
Validating the CENITH 💬 package as a new approach for tree segmentation 💬 alpine treelines

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1 Introduction

Eversince the beginning of biogeographical research, the conspicuous structure of alpine treelines has been of great interest for researchers all over the world [Slatyer and Noble, 1992]. By comparing the spatial properties of alpine treelines on different continents, mountain ranges or even just differently exposed slopes, one may notice significant differences in the spatial patterning of those treelines [Harsch and Bader, 2011].

ith the dawn of satellite remote sensing in the 1960's, large scale investigation on spatial structures in alpine tree lines could be conducted [Moore, 1979]. Especially active remote sensing in the form of light detection and ranging (LiDAR) proved valuable. Yielding point cloud data, LiDAR made it easier to segment individual trees [Latifi et al., 2015]. Since this was at first done manually, within the last few decades a rush of automated segmentation approaches flooded the scientific landscape [Guan et al., 2015, Li et al., 2012, Reitberger et al., 2009, Rahman and Gorte, 2009]. Most of the algorithms nowaday used for tree segmentation are based on statistical methods invented for different purposes, such as nearest neighbour approaches [Silva et al., 2016] or growing region algorithms [Dalponte and Coomes, 2016]. Different vegetation zones may require different approaches. So come, that on the one hand, Allen and Walsh mainly used an unsupervised classification approach (not further specified) for their analysis of alpine treelines in the Glacier National Park, Montana [Allen and Walsh, 1996]. On the other hand Wang et al. used a O(r)-ring statistical methods for their study of the treeline patterns of the south-eastern Tibetan Plateau [Wang et al., 2012].

Many of the segmentation approaches mentioned, and even beyond those, are quite error-prone under difficult circumstances [tnam and Falk, 2014]. Most of the methods have a hard time dealing with tree shadows, shrubs and krummholz or steep slope inclinations. The scripting language R already provides different packages for LiDAR-based tree segmentation, such as lidR [Jean-Romain et al., 2020], rLiDAR [Silva et al., 2017] and uavRst [Meyer and Reudenbach, 2018]. Those packages do not perform perfectly on all occasions and their functions are rather hard to grasp for beginners. Therefore, Andreas Schönberg (2020) introduced the

CENITH package in R [Schönberg, 2020]. It is supposed to provide an easy-to-use set of functions for parameter tuning and tree segmentation and to perform well, regarding shadows and slope inclination. The purpose of the present study was to use Schönberg's CENITH package from a beginners viewpoint and evaluate its user friendliness, applicability and performance compared to the already established packages lidR, rLiDAR and uavRst. Therefore, the segmentation functions dalponte2016 (lidR), silva2016 (lidR), li2012 (lidR/rLiDAR) and chmseg_FT (ForestTools/uavRst) were compared to the TreeSeg function of the CENITH package using manually inserted validation ground truth.

2 Materials and Methods

2.1 Study Site

The study area is located in the Austrian region Vorarlberg, in the northern part of the European Alps. The area was divided into four study sites. They are exposed at the southern slope of Mt. Zimba at approximately 47°05'00.7"N 9°47'47.4"E. The main tree species occurring in the area of interest is the Bog pine (*Pinus mugo*), as well as different species of shrubs. The former often occurs as krummholz. To fit the purpose of investigating treeline patterns, all four study sites are located within the treeline ecotone.

The first site (see figure 1) is dominated by shrubs and lies at the slope with the steepest inclination. The patch of shrubs used for the segmentation approach is the highest vegetational structure in this part of the slope. Study site 2 lies about 300 m eastwards of the first one. This site is considered to contain more krummholz, as was assumed by manual image supervision. The area used for segmentation purposes is located at the north-western border of the study site. The thinning of the vegetation at this site is more gradual than at the first one, to a lower inclination. The vegetation at the third site is composed of trees as well as shrubs, whereas site 4 merely includes trees. Both sites contain large amounts of bare rock and represent the upper just the upper limits of the treeline ecotone. Study site 4 includes a patch of trees in the north-eastern corner, which was used for the tree segmentation.

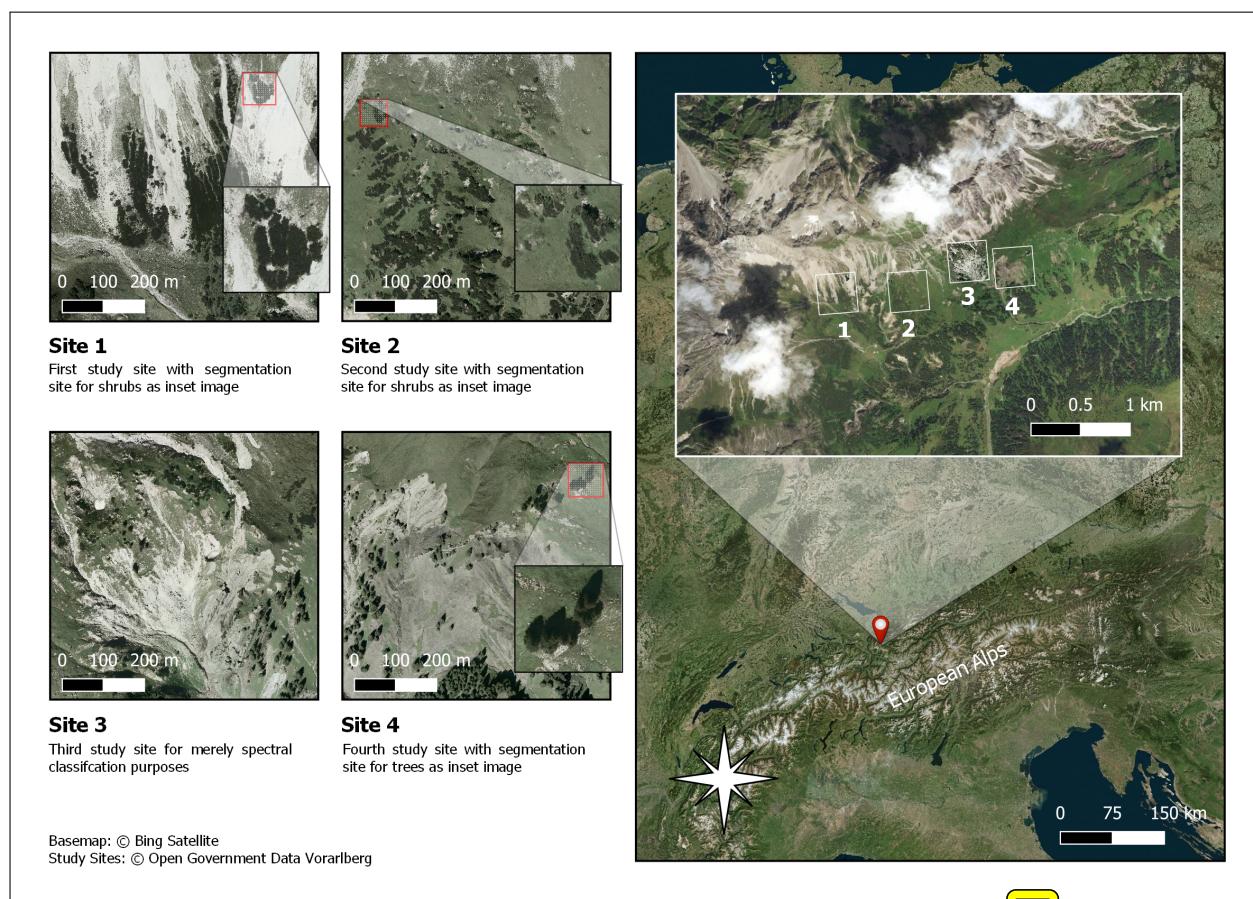


Figure 1: Location map of the study sites. The RGB images of Vorarlberg were obtained from data.vorarlberg.gv.at and are open source.

