab Software." Accessed November 8. https://es.mathworks.com/products/matlab.html.

Mitchell, Jessica J, Nancy F Glenn, Temuulen T Sankey, DeWayne R Derryberry, Matthew O Anderson, and Ryan C Hruska. 2011. "Small-Footprint LiDAR Estimations of Sagebrush Canopy Characteristics." *Photogrammetric*

Engineering & Remote Sensing 77 (5). American Society for Photogrammetry and Remote Sensing: 521–530.

Optech. 2011. *Lynx Mobile Mapper Survey Operation Manual*.

Otsu, N. 1979. "A Threshold Selection Method from Gray-Level Histograms, IEEE T. Syst. Man Cyb., 9, 62–66."

Puente, I., H. González-Jorge, B. Riveiro, and P. Arias. 2013. "Accuracy Verification of the Lynx Mobile Mapper System." *Optics and Laser Technology* 45 (1): 578–586. doi:10.1016/j.optlastec.2012.05.029.

Puente, Iván, Higinio González-Jorge, Joaquín Martínez-Sánchez, and Pedro Arias. 2014. "Automatic Detection of Road Tunnel Luminaires Using a Mobile LiDAR System." *Measurement* 47. Elsevier: 569–575.

Puente, I, H González-Jorge, P Arias, and J Armesto. 2011. "Land-Based Mobile Laser Scanning Systems: A Review." Citeseer.

Puttonen, Eetu, Anttoni Jaakkola, Paula Litkey, and Juha Hyyppä. 2011. "Tree Classification with Fused Mobile Laser Scanning and Hyperspectral Data." *Sensors* 11 (5). Molecular Diversity Preservation International: 5158–5182.

Riveiro, B, H González-Jorge, J Martínez-Sánchez, L Díaz-Vilariño, and P Arias. 2015. "Automatic Detection of Zebra Crossings from Mobile LiDAR Data." *Optics & Laser Technology* 70. Elsevier: 63–70.

Rutzinger, Martin, Arun Kumar Pratihast, S Oude Elberink, and George Vosselman. 2010. "Detection and Modelling of 3D Trees from Mobile Laser Scanning Data." *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci* 38: 520–525.

Saarinen, N, M Vastaranta, M Vaaja, E Lotsari, A Jaakkola, A Kukko, H Kaartinen, M Holopainen, H Hyyppä, and P Alho. 2013. "Area-Based Approach for Mapping and Monitoring Riverine Vegetation Using Mobile Laser Scanning." *Remote Sensing* 5 (10): 5285–5303. doi:10.3390/rs5105285.

Sanmiquel Pera, Lluís. 2003. "Métodos Planimétricos: Radiación, Tinerario, Intersección."

Sirmacek, Beril, and Roderik Lindenbergh. 2015. "AUTOMATIC CLASSIFICATION OF TREES FROM LASER SCANNING POINT CLOUDS." *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences* 2.

Soilán, M, B Riveiro, J Martínez-Sánchez, and P Arias. 2016. "Automatic Road Sign Inventory Using Mobile Mapping Systems." In *The International Archives of* *the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2016 XXIII ISPRS Congress*. Vol. 3.

Streutker, David R, and Nancy F Glenn. 2006. "LiDAR Measurement of Sagebrush Steppe Vegetation Heights." *Remote Sensing of Environment* 102 (1–2). Elsevier: 135–145.

Torr, Philip H S, and Andrew Zisserman. 2000. "MLESAC: A New Robust Estimator with Application to Estimating Image Geometry." *Computer Vision and Image Understanding* 78 (1). Elsevier: 138–156.

Ussyshkin, Valerie. 2009. "Mobile Laser Scanning Technology for Surveying Application: From Data Collection to End-Products." In *FIG Working Week*.

Vepakomma, U, and D Cormier. 2017. "Potential of Multi-Temporal UAV-Borne Lidar in Assessing Effectiveness of Silvicultural Treatments." In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 42:393–397. doi:10.5194/isprs-archives-XLII-2-W6-393-2017.

Wang, H, D Mirota, and G D Hager. 2010. "A Generalized Kernel Consensus-Based Robust Estimator." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 32 (1): 178–184. doi:10.1109/TPAMI.2009.148.

Wang, J, H Gonzalez-Jorge, R Lindenbergh, P Arias-Sanchez, and M Menenti. 2014. "Geometric Road Runoff Estimation from Laser Mobile Mapping Data." *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 2 (5).

Plan Especial de Protección Civil Ante Emerxencias Por Incendios En Galicia. http://www.fegamp.gal/sites/default/files/artigos/descargas/peifogagal-definitivopublicadodog.pdf.

Xunta de Galicia. 2018. "Distritos Forestales." *Distritos Forestales*. http://mediorural.xunta.gal/es/areas/forestal/ordenacion/distritos/.