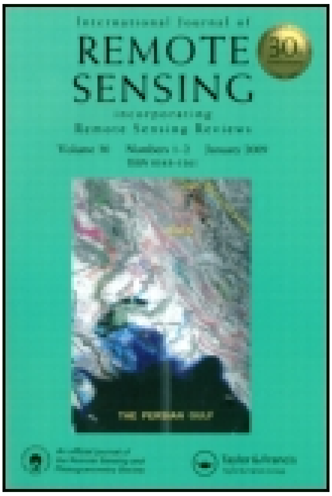

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Experimental evaluation of ALS point cloud ground extraction tools over different terrain slope and land-cover types

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The article presents an evaluation of different terrain point extraction algorithms for airborne laser scanning (ALS) point clouds. The research area covers eight test sites with varying point densities in the range 3–15 points m^{-2} and different surface topography as well as land-cover characteristics. In this article, existing implementations of algorithms were considered. Approaches that are based on mathematical morphology, progressive densification, robust surface interpolation, and segmentation are compared. The results are described based on qualitative and quantitative analyses. A quantification of the qualitative analyses is presented and applied to the data sets in this example. The achieved results show that the analysed algorithms give classification accuracy depending on the landscape and land cover. Although the results for flat and mountainous areas as well as for sparse and dense vegetation are in line with previous tests, this analysis provides an overview of situations in which the quantitative evaluation is not enough to correctly assess the classification results.

1. Introduction

The digital terrain model (DTM) is a prerequisite for the modelling of many processes in geography and the environmental sciences, e.g. geomorphology (Brock and Purkis 2009; Rayburg, Thoms, and Neave 2009; Höfle and Rutzinger 2011), hydrology and hydraulic engineering (Thoma et al. 2005; Tymków and Borkowski 2006; Mandlburger et al. 2009), and forestry (Hyyppä et al. 2008; Popescu and Zhao 2008; Zhao, Popescu, and Nelson 2009). It is the surface of superficial water run-off and the base for plant growth. Its extraction, especially in forested areas, is difficult, because of the difficulty of moving in the forest using terrestrial methods and as a result of the reduced visibility from airborne acquisition. Airborne laser scanning (ALS) is unique because it can penetrate the forest canopy through small gaps in the foliage and, thus, partially identify the forest ground from an airborne position (Axelsson 2000; Næsset 2002; Wagner et al. 2008; Korpela et al. 2009; Véga et al. 2012; Bretar and Chehata 2010).

Collecting measurements over forests by ALS is, however, not enough to obtain a DTM because many reflections from the canopy and the understory are recorded (Liu 2008). Extraction of the ground points is therefore a filtering task (Liu 2008; Meng et al. 2009; Wang et al. 2009; Mongus and Žalik 2012; Susaki 2012).

As ALS technology is becoming more accessible and widely used for geospatial analyses, the necessity to implement tools to process the data arises. For a user who is

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interested in extraction of the ground data for DTM generation, the most important information for selecting the right tool and the algorithm for ground data extraction is how fast the software will process the data and how time-consuming the adjustment of the optimal parameters is in order to achieve high-quality results. Such tools need to be adapted to the data format and the purpose of the analyses. Finally, users also have to have knowledge on how to verify the correctness and the quality of the processed data.

A number of algorithms have been suggested (Kraus and Pfeifer 1998; Axelsson 2000; Vosselman 2000; Ruppert et al. 2000; Haugerud and Harding 2001; Evans and Hudak 2007; Kobler et al. 2007; Wei-Lwun et al. 2008; Véga et al. 2012; Mongus and Žalik 2012; Pingel, Clarke, and McBride 2013) for extracting the ground. These algorithms consist of different concepts for the data-filtering process. Some of them have been implemented in commercial software packages. To verify the accuracy of ground filtering, several comparisons have been performed (Sithole and Vosselman 2004; Zhang and Whitman 2005; Chen et al. 2007; Baligh, Valadan Zoej, and Mohammadzadeh 2008; Meng, Currit, and Zhao 2010). Our contribution approximately follows along this line of approach, although with the inclusion of three special considerations.

First, we want to consider the implementation of existing algorithms. This means that our findings can be used by the scientific community without the need to develop or implement the algorithm anew. Second, to verify the flexibility of the algorithms, we used areas covered by different land-cover types and terrain slopes. Finally, the assessment of the ground extraction quality consists of a qualitative and a quantitative analysis, both being in a formal setting.

A detailed description of a majority of the proposed algorithms can be found in several publications (Pingel, Clarke, and McBride 2013; Sithole and Vosselman 2004; Pfeifer and Mandlburger 2008). Here we present a general summary of approaches for ALS data filtering. The algorithms developed for the ground data extraction can be distinguished, depending on the concept by a few general categories. First we discuss simple filters (Pfeifer and Mandlburger 2008), which work on assigning the lowest elevation value within the reference unit, e.g. pixel.

Another group are the morphological filters (Vosselman 2000). These ground extractors work on morphological operators applied for greyscale images (Susaki 2012; Zhang et al. 2003). Generally, these filters work on the differences in elevation in the analysed images. If the differences are higher within a selected kernel size than a predefined threshold value, the data are assigned as off-terrain objects (Pingel, Clarke, and McBride 2013). In Zhang et al. (2003) it is assumed that the slope is constant, and the terrain slope is used to determine the thresholds for different kernel sizes. Kobler et al. (2007), Chen et al. (2007), and Pingel, Clarke, and McBride (2013) reported modifications of the basic filter principle. In a parameter-free (PF) algorithm (Mongus and Žalik 2012), the authors suggest gradually increasing the grid resolution and decreasing the window size.

The next group of methods works on progressive densification (PD) (Pfeifer and Mandlburger 2008). These methods start on seed points, and advance by adding more data that represent the terrain. They work on rebuilding the ground progressively. An example is the filter of Axelsson (2000), implemented in the commercial TerraScan software. A variation is given by Isenburg (LAStools 2013) in the LAStools package.

The contrast to the densification methods are surface-based (SB) filters, e.g. the Kraus and Pfeifer (1998) robust interpolation algorithm applied in the commercial SCOP++ software. Here it is assumed that all of the data represent the terrain, and next, points that do not fit to the surface are iteratively rejected. Other variations were proposed by Elmqvist (2001) and Brovelli, Cannata, and Longoni (2004).

The last group of filters works on segmentation (S) (Pfeifer and Mandlburger 2008). First, the data are separated into segments, which represent a homogenous type of objects, and next these segments are clustered into a few main groups of objects according to their geometry. Examples are proposed by Sithole (2005) and Lu et al. (2009).

From each group at least one available implementation is tested.

The article is organized as follows: Section 2 describes the test areas and data used for the analyses. In this section we also described the ground extractors chosen for filtering and the methods used for result evaluation. The results are presented in Section 3. The discussion and conclusion with respect to the available literature are described in Sections 4 and 5.

2. Data and methods

2.1. Test sites

Eight test sites were selected in the Małopolska province as research areas (Figure 1), Małopolska being located in the southern part of Poland. This region is characterized by various types of land cover and terrain slope (Kondracki 1994). The northern part is dominated by lowlands with the Vistula river valley. In the southern part are the Tatry Mountains, which are part of the Carpathian Mountains. The research areas were characterized by their land cover; in Table 1 we introduce division of the vegetation into herbs, bushes, and trees. The density of the forests (Table 1) is a sorted order (single trees, low, medium, dense, and very dense) based on the visual appearance of the point cloud.