2.2 Data

The  data source, relevant for the segmentation, was very high-resolution airborne LiDAR data, obtained by a drone. The yielded point cloud data was furthermore processed to be partially used as a high-resolution digital elevation and surface models with a spatial resolution of approximately 0.13 m. Further, RGB images were used for the spectral classification. Additionally, infrared images were used for the spectral classification  After use of the RGB images and the LiDAR data for treetop identification, validation shapefile were created.

2.3 Preprocessing

Because the LiDAR data contained artefacts, all points higher than 30 m above ground were eliminated. Hence, just trees and shrubs remained. Still, the data contain some errors, which could not be rectified within the margins of this study. 

2.4 Established segmentation algorithms

2.4.1 lidR - Dalponte

The segmentation approach developed by Dalponte and Coomes is based on individual tree crowns (ITC). The ITC's are identified from the LiDAR point cloud by using a region-growing algorithm. For their ITC delineation they adapted a relatively simple method, introduced by Hyppä et al. [Hyppä et al., 2001]. This approach is able to find local maxima within a canopy height model (CHM) raster. Those maxima are identified as individual tree tops. Following, it uses a decision tree to "[...] grow individual crowns around the local maxima." [Dalponte and Coomes, 2016]. There are several steps the algorithm goes through: (1) The first one is a low-pass filter that smoothes the rasterized CHM to reduce the number of local maxima. (2) Secondly, a moving window approach is applied to identify local maxima. A local maximum is detected, when a pixel's value is greater than all other values within the window. (3) Then, every local maximum identified is labeled as a initial region around which a "tree crown can grow". This is done by extracting the height of the four neighbouring pixel. They are added to the potential "tree crown" if their vertical distance and height are less some user-defined value. (4) This is done iteratively as long as no more pixels are added. (5) At last, the first-return values from the LAS points are extracted and are turned into polygons by applying a 2D convex hull [Dalponte and Coomes, 2016]. Note, that this approach can be viewed as semi-automatic, since the user has to set the size of the moving window, the small-tree cut-off height and the height difference threshold. Dalponte's algorithm is provided by the function `dalponte2016` of the lidR package.

Approach: After loading the CHM and the LAS-files, we segmented the trees using the `segment_trees` function (lidR). Inside this function, the Dalponte's algorithm was used as the individual tree segmentation function. This procedure was repeated for shrubs and tree-shrub-layers (for parameters see Table 1.). Finally, the results were converted to polygons using the `tree_polygons` function.

	th_tree	th_seed	th_cr	max_cr
trees	2	0.45	0.55	10000
shrubs	0.6	0.45	0.55	10000
tree-shrub	0.6	0.45	0.55	10000
tree-shrub (tree)	2	0.45	0.55	10000
tree-shrub (shrub)	0.6	0.45	0.55	10000

Table 1: Parameters for the `dalponte2016` function

2.4.2 lidR - Silva

Silva et al. state in their 2016 paper a new and promising approach for individual tree segmentation based on the on the rLiDAR package. For the individual tree detection the `FindTreesCHM` function is applied to the CHM raster. As in Dalponte's function, it as well uses a local maximum algorithm and a moving window method to detect treetops. For the individual crown delineation it uses the `ForestCAS` function from the rLiDAR package. This function start by applying a variable radius crown buffer to set limits for the initial crown area. Afterwards, the variable radius is calculated for the individual tree by multiplying the tree height (LiDAR-derived) by a user-set factor. The merged tree polygons are determined using an area delimitation (see Silva et al. 2016 for more detailed information). The data is then split using a centroidal voronoi tessellation approach [Aurenhammer and Klein, 1999]. This is done to isolate the individual tree polygons. The polygons are then clipped from the

CHM [Silva et al., 2016]. The method is provided by the `silva2016` function of the lidR package.

Approach: The approach is the same as for the `dalponte2016` function, since both function operate inside the `segment_tree` function (lidR) (parameters below).

	max_cr_factor	exclusion
trees	0.6	0.3
shrubs	0.6	0.3
tree-shrub	0.6	0.3
tree-shrub (tree)	0.6	0.3
tree-shrub (shrub)	0.6	0.3

Table 2: Parameters for the `silva2016` function

2.4.3 lidR - Li

In 2012 Li et al. developed a new method for individual tree segmentation based on the relative spacing between trees. Generally, the spacing between the tops of trees is larger than the spacing at the base. This approach takes a LiDAR point cloud and identifies the target tree by including points that are nearby, while excluding points further away. To overcome the difficulty of overlaps at the bottom of the tree, the points are classified sequentially, from top to bottom. Hence, points with a larger spacing than the set threshold can be excluded. A minimum spacing rule dictates the spacing for included points. The method is provided by the `li2012` function of the lidR package.

Approach: After loading the CHM and the LAS-files, we segmented the trees using the `segment_trees` function (lidR). Inside this function, the `li2012` algorithm was used as the individual tree segmentation function. This procedure was repeated for shrubs and tree-shrub-layers (for parameters see Table 1.). Finally, the results were converted to polygons using the `tree_hulls` function. (parameters below).

	dt1	dt2	R	Zu	hmin	speed_up
trees	1.5	2	1	15	5	10000
shrubs	0.5	1	1	5	0.2	10
tree-shrub	1.5	2	2	15	0.6	10
tree-shrub (tree)	1.5	2	2	15	2	10
tree-shrub (shrub)	1.5	2	2	15	0.6	10

Table 3: Parameters for the `li2012` function

2.4.4 uavRst

The `uavRst` package, introduced by Christoph Reudenbach, contains three valuable functions that are of interest for the purpose of this study.

The first function is the `chmseg_FT` function. It is based on the ForestTools package and uses an approach based on the imagr watershed algorithm. From an input tree position shapefile and a CHM it calculates crown area based on a watershed algorithm. The output format can be defined by the user. Further input variables are the minimal tree height, the radius of the moving window and a boolean input for verbosity [Meyer and Reudenbach, 2018].

