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DETERMINING THE NUMBER OF TREES USING AIRBORNE LASER SCANNING AND TRUE ORTHOIMAGERY

OKREŚLANIE LICZBY DRZEW Z WYKORZYSTANIEM LOTNICZEGO SKANOWANIA LASEROWEGO I PRAWDZIWYCH ORTOFOTOMAP

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Introduction

A multi-level forestry model, which is not only to predict income, requires accurate and rapid information about its resources. Precisely determined parameters such as diameter at breast height (dbh), height, canopy closure and volume are essential for proper decision making and therefore for forest management. Typical methods of tree/forest measurement in Poland are based on statistical methods and define average stand parameters from surveys done on selected areas (grid of forest inventory plots).

It has been shown by many authors that CIR images and airborne laser scanning (ALS) data are suitable for determining selected forest parameters (Dubayah, Drake 2000; Lefsky et al., 2002). The main issue with airborne laser scanning, for forests concerns the vertical structure (Hyyppä et al., 2006; Wężyk et al., 2008). Airborne images (photos or line scanner multi- or hyperspectral imagery), on the other hand, can deliver information about tree species and health conditions by means of interpretation and classification (Wężyk et al., 2003; Lillesand et al., 2007). Both types of data can be used for determining tree numbers, tree density and spatial arrangement (Brandtberg, Walter, 1998; Leckie et al., 2003; Wang et al., 2004; Koch et al., 2006). The number of trees in the forest unit changes over the time. The older the forest stand is, the fewer tree stems it has, and even if planted in a regular order, different habitat conditions and competition between them, lead to diversified spatial distribution of trees in the stand.

The use of ALS data for counting trees in a forest, has been the subject of many studies. The approach used by most authors is based on so called "watershed segmentation" (Bleau, Leon, 2000; Kwak et al., 2007), a procedure based on GIS spatial analysis of the inverted Canopy Height model (CHM) built on the first pulses reflected from the crown surface and registered by an airborne scanner. This method results in delineating regions (crown surfaces) which share the same outflows.

Other methods are based on remotely sensed imagery (airborne digital photos, line scanner), on which Object Based Image Analysis (Wężyk, de Kok R., 2005; Tiede, Hoffmann, 2006; Wężyk et al., 2006) is performed in order to find tree crowns. So called "hot-spots" have a macrostructural component in the bi-directional reflection properties of solar energy in the landscape as well as a typical microstructural feature in the tree canopy. These "hot-spots" in tree crowns shares some similarity with equal effects on other scales, particularly in the sense that shadow components are not detectable within, but very easy to find directly around, crowns. Therefore "hot-spots" can be retrieved using features with relational attributes towards their neighborhood.

Segmentation decisions assign local populations of pixels which share a common spectral property (Maier et al., 2008; Tiede et al., 2008). Although segmentation can be considered a special form of classification, the crucial part in segmentation is the establishment of the unique features of each local population based upon a very small range of common properties among spatial (and local) neighboring pixels and their characteristic differences to neighboring pixel-populations, not necessarily in the immediate vicinity of these local pixels. The segmentation process results in local pixel populations with a unique identity. Based upon the total combination of attributes, each of these pixel populations is (almost) unique, especially in shape, area and of course in the neighborhood. Only a relatively small set of these attributes are considered in the sequential classification process afterwards. Registered local pixel populations can also be regarded as image object-primitives or basic image objects. Classification does not concern the uniqueness of each member inside the population, but stresses the common properties over a wide range of features among the members, not locally, but within the feature space. Class membership is based upon a small selection of attributes compared to the total amount of attributes assigned to a local pixel population or image object primitive. A perfect segmentation setting for forest inventory purposes would allow registration of the hot-spots as a local population with a unique identity. The relative deviation from its complete surrounding populations, which do not lack shadow properties, makes it easy to assign tree crown hot-spots fully automatically. The relative properties concerning their neighborhood are unique and repetitive through several scales and solar conditions. Transferability is therefore inherent to the standard behavior of tree crown hotspots and their surroundings. The structure of the tree, as it strives to capture sunlight, must create shadow prone areas within and around the light intercepting branch/leaf skeleton. Ideal cases are scale levels for hotspots, where at least 20 pixels are part of the crown center. This would be effective in crown areas higher larger than 10 metres in height and with image resolutions better than 0.5 m. The automatic registration of tree hotspots as part of a shadow containing the crown as well as shadow surrounding the crown area makes it possible to assign a unique identity to each individual crown shaped complex. For trees with a simple, monopodial shape, this would be identical to a nearly complete tree crown structure. For non monopodial and complex tree shapes, these properties are less successful. The beech tree family, being well known for it's crown complexity and the inability to recognize individual within tree populations, by visual as well as automatic image interpretations. Because of the huge variety in crown shapes among species and ecotypes, the general trend is in favor of a crown that optimizes light interception and strives for continuous height increment. This would favorites crown shapes showing hotspots and often a single hotspot per crown.

