Philipps-Universität Marburg

Department of Geography

Tree Crown Segmentation Algorithms on RGB Imagery Derived Canopy Height Models

- Reliability Testing in Comparison to LiDAR Data

Master Thesis

Supervisors:

Dr. Christoph Reudenbach

Prof. Dr. Thomas Nauss

Submitted by:

Finn Möller
Matr.No.: 2743248

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Abstract

Only a few studies researched the possibility to use low budget UAV derived aerial RGB imagery for open source crown segmentation processes in R-Studio. This study aims to test established crown segmentation algorithms and corresponding tree finding algorithms on RGB imagery derived canopy height models in comparison to LiDAR-derived canopy height models, as well as a possible use of a RGB digital surface model instead of a canopy height model. A direct comparison between produced canopy height models, detection of tree positions, tree heights and crown shapes is conducted. The researches show that a RGB imagery derived canopy height model is suitable for crown segmentations while the use of a digital surface model is only useful to detect tree positions. Within the compared algorithms two perform well and one leads to worse results, especially concerning with the crown shapes. It is concluded that low budget RGB imagery can be used for crown segmentation processes with selected algorithms and produces reliable results without risking too much accuracy loss compared to LiDAR findings.

Acknowledgements

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Acronyms

ALS	Airborne Laser Scanning
LiDAR	Light Detection and Ranging
DBH	diameter at breast height
AGB	above ground biomass
CHM	canopy height model
UAV	unmanned aerial vehicle
SfM	structure-from-motion
CSA	crown segmentation algorithm
DSM	digital surface model
DTM	digital terrain model
TP	true positive (correct detection, RGB LiDAR match)
FN	false negative (omission error, only found in LiDAR)
FP	false positive (commission error, only found in RGB)
r	recall
p	precision
F	F-score
MED	maximum euclidean distance
MHD	minimum height difference
HD	height difference

Introduction

The use of Airborne Laser Scanning (ALS), also referred to as Light Detection and Ranging (LiDAR), is an established monitoring method to acquire three-dimensional forest canopy structures (Wulder *et al.*, 2008; Kaartinen *et al.*, 2012). LiDAR-derived point clouds are used to obtain information regarding forest inventories such as count of tree, tree height, crown shape and diameter, as well as allometry derived parameters like diameter at breast height (DBH) and aboveground biomass (AGB) (Jucker *et al.*, 2017; Mohan *et al.*, 2017). In order to extract this information from the point cloud, two different methods were tested in the past decades, one using the point cloud directly and one using a point cloud derived canopy height model (CHM) (Jakubowski *et al.*, 2013). In this study, the latter method was chosen because it is of higher interest to compare directly within one approach and not between two approaches. Additionally, a trend study by (Zhen *et al.*, 2016a) ascertained that 66.2% of the examined studies used a CHM approach. In order to generate forest inventory information from LiDAR-derived CHMs many algorithms are established, whereby the application of a local maxima detection algorithm on a LiDAR-derived CHM is an established workflow (Koch *et al.*, 2006; Zhen, Quackenbush and Zhang, 2016; Mohan *et al.*, 2017).

Although LiDAR is well established and produces satisfactory results there is an increasing interest in the use of an unmanned aerial vehicle (UAV) to produce high-resolution imagery in order to generate information analogous to LiDAR data (White *et al.*, 2013). For the processing of large amounts of high-resolution imaging data so-called structure-from-motion (SfM) techniques are used. In doing so, 3D point clouds are generated through the matching of features in multiple images with the help of corresponding software, in this case namely PhotoScan from Agisoft (Mohan *et al.*, 2017). This common method is allocated in the photogrammetry, which is a group of remote sensing methods applied to photographies.

The interest in the use of imagery for acquiring accurate individual tree information can be attributed to many needs, such as reducing the operational costs, gaining a higher spatial and temporal resolution, being independent of cloud cover and a safer work environment (White *et al.*, 2013). In this study, the cost factor is of special interest. Therefore this thesis focuses on the use of RGB imagery and open source software.