Approach: The tree position layers and the CHM's were loaded. This time, the CHM's were smoothed by applying a Gaussian filter. The filter proved to yield better results in the end. Window sizes for the Gaussian filter: trees = 39; shrubs = 11; tree-shrub = 39. Further, the `chmseg_FT` function was applied to trees, shrubs and tree-shrub layer (parameters below).

The second function is the `chmseg_RL` function. It is based on the rLiDAR package and is based on the generic approach of [Silva et al. 2016] as described above. The advantage of the `chmseg_RL` function is its user friendliness, since no LAS-file is necessary. The function requires only a CHM raster and a tree position matrix. The input parameters are the maximal crown area and an exclusion factor [Meyer and Reudenbach, 2018] (see 2.4.2).

	minTreeAlt	format	winRadius	verbose
trees	2	polygons	1.5	FALSE
shrubs	0.6	polygons	1.5	FALSE
tree-shrub	0.6	polygons	1.5	FALSE
tree-shrub (tree)	2	polygons	1.5	FALSE
tree-shrub (shrub)	0.6	polygons	1.5	FALSE

Table 4: Parameters for the chmseg_FT function

Approach: The tree position layers and the CHM's were loaded. Again, the CHM's were smoothed by applying a Gaussian filter. Window sizes for the Gaussian filter: trees = 15; shrubs = 39; tree-shrub = 15. Further, the chmseg_RL function was applied to trees, shrubs and tree-shrub layer (parameters below).

	maxCrownArea	exclusion
trees	10000	0.4
shrubs	5000	0.4
tree-shrub	5000	0.4
tree-shrub (tree)	5000	0.4
tree-shrub (shrub)	5000	0.4

Table 5: Parameters for the chmseg_RL function

The third function is the chmseg_ITC function. It is based on the LiDAR-derived ITC approach by Dalponte. Like the chmseg_RL function, the chmseg_ITC function requires not point cloud data input. Just a rasterized CHM is needed. Further, a EPSG code for a coordinate reference system (CRS), a moving window size, a threshold for the seed and the crown, the minimum tree height, and the maximum crown area are required [Meyer and Reudenbach, 2018].

Approach: The rasterized CHM was loaded. As for the chmseg_RL function, the CHM's were smoothed by applying a Gaussian filter. Window sizes for the Gaussian filter: trees = 19; shrubs = 19; tree-shrub = 19. Further, the chmseg_FT function was applied to trees, shrubs and tree-shrub layer (parameters below).

	EPSG	movingWin	TRESHSeed	TRESHCrown	minTreeAlt	maxCrownArea
trees	31254	31	0.45	0.55	2	10000
shrubs	31254	11	0.45	0.55	0.6	10000
tree-shrub	31254	33	0.45	0.55	0.8	10000
tree-shrub (tree)	0.2	0.9	2	10	50000	
tree-shrub (shrub)	0.6	0.7	0.2	10	50000	

Table 6: Parameters for the chmseg_ITC function

2.5 CENITH

CENITH is a wrapper tool for the ForestTools package, to search the most well-suited parameters iteratively and perform the segmentation task. Its main functions are BestSegVal and TreeSeg. Furthermore, it provides a k-fold cross-validation function (TreeSegCV).

BestSegVal is a supervised approach and uses computed tree positions to validate the fitting values. It iterates of the input parameters and finds the best fitting ones. If errors are encountered, the loop continues and returns NA for the corrupted iteration. The function provides a filter parameter, that applies a sum filter to the CHM by a moving window approach. BestSegVal return a table of fitted parameters. The function requires a rasterize CHM and estimated tree positions in form of vector layer.

Approach: After the CHM's and position shapefiles were loaded, the BestSegVal function was applied to all the categories (trees, shrubs, tree-shrub) (parameters below).

	a	b	h	MIN	MAX	filter
trees	0.1-0.9 (by 0.1)	0.1-0.9 (by 0.1)	2-20 (by 1)	10	500000	3
shrubs	0.1-0.9 (by 0.1)	0.1-0.9 (by 0.1)	0.1-2 (by 0.1)	10	500000	3
tree-shrub	0.1-0.9 (by 0.1)	0.1-0.9 (by 0.1)	0.2-4 (by 0.2)	10	500000	3
tree-shrub (tree)	0.1-0.9 (by 0.1)	0.1-0.9 (by 0.1)	2-20 (by 0.2)	10	500000	3
tree-shrub (shrub)	0.1-0.9 (by 0.1)	0.1-0.9 (by 0.1)	0.2-5 (by 0.2)	10	500000	3

Table 7: Parameters for the BestSegVal function

a: numeric - single value, combination of values or sequence for MovingWindow
b: numeric - single value, combination of values or sequence for MovingWindow
h: numeric - single value, combination of values or a sequence for the maximum height of trees (in meter) to detect trees.

MIN: numeric - single value, combination of values or a sequence of minimum area for crowns. Smaller polygons are cropped Default = 0

MAX: numeric - the maximum area for crowns. Larger polygons are cropped. Default=1000

[Schönberg, 2020]

The **TreeSeg** function uses a watershed algorithm to compute polygon segments for tree crowns. The algorithm uses a moving window to identify local maxima in the rasterize CHM to compute the segments. For the computation of the tree crown segments the function requires only a rasterize CHM.

Approach: After BestSegVal yielded a table with the best-fitting values, the ones with the highest hitrate and most appropriate amount of identified segments were inserted to TreeSeg. Again, this function was applied to trees, shrubs, as well as to tree-shrub.

3 Results

The BestSegVal function of the CENITH package yielded the following parameters to be the best fitting ones

	a	b	h	MIN	MAX
trees	0.1	0.5	2	10	50000
shrubs	0.9	0.9	0.2	10	50000
trees & shrubs	0.1	0.9	0.2	10	50000
tree-shrub (tree)	0.2	0.9	2	10	50000
tree-shrub (shrub)	0.6	0.7	0.2	10	50000

Table 8: Best fitting parameters for TreeSeg according to the output of BestSegVal

The tables 9-13 show the number of tree segments that the different algorithms yielded. Further, the number of validation points, lying inside and outside the constructed polygons are presented. The results of li2012 are not presented in the results due to its failure to yield a proper segmentation in areas with slope inclination. (figure 2).



Figure 2: Polygons computed by li2012 (lidR) for trees. It failed entirely to segment any trees correctly and was therefore not taken into account in further investigation. This study site is supposed to be the easiest for the algorithms.

