ALS FOR TERRAIN MAPPING IN FOREST ENVIRONMENTS: AN ANALYSIS OF LIDAR FILTERING ALGORITHMS

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ABSTRACT

Remote sensing enables the recording of accurate geomorphological data with the capability to efficiently cover large areas. However, the presence of vegetation makes the use of remote methods for terrain mapping difficult. LiDAR (Light Detection And Ranging) data collection by means of ALS (Airborne Laser Scanning) can be a solution for forestry projects, as the laser pulses cross the entire forest canopy and reach the soil underneath. In order to obtain an accurate digital terrain model, the ALS data must be processed, so as to determine which returns are at ground level. This process is called filtering or classification.

This paper aims to provide a performance analysis of nine algorithms for ALS data classification. The algorithm performance is reviewed for the case of mountainous terrain, characterised by moderate and steep slopes and forest vegetation of a generally high consistency. Out of the nine algorithms tested, two are commercial ones and the others are free.

Our findings suggest that the Lasground-new algorithm implemented in the LAStools (Rapidlasso) software package provides the most accurate results, with a Root Mean Square Error of elevation values for the study site of 0.34 metres (with over 80 percent of the area having an elevation error of less than 0.20 metres) and an average *RMSE* for the field plots of 0.66 metres. Reference data for *RMSE* calculation is a DTM interpolated from the ALS point cloud, as classified by the data provider. Some of the free algorithms tested provide relatively similar results in terms of *RMSE* (for example, MLS and SMRF have *RMSE* values of 0.56 metres and 0.60 metres, respectively). The correlation between ground slope and RMSE of elevation values is considered for the eight field surveyed plots, with R^2 having a value of 0.89.

Taking into account the difficult test conditions (topographically complex surface with dense canopy cover) we consider ALS data to be a possible solution for collecting geomorphological data for forestry applications, as long as data at a relatively low spatial resolution is sufficient.

KEYWORDS

LiDAR, ground filtering, forest cover, Airborne Laser Scanning, DTM.

INTRODUCTION

A digital representation of the ground surface is a valuable resource in forestry. Use cases for such a representation include: planning forest harvesting operations, determining forest inventory parameters (1), forest network optimisation and forest road planning (2,3). A DTM (Digital Terrain Model) also serves as an intermediary product for canopy height modelling or biomass estimation from ALS data (4). Traditionally, geomorphological data has been collected via topographical surveys (not suitable for large areas and difficult to manage in steep, forested areas) or using photogrammetric methods. Due to the presence of vegetation cover, the application of a photogrammetric approach for collecting ground data is very problematic. Furthermore, since photogrammetry (stereo aerial photography) is a passive remote sensing method, the dense crown cover and the shadowing specific to forest environments poses an additional problem.

Laser scanning (also called LiDAR - Light Detection And Ranging) data can be collected from airborne platforms (ALS - Airborne Laser Scanning) and has the capability to penetrate forest cano-

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pies (5), mapping not only the forest structure, but also the ground underneath it (3). Therefore, the technology is suitable for forestry applications, so its use has been constantly increasing (6). In the past decade, ALS has become the preferred method of collecting elevation data (7), especially in forested areas.

The comparison of filtering accuracies achieved by different algorithms has been an active field of research in the past decades. In (8) eight test sites were established, both urban and rural. While some of the samples include dense vegetation, most of them contain urban or rural landscapes, with buildings, bridges and other man-made structures. Eight filters are compared, with a qualitative and quantitative assessment being carried out (8). The study's intent is not a conclusive ranking of the filters' performance. Instead, challenging conditions are identified and the way different filters are affected by them are discussed. In (9) a comparison of three filtering algorithms for three test sites is carried out, one of which is described as high-relief forest. A qualitative analysis of filtering errors for this site is reported, indicating that the Maximum Local Slope algorithm is best, with regard to the removal of low vegetation. The performance of five filters for eight sites is tested in (10), with various land cover and slope conditions. An extensive qualitative and quantitative analysis is presented. Of note is the formal approach of the qualitative analysis, with the spatial extent of error types (such as vegetation or building errors) being determined and compared. (11) focuses on open-source algorithms, testing seven filters on two test sites located in a mediterranean forest environment. Following an approach similar to (9), filtering errors are considered on a point-basis (type I and type II errors). The influence of factors such as ground slope, land cover or point density on the error rates is also investigated.

The objective of this paper is to determine how filters perform in conditions of steep terrain and dense forest cover. The filters tested for this paper are all considered in at least one of the papers cited above and our approach to filtering is a common one. However, filtering performance is estimated from a different perspective. Instead of considering the percent of incorrectly classified points, the magnitude of elevation errors in a DTM interpolated from the ALS point cloud is determined. To that extent, not only the number of incorrectly filtered points is relevant, but also their position (especially height above ground). Furthermore, we incorporate field data collected with survey-grade equipment into the analysis.