The first test site is Brzeszcze (0.1024 km^2), located in the western part of the Małopolska. This terrain represents a valley of flat terrain (Table 1), which is covered by various types of vegetation, forest, and grassland. The second test area is Dąbrowica (0.1764 km^2), which constitutes fields and dense, natural and deciduous forest located on a small hill. The third research area is Grobelczyk (0.1764 km^2). This terrain constitutes a part of the Niepołomice Forest, a protected forest complex in the Sandomierz Basin. This test site is characterized by very dense deciduous forest on a flat area dominated by oak, alder, hornbeam, and birch species. The subsequent terrains are Jawiszowice (0.0676 km^2), with a village on a terrain of low slope (Table 1) with various types of buildings and trees, and Krokiew (0.0576 km^2), which represents a mountainside with steep slope (Table 1), covered by coniferous forest dominated by spruce species. The last three test areas are Sienna (0.1024 km^2), Szczurowa (0.0506 km^2), and Zakopane (0.0441 km^2), constituting the following types of terrain: a mountainous area with valleys covered by natural deciduous forest; a village on a flat area with homogenous types of building; and a village in the mountains.

2.2. The data

The ALS data used in this research were gathered using Riegl LMS-Q680i and LMS-Q560 laser scanners with rotation mirrors (Riegl 2013). The data were collected over several time periods: in August 2007 for the two test areas (Table 1), and for all other six areas from June to July 2010 (Table 1). The vertical accuracy of the data has been evaluated using GPS ground measurement, indicating an accuracy root mean square (RMS) between 0.1 m and 0.2 m; for every test area several measurement were made.

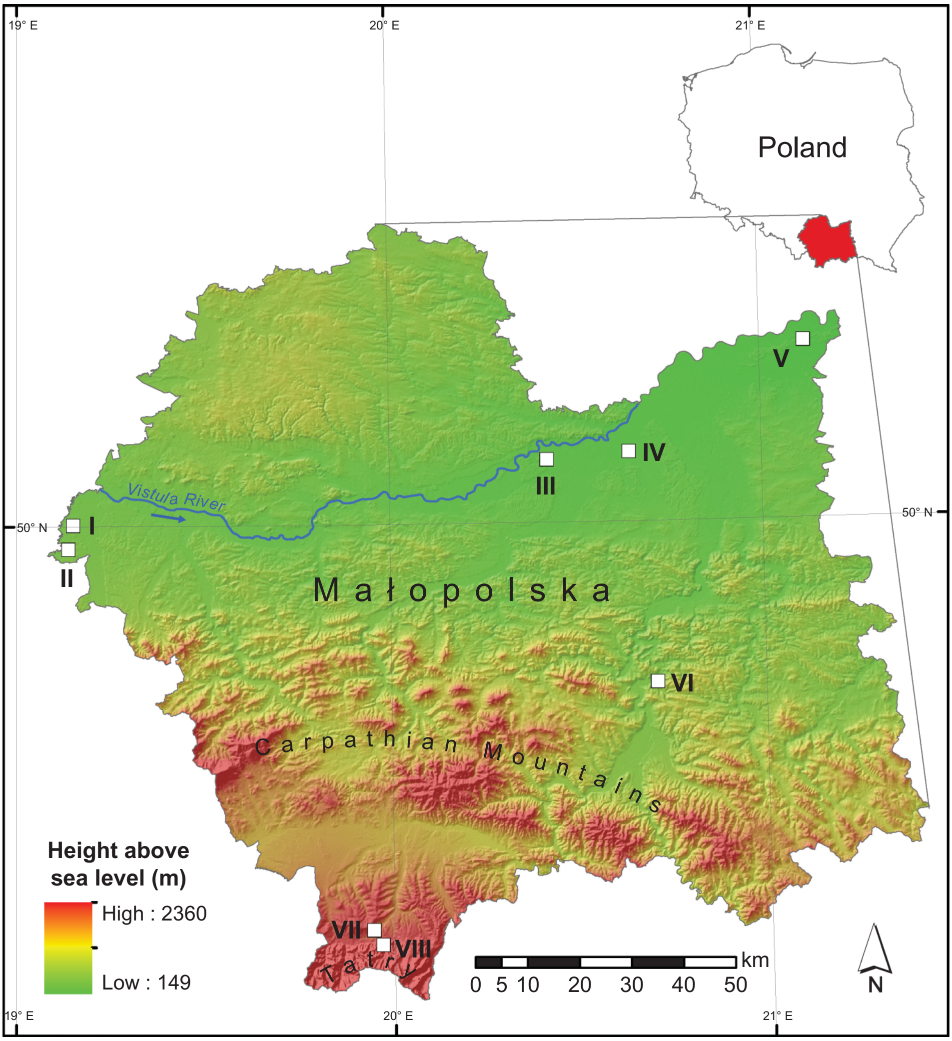

Figure 1. Area of research with the location of test sites: I – Brzeszcze; II – Jawiszowice; III – Grobelczyk; IV – Szczurowa; V – Jawiszowice; VI – Sienna; VII – Zakopane; VIII – Krokiew.

The last echo density of the data ranged between 3 and 15 points m^{-2} (Table 1). The density of the data was estimated by dividing the number of points representing the last reflection per unit area.

2.3. *Tested ground extractors*

In this article, approaches based on mathematical morphology, PD, robust surface interpolation, and S were compared. In our comparison, as was mentioned before, we focused on the evaluation of algorithms that are implemented in available software. The reason is that we would like to verify only those algorithms that, without implementation of the algorithm, are available for the user. Therefore, below we attach a short description of both: the algorithm and the parameters as well as the software applications.

Table 1. Data and research area characteristics; *vegetation height (Δh) division in metres: (x) herbs where $\Delta h \in [0.2; 0.5)$, (xx) bushes where $\Delta h \in [0.5; 5)$, and (xxx) trees where $\Delta h \in [5; +\infty)$; **forest density: single trees, low density (x), medium dense (xx), dense (xxx), very dense (xxxx).

						Land cover			
							Forest		
Area	Data collection date	Data density (points m^{-2})	Total number of points	Ground point ratio (%)	Mean terrain slope (%)	Open and Fields*	Height*	Density**	Buildings (number)
Brzeszcze	12 June 2010	2.85	73505	36.29	3.10	x	xx, xxx	x, xx, xxx	
Dąbrowica	17 June 2010	4.89	181575	38.72	4.69	x	xx, xxx	xx, xxx	
Grobelczyk	12 June 2010	4.61	273359	4.99	1.44		xxx	xxxx	
Jawiszowice	12 June 2010	4.95	61803	58.19	5.44	x	xxx	single trees	4
Krokiew	24, 27 August 2007	6.47	76069	37.55	30.69		xx, xxx	xx	
Sienna	2 July 2010	7.99	136849	44.07	23.04	x	xx, xxx	xxx, xxxx	1
Szczurowa	12 June 2010	3.37	44600	52.72	2.92	x	xxx	single trees	15
Zakopane	24, 27 August 2007	15.17	161789	49.58	15.94	x	xx, xxx	xxx	6

2.3.1. Morphological filters

From the group of morphological filters, the progressive morphological filter (PMF) proposed by Zhang et al. (2003) and the PF approaches by Mongus and Žalik (2012) were evaluated. Using a gradually increasing window size the PMF detects various sizes of off-terrain objects step by step, depending on the elevation difference threshold. The algorithm of Zhang et al. (2003) as implemented in the commercial software LIS of Laserdata GmbH was used (Wichmann 2011).

The ground extraction in LIS works on a raster based on the point cloud *Z* coordinates (Wichmann 2011). A 0.5 m spatial resolution was selected, because of point cloud density. The three most important parameters were tested: the initial threshold dh_0, which represents the initial elevation difference threshold; the terrain/slope *s*, which represents the maximum slope of the terrain taken into account; and the increasing window size w_k, which can be either linear or exponential (Table 2) (Wichmann 2012). The window size (w_k) was selected to remove the largest building on the tested terrain; in a linear increase this was selected as $w_k = 2bk + 1$, where *k* is the number of iterations and *b* is the radius; in an exponential increase this was given by $w_k = 2b^k + 1$ (Wichmann 2012). In our test sites, the width of the largest building is 20 m, namely the largest kernel size that had to be applied was 41 pixels (20.5 m) for a linearly increasing window size and 65 pixels (32.5 m) in an exponential mode. For the parameters applied and the result ID (identification number) please refer to Table 2. The last step was the point cloud data classification based on the generated raster with ground elevation.