All algorithms seem to perform accurate for the segmentation of trees. All of them captured all validation points. While some (Silva and rLiDAR) computed polygons for every tree, others such as Dalponte and ForestTools drew polygons around groups of tree (see figure 2). CENITH segmented all trees accurately.

algorithm	segments	inside	outside	validation points
Dalponte	11	13	0	13
Silva	13	13	0	13
rLiDAR	13	13	0	13
ForestTools	12	13	0	13
CENITH	13	13	0	13

Table 9: Performance of the different algorithms in regards to the number of **tree** segments created and the number of validation points lying inside and outside the computed polygons

algorithm	segments	inside	outside	validation points
Dalponte	122	122	3	125
Silva	125	125	0	125
rLiDAR	125	121	4	125
ForestTools	125	125	0	125
CENITH	136	123	2	125

Table 10: Performance of the different algorithms in regards to the number of **shrub** segments created and the number of validation points lying inside and outside the computed polygons

algorithm	segments	inside	outside	validation points
Dalponte	46	46	1	47
Silva	47	47	0	47
rLiDAR	47	42	5	47
ForestTools	31	31	16	47
CENITH	22	17	30	47

Table 11: Performance of the different algorithms in regards to the number of **tree & shrub** segments created and the number of validation points lying inside and outside the computed polygons

algorithm	segments	inside	outside	validation points
Dalponte	8	8	0	8
Silva	8	8	0	8
rLiDAR	8	8	0	8
ForestTools	8	8	0	8
CENITH	8	8	0	8

Table 12: Performance of the different algorithms in regards to the number of **tree & shrub (tree)** segments created and the number of validation points lying inside and outside the computed polygons

algorithm	segments	inside	outside	validation points
Dalponte	38	38	1	39
Silva	38	31	8	39
rLiDAR	39	30	9	39
ForestTools	39	39	0	39
CENITH	24	18	21	39

Table 13: Performance of the different algorithms in regards to the number of **tree & shrub (shrub)** segments created and the number of validation points lying inside and outside the computed polygons

For the segmentation of shrubs, Silva and ForestTools were able to include all validation points, while Dalponte missed 3, rLiDAR 4 and CENITH also 4. Again, CENITH computed noticeably less segments than the other algorithms, while including approximately the same number of validation points as Dalponte and rLiDAR (see figure 3).

Coming to the combined layer (trees and shrubs), only Silva's algorithm segmented trees as well as shrubs correctly. While Dalponte's method missed one validation point, rLiDAR and ForestTools scored lower, with 16 missed points, respectively. CENITH performed very inaccurate for the combined layer, missing 39/47 validation points. As shown in figure 4 it segmented the trees correctly, but could not discriminate the shrubs.



Figure 3: The tree segmentation was done by the mentioned algorithms and the polygon were then classified by a random forest classifier to point out falsely segmented trees