With reference to their user comfort and reliability three crown segmentation algorithms (CSAs) and two tree finding algorithms (TFAs) were selected for this study. Their functioning will be explained later on. All of them are parts of established R-packages and therefore a free to use software (R Core Team, 2018). Two of them based on studies from recent years (Dalponte *et al.*, 2015; Silva *et al.*, 2016) and one bases on a study from Meyer and Beucher from 1990 (Meyer and Beucher, 1990)

Only a few studies already tested the possibility of RGB imagery derived crown segmentation (Guerra-Hernández *et al.*, 2016; Mohan *et al.*, 2017). One study comparable to this thesis is written by Mohan et al from 2017. They also used the implementation of the local maximum algorithm from Silva et al., 2016 within the rLiDAR package in R for individual tree identification on a UAV derived CHM. The achieved results depicted an acceptable accordance of individual tree detection from UAV derived CHMs in an open canopy forest (Mohan *et al.*, 2017).

The possibility of satisfying results for information on forest inventory parameters through UAV derived RGB imagery seems to be given, referring to the available findings of accomplished examinations. Referring to the results of Mohan et al 2017, the question arises as to whether the use of another algorithm leads to similarly good, perhaps even better, results. Since LiDAR so far is the established tool, this study compares the results, derived from RGB Imagery CHMs with results from LiDAR data, in order to answer the question if low budget UAV derived RGB Imagery, processed with operationally available algorithms, can achieve results which are comparable to LiDAR results.

Despite mentioned advantages, UAV imagery derived point clouds have one main disadvantage, namely the lack of ground area detection. Thus the creation of a reliable digital terrain model (DTM) in order to generate a CHM is of special interest and difficulty. Although these difficulties exist this study will try to use UAV and LiDAR point clouds in order to produce similar CHMs. In those cases where it is not possible to generate a functional DTM, it could be useful to get information regarding the number of trees and crown metrics by solely using a digital surface model (DSM). The possibility to do so shall be reviewed.

In summary, the aim of this study is to check whether or not a) RGB imagery derived point clouds are able to produce suitable CHMs and DSMs for crown segmentation algorithms (CSA); b) selected CSAs generate reliable results when used on RGB imagery derived CHMs/DSMs and how well they perform; c) a DSM approach is able to get reliable information about tree counts and crown shapes.

Methods

Study area

The two study sites are located in a mixed forest close to the village Caldern belonging to the district Marburg-Biedenkopf in Hessen, central Germany. They are located at 300 to 360 meters above sea level. To get various research conditions an orthomosaic (see chapter: Point clouds) of the

RGB images was used to select the sites empirically in terms of species composition. In order to check the capability in detecting deciduous site one only consists of those. To research the effects of different tree categories (deciduous and coniferous) and corresponding tree height differences, site two contains deciduous and coniferous by little visible ground area. Due to a lack of appropriate area within the point cloud, site one and two have the upper left (site 1) and the bottom right (site 2) corner in common. To ensure as much as possible comparability all sites are of the same size (approx. 55x55m).