The second algorithm evaluated is the PF. This method uses thin plate spline (TPS) interpolation to avoid misclassification caused by the difference in altitude of the terrain (Mongus and Žalik 2012). The generated surface is iterated towards the ground for this purpose, where top-hat scale space is obtained by gradually decreasing the window size. This algorithm is implemented in the commercial gLiDAR – Advanced Modeler software tool.

The first step in gLiDAR is selection of the DTM properties, which are the resolution of the generated DTM, interpolation resolution, and the low outlier size. In this step we used the default properties, because the surface resolution was equal to the resolution assumed in this study, and other default parameters were sufficient. The next step is ground filtering, where only the size of the largest object to be removed from the ground can be specified (20 m, see above). After ground filtering the user can improve the achieved result using three correction parameters: minimal ground response $\min_{res}$, maximal ground response $\max_{res}$, and the factor *F* (Table 2). These three parameters determine, respectively: the height difference between DTM and the point that will be assigned as ground; the height threshold above which the points will be classified as off-terrain; and the ratio between the size of the off-terrain features and their responses obtained in the top-hat scale space.

2.3.2. PD filters

From the PD filter the implementation (LAStools 2013) was chosen. Using a triangular irregular network (TIN) a surface is generated from below to the laser points. For all data the statistics describing the distance to the TIN facets are collected. Based on the statistics calculated, seed points are selected and using chosen threshold values the surface is iteratively densified (Axelsson 2000). The algorithm in the LAStools (LASground) works on bulged triangles.

Table 2. Combination of parameters used for ground extraction in: progressive morphological filter (PMF), segmentation (S) algorithms applied in LIS for SAGA GIS software, parameter free algorithm (PF) in gLiDAR software, progressive densification (PD) algorithm in LAStools and surface-based algorithm (SB) applied in SCOP++ software. For explanation of abbreviations and parameters in the table please refer to section 2.3.

		Result ID															
Algorithm	Parameter	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
PMF	w_k	Linear (20 iterations)								Exponential (5 iterations)							
	dh_0 (m)	0.2				0.25				0.2				0.25			
	s (rise/run)	0.05	0.1	0.15	0.2	0.05	0.1	0.15	0.2	0.05	0.1	0.15	0.2	0.05	0.1	0.15	0.2
PF	min_{res} (m)	0.1								0.3							
	max_{res} (m)	0.5				1				0.5				1			
	F	0.0	0.05	0.1	0.15	0.0	0.05	0.1	0.15	0.0	0.05	0.1	0.15	0.0	0.05	0.1	0.15
PD	tt	*fh*				*tf*				*cw*				*m*			
	g	*d*	*f*	*ef*	*uf*	*d*	*f*	*ef*	*uf*	*d*	*f*	*ef*	*uf*	*d*	*f*	*ef*	*uf*
SB	g_{res} (m)	0.5								1							
	m_{acc} ; f; c	0.05; 1; 1															
	hrf	*ld*	*ldtmd*	*lds*	*ldw*	*lfd*	*lfdtmd*	*lsf*	*ld*	*ldtmd*	*lds*	*ldw*	*lfd*	*lfdtmd*	*lsf*		
S	w_k	Linear (20 iterations)								Exponential (5 iterations)							
	max_d (m)	0.1		0.2		0.3		0.4		0.1		0.2		0.3		0.4	
	max_{DZg} (m)	0.2	0.3	0.2	0.3	0.2	0.3	0.2	0.3	0.2	0.3	0.2	0.3	0.2	0.3	0.2	0.3

For terrain point extraction, two predefined sets of parameters describing the terrain characteristics are available: the terrain type *tt* (Table 2) provides information about the terrain to be classified. This means that before classification a visual inspection of the data is necessary. Generally, for forested areas *fh* a 5 m step size should be applied, for towns *tf* the step size increases to 10 m, for cities *cw* to 25 m, and for large cities *m* with very large buildings the step size increases to 50 m (LAStools 2013). The second parameter *g* (Table 2) applied in the classification decides on the ground surface smoothness. Here, four different granularities can be applied: default *d*; fine *f*; extra-fine *ef*; and ultra-fine *uf*. For all classified data sets, horizontal and vertical units in metres were specified. The results were described with an ID number (Table 2).

2.3.3. *Surface interpolation filters*

In this study, we used the hierarchic robust interpolation approach by Kraus and Pfeifer (1998) as implemented in the commercial SCOP++ software package (Trimble 2012). In this strategy, first an averaging surface through all laser points is computed. Next, based on the distance between each point in the data set and the surface a weight parameter is determined; points below the averaging surface obtain a higher weight and, thus, have more influence on the run of the surface in the subsequent iteration. The described approach is, furthermore, embedded in a hierarchical coarse-to-fine framework (Pfeifer, Stadler, and Briese 2001). Based on the final DTM surface, the point cloud is classified into terrain and different classes of off-terrain points by analysing the vertical distances between the laser points and the DTM.

In the SB filter in SCOP++ it is possible to extract bare-ground on the basis of several default hierarchic robust filtering *hrf* strategies, respectively: Lidar Default *ld*, Lidar DTM Default *ldtmd*, Lidar Default Strong *lds*, Lidar Default Weak *ldw*, Lidar Feat Default *lfd*, Lidar Feat DTM Default *lfdtmd*, and Lidar Simple Filter *lsf* (Table 2). In all of these strategies a sequence of steps is applied, which, together with the corresponding parameters of the respective steps, decide on the classification results (SCOP++ 2010). To evaluate the influence of pixel size, with respect to the data density, for the filtering process, the strategies were applied using a 0.5 m and a 1 m grid resolution g_{res} (Table 2). We also specified mean accuracy m_{acc} parameter as the filter value of the bulk data, computation *c*, which allows a decision to be made between a faster and more extensive computation, and filtering *f* parameter, which builds a weight function of filter steps and the filter values of the bulk data of the filter (SCOP++ 2010). For the results ID and the individual parameters threshold, please refer to Table 2.

2.3.4. *S filters*

From this filtering concept the S algorithm available in LIS was tested (Wichmann 2012). The algorithm works with plane fitting. In each point a best-fitting plane is determined from the neighbouring points, which is used for segmentation. The classification is performed for the entire segment based on its properties using threshold values. In this S strategy it is possible to use several parameters for plane fitting, which influence the ground segment detection.

Two parameters of the S were tested: the increasing window size w_{k} and the maximum distance of a point to the model plane $\max_{\mathrm{d}}$ (Wichmann 2012) (Table 2). The kernel size in the w_{k} parameter was selected the same as in PMF; other parameters were set using the default values. The last step was to differentiate the generated segments into terrain and off-terrain objects. This was achieved in the *Classify Segments* module. Here two possibilities, $\max_{DZg}$ determining the maximum difference between ground and a point to be classified as ground (Wichmann 2012), were tested. The result ID and the parameters threshold are listed in Table 2.

2.4. Evaluation methods

2.4.1. Reference data generation through manual classification

Reference data is necessary in the verification of the filtering correctness. A frequently used technique to generate a point cloud reference data is to classify it manually (Kobler et al. 2007; Sithole and Vosselman 2004; Waldhauser et al. 2014).

In this research, DTMaster (from Trimble) was chosen for manual classification. We generated reference data for transects across each test site. To achieve representative data, we selected areas representing the heterogeneity of the terrain, i.e. a variety of objects. The transect width in the individual test site depends on the point cloud density and the terrain complexity; for more complex terrains with higher point density we selected smaller areas. The length and width of the transect areas for each individual test site were as follows: Brzeszcze (length 320 m, width 70 m); Dąbrowica (420 m, 78 m); Grobelczyk (590 m, 85 m); Jawiszowice (260 m, 48 m); Krokiew (340 m, 33 m); Sienna (450 m, 33 m); Szczurowa (225 m, 54 m); and Zakopane (535 m, 38 m).