In addition to these methods, we have adopted a technique based on data fusion: ALS cloud point and true orthoimagery. The method uses a single NIR band from available line scanner bands (TopoSys) to classify areas covered by high vegetation (pine crowns). The plant spectral response is much more distinct within the invisible range (NIR; 750–900 nm) and generally pixel values are highest when illuminated part of tree crowns ("hot-spots"). This fact was used as the base of our second approach, in the fusion method it was only a mean to mask areas overlaid by pine crowns and specify the regions for watershed segmentation.

Generally, tree counting procedures based on ALS data lead to underestimation of the tree numbers. However, Persson et al. (2002) have shown that 71% of correctly recognized trees represents 91% of the total stem volume in a stand. The smaller the crown is, the more difficult it is to detect, however a small crown also means a low timber volume.

The errors which can occur during automatic tree detection, using both ALS and image data, are of two types. First, the so called commission errors can occur – when an object (e.g. branch) is incorrectly detected as a tree or one tree is recognized as many trees (due to delineation inside the crown). Secondly, one can experience omission errors – where an existing tree is not recognized (Wulder et al., 2000). These two types of errors describe the approach more precisely than only the detected number of trees.

The purpose of this study was to test the different approaches of determining the number of trees using ALS and true orthoimagery datasets and compare the results to a reference.

Materials and methods

Study area

The study transect was located in the central-west Poland, in the Milicz Forest District RDLP Wrocław (WGS84: 51°27' N; 17°12' E), covering approximately 3.2 ha. The area was selected from a homogeneous part of a subcompartment (236a) covered by Scots Pine forest (*Pinus sylvestris* L.). The age of the stand, according to Polish State Forest database (SILP/LAS), was 107 years, the mean height was 23 m and the dbh was 30 cm.

Reference data

Tree crowns were manually digitised on screen from the CIR true orthoimagery, highlighted by CHM to be used as the reference data. The total number of tree crowns digitized in the transect was 1515 (ca. 473 trees/ha). An additional check study was done, based on on-screen digitizing from the RGB orthophotos generated from aerial images (UltraCam Vexcel; 0.15 m pixel resolution). The results show that using only radiometrical response, without information about the height of the trees, leads to errors of omission.

ALS and line scanner TopoSys data

The ALS data were collected in July 2007 using a TopoSys glass fibre scanner Falcon II. The average flight height was 550 m above the ground. Mean point density was ca. 14 pts/m^2. True orthoimagery (16 Bit; 4 bands: R, G, B, NIR) was acquired simultaneously with ALS data, with the pixel size equal to 0.25 m. During the study, the authors experienced problems with generating correct canopy models in the overlapping areas of scans because of different point densities, therefore the shape of the study area was chosen to contain only single scan from the many acquired during the scanning campaign. Solving this problem will be the subject of separate studies.

To determine the number of trees, different approaches were used. The first one was based only on ALS point clouds, the second one, on segmentation of true orthoimagery with a small contribution of height from LiDAR data. The third method was an experimental fusion of ALS data and single NIR-band true orthoimage.

CHM generation and watershed segmentation

To define the number of trees using the "GIS watershed" approach, the CHM was generated using different parameters and algorithms. First, the DTM was created (Terrasolid Ltd.) and used to normalize the ALS point cloud. This dataset was used for different types of canopy modeling. The models differ in pixel size, filtering method and local maxima and minima preservation (Table 1, Fig. 1). All these parameters were defined using the FUSION software (McGaughey, 2007).