METHODS

Study area

The area of interest is located in the Vâlcea County of Romania, near the Lotru Valley of the Southern Carpathians. The relief is mountainous with steep slopes and dense canopy cover, consisting mostly of spruce (*Picea abies* Karts.) and beech *(Fagus sylvatica* L.) stands, both pure and mixed. Spruce average age is between 60 and 90 years and average height is around 25-30 metres. Beech average age is between 80 and 100 years and average height is around 23-26 metres. Spruce stands do not have significant undergrowth, while stands where beech is predominant have around 0.2-0.4 undergrowth cover, with an average height of 2-4 metres.

Mean Sea Level (MSL) of the study area is 630 metres.

A study site with an area of 1.17 km^2 mostly covered by forest was delimited for the purposes of evaluating the filtering performance of the algorithms considered. Figure 1 shows the extent of the study site and the field plot locations.

For a better estimation of error magnitude, a topographical survey was carried out for eight field plots (seven plots with forest cover and one additional plot for reference) located near the study site. The characteristics of these plots are presented in Table 1. In the interest of clarity, we will hereafter refer to the large area previously described as the *study site*, the field survey sites as *plots no.1-7* and the control site as *reference plot.*

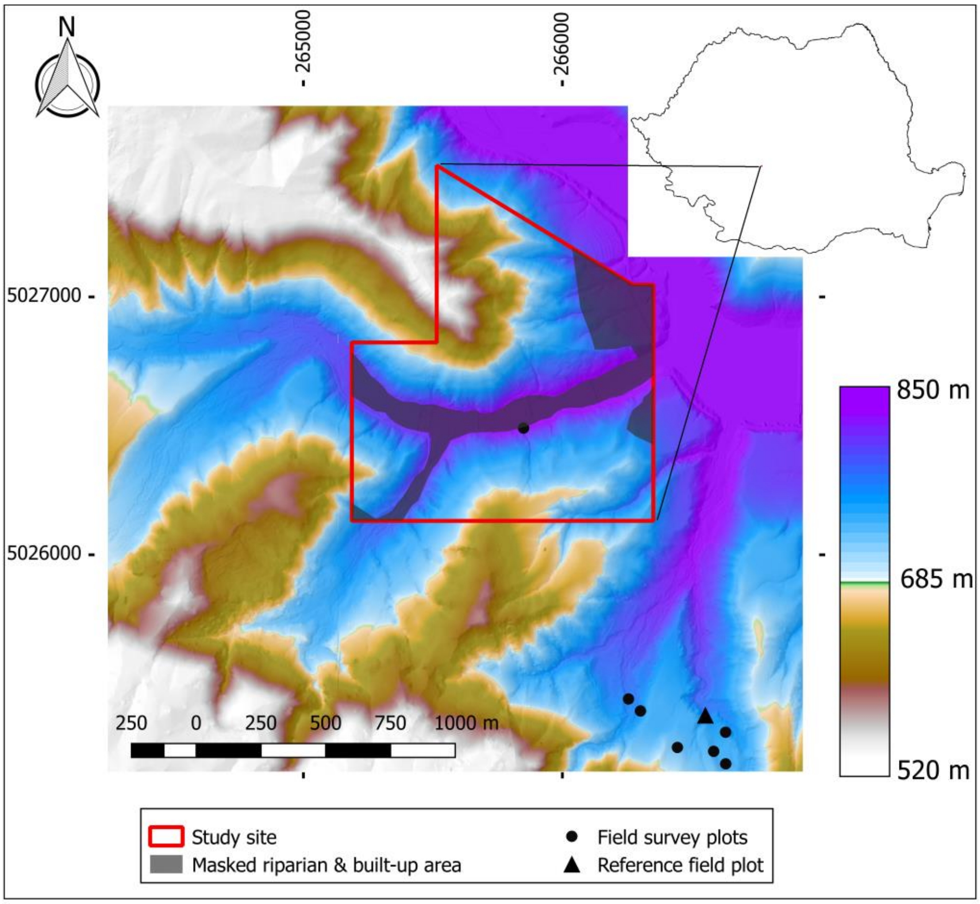

Figure 1: Map of study site and field plots. Coordinate reference system: Universal Transversal Mercator, zone 35N.