To verify the correctness of manual classification the data for the Sienna test site were classified two times by two different experienced participants. The differences in the classification did not exceed 0.5% of all analysed points in this area. The ground point ratio for all test areas is represented in Table 1. The highest number of ground points (Reference GP) was recorded in case of three data sets: Jawiszowice, Szczurowa, and Zakopane, representing built-up areas. In the Grobelczyk area the ground points were represented by 4.99% (Table 1), which is because of the land cover of this terrain and also the data collection time. This area is covered by very dense, deciduous forest. The data were collected in June in a leaf-on condition, which results in low ground point ratio.

2.4.2. Qualitative evaluation

Qualitative verification of ground extraction is made on the basis of a visual inspection of the results (Meng, Currit, and Zhao 2010). These types of analyses allow determining the general type of objects, and the spatial distribution of misclassifications. Basically, in this analysis it is verified how the algorithm works in building and vegetation filtration, because these two types of features represent the biggest part of the objects on the terrain. The method for visual quality evaluation by visual examination is detailed in Sithole and Vosselman (2004). Below we point out the issues specific to our test areas.

The qualitative analysis is performed for land-cover classes. It is based on the derived models of the surface.

We verified whether the algorithm removes all buildings, or if not, on which type of buildings and on which type of terrain it fails to do so. Moreover, we analysed the local neighbourhood of the object, because this could have an influence on any misclassification. For vegetation the height of the incorrectly classified vegetation was assessed, their area, and density in comparison to the ground points on this terrain. As in building analysis it should also be related to the terrain type and the immediate local neighbourhood. The important issues in our test sites were also terrain discontinuities, especially in

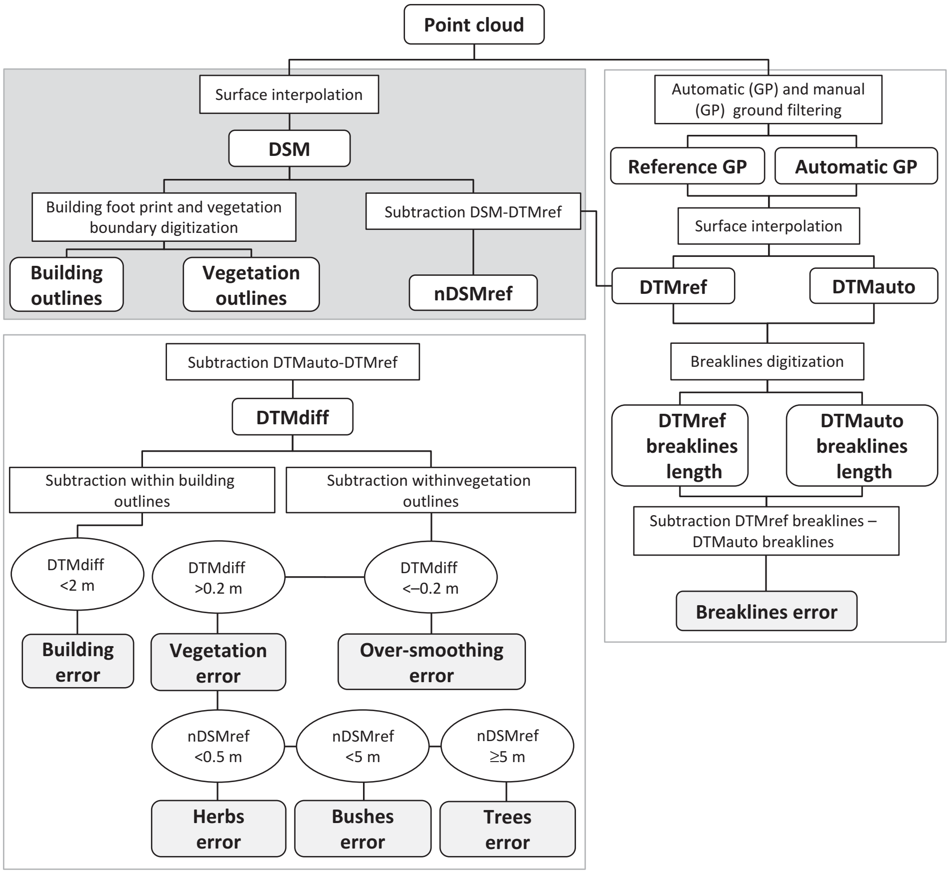

Figure 2. The qualitative analyses workflow. For abbreviations please refer to Section 2.4.2.

built-up and mountainous areas, because reducing these discontinuities leads to a loss of information and a misrepresentation of the terrain.

To compare the filtering methods, we suggest a quantification of the results. Our qualitative evaluation is applied to analyse spatial distribution of non-removed objects or a part of objects, e.g. building, tree, sharp ridges. Because there are a few types of wrongly filtered objects, the evaluations have to be carried out separately.

According to our methodology presented in Figure 2, first the data are divided into areas, representing different types of objects. We have done this on a basis of digitization of buildings and vegetated areas supported by information from the point cloud, DTMs, digital surface models (DSMs), and ortophotomap (Figure 2). The example of manually refined vegetation and building boundaries for Szczurowa test site is represented in Figure 3. The same procedure was applied to delineate breaklines on the terrain. The breaklines were delineated on a basis of DTMs generated from the reference data (Reference GP) as well as from automatic classification (Automatic GP). To evaluate the breakline error, the lengths of the generated breaklines for the reference data (DTMref breaklines length) and for automatically classified data (DTMauto breaklines length) were compared (Figure 2).

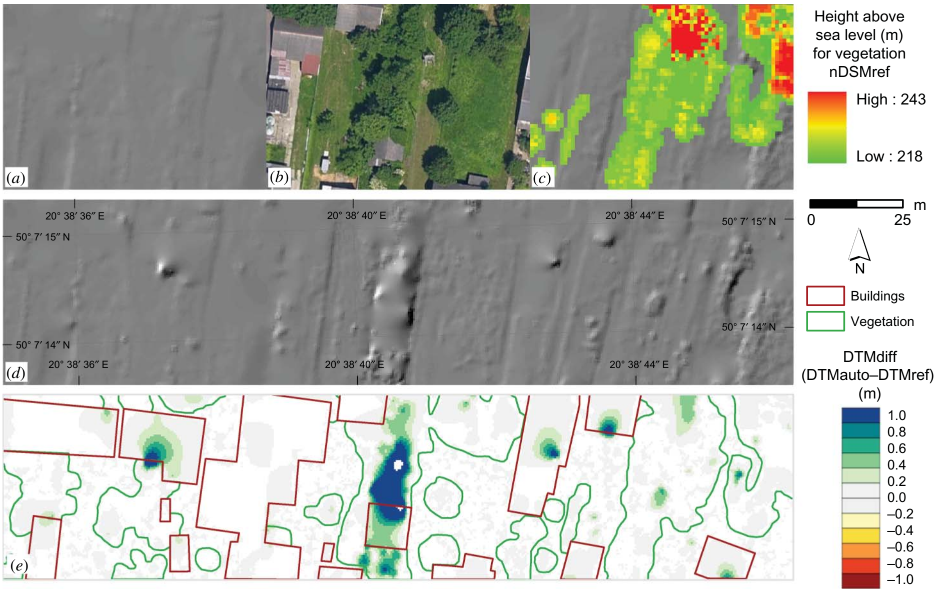

Figure 3. Example for the qualitative evaluation in the Szczurowa test site: (*a*) shading for reference DTM (DTMref), (*b*) an ortophotomap, (*c*) shading for reference DTM and difference model between DSM and DTMref (nDSMref), (*d*) shading for DTM generated on the basis of automatic classification (DTMauto), and (*e*) the difference model between DTMref and DTMauto (DTMdiff). The location of the test area is shown in Figure 1 (IV Szczurowa).