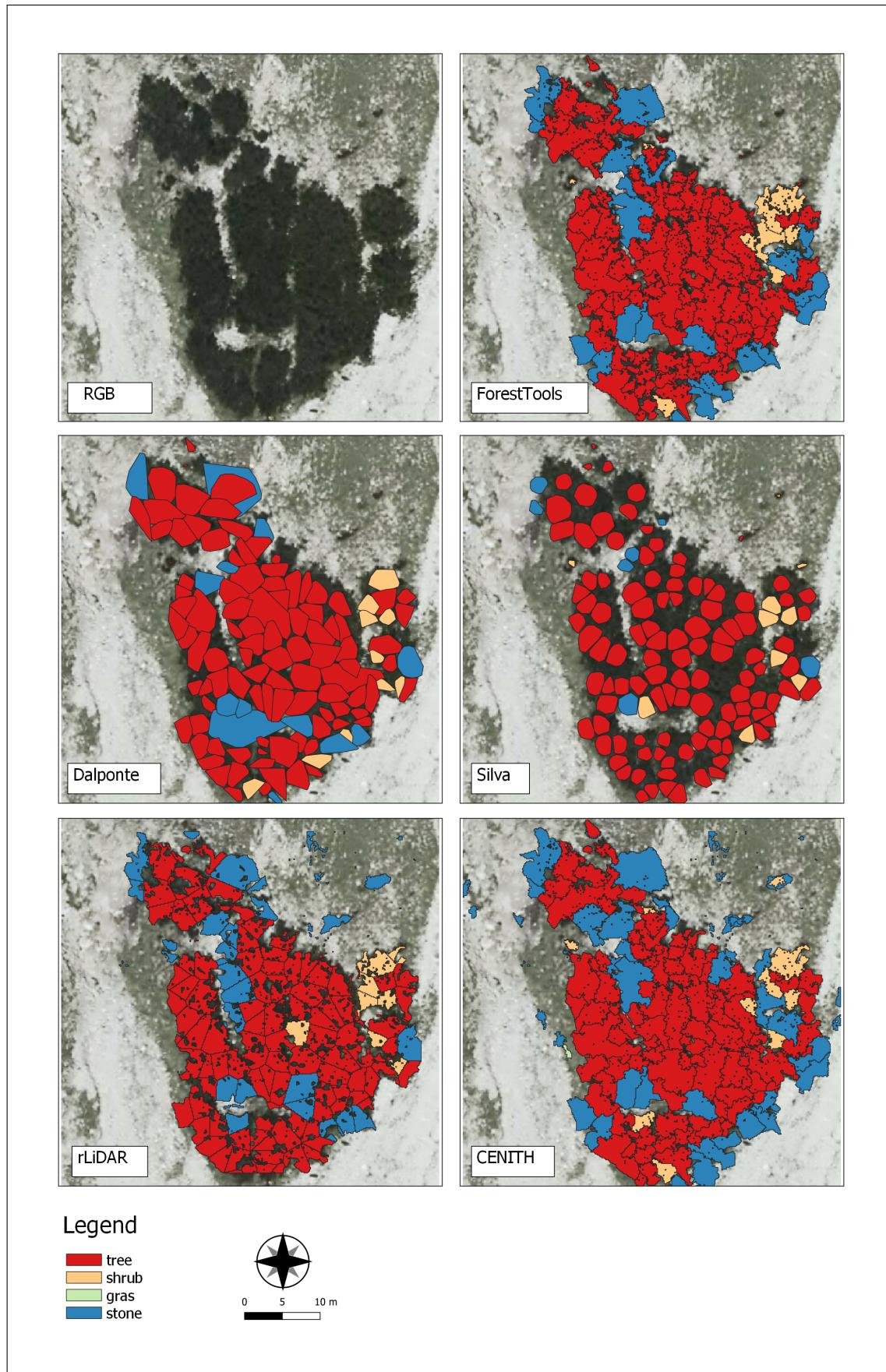


Figure 4: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

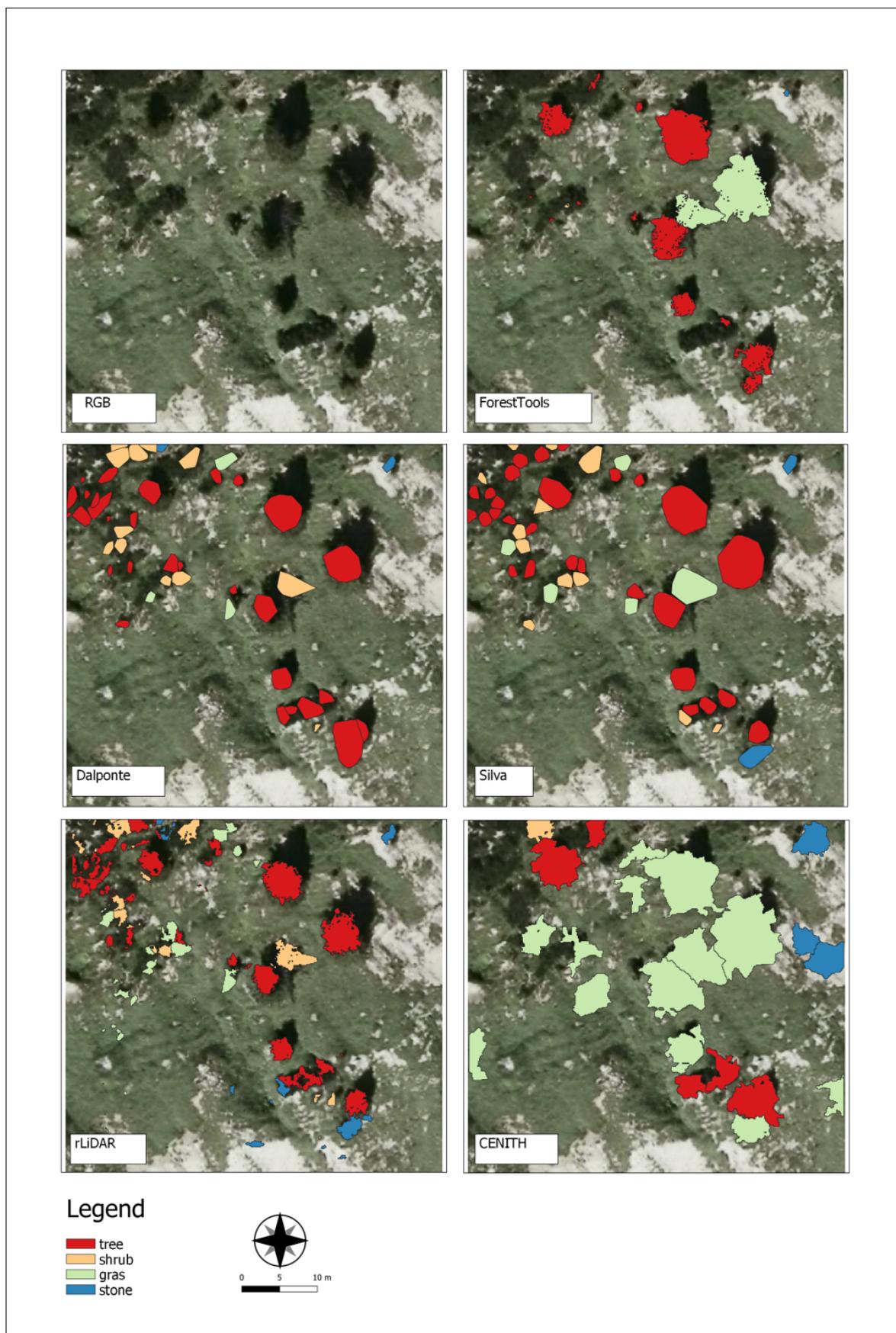


Figure 5: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

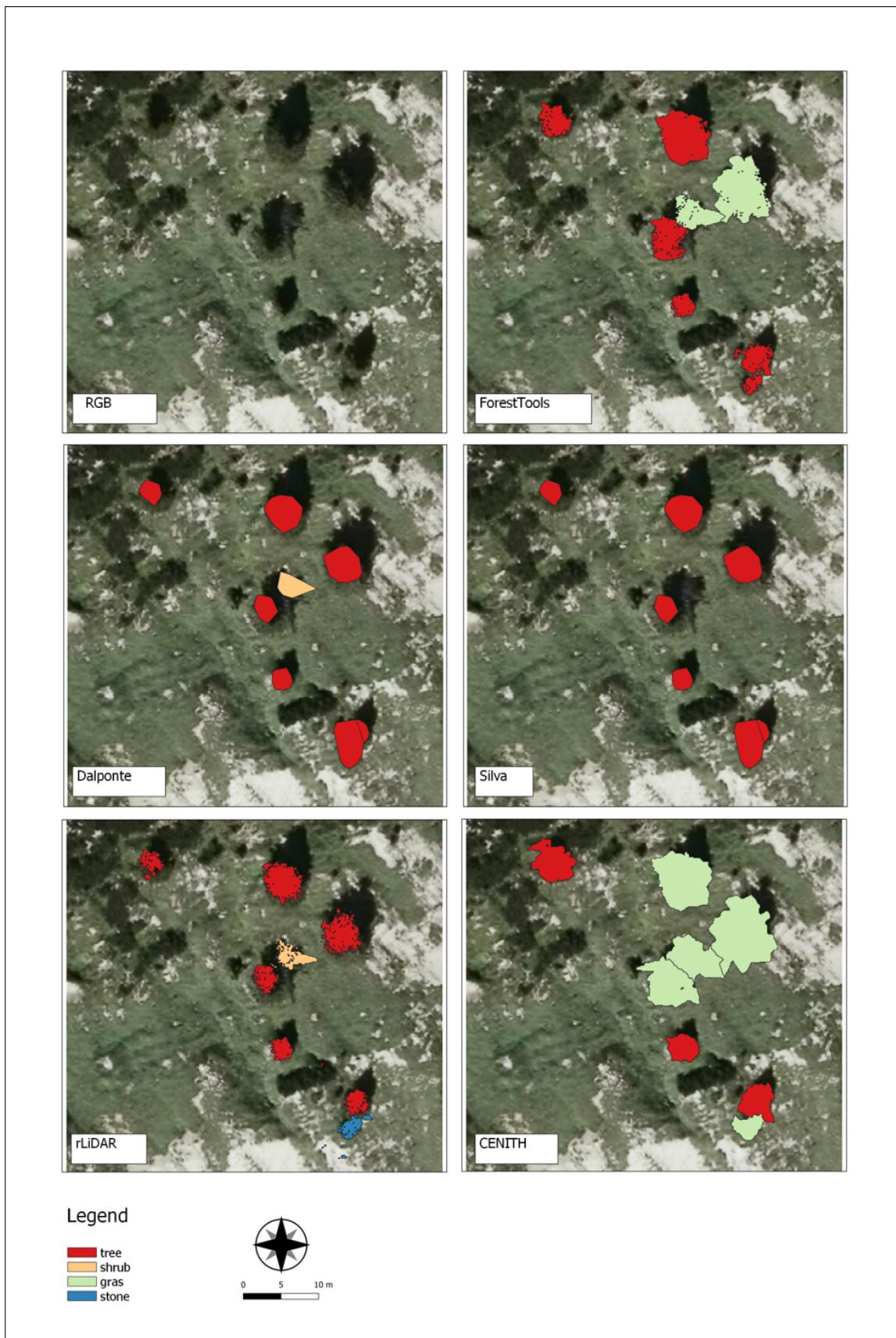