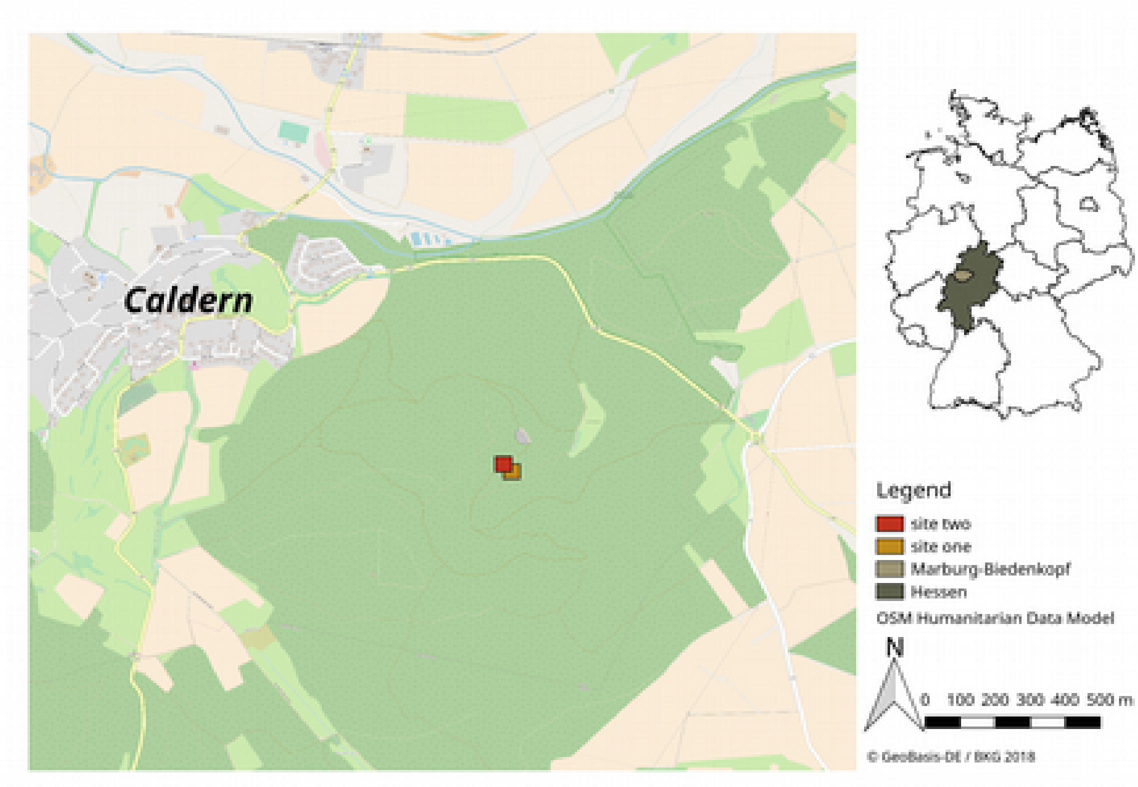


Fig. 1: Study site locations

Fig. 2: Orthoimages of the sites

Data

Point clouds

Airborne laser scanning (ALS) is increasingly accredited for mapping forest inventories (Coomes *et al.*, 2017). The LiDAR point cloud used in this study is a product provided by an administration on state level, the "Hessische Verwaltung für Bodenmanagement und Geoinformation" (HVBG). The point cloud is generated with a combination of three systems: A GNSS-receiver (e.g. NAVSTAR-GPS = NavigationSystem with Timing and Ranging - GlobalPositioning System) marks the punctual position of the airplane, an inertial system (INS = Inertial NavigationSystem) determines the attitude (vertical angle along and across the flight line, horizontal angle) and a laser scanner sends beams in a predefined angle to the ground and measures the distance via the return time. The accuracy per point is approx. 15 cm in height and 30 cm in position (HVBG, 2018). The data was recorded in winter 2009/2010. Due to the fact that no exact date is available no further information regarding the leaf conditions are known. Since a study of Brandtberg *et al* from 2003 showed that it is possible to get crown information even from leaf-off trees no irresponsible negative effects are expected. The used RGB images were shot with the 16 MP (rolling shutter) RGB camera of a parrot sequoia at the end of August 2017. The used camera is no low budget product because it is a multispectral camera, but it could be switched with any comparable low budget RGB camera. An autonomous flight plan was generated with the help of the R-package uavRmp, a package designed for autonomous UAV mission planning for low budget drones (Reudenbach, 2018c). The flight plan captured an area of approx. 195000 square meter with an overlap of 80%. The resulting RGB photos were post-processed with the Agisoft software PhotoScan resulting in the used 3D point cloud and an orthoimage of the scene (Agisoft PhotoScan Professional (Version 1.3.5)).