The watershed segmentation algorithm was performed (ArcGIS ESRI) on each of the surface canopy models (GRID) in order to find which pixel size and filtering parameters are optimal for deriving the number of trees closest to the reference value. In most cases, the watershed algorithm produced a result in which many segments were too small, especially for CHMs with pixel size 0.25 m. Knowing the average size of a crown, polygons smaller than 1 m^2 were removed in such cases.

Table 1. Parameters used for creating different CHMs

CHM	Pixel size [m]	Filter	Preserving maxima and minima
A1	0.25	none	–
A2	0.25	smooth (3x3), median (3x3)	–
A3	0.25	smooth (3x3), median (3x3)	+
A4	0.25	smooth (5x5), median (5x5)	–
A5	0.25	smooth (5x5), median (5x5)	+
A6	0.25	smooth (9x9), median (9x9)	–
A7	0.25	smooth (9x9), median (9x9)	+
B1	0.5	none	–
B2	0.5	smooth (3x3), median (3x3)	–
B3	0.5	smooth (3x3), median (3x3)	+
B4	0.5	smooth (5x5), median (5x5)	–
B5	0.5	smooth (5x5), median (5x5)	+
B6	0.5	smooth (9x9), median (9x9)	–
B7	0.5	smooth (9x9), median (9x9)	+
C1	1.0	none	–
C2	1.0	smooth (3x3), median (3x3)	–
C3	1.0	smooth (3x3), median (3x3)	+
C4	1.0	smooth (5x5), median (5x5)	–
C5	1.0	smooth (5x5), median (5x5)	+
C6	1.0	smooth (9x9), median (9x9)	–
C7	1.0	smooth (9x9), median (9x9)	+

Object oriented image analysis (OBIA)

Definiens Developer ver. 7.0.8 was used to segment the image to gather the tree-crown "hot-spots". The segmentation was based upon derived channels from the original NIR/Red/Green/Blue color composite (line scanner TopoSys; 25 cm pixel; 16 Bit). The first derived channel was a Principle Component (PC1) and the second and third channels were edge detection imagery. After initial classification of the "hot-spots", a relaxation of the segmentation took place, with the scale factor equal to 35, to increment the area of the "hot-spot" and let it merge (object based fusion) with its direct edges: border/frame (Wężyk, de Kok R., 2005). This step allows the creation of crown hotspots with an area of more than 1.5 m^2 (>25 pixels). The nDSM (CHM) employed in this method was used to cut off objects below 7.0 m height.

It is notable that 'hot-spot's in tree crowns share some similarity with equal effects at other scales, particularly in the sense that shadow components are non existent within these hotspots, but clearly detectable directly in image objects (and here in edges) surrounding crown hotspots. The biophysical property of the crown hotspot is related to tree crowns in general and does not depend on solar angle or season. This makes this feature reliable and transferable.

Figure 2 presents OBIA result, with a single detected hotspot marked in red.

Analysis based on data fusion

The not perfect results produced by the two approaches showed the authors the necessity to test an additional solution: the fusion of ALS and image datasets (Fig. 3). Standard watershed segmentation methods lead to incorrect estimation of the number of trees when the crown shape is too complex or when there are smaller crowns or undergrowth in the gaps (Kwak et al., 2007). To overcome this problem, a mask containing tree crowns was created based on NIR band (true ortho) to limit the areas for the watershed segmentation. The first step was the reclassification of NIR band, into two classes. The threshold value (<1945) was chosen in order to separate tree crowns from the rest of the image (mainly shadows). The mask (0 and 1) was filtered and generalized and then multiplied by CHM height value, creating a new dataset for watershed segmentation.

Results

The results of the „GIS watershed" CHM segmentation (Table 2) were used as preliminary verification of the suitability of the canopy surface created for analysis. It was clearly observed that a small pixel size (0.25 m), together with lack of a small degree of filtering (smooth and median filter) leads to overestimation of the tree number (i.e.: A1 and A2). On the other hand, a pixel size of 1.0 m and/or to strong filtering, leads to its underestimation (i.e.: B6, C2÷C7). The results were additionally filtered in order to remove poligons (segments) smaller than 1m^2. These polygons, in most cases, especially eith the models with small pixel size, were a result of wrongly performed segmentation by the program. In addition, in a mature pine forest stand (107 years), the probability that tree crown area is smaller than 1m^2 is very low. Especially for CHM based on small pixel size, this treshold resulted in reducing the commision