Table 1: Characteristics of field survey plots

Field plot. number	Area (m^2)	Average slope (degrees)	Average canopy density (%)	ALS data density ($points/m^2$)	ALS data density (points in class *ground*/m^2)
Reference plot	2652	13.9	22.97	5.1	2.8
1	1184	25.4	95.02	5.1	0.2
2	988	27.1	96.73	7.8	0.2
3	688	33.6	92.60	9.2	0.4
5	1045	18.9	96.98	8.7	0.3
6	1856	19.1	84.34	8.0	0.7
7	1584	12.5	90.91	7.2	0.6
8	889	21.4	77.90	8.3	0.7
Average	**1360.8**	**21.5**	**82.2**	**7.4**	**0.7**
St. dev.	**644.5**	**7.0**	**24.8**	**1.6**	**0.9**

ALS data

ALS data was collected with an airborne platform equipped with two RIEGL LMS-Q560 sensors, in two flight campaigns carried out in 2008 and 2011. No noteworthy meteorological or forestry-related events took place between the two acquisition dates. Since there is a degree of overlap between the areas covered in the two flight campaigns, the average point cloud density for the study site is relatively high (15 points/m^2). Both flight campaigns were taken in July, during full leaf phenophase.

The point cloud classification was provided by the company responsible for the data acquisition, using the Terrascan (Terrasolid) software package with additional manual corrections. An extensive visual analysis of the classification result did not highlight any significant errors. The average density of the points in the *ground* class is 0.82 points/m^2.

Field survey data

In order to record accurate elevation data for the eight field plots described in Table 1, topographical surveys were carried out using a Leica TCR 407 total station. All traverses were designed as closed or closed-loop, with control points positioned by GNSS measurements carried out by PPK (Post-Processed Kinematic) with two Leica SR20 receivers.

Twelve GNSS points were measured, out of which four were used as base points for post-processing. All points were positioned outside forest cover, in relatively unobstructed areas. A 15-degree cut-off mask and a minimum of 5 SV (Satellite Vectors) for logging positions were set. Occupation time for base points was set at 90 minutes (5400 epochs), while points determined by rover were occupied for 30-45 minutes (1800 – 2700 epochs). All rover points are within 1-km range from the base point to which they were linked during post-processing. Most PDOP (Position Dilution Of Precision) values are between 1 and 3.

Ground filtering

ALS data is stored as 3D point clouds containing the pulse returns from the ground or various objects above it (such as power lines, buildings or vegetation). For each return, additional information (number of echoes, intensity, scan angle, GNSS timestamp) is recorded. In order to interpolate an accurate DTM, the points corresponding to the ground returns have to be extracted from the initial point cloud (12). This process is called *ground-filtering* or simply *filtering* (7,13).

Algorithms for ground filtering

Numerous algorithms for ALS data filtering have been developed in the last decades. The algorithms included in this analysis are described below.

- *GroundFilter:* an algorithm based on linear prediction, implemented in the Fusion software and based on (14). A surface is interpolated from all points, so lies between the ground and the top of the canopy. Then, weights are assigned to every point, based on its residual value (distance to surface). Among the parameters of the weighing function, of particular interest are the shift value *g* (points with a negative residual larger than *g* are assigned a weight of 1.0) and the above ground offset parameter *w* (points with a positive residual larger than *g*+*w* are assigned a weight of 0.0). The process is iterative, the subsequent surface being attracted to points with higher weights (which are likely to be closer to the bare-earth surface). The number of iterations is set by the user. Further referenced as *Kraus & Pfeifer.*
- *Maximum Local Slope*: implemented in the free ALDPAT (Airborne LiDAR Data Processing and Analysis Tools) package and detailed in (9). In this implementation, a grid (with a cell size set by the user) is overlaid on the ALS data. A point is classified as *ground* if the maximum value of slope between it and any other point within a specified radius is above a set threshold (parameter *slope*). Further referenced as *MLS.*
- *Elevation Threshold with Expand Filter*: also implemented in ALDPAT and detailed in (9). A grid of square cells is overlaid on the ALS dataset and the point with the lowest elevation in each cell is identified. All other points are considered above ground and therefore discarded. In the next iteration, the grid cell size is doubled. All points inside a specific cell with elevation greater than a threshold above the minimum elevation of the cell are discarded. The elevation threshold is determined as the product between a terrain slope parameter and the current cell size. Further referenced as *ETEW.*
- *Height Filtering*: part of the open-source software BCAL (Boise Center Aerospace Laboratory) LiDAR Tools, is developed specifically for ground retrieval in areas covered by saggebrush vegetation (15). The algorithm is grid-based, with the cell size set by the user. A surface is interpolated from the lowest point in each cell. Afterwards, all points that are below

the surface, along with points that are above the surface but not over a specified threshold, are labelled as ground. Further referenced as *BCAL.*