Next we evaluated height difference models (DTMdiff) between the surfaces generated from tested software applications (DTMauto) and from the reference data (DTMref) (Figure 2). The DTMdiff models (Figure 3) were separately subtracted within the buildings and vegetation outlines. To detect the errors caused by non-filtered buildings from the ground a height assumption was applied. It was established that if the height differences (DTMdiff) inside the buildings' outlines are greater than 2 m, the pixels would be assigned as a building errors. The 2 m assumption was applied on the basis of several tests and a visual inspection of the results. Because the buildings should be higher than 2 m we assumed that this threshold is sufficiently good to verify whether some buildings were wrongly included in the ground class. The height threshold was introduced to avoid other small errors caused not by wrongly filtered buildings, but by differences in the interpolated DTM surface.

Discrimination in height was also applied in the outlines of vegetated areas. First a reference normalized DSM (nDSMref) representing our vegetation division for herbs, bushes, and trees was evaluated (Figure 2) – (definition in Section 2.1 and in Table 1). Second, the nDSMref surface was subtracted to the vegetation boundary (Figure 3). Based on the delineated boundaries the DTMdiff from all of the results were evaluated separately. This allowed the evaluation of the scale of wrongly filtered vegetation from the ground. To eliminate the influence of surface interpolation, a 0.2 m buffer was applied; it was assumed that non-filtered vegetation (vegetation error) is represented by differences higher than 0.2 m. The threshold was chosen on a basis of tests and our knowledge on the data.

Additionally, the extent of terrain over-smoothing was verified in the vegetation outlines. Here, to count the areas that were over-smoothed, the same 0.2 m buffer was applied. The pixels with a height difference smaller than −0.2 m were included as over-smoothed areas (Figure 2).

2.4.3. Quantitative evaluation

In a quantitative analysis the classification is verified numerically using three basic parameters: Type I, Type II, and Total errors (Sithole and Vosselman 2003). The first parameter represents the percentage of terrain points that are classified as off-terrain. The parameter is evaluated on the basis of Equation (1), where a is the count of terrain points that have been correctly identified as terrain and b is the count of terrain points that have been incorrectly identified as off-terrain.

$$\text{Type I error} = b/(a+b). \tag{1}$$

The second parameter counts the percentage of points that represent off-terrain, but are classified as terrain. In Equation (2), c is the count of off-terrain points that have been incorrectly identified as terrain and d is the count of off-terrain that has been correctly identified as off-terrain.

$$\text{Type II error} = c/(c+d). \tag{2}$$

The third parameter represents the total amount of wrongly classified data and is calculated based on Equation (3), where e is the total number of points tested.

$$\text{Total error} = (b+c)/e. \tag{3}$$

The quantitative analysis is performed using the spatial co-location assumption. It is assumed that if the X, Y, Z coordinates of two compared points from two different data sets are equal or if their difference is very close to zero, then their classifications can be compared.

3. Experimental results

3.1. Qualitative assessment

All classified data sets were compared with the manual reference data qualitatively (Table 3). To simplify and shorten the description we treated bushes and trees together. We also omitted herbs, because no misclassification occurred in this class. For explanation of the abbreviations used in this chapter, please refer to Table 2 and Section 2.3.

Generally, in flat, vegetated areas (Brzeszcze, Dąbrowica and Grobelczyk) the best results were achieved on the basis of PMF. In the Brzeszcze test site the bushes and trees error in seven results from PMF counts less than 2 m^2 (Figure 4(*a*)) and the over-smoothing error in all results (without PMF 1) counts less than 220 m^2 (Figure 4(*b*)). They were not cumulated, which means that there was no large over-smoothed area but single pixels spread out through the entire vegetated area. As seen in Figure 4(*c*) in the PF filter a boundary effect in the vegetation class occurs. The boundary effect means wrongly classified points on the border of the data set, which occurs due to the lack of data for computation outside the boundary. Also in Dąbrowica the best results were achieved for PMF. The vegetation error was counted between 513 and 550 m^2 and was concentrated in

Table 3. Qualitative results example of the tested algorithms for Jawiszowice (J) and Zakopane (Z) test sites.

Algorithm (result ID)	Number of wrongly filtered buildings and other objects				Lengths of breaklines				Total area of mapped vegetation (m^2)		Area of vegetation errors (m^2)			
	Buildings $\Delta h > 2$ m		Other objects $\Delta h > 0.2$ m		Preserved (m)		Removed (m)				Over-smoothing $\Delta h < -0.2$ m		Bushes and trees $\Delta h > 0.5$ m	
	J	*Z*	*J*	*Z*	*J*	*Z*	*J*	*Z*	*J*	*Z*	*J*	*Z*	*J*	*Z*
PMF (1)	0	0	2	5	163	130	20	42	3995	5133	229	604	189	572
PMF (2)	0	0	2	5	163	130	20	42	3995	5133	186	507	199	599
PMF (3)	0	0	2	5	163	130	20	42	3995	5133	165	324	203	714
PMF (4)	0	0	2	5	163	130	20	42	3995	5133	153	278	203	759
PF (1)	1	0	1	3	183	148	0	24	3995	5133	194	475	298	397
PF (2)	1	1	1	5	183	148	0	24	3995	5133	57	179	264	730
PF (3)	1	1	1	5	183	148	0	24	3995	5133	32	230	268	673
PF (4)	1	1	1	5	183	148	0	24	3995	5133	32	167	266	756
PD (1)	2	1	2	4	183	148	0	24	3995	5133	94	271	8	432
PD (5)	0	0	1	4	183	148	0	24	3995	5133	106	347	1	338
PD (9)	0	0	1	4	119	148	64	24	3995	5133	451	694	1	377
PD (13)	0	0	1	4	119	133	64	39	3995	5133	625	489	1	356
SB (1)	3	2	3	7	168	150	15	22	3995	5133	32	111	294	1536
SB (2)	2	1	3	2	183	148	0	24	3995	5133	47	282	199	417
SB (3)	2	0	3	7	168	159	15	13	3995	5133	28	86	302	1513
SB (4)	3	2	3	7	168	159	15	13	3995	5133	32	111	290	1537
S (1)	0	5	2	6	163	158	20	14	3995	5133	243	237	81	1964
S (2)	0	5	3	6	163	158	20	14	3995	5133	223	237	81	1966
S (3)	0	5	3	7	163	158	20	14	3995	5133	293	217	76	2001
S (4)	0	5	3	7	163	158	20	14	3995	5133	280	218	83	2004

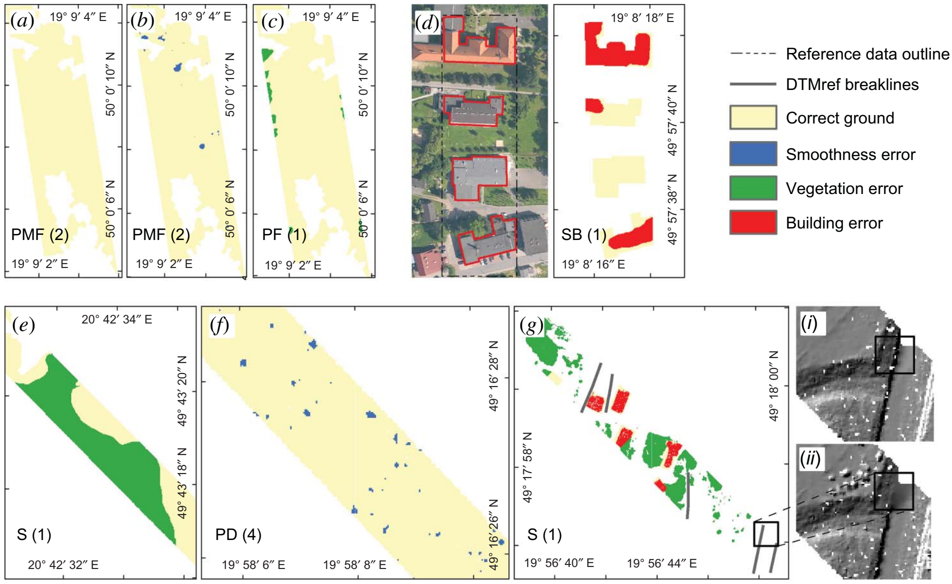

Figure 4. The qualitative results for analysed test sites, where: (*a*)–(*c*) Brzeszcze test site; (*d*) Jawiszowice test site; (*e*) Sienna test site; (*f*) Krokiew test site; (*g*) Zakopane test site; (*i*) shading for reference DTM; and (*ii*) shading for DTM generated on the basis of automatic classification. Abbreviations in the figure represent the analysed algorithm, and in the bracket the number of the results. The location of each test area is shown in Figure 1.