CHM and DSM creation

There are two ways to use a 3D point cloud in tree segmentation processes. One uses the point cloud directly and the other one generates a point cloud derived raster image. In this study, the latter was chosen because it is of higher interest to compare directly within one approach and not between two approaches, but not because one of them is more suitable. In addition, a trend study ascertained that 66.2% of the examined studies used a CHM approach (Li *et al.*, 2012; Zhen, Quackenbush *et al.*, 2016). Various studies in the past used LiDAR-derived CHMs for crown segmentation processes successfully (Silva *et al.*, 2014, 2016; Dalponte and Coomes, 2016) or multispectral imagery (Brandtberg and Walter, 1998). Few cases used RGB imagery (Guerra-Hernández *et al.*, 2016; Mohan *et al.*, 2017). Most of them unite in not explaining their creation process transparently. Therefore, the instructions by Jean-Romain Roussel and Martin Isenburg, which are based on the pit free CHM algorithm by Anahita Khosravipour and the corresponding software (LasTools, R base), were used to create a LiDAR-based CHM (Isenburg, 2014; Roussel, 2017; Roussel, 2018; Khosravipour et al., 2013). The three staged algorithm basically categorises ground points to normalise the point cloud, creates a number of DSMs on different height steps which are finally stacked to a CHM containing only the highest points of the stack on pixel level. A 0.5 meter resolution was chosen to fit the position accuracy of the point cloud and match the suggestion of a comparable study (Dalponte *et al.*, 2015). Assuming that the given recommendations of the instruction produce sufficient results the instruction parameters were maintained (Roussel, 2018). Afterwards, the resulting CHM was median filtered by a 3x3 pixel window to avoid outliers which could lead to misinterpretations by the crown segmentation algorithms.

To create the RGB imagery derived DSMs the R-package uavRst was used with a resolution parameter of 0.5 meters to fit the LiDAR-derived CHM (Reudenbach, 2018b; Reudenbach, 2018a). Due to the fact that imagery based point clouds only consist of surface points, it is of particular importance to either have sufficient clearings or treeless or rather completely unvegetated areas in order to create a usable DTM. To use as many reliable ground contacts as possible the uavRst DTM creation algorithm was adapted. Firstly the algorithm browses the RGB imagery derived point cloud and constructs a spatial points map based on local minima in different window sizes. Secondly, it uses each point of the mentioned point map to search points in a point map of the next lower resolution. The search window is a defined square buffer around points of the first map. Points which do not exceed a variable maximum height difference are selected. Step two is repeated on the points selected in the previous run until no smaller resolution is available. The result is a spatial point map containing only those points which are most likely ground points located relatively close to their original position. Finally, those points are spline interpolated on a selected resolution (Fig. 3). The CHM creation is basically a subtraction of the DTM from the DSM which is cleaned of negative values. Corresponding to the LiDAR CHM a 3x3 pixel median filter was applied.