- *Multiscale Curvature Classification* (16): distributed as a free executable (*MCC-LIDAR*). A surface is interpolated by TPS (Thin-Plate Spline) from the ALS data at a resolution defined by the scale parameter. Surface curvature is calculated and any returns that exceed the curvature threshold are labelled as *non-ground* and discarded. These steps are carried out iteratively until a convergence threshold is achieved. This process takes place three times, at multiple scale domains (0.5 times scale, 1 times scale and 1.5 times scale). All points that are still not discarded after the model converges at the third scale domain are classified as *ground*. The algorithm is specifically developed for ALS data filtering in high biomass forest environments. Further referenced as *MCC*.
- *gLidar* (17): distributed as a free executable (GeMMA Lab). The algorithm uses a top-down approach, in which a surface interpolated by TPS is gradually advanced towards the ground. Starting from a resolution determined by window size, points are filtered out iteratively, at decreasing resolutions. Filtering is done by calculating the residuals of points from the interpolated surface. A top-hat transformation is used to compare residuals for neighbouring points, in order to identify high-outliers which are removed. Further referenced as *Mongus & Žalik.*
- *Simple Morphological Filter* (18): freely available as a tool for MATLAB (MathWorks). This is a progressive morphological filter, which uses mathematical morphology to identify ground points. A minimum raster surface is determined, using the lowest elevation of the points within each cell. Then, an iterative sequence of morphological operations (called opening and closing) are performed, taking into account a window size (the maximum size of above-ground objects) and a slope value (the maximum terrain slope) set by the user. The product of this series of operations is the classification of each cell in the raster as either *bare-earth* or *object*. Ground elevation values for *object* cells are determined from neighbouring *bare-earth* cells, by the interpolation technique of inpainting. Thus, the raster surface is a rough DTM used to classify the original point cloud. When the vertical distance between a point and the DTM does not exceed the elevation threshold (calculated as the sum between a base elevation threshold and a scaling factor applied to the terrain slope), that point is classified as *ground*. Further referenced as *SMRF*.
- *Lasground*: a commercial filter, part of the LiDAR processing toolkit LAStools (Rapidlasso). The algorithm is similar to the adaptive TIN (Triangular Irregular Network) algorithm developed by (19). Details about the implementation are scarce, but generally an adaptive TIN filter works in this manner: a TIN is generated from seed points (lowest elevation within a user-defined grid) and is then progressively densified by adding points to the network. Whether a point is added or not depends on its distance to the TIN facet below it and the angles to that facet's nodes. This process of TIN densification is carried out in iterations, until no further points are added. The final TIN should resemble the bare-earth surface and all its nodes are considered to be ground points. In the LAStools implementation, the '*extra-fine'* parameter intensifies the search for viable seed points, improving the results for steep areas.
- *Lasground-new:* a completely redesigned version of *Lasground*, which is intended for better performance in complex terrain (for example steep hills near built-up areas). Also part of the LAStools package (Rapidlasso).

Algorithm optimisation

Every algorithm tested requires a number of parameter values set by the user, which control the filtering process. It is not always clear which parameter values would lead to the most accurate filtering. Therefore, we establish a number of parameter combinations for each filtering algorithm, starting from the default values (or values proposed by authors of previous research) and incrementing and decrementing each parameter values, until no increase of performance is observed. Depending on the number of parameters that influence the accuracy of filtering, the number of combinations tested per algorithm is between 25 (for ETEW) and 104 (for *Kraus & Pfeifer*).

For each of the 568 total combinations, the following approach is taken:

- a DTM is generated via Inverse Distance Weighted (IDW) interpolation at a 1.0-m resolution;
- the Root Mean Squared Error (*RMSE*) is calculated for that DTM, by subtracting the cell values of that DTM from the cell values of the reference DTM. The reference DTM is interpolated (also by IDW, 1.0-m resolution) from the points labelled as ground in the classification provided by the company that acquired the data;

Afterwards, the most accurate combination of parameter values (that leads to the lowest *RMSE*) is identified for each algorithm (Table 2).

The optimisation of algorithms is carried out only for the study site, with the same parameter values applied when filtering ALS data for the field plots.

Table 2: Final parameter combination for the algorithms tested; only parameters that are changed from their default values are shown.

Algorithm	Parameter values
Lasground-new	step = 20, extra-fine
Lasground	step = 4, extra-fine
MLS	cell size = 0.75, slope = 1.25, radius = 10
SMRF	cell size = 3.5, window = 9, slope = 0.4, scaling = 1.25, elevation threshold = 0.5
ETEW	cell size = 0.5, slope = 1.0, iterations = 5
Mongus & Žalik	window = 15, k = 0.0, n = 0.2
MCC	scale = 1.5, curvature threshold = 0.7
Kraus & Pfeifer	w = 1.6, g = -1.7, iterations = 4
BCAL	step = 13, threshold = 0.5

Error analysis

In addition to elevation errors, the errors relating to various products typically derived from a DTM are considered. These are: slope error, aspect error and feature classification error. The feature classification error refers to the differences between a feature map (with a classification of the terrain as channels, ridges and planar areas) and the reference feature map.