one area with sparse ground data. The lowest vegetation error in Dąbrowica (fields, dense forest, hills) was achieved on a basis of PD algorithm, in 12 of 16 results; the area of wrongly filtered vegetation was smaller than 32 m^2. However, the over-smoothing error counted between 290 and 1069 m^2 and it was grouped in a few places representing more rough terrain. In the Grobelczyk test area (dense deciduous forest) in 13 results from PMF there was no over-smoothing error, the vegetation error was between 619 and 1621 m^2 and it was grouped in three places covered by very dense forest where the shortest distance between two nearest points, assigned as the ground in the reference data, was larger than 15 m. Also in the PD algorithm in the majority of the results there was no vegetation error. The over-smoothing error here was relatively low and ranged between 135 and 603 m^2; however, it was spread out within the test site in several 30–50 m^2 areas. The highest vegetation error was observed on the basis of the PF algorithm; in every result it was higher than 4000 m^2. Such high error in the PF algorithm was caused by the boundary effect of the data.

In flat, built-up areas almost all of the compared algorithms achieve good results. In the Jawiszowice test site all the buildings were correctly filtered on the basis of all results from the PMF and S algorithms (Table 3). The highest number of non-filtered buildings was observed in SB 1, 4, 5 (Figure 4(*d*)) and PF 16 where three of four buildings were assigned as terrain. In the Szczurowa test site the results were similar; moreover, the PMF and S algorithms correctly filtered all the buildings. The worst results were observed in 6 and 13 results from SB in the Szczurowa test site where seven of 14 buildings were assigned into the ground class.

Highly accurate ground filtering results in mountainous vegetated areas are obtained based on PMF, PD, and SB algorithms. Two exceptions are the 5 and 12 results from SB.

In every applied algorithm it was possible to extract the ground on steep slope covered by deciduous forest at the Sienna test site. The smallest over-smoothing, as in previous test sites, was achieved based on PMF. In the analysed mountainous test area the S algorithm provides the worst results, which occur in one large area (Figure 4(*e*)). The vegetation error inside this area is higher than 3103 m^2, which constitutes almost 34% of the wrongly filtered area inside the vegetation outline. In the Krokiew test site the results are similar to the previous area. The vegetation error on the basis of PMF, PD, and SB algorithms was small. Because this test site represents a rough steep slope with a uniform gradient, the over-smoothing, in PMF, PD, and PF, was spread out into the whole area as small (a few square metres) blobs; the example is shown in Figure 4(*f*).

The SB (not including results from 5 and 12) and also PD algorithms give the best results in mountainous agricultural areas with buildings. In that kind of terrain more breaklines occur than in natural environment areas, so during the verification of the filtering quality this parameter should be included in the analyses. In Table 3 we see that the largest length of the removed breaklines was observed on the basis of PMF and the lowest was achieved in SB and S. However, the S failed in vegetation and building filtering. In Table 3 and Figure 4 (*g*) it is shown that five out of six buildings were assigned as ground. Moreover, the bushes and trees error constitutes almost 39% of the area inside the vegetation outlines. Good results were also achieved in PF. In the first result (PF 1) the algorithm correctly filtered all the buildings; however, the over-smoothing is larger here than in the 2, 3 and 4 results, the reason being the parameter thresholds.

The qualitative results show that most of the algorithms do not provide good results for the classification of dense vegetation or objects on high slope areas, especially when there are few or hardly any ground points under the tree canopy. Those objects are classified as ground or are removed from the ground class together with the terrain points. In such cases all the filter algorithms work too local. The first variant was observed in results where very liberal thresholds were selected and the second when rigorous parameters were applied. Obviously, the vegetation easiest to remove is in flat areas applying a rigorous threshold.

In build-up areas the applied algorithms give good results in the Szczurowa test site because the buildings here have a simple shape and are small. Some difficulties occur in places where a tree canopy is in the vicinity of buildings (SB 6, 13). This situation was also observed in high slope areas in the Zakopane test site, especially in places where there is a small distance between the roof and the ground (SB 5, S 1–16). Figure 5 shows that some algorithms have difficulties with flat roof filtering (PD 1–4); however, on increasing the step size to 10 m the building is correctly removed from the ground.

The qualitative analysis shows also the threshold-parameter influence on breaklines, discontinuity, and roughness quality, especially in mountainous areas. In most of the analysed algorithms stricter thresholds caused removal of breaklines. The surface generated on the basis of ground class was also smoother and did not contain all the details on the terrain. This was observed in all the results from the S in Krokiew and Sienna and in the 9–16 results in the PD algorithm. The low and outlier points do not have a large influence on classification accuracy, and all tested algorithms remove these points from the ground class mostly correctly.

The qualitative results were also analysed with respect to the parameters applied. The results show that in the PMF the most important is a terrain slope *s*; other parameters hardly have an influence. Lower terrain slope (in our study it was 0.05) allows the majority of off-terrain objects to be removed from the ground. Increase in the *s* parameter threshold results in a higher number of off-terrain objects in the ground class. However, in

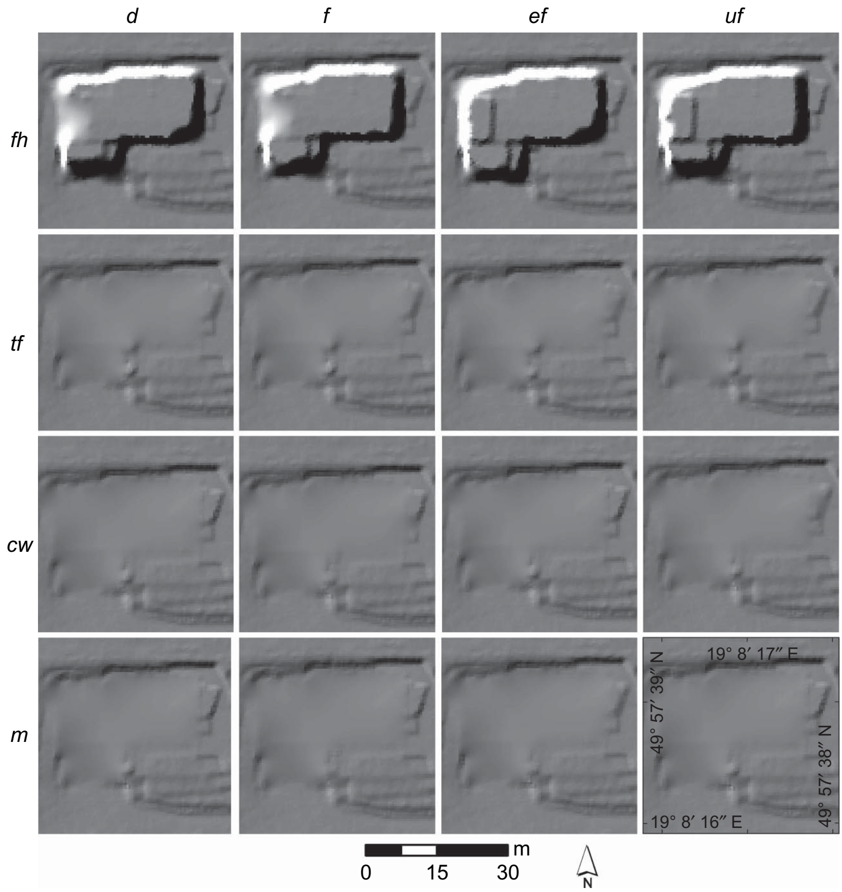

Figure 5. Shaded relief representing the filtration results for PD algorithm; *fh, tf, cw*, and *m* represent the step size, and *d, f, ef*, and *uf* represent the granularities. For abbreviations' descriptions please refer to Section 2.3.2.