Table 2. "GIS watershed" segmentation results. Reference number of trees: 1515

CHM	Number of detected trees			
	all crowns		after polygons removal <1 m^2	
	trees	%	trees	%
A1	10.647	602.8	8210	441.9
A2	2.598	71.5	2199	45.1
A3	2.764	82.4	2388	57.6
A4	**1.621**	**7.0**	**1268**	**-16.3**
A5	**1.679**	**10.8**	**1296**	**-14.5**
A6	1.042	-31.2	753	-50.3
A7	1.049	-30.8	760	-49.8
B1	3.013	98.9	2877	89.9
B2	**1.277**	**-15.7**	**1106**	**-27.0**
B3	**1.280**	**-15.5**	**1144**	**-24.5**
B4	841	-44.5	660	-56.4
B5	859	-43.3	677	-55.3
B6	340	-77.6	267	-82.4
B7	330	-78.2	264	-82.6
C1	**1.078**	**-28.8**	**1077**	**-28.9**
C2	506	-66.6	503	-66.8
C3	545	-64.0	543	-64.2
C4	229	-84.9	226	-85.1
C5	239	-84.2	238	-84.3
C6	78	-94.9	78	-94.9
C7	75	-95.0	75	-95.0

errors. Further accuracy analyses were carried out for models where the derived number of trees is ± 30% from the reference (bold in Table 2).

The GIS spatial analysis with the reference data (crown outline polygons) and watershed algorithm derived centroids showed (Table 3) that both commission (objects wrongly detected as trees) and omission errors (trees not detected) occurred.

The results of the two approaches and additional data fusion method differ from the reference data gathered through on-screen digitization (Table 4, Fig. 4). With the "GIS watershed" approach, the best results have been derived from the A4 CHM surface (pixel size: 0.25 m, smooth filter 5x5; median filter 5x5; without preserving local maxima and minima). The OBIA approach derived results equal to 74.5% of correctly detected trees. The result of the data fusion method led to the detection of 72.6% trees correctly. The commission errors were lowest using the "GIS watershed analysis" (4.3%) and almost twice as high using OBIA (8.1%) and the data fusion method (8.9%). Conversely, the omission errors were highest concerning the "GIS watershed" approach (28.4%) and lowest for data fusion method (16.4%).

Table 3. Detailed watershed segmentation results. Reference tree number: 1515

Results		CHM surface									
		A4		A5		B2		B3		C1	
		all	filtered	all	filtered	all	filtered	all	filtered	all	filtered
Detected trees	trees	1621	1268	1679	1292	1277	1104	1280	1141	1078	1060
	%	107,0	83,7	110,8	85,3	84,3	72,9	84,5	75,3	71,2	70,0
Correctly detected trees	trees	984	1015	984	1017	968	970	974	979	914	913
	%	65,0	67,0	65,0	67,1	63,9	64,0	64,3	64,6	60,3	60,3
Commission error	trees	236	65	410	134	215	99	208	106	116	105
	%	15,6	4,3	27,1	8,8	14,2	6,5	13,7	7,0	7,7	6,9
Ommission error	trees	411	430	393	416	513	512	493	505	568	572
	%	27,1	28,4	25,9	27,5	33,9	33,8	32,5	33,3	37,5	37,8

Table 4. Results of analysed approaches. Reference number of trees: 1515

Method		GIS watershed (A4, filtered)	OBIA (filtered)	Data fusion NIR + CHM
Detected trees	trees	1268	1487	1576
	%	**83.7**	**98.2**	**104.0**
Correctly detected trees	trees	1015	1129	1100
	%	**67.0**	**7.5**	**72.6**
Commission error	trees	65	122	135
	%	4.3	8.1	8.9
Omission error	trees	430	265	249
	%	28.4	17.5	16.4

Discussion and conclusions

This study confirmed that important forest taxation parameters like the number of trees can be determined using remote sensed data, ALS cloud point or multispectral true orthoimagery. The analyses showed, however, that approaches based only on the CHM lead to a higher estimation error than image analysis (segmentation) or both fusioned lidar and image datasets. The most accurate results were obtained using the OBIA method, slightly lower using data fusion. Automatic tree detection using only ALS data is possible, however some improvement is needed. The crucial factor mainly influencing the output, is the characteristic of the canopy height model (resolution, filtering parameters). The better the model describes actual canopy shape, the better are the results. Therefore the density of points is very important.