Influence of ALS point density on filtering accuracy

To better understand the effect of the point cloud's density on the filtering accuracy, the initial dataset was artificially reduced, by randomly eliminating 60 percent of the points, in 10 percent increments. RMSE values are calculated for each reduced dataset.

RESULTS

RMSE values for filtering algorithms

The *RMSE* values of the elevation errors for each of the filtering algorithms are presented in Table 3, along with the total number of points identified as ground.

Overall, the most accurate filtering is achieved by the *Lasground-new* algorithm, closely followed by its older version *Lasground*. Both are based on TIN-densification. These are followed (in terms of RMSE values) by the three algorithms based on surface-interpolation (*MLS, SMRF, ETEW*) and the four algorithms that use mathematical morphology (*Mongus & Žalik, MCC, Kraus & Pfeifer, BCAL*). These findings are in part confirmed by the *RMSE* values for field plots, where the DTM interpolated from the filtered ALS data is compared against the DTM interpolated from ground survey data (Table 4).

The reference plot was surveyed to serve as a benchmark for contrasting *RMSE* values. It is located outside forested areas and is partly covered with shrubs. Note that most of the algorithms have similar performances here, with *RMSE* values between 0.25-0.30 m. Field plots no. 1-3 are located in mixed spruce/beech stands and have higher *RMSE* values than field plots no. 4-7 (located in spruce stands). This might imply a certain influence of forest composition on the accuracy of ground filtering.

Table 3: RMSE values for elevation error and number of points in class ground identified.

Algorithm	***RMSE* study site all returns (m)**	***RMSE* study site last returns (m)**	**Change in *RMSE* (%)**	***RMSE* average for field plots (m)**	**No. of points in class ground (mil.)**
Lasground-new	0.34	0.38	+ 12%	0.66	2.37
Lasground	0.53	0.52	- 2%	0.68	3.07
MLS	0.56	0.61	+ 9%	0.68	0.91
SMRF	0.60	0.62	+ 3%	0.70	3.60
ETEW	0.61	0.65	+ 7%	0.72	1.62
Mongus & Žalik	0.76	0.74	- 3%	0.73	3.61
MCC	0.79	0.67	- 15%	0.88	3.56
Kraus & Pfeifer	1.23	1.36	+ 11%	0.99	0.59
BCAL	2.25	2.42	+ 8%	3.14	1.99

Table 4: RMSE values for elevation error for field plots.

Algorithm	**Ref. plot (m)**	**Plot 1 (m)**	**Plot 2 (m)**	**Plot 3 (m)**	**Plot 4 (m)**	**Plot 5 (m)**	**Plot 6 (m)**	**Plot 7 (m)**	**Avg. *RMSE* for algo-rithm (m)**	**St. dev. of *RMSE* values (m)**	**Coefficient of variance of *RMSE* values (%)**
Lasground-new	0.25	0.92	1.04	1.24	0.40	0.54	0.31	0.59	0.66	0.36	55
Lasground	0.26	0.97	1.04	1.24	0.40	0.56	0.33	0.67	0.68	0.36	53
MLS	0.25	0.99	1.09	1.23	0.38	0.54	0.31	0.66	0.68	0.38	55
SMRF	0.27	1.03	1.09	1.30	0.42	0.55	0.32	0.64	0.70	0.39	55
ETEW	0.26	1.02	1.27	1.24	0.40	0.56	0.32	0.66	0.72	0.41	57
Mongus & Žalik	0.26	0.99	1.14	1.29	0.41	0.55	0.47	0.74	0.73	0.37	51
MCC	0.26	1.41	1.04	1.39	0.47	0.57	0.46	1.43	0.88	0.49	56
Kraus & Pfeifer	0.50	1.56	1.22	1.30	0.57	1.22	0.59	0.94	0.99	0.40	40
BCAL	0.49	5.90	5.51	2.28	5.84	0.99	2.02	2.08	3.14	2.25	72
Avg. *RMSE* for plot	**0.31**	**1.64**	**1.60**	**1.39**	**1.03**	**0.68**	**0.57**	**0.93**	-	-	-

The *RMSE* values for the field plots are significantly higher than the *RMSE* for the study site, for every filtering algorithm tested. Likely causes for these increased error values are: the high canopy density of the field plots (minimum 78%, average 82%) limiting ALS ground penetration, errors inherent to surveying and effects of surface interpolation. The fact that filter parameters were optimised only for the study site (not for the field plots) also has to be taken into account.