the tested mountainous areas, a low *s* parameter has influence on removing parts of the terrain, especially in high slope areas and sharp edges (see also Kobler et al. 2007). In the PF algorithm the results depend on the specified kernel size. If it is too small, the buildings will not be correctly filtered from the ground. The results depend also on the minimum residual applied. To achieve good results in flat areas a lower min_{res} can be specified, but in mountainous areas this parameter should be increased to reduce the over-smoothing. The max_{res} parameter is also important, especially in mountainous areas, because the usage of too low max_{res} constitutes a rejection of points, which could represent the ground. In the PD algorithm the best results were observed on the basis of strategies with a 10 m step size. Smaller step size constitutes a smaller number of correctly filtered objects from the ground, although the ground class is rough. Larger step size removes a larger number of objects from the ground, but also increases the over-smoothing. The granularity parameter has little influence on the classification. In the SB algorithm the best results were observed using *lds* (Lidar Default Strong) and *ldtmd* (Lidar DTM Default). We did not observe a larger difference between the results for different grid resolutions; however, the reason could be only two applied grid resolutions. From the

LIS S algorithm all the applied parameter thresholds give good results only in the flat, built-up parts of the Szczurowa test site. The most problematic, for this algorithm, are vegetated areas, because it is difficult to define segments for spread-out data representing a forest compared with compact buildings or bare-ground areas.

3.2. Quantitative assessment

The results show that in each test site the lowest Type I error was achieved using the PMF and PF algorithms (Table 4). According to the statistics it is possible to detect that the lowest Type II error was achieved in four test areas using S in LIS and in other test sites using PF, PD, and SB algorithms. The lowest Total error was observed in almost every test site based on the PMF with different threshold parameters. Only in the Zakopane and Jawiszowice test sites the lowest total error results were obtained using the PF algorithm. In the Zakopane (mountain, built-up) low Total error was also obtained using SB, being respectively, results 2, 9, 6, and 13.

Nevertheless, the results show also that the lowest Type I error is correlated with the higher Type II error – see the third and fourth columns in Table 4. The consequence of this is that the surface generated based on the smallest Type I error will contain a number of off-terrain objects. Similarly, the results also show that the surface generated on the basis of the lowest Type II error will be smoother due to a higher Type I error – see the seventh and eighth columns in Table 4.

Furthermore, the results presenting the smallest Type I error and Type II error in Table 4 are not synonymous with the best ground classification. The explanation for this can be found in Figure 6, where three results for the Brzeszcze and Zakopane test sites were compared. As is shown in the figure in the lowest Type I error (Figures 6(*a.i*) and (*b.i*)) a number of off-terrain objects are visible on the ground. In the images with the lowest Type II error (Figures 6(*a.iii*) and (*b.iii*)) too many ground points are removed from the ground class.

To verify the algorithm flexibility for different terrain types we also evaluated Total average error for all of the test areas. Total average error was evaluated as an average of the lowest Total error in each algorithm for all test sites. The results show that PF, PMF, and SB give misclassification lower than 3%, and on a basis of PD and S this error is higher than 5%.

3.3. Qualitative and quantitative assessment

Based on qualitative and quantitative analyses, decisions were made with regard to which algorithm gives the best results with respect to the quantitative and visual verifications. It was assumed that the best algorithms (and their parameters) were those that had quantitative results smaller than 1% together with high-quality qualitative results. For some test sites a 1% assumption was not possible because the smallest errors were higher than this predefined value. The selected algorithms and their parameters are in the last four columns in Table 4.

It was observed that in mountainous, forested, and built-up areas the best results were achieved using the *ldtmd* (Lidar DTM Default) settings in the SB algorithm. Although the PF algorithm has the smallest Total error in these areas, the qualitative results are rather poor, because of the boundary effect. In forested mountainous areas with very few ground points and in hilly built-up areas the best results were achieved using *tf* (towns or flats) parameters settings from the PD algorithm with granularities, respectively, *d*/*f*; *ef* (default/

Table 4. Type I, Type II, and Total errors in test areas.

Test area	Errors for the lowest Type I error achieved from all analysed parameters in software tools				Errors for the lowest Type II error achieved from all analysed parameters in software tools				Optimized parameters selected on a basis of qualitative and quantitative evaluation			
	Algorithm (result ID)	Type I error (%)	Type II error (%)	Total error (%)	Algorithm (result ID)	Type II error (%)	Type I error (%)	Total error (%)	Algorithm (result ID)	Type I error (%)	Type II error (%)	Total error (%)
Brzeszcze	PMF (16)	0.1	4.5	2.9	PD (7)	0.1	31.1	11.3	PMF (13)	1.9	0.7	1.1
Dąbrowica	PMF (16)	0.4	1.2	0.9	S (1)	0.1	12.1	4.7	PMF (7)	1.7	0.5	1.0
Grobelczyk	PMF (11)	0.1	0.1	0.1	SB (3)	0.0	12.5	0.6	PMF (13)	0.1	0.0	0.0
Jawiszowice	PF (14)	1.1	3.6	2.2	S (1)	0.5	11.2	6.7	PD (7)	4.9	0.9	3.2
Krokiew	PF (12)	3.7	1.6	2.3	S (1)	0.2	63.1	23.8	SB (2)	14.4	0.7	5.8
Sienna	PMF (8)	2.3	2.0	2.2	S (1)	0.4	17.3	7.8	PD (5/6)	7.8	0.8	3.9
Szczurowa	PMF (12)	0.0	5.7	2.7	PF (1)	0.4	8.3	4.5	PMF (1)	2.0	1.6	1.8
Zakopane	PF (15)	4.0	5.2	4.6	PF (1)	1.3	24.5	12.8	SB (2)	10.4	2.1	6.2

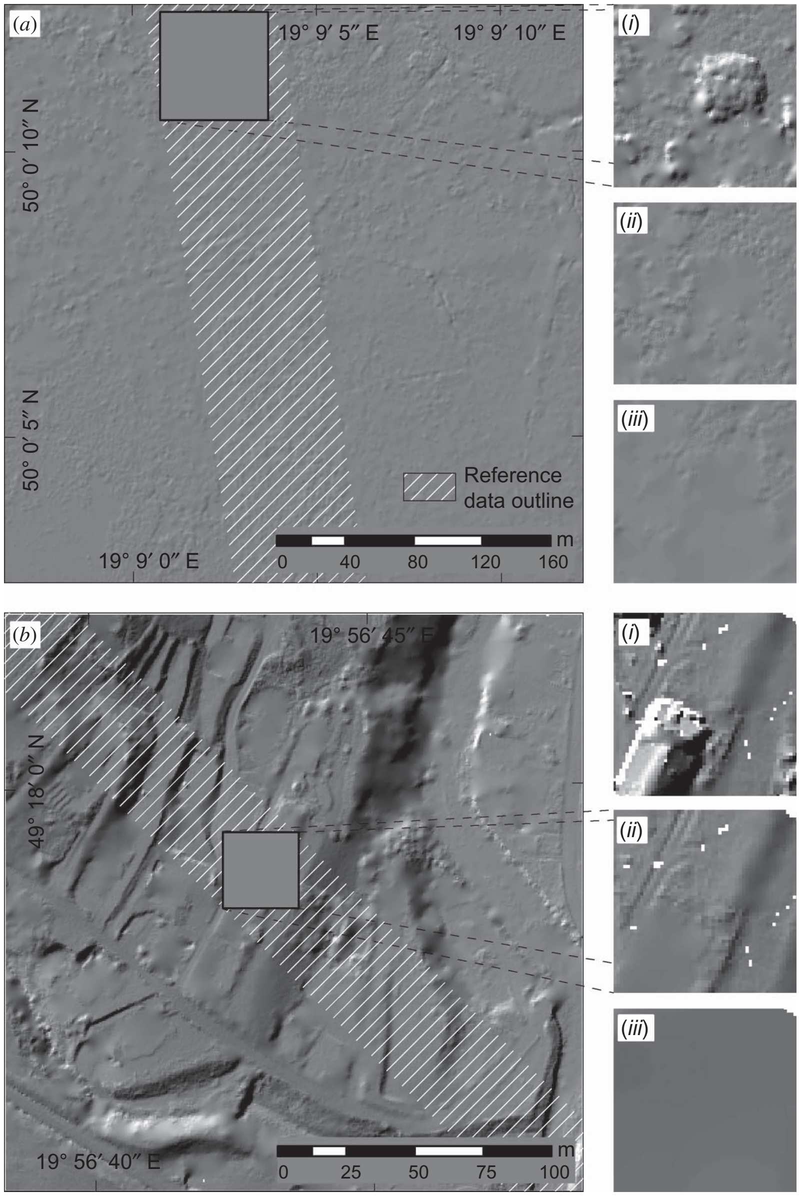

Figure 6. Ground filtering examples in the Brzeszcze (*a*) and Zakopane (*b*) test sites; (*i*) the lowest Type I error, (*ii*) the reference data, and (*iii*) the lowest Type II error.

fine; extra fine). In other areas the best results were achieved using the PMF with various parameters.