Compared to research done by other authors, the density of ALS data can influence the results. The study by Holmgren and Persson (2004) of pine stands showed results of detecting the number of trees at 75%, based on 1.2 points/sqm ALS dataset. A higher density of points can provide better results. Maltamo et al. (2004), using point cloud with density of 10 points/sqm achieved better results in similar pine stand (94%).

Special attention has to be paid to the results of the data fusion method. The improvement of accuracy in detecting trees is clearly seen: simple analysis (reclassification, creating mask) enabled an increase in the number of all detected trees of about 20% (from 83.7% to 104.0%); increasing the accuracy of about 5% (from 67.0% to 72.6%) and lowering the omission error to around 8% (from 28.4% to 16.4%).

Compared to research done by Wang et al., who used Treesvis software for the same study area in Milicz, our results are slightly better. A number of test plots (no. 8, 9, 10 and 11) used by Wang et al. are located the same compartment as our transect. The average accuracy value for those plots was only 50.0% (Wang et al., 2008), which can be explained by the different, non-homogeneous spatial distribution of the tree crowns.

Knowing the actual number of trees in a forest stand and their density is important not only for the forest owner, for whom this information can be treated as an indicator of certain treatment of the forest. In addition, the number of the stems and their locations is important to determine the spatial distribution of the trees in a compartment, which allows for planning for the final cuts or thinning (i.e. the shape of the area of clear cuts).

Additional work is still needed concerning the estimation of the number of trees in a stand form remotely sensed data, especially for detecting trees of different age, species composition and stand structure.

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Streszczenie

Stosowany obecnie model leśnictwa wielofunkcyjnego wymaga aktualnej i dokładnej informacji o jego zasobach. Jednym z wielu ważnych parametrów drzewostanu jest liczba drzew i ich przestrzenne rozmieszczenie. Obie te cechy zmieniają się w czasie życia drzewostanu. Im starszy jest drzewostan tym mniej drzew posiada. Pomimo faktu, że drzewa sadzone są z reguły w regularnej więźbie, zróżnicowanie warunków siedliskowych oraz konkurencja pomiędzy drzewami prowadzi do niejednakowego przestrzennego rozmieszczenia drzew oraz zróżnicowania ich rozmiaru. Celem badań było określenie liczby drzew w drzewostanie sosnowym (Pinus silvestris L.) na podstawie danych z lotniczego skaningu laserowego (ALS) oraz obrazu pozyskanego za pomocą skanera linijkowego (true ortho RGB/NIR). Analizy zostały przeprowadzone w wybranym transekcie 107 letniego drzewostanu na terenie nadleśnictwa Milicz. Jako danych referencyjnych użyto liczby drzew określonej na podstawie zwektoryzowanych koron. Dwie różne metody zostały zastosowane do automatycznego określenia liczby drzew i ich położenia. Pierwsza metoda, nazwana „GIS watershed" oparta była na modelach koron generowanych z danych ALS. Zastosowano różne algorytmy w celu znalezienia optymalnego modelu jak najdokładniej reprezentującego powierzchnię koron drzew. Druga metoda nazwana OBIA oparta była o segmentację oraz klasyfikację obrazu true ortho (R, G, B, NIR) i prowadziła do wykrycia tzw. hot-spot. Zastosowano również metodę łączącą dane lidarowe oraz true ortho (data fusion). Do porównania uzyskanych wyników zastosowano analizy przestrzenne. Wyniki wskazują że zarówno dane ALS jak i dane obrazowe mogą być użyte do określania liczby drzew w rębnym drzewostanie sosnowym. Dokładność wykrycia drzew wyniosła 67% dla metody pierwszej (ALS) oraz 74.5% dla metody drugiej (true ortho). Połączenie zestawów danych zaowocowało wynikiem równym 72.6%. Badania będą kontynuowane w celu poprawy rezultatów dla zastosowanych metod, również dla drzewostanów w innym wieku i o innym składzie gatunkowym.