The number of ground points identified by each algorithm varies from 0.59 mil. points to 3.61 mil. points (Table 3). When comparing with the number of ground points as identified by the data provider (1.3 mil. points), it seems that most algorithms fail to filter out a significant number of non-ground points. Possibly a large number of these omitted points are closer to the ground surface (for example returns from understory vegetation) so their impact on the overall *RMSE* is relatively low. The height above ground of unfiltered non-ground points affects the *RMSE*, rather than their number.

RMSE values are also determined for working only with the last returns of each laser pulse. The changes in accuracy suggest that using only these last returns does not have a significant impact on the filtering result for the study site, with most results having a relatively low decrease in accuracy (Table 3). A notable exception is the *Multiscale Curvature Classification* algorithm, for which the overall accuracy increases by 15%.

Spatial distribution of errors

In order to analyse the spatial distribution of the elevation errors, the values were classified. Class boundaries were established taking into account technological considerations of forest operations (such as forest harvesting). Besides elevation error, the slope, aspect and feature classification error was also determined. All error values are transformed to absolute values. Class boundaries are presented in Table 5.

The area coverage for each error class is presented for *Lasground-new* and *MLS*, two of the best performing algorithms (Table 5). The classified elevation errors are also presented in graphical form for the filtering result of the *Lasground-new* algorithm (Figure 2).

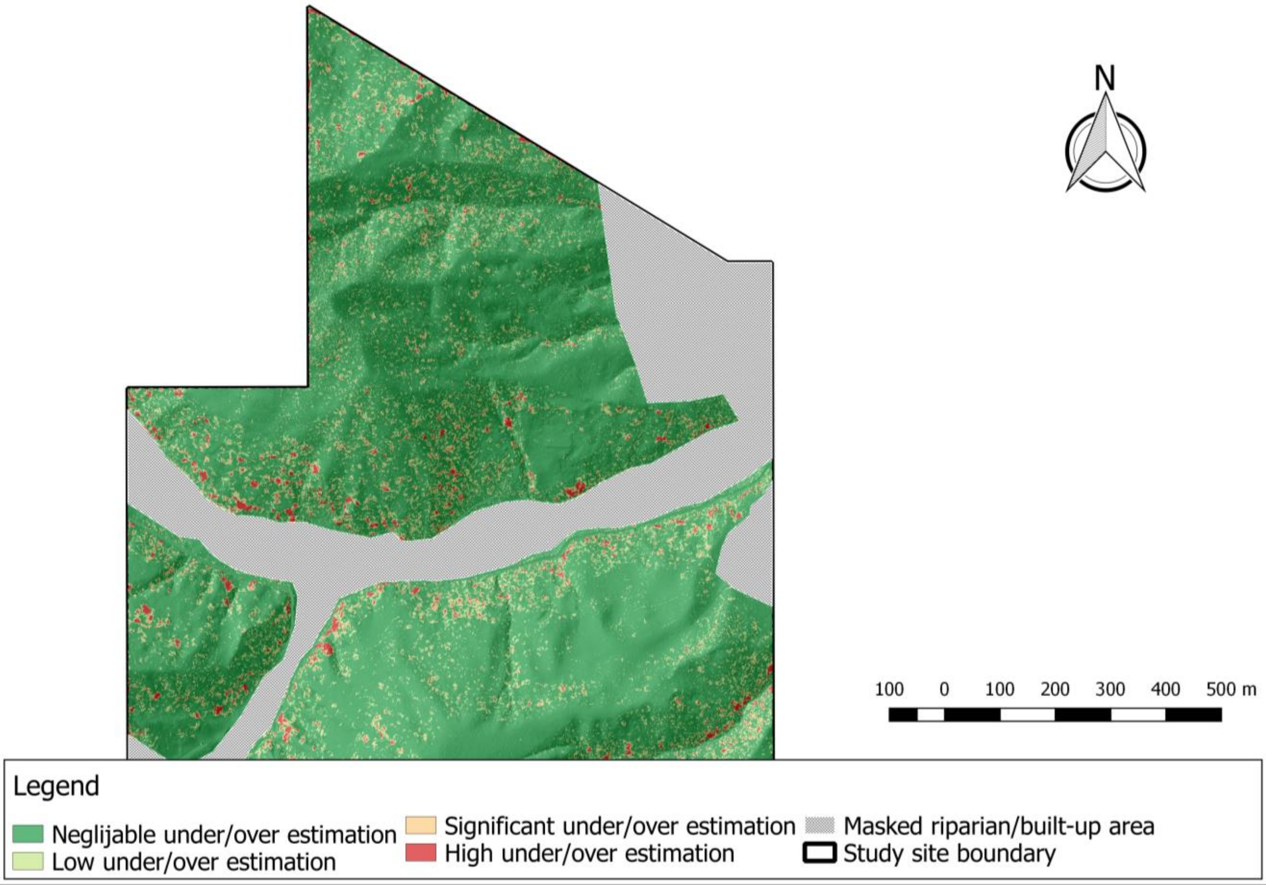

Figure 2: Map of classified elevation errors resulting from filtering with the lasground-new (Rapidlasso) algorithm.