Figure 6: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

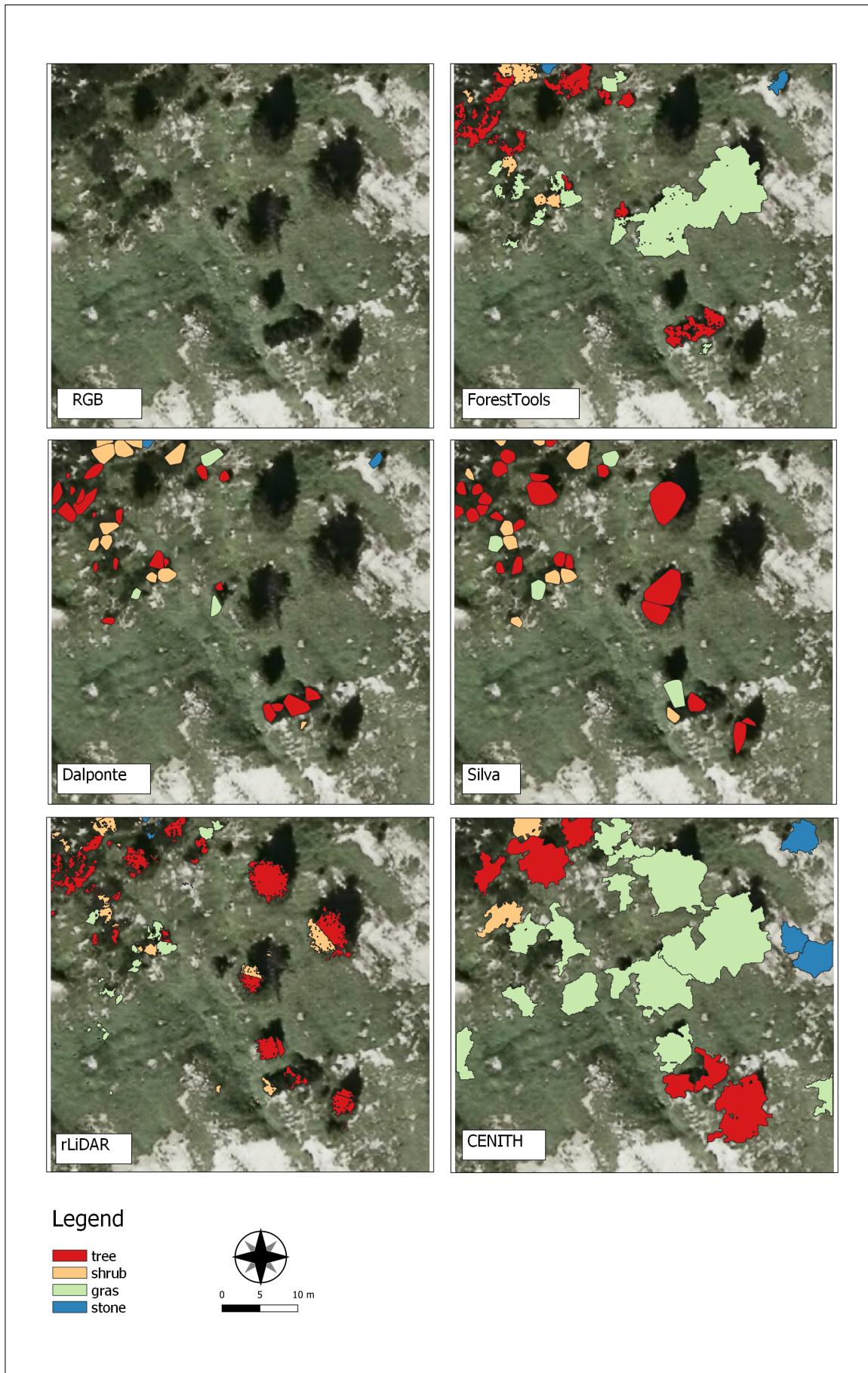


Figure 7: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees



Figure 8: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

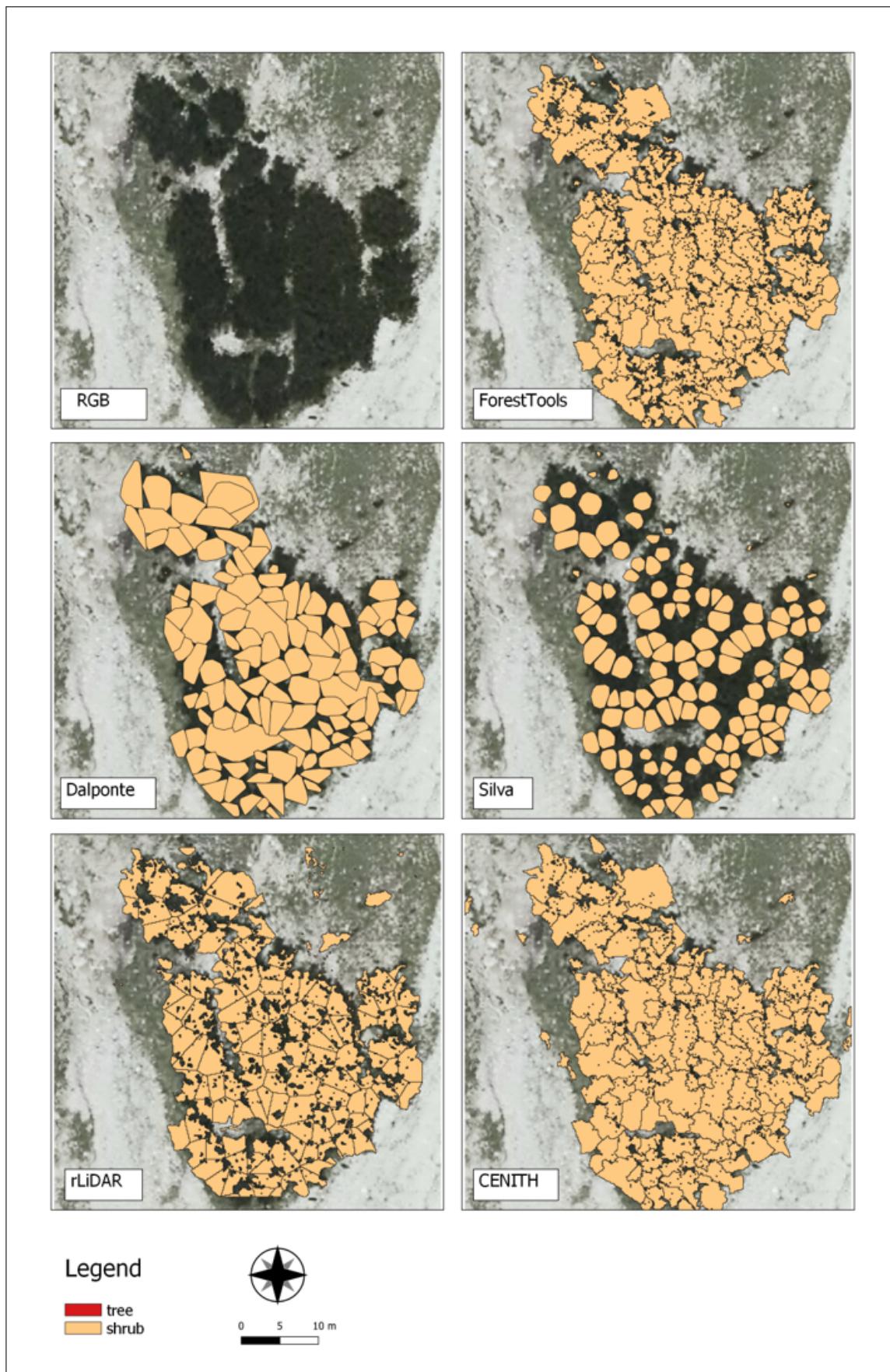