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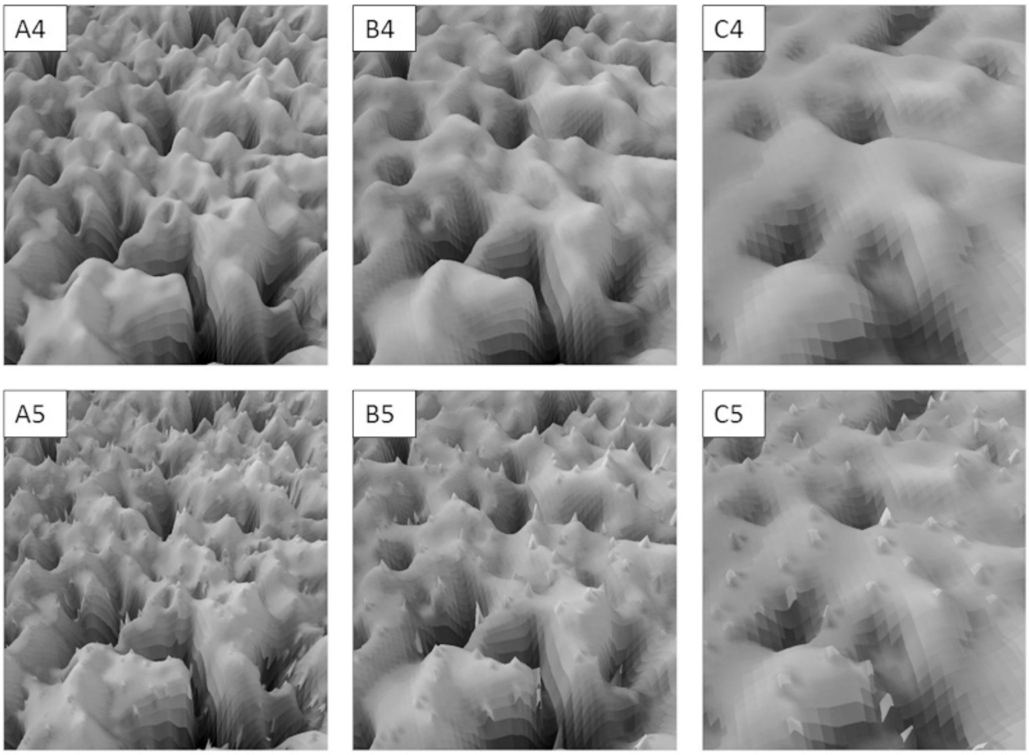

Figure 1. Differences between Canopy Height Models. Surfaces: A5, B5 and C5 preserve local peaks

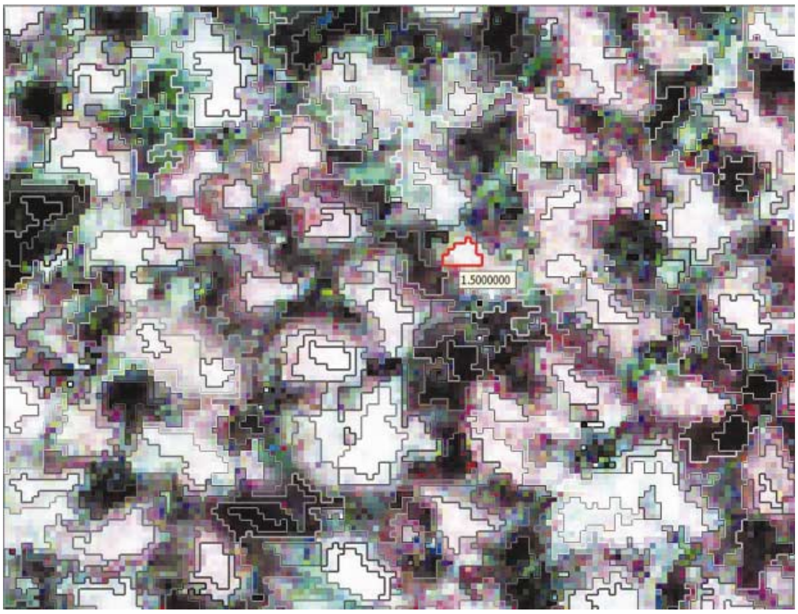

Figure 2. Object oriented image analysis (OBIA) result, with a single detected hotspot marked in red