Table 5: Classification of elevation, slope, aspect and feature classification errors.

Type of error	Error class	Upper/lower limit of class		Area coverage (percent of study site area)	
				Lasground-new	*MLS*
Elevation error (metres)	Negligible under/over estimation	0.00	0.20	84.24	79.96
	Low under/over estimation	0.20	0.50	10.82	13.36
	Significant under/over estimation	0.50	1.00	3.24	3.86
	High under/over estimation	1.00	-	1.70	2.81
Slope error (degrees)	Negligible under/over estimation	0.00	5.00	88.62	85.22
	Low under/over estimation	5.00	10.00	7.82	9.88
	Significant under/over estimation	10.00	20.00	2.70	3.34
	High under/over estimation	20.00	-	0.86	1.55
Aspect error (degrees)	Negligible under/over estimation	0.00	5.00	70.28	62.55
	Low under/over estimation	5.00	10.00	18.06	21.83
	Significant under/over estimation	10.00	25.00	8.34	10.62
	High under/over estimation	25.00	-	3.32	5.00
Feature classification error	Correct classification	-		91.98	93.41
	Planar areas incorrectly classified			2.32	2.15
	Channel areas incorrectly classified			2.77	2.10
	Ridges incorrectly classified			2.93	2.33

Effect of ALS point density on the accuracy of the ground surface representation

As expected, the decrease of the ALS point density has an impact on the accuracy of the generated ground surface. However, the increase in *RMSE* values is not consistent across algorithms (Figure 3). Note for example the significant decrease in accuracy for *Lasground* (almost 60% increase in *RMSE* at 40% ALS point density), compared with the relatively stable accuracy for the *MLS* algorithm (less than 30 percent increase in *RMSE* for the same density). This could be linked to the fact that *MLS* is based on mathematical morphology, a method that might fare better at lower point densities when compared to the surface or TIN-based interpolation methods. This would explain the relatively low decrease of accuracy for *SMRF*, another morphological filter.

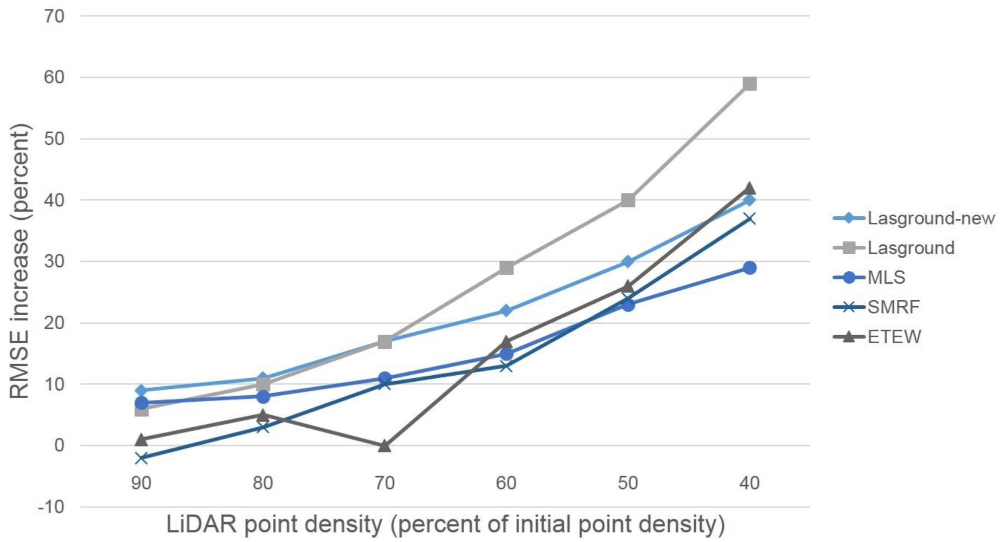

Figure 3: Increase of RMSE values with decreasing ALS point density. Only the five best performing algorithms are represented.

Elevation errors in relation to ground slope

The average *RMSE* of elevation errors (with filtering by *Lasground-new*) for each field plot was found to be related with the average slope of the plots, as determined from the ground survey data (Figure 4). The correlation coefficient (adjusted R^2) is 0.89. The reference plot was excluded from the correlation analysis.