Figure 9: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

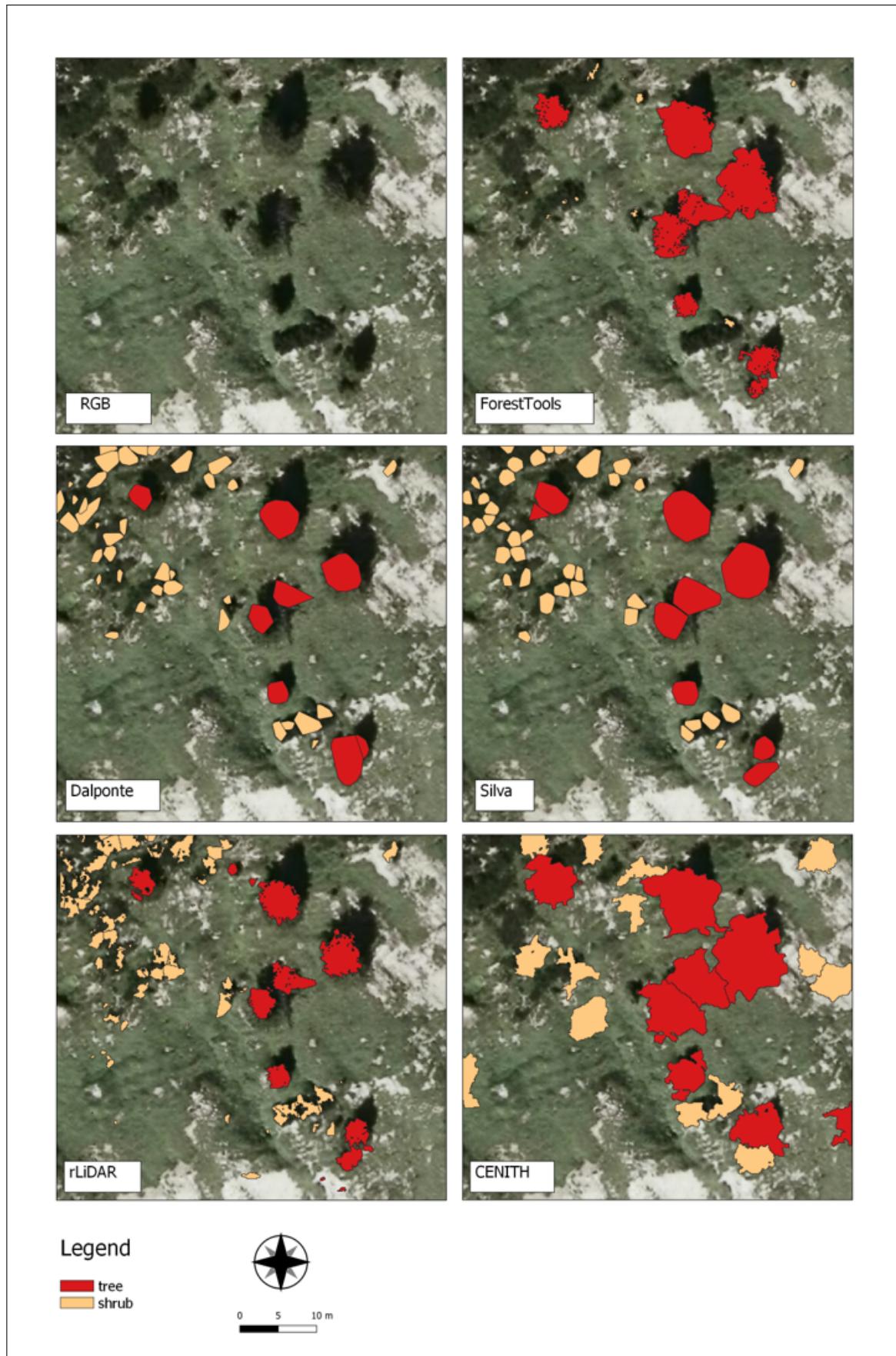


Figure 10: The tree segmentation was done by the mentioned algorithms and the points were then classified by a random forest classifier to point out falsely segmented trees