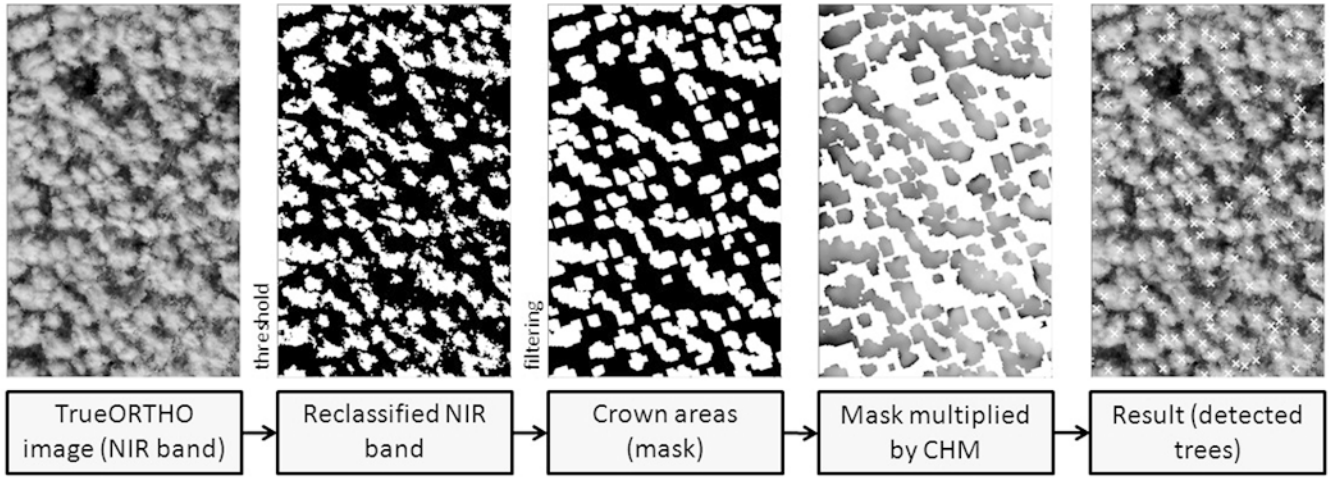

Figure 3. Data fusion (True ortho + ALS) approach

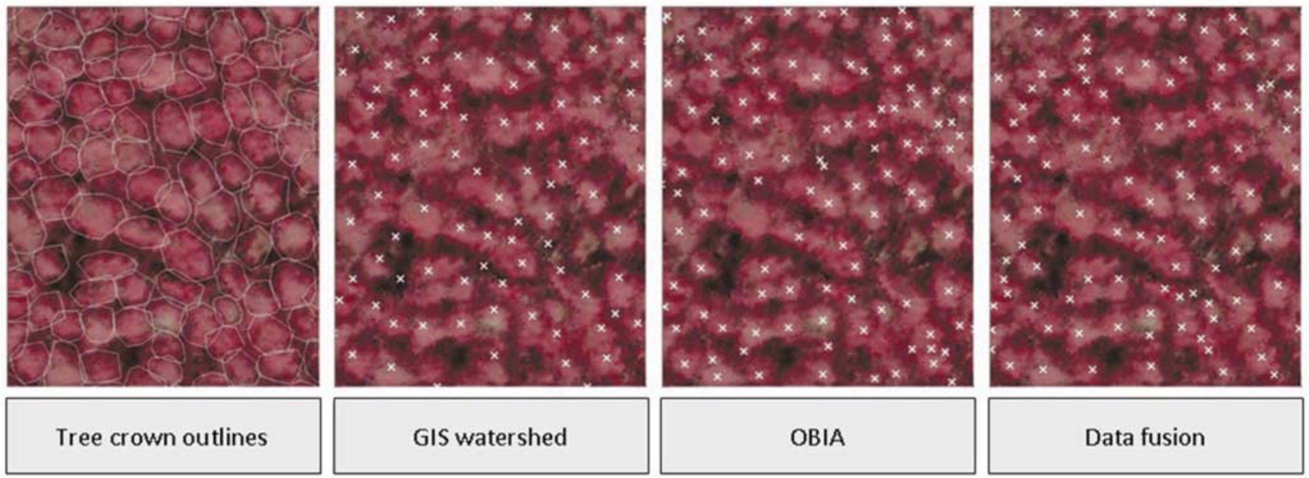

Figure 4. Results of all used approaches presented on a subset of study area