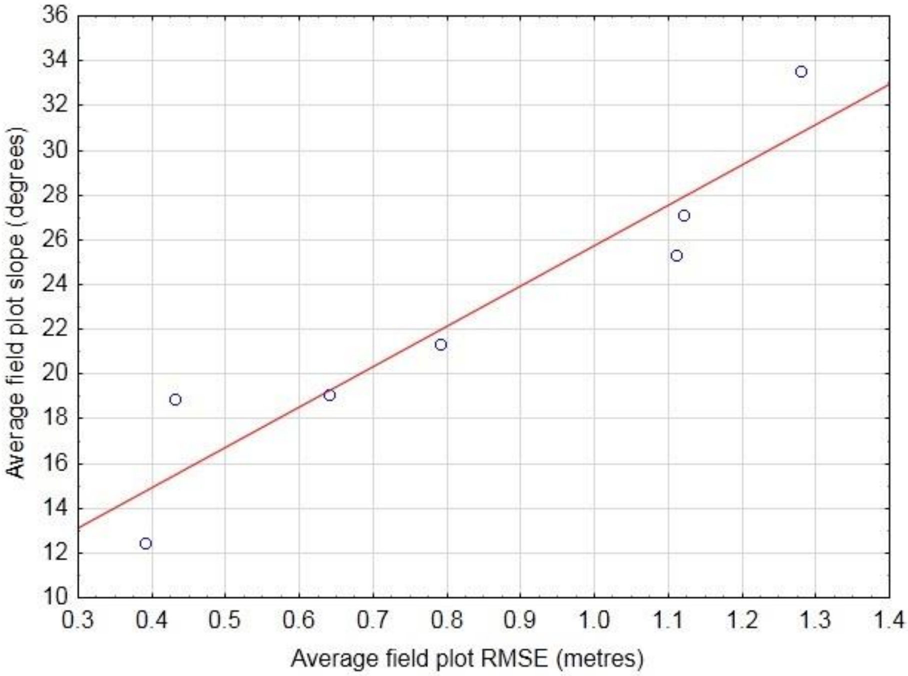

Figure 4: Correlations between average RMSE of elevation values and average slope, for survey field plots.

While this indicates that the variability of RMSE could be explained by the average slope of a field plot, in order to extrapolate such a claim to other terrain and canopy conditions significantly more data points would be required. Such an analysis goes beyond the scope of the present research.

CONCLUSIONS

Automatic ground filtering of ALS data for steep, forested areas can lead to results comparable in accuracy to those obtained via manual classification, but requires an extensive process of parameter optimisation. However, this is relatively straightforward when compared to the process of manual classification. At least as important as the choice of parameters is the choice of the filtering algorithm itself. The RMSE values for the nine algorithms included in this analysis range from 0.34 to 2.25 metres, with a coefficient of variance of 64 percent.

The most accurate results were produced by *Lasground-new*, with algorithms such as *Lasground, MLS* or *SMRF* also leading to relatively good ground surface representations. Relatively poor performances were given by *Kraus & Pfeifer* and *BCAL*. For the first one, this could be explained by the fact that linear-prediction is not particularly suitable for steep terrain with variable topography (20). In the case of *BCAL*, the poor performance is expected when considering that the algorithm was developed for the specific purpose of terrain extraction in saggebrush conditions, which are very different from high biomass forest environments.

Field plot data suggests an apparent correlation between ground slope and filtering accuracy (adjusted R^2 = 0.89). While this is in line with previous research (21,22,12), for further investigations more data points are required.

ALS point density is also found to have an effect on the accuracy of the surface representation, but the effect varies between algorithms. Our initial findings seem to suggest that morphological filters (such as *ETEW* or *SMRF*) fare somewhat better at lower ALS point densities but this is yet to be confirmed.

Further research would benefit from a more extensive ground survey and additional filtering algorithms to test. Of importance is also a better understanding of possible filtering error sources, such as canopy density, forest composition and surface ruggedness.

Overall, given the fact that forest environments are a challenge for any filtering approach (11,23,6), especially when data is collected in leaf-on conditions, we find that the results are promising. The best result for the study site has a RMSE value of 0.34 metres, with over 80 percent of the area having an elevation error below 0.20 metres and a slope error below 5 degrees. Given the fact that about 5% of the study area has an elevation error of more than 0.50 metres, manual corrections are needed to ensure high-quality products are obtained.

In summary, ALS data can be a solution for collecting geomorphological data for forestry applications, as long as one takes into account the extensive parameter optimisation necessary to obtain an accurate surface representation. The fact that only a small percentage of the laser pulses reach the ground in densely forested areas, especially in leaf-on conditions, limits the applicability of ALS data when a fine scale representation of the ground surface is required.

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