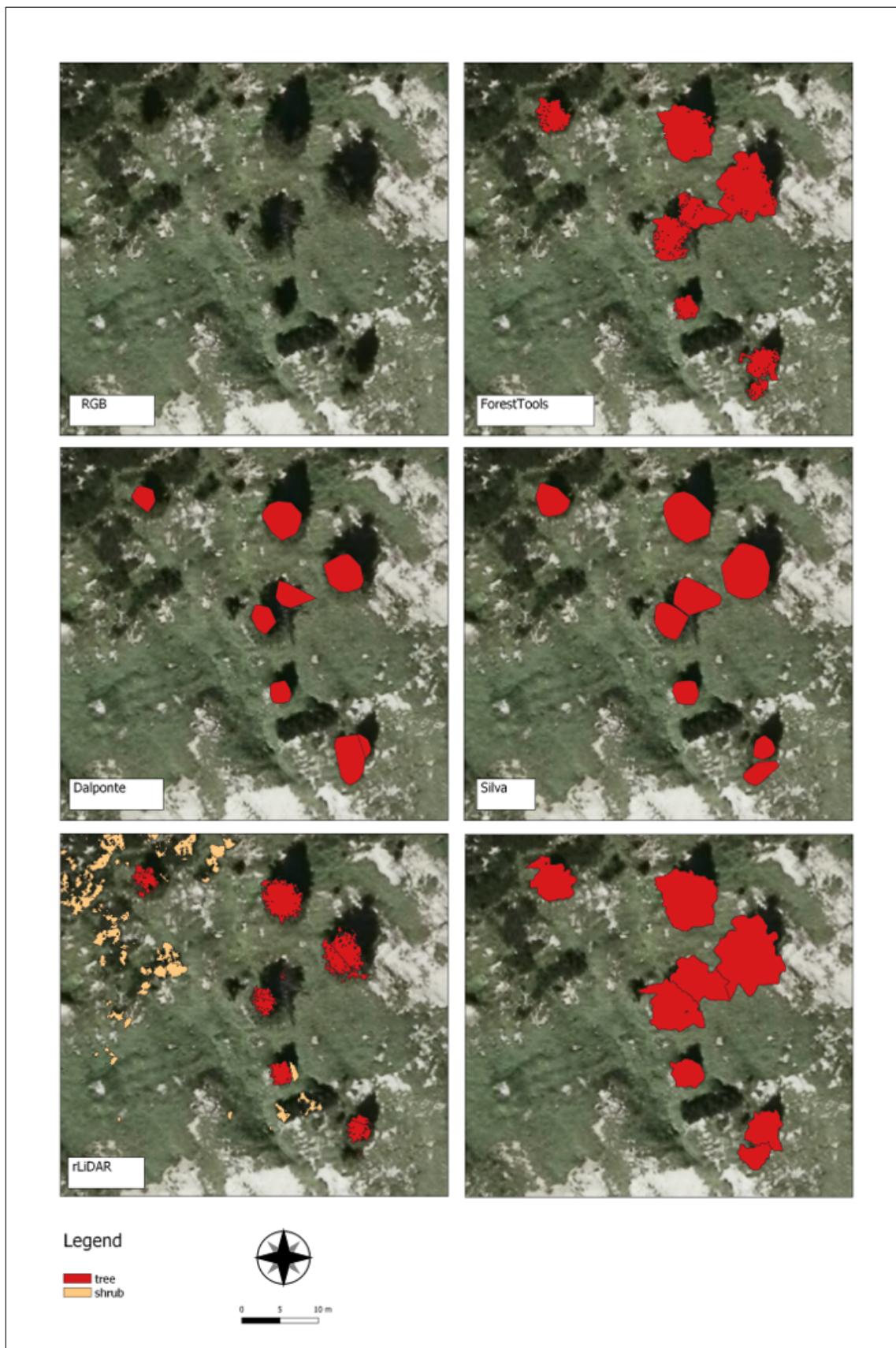


Figure 11: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

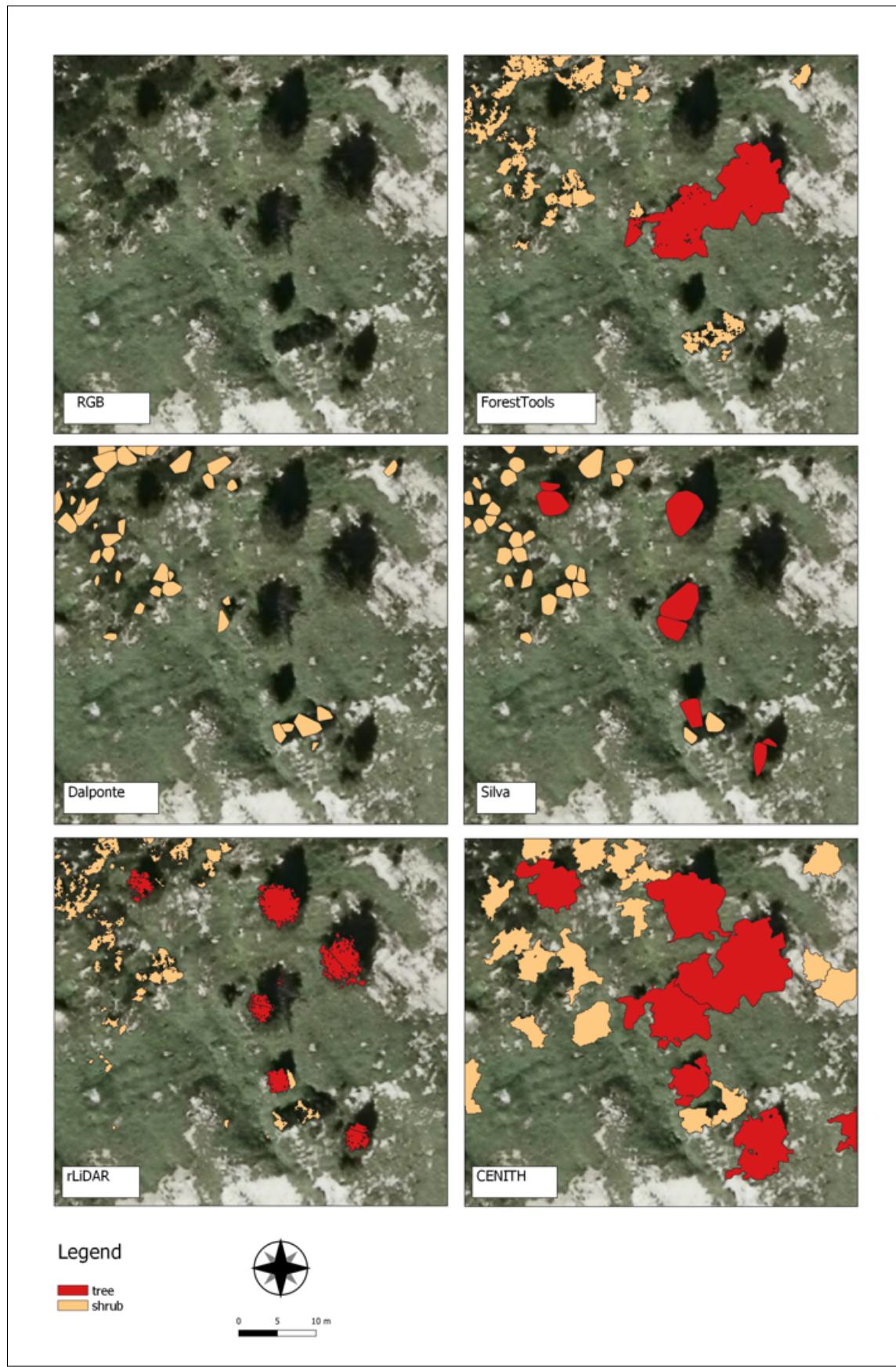


Figure 12: The tree segmentation was done by the mentioned algorithms and the polygons were then classified by a random forest classifier to point out falsely segmented trees

4 Discussion

CENITH performed reasonably well on the segmentation of trees and shrubs separately. It segmented only the trees in the combined layer. Since it is not supposed to be a shrub segmentation tool, rather than a tool for tree segmentation it lays within the margins of an acceptable result. Furthermore, the purpose of this study, was to validate CENITH's applicability on the tree segmentation in alpine treelines. Hence it identified all trees properly, a flawless workflow can be stated. Compared to the other algorithms, CENITH offers two very easy-to-use functions for the segmentation approach and one for validation. All other tested algorithms require either or the use of LAS-file point cloud data. For beginners, this might be complicated and is quite RAM intensive. CENITH requires only high resolution CHM's to perform the segmentation.

The downside of the package is the long computation time of the BestSegVal function, which took about 1 1/2 days to find the best parameters. Nevertheless, the function can be parallelized which decreases the computation time significantly.

5 Conclusions

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