4. Discussion

Filtering off-terrain points is, according to the qualitative analysis, the easiest for buildings with simple geometry, then a little difficult for high vegetation, and the most difficult for very dense vegetation. This can be seen from Table 3 and how the categories of failures relate to the land cover. However, this process is more complex, so we cannot state that filtering of every type of buildings will be easier than for every type of vegetation. Here, the influence is also the spatial distribution of the objects and the terrain type.

The quantitative analysis shows that mountainous areas (Krokiew, Sienna, and Zakopane) pose a very big challenge, and filtering above terrain can only be accomplished by some over-smoothing of the terrain and through breakline removal or by selecting a more liberal parameters threshold, to reduce the Type I error, and manually improving the automatic filtering by removing the objects from the ground.

Filtering based on available algorithms, when applied in software, depends on user knowledge and also the program interface. Out of all the tested software the easiest and the fastest filtering was possible in LAStools. This software allows data processing with different parameters using a batch file. In SCOP++ a command line language is also available, but this is more complex. In gLiDAR in order to apply the algorithm for ground extraction, the user has only to specify a few parameters. Furthermore it is possible to verify the results visually during changing the parameters thresholds. The most time consuming was the classification using LIS software, especially S, because in this method it was necessary to apply six modules sequentially.

Verification of a ground class extraction with reference data is one of the most important issues in classification correctness determination (Meng, Currit, and Zhao 2010). As has been described in the article, manual classification is one of the possibilities to achieve reference data. In the available literature (Baligh, Valadan Zoej, and Mohammadzadeh 2008; Meng, Currit, and Zhao 2010; Sithole and Vosselman 2003) this process was also indicated as a good solution for results verification. The other possibility is a GPS measurement. However, this method can be used only to verify the correctness of the DTM. This method cannot be applied to verify the correctness of the filtering process at the point cloud level.

The accuracy of the filtering depends on the terrain complexity (breaklines, buildings, dense vegetation), point cloud density, seasonality (penetration rate) (Bretar and Chehata 2010), the methods used for ground extraction, and the threshold parameters used in the applied algorithm. Nevertheless, the results also show that not all the analysed algorithm applications give a high-quality filtering for all tested land-cover types and terrain slope. Although the results depend also on the parameter thresholds (Baligh, Valadan Zoej, and Mohammadzadeh 2008), it is possible however to draw general conclusions in all of the analysed methods.

The PD ground extraction algorithm gives satisfying results in all research areas. Furthermore, the positive aspect of this algorithm is its simple software interface. However, it was observed that compared with the reference data and also other software package algorithms, the PD based on ground filtering generates a smoother surface.

The PMF filter in LIS enables one to obtain good ground extraction for all land covers in flat and low slope areas. Moreover, the ground class is rougher and contains all the details present on the terrain. Nevertheless, to use a PMF ground algorithm in LIS software it is necessary to apply a few steps and specify several thresholds, which may cause difficulties for an inexperienced user.

The PF algorithm in gLiDAR software, in general, gives good results in all analysed terrain types. However, it generates misclassification on the boundary of the data sets. The boundary effect can be solved by overlapping of neighbouring data sets; however, if users do not have at their disposal this data, the errors have to be erased manually.

Of all the analysed methods the robust interpolation algorithm (SB) in SCOP++ software gives the best results in mountainous areas. The reason for this is the discontinuities on the terrain and breaklines preservation. However, the method fails in very densely vegetated areas. The tool has a simple interface; the user has only to choose between the predefined defaults filter strategies. In addition, it is also possible to change the threshold parameters and to work on user strategies (see Razak et al. 2013, filter for forested landslide analysis).

The S algorithm in LIS enables correct results in built-up flat areas. However, in forested and mountainous areas, above all in high slope terrain with dense vegetation, and a small number of laser scanner reflections from the ground, the applied algorithms fails. The reason for this is that trees are usually less smooth in texture than buildings and ground segment distinction in these areas is difficult (Zhang and Whitman 2005). Moreover, the S method is not simple to apply, and in order to achieve a ground class from segments it is necessary to apply several steps.

The Type I error and Type II error confirm the conclusion contained in the Sithole and Vosselman (2004) article: lowering one error type at the cost of an increase in the other. Additionally, it was observed that the lowest Type I error, from amongst all the analysed software applications, was achieved based on the PMF. Exceptions are mountainous areas where the Type I error results were similar or worse with respect to other algorithms.

Based on conducted analyses we state that the verification of the filtering process should include numerical evaluation (Type I, Type II, and Total error) and also visual inspection of the extracted ground class. The quantitative results provide information about the amount of wrongly filtered data, but do not provide an answer about the spatial distribution of these errors. To accomplish this, we have to look at the data or use statistical methods that allow estimating the spatial distribution of errors. The quantification of the qualitative assessment allows verifying the type of wrongly extracted objects from the ground, and also checking the height difference between the ground and wrongly filtered objects. This allows users to assess the influence of the misclassification on the correctness of the DTM. Moreover, quantitative verification does not have to represent the impact of the size of the error to the DTM height accuracy. For example, high Type II error does not necessarily mean that the applied algorithm gives poor results, because this error could be spread close to the ground surfaces, which does not have large influence on the terrain elevation accuracy. On the other hand, low Type II error does not always mean that the terrain class will be correct, because wrongly filtered points may represent part of building (a roof), which will have an impact on DTM height accuracy.

Our research confirms the influence of seasonality. Additional difficulties in the ground extraction process occur, especially in forested areas.

Some potential in future methods for ground extraction could be the use of full-waveform data, because they contain information about the echo width, which can be used to determine the laser beam ground reflections (Pfeifer and Mandlburger 2008; Mücke, Hollaus, and Prinz 2010; Lin and Mills 2009).

5. Conclusions

This article presented the differences in bare-ground extraction from ALS data based on several concepts of filter algorithms, which have an implementation in software.

The method suggested for evaluation of the quality consists of a qualitative part, which is based on land cover, and assesses the derived models, and a quantitative part, which works on the point cloud directly.

The results show that from amongst the compared algorithms there is no single method that gives the best results for each analysed type of terrain – slope and land cover. However, it is possible to draw general conclusions with regard to the methods and applied parameters. In the PD algorithm the user should focus on selecting the step size, which should fit the terrain type. However, the user should note that with an increase of step size, the ground surface is over-smoothed. In the PF algorithm the size of the largest buildings must be considered, and the correction of the parameters needs user input. For the LIS Progressive Morphological Filter algorithm, the user has to specify the maximum window size, and focus on the initial threshold, and the slope of the terrain for which the filter will be applied. The SB algorithm from SCOP++ enables ground filtering on a predefined mode level; the user need only choose the appropriate strategy. Additionally, an improvement of the parameter settings is also possible.

Summarizing filtering using existing tools still requires knowledge of the area and an awareness of the application for the DTM in order to minimize the relevant errors.

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