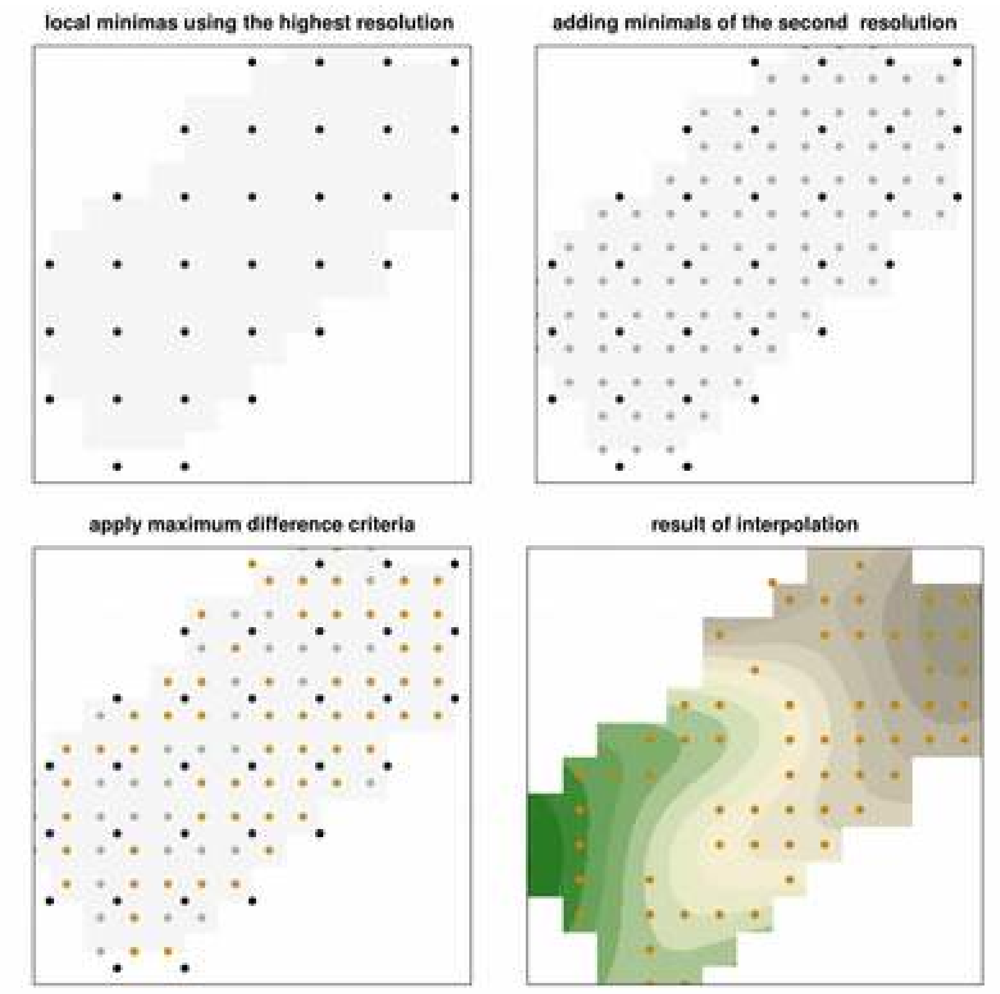


Fig. 3: Schematic workflow of the DTM algorithm

CSAs and TFAs

As already mentioned, in the past decades many CHM based crown segmentation algorithms were tested and established (Silva *et al.*, 2014, 2016; Dalponte and Coomes, 2016). To identify suitable crown segmentation algorithms studies were sifted and were selected regarding their reliability, degree of establishment, operability and if they are free to use. Two of three of the selected algorithms use a tree position raster map as input and therefore offer a matching TFA.

The first pair of CSA and TFA is implemented in the ForestTools package in R. The latter implements a variable window filter algorithm and the crown segmentation implements a watershed algorithm (Meyer and Beucher, 1990; Popescu and Wynne, 2004).

The second algorithm is an adaption of an algorithm invented by Hyppaä et al. 2001 by Michele Dalponte and is implemented in the itcSegment package Dalponte, 2018; (Dalponte *et al.*, 2015). It is the only selected algorithm which uses a tree-finding algorithm internally. As the package explanation says, "The ITC delineation approach finds local maxima within a rasterized CHM, designates these as treetops and then uses a decision tree method to grow individual crowns around the local maxima" (Dalponte, 2018, p. 5). The Hyppaä algorithm proofed its reliability in a benchmark study comparing delineation methods (Eysn *et al.*, 2015).

Another well-established algorithm pair is an algorithm by Carlos Silva which is integrated into his own package rLiDAR (Silva, 2018). The TFA uses a local maxima filter with a fixed window size. The CSA uses a centroidal voronoi tessellation approach (Aurenhammer, 1991) to split predefined buffers around all found trees and clips the resulting area from the CHM by excluding pixels below a percentage threshold of the tree height (Silva *et al.*, 2016).

Due to the lack of field-based references, it was tried to estimate the number of trees in each site visually by examining the orthoimage (Fig. 2). Referring to the thus obtained count of trees, the LiDAR processes were minimally adjusted and used as references for the comparison. To offer a comparability between LiDAR and RGB based results as few as possible parameters were changed from the predefined algorithm settings in all cases. The most important modification was the adjustment of the search window size because it is an easy to handle possibility to generate comparable results in terms of count of tree. This modification was conducted in order to get the most similar tree number between LiDAR and RGB and to be as close as possible to the visually counted tree amount. In addition, a maximum crown diameter of 150 and a minimum tree height of 2 meters was selected if necessary. Several tests showed that a finer modification of settings can result in more detailed matches, but for the purpose of investigating how reliable selected algorithms are when used on a RGB CHM, a fine tuning was rejected.

Validation

The CHMs and the RGB derived DSM were compared in terms of position and elevation. To verify the position both CHMs were analysed and visually similar points were marked. The marked points were overlayed to see the relative position to each other. Hereby a GPS shift was determined. To focus on the segmentation process and not on the possibly UAV derived GPS errors this shift was simply removed by moving the RGB CHM to fit the LiDAR CHM visually. Elevation differences were examined by subtracting the RGB derived CHM from the LiDAR-derived CHM. Subsequent the subtraction raster was classified in various difference ranges and the pixels of each class were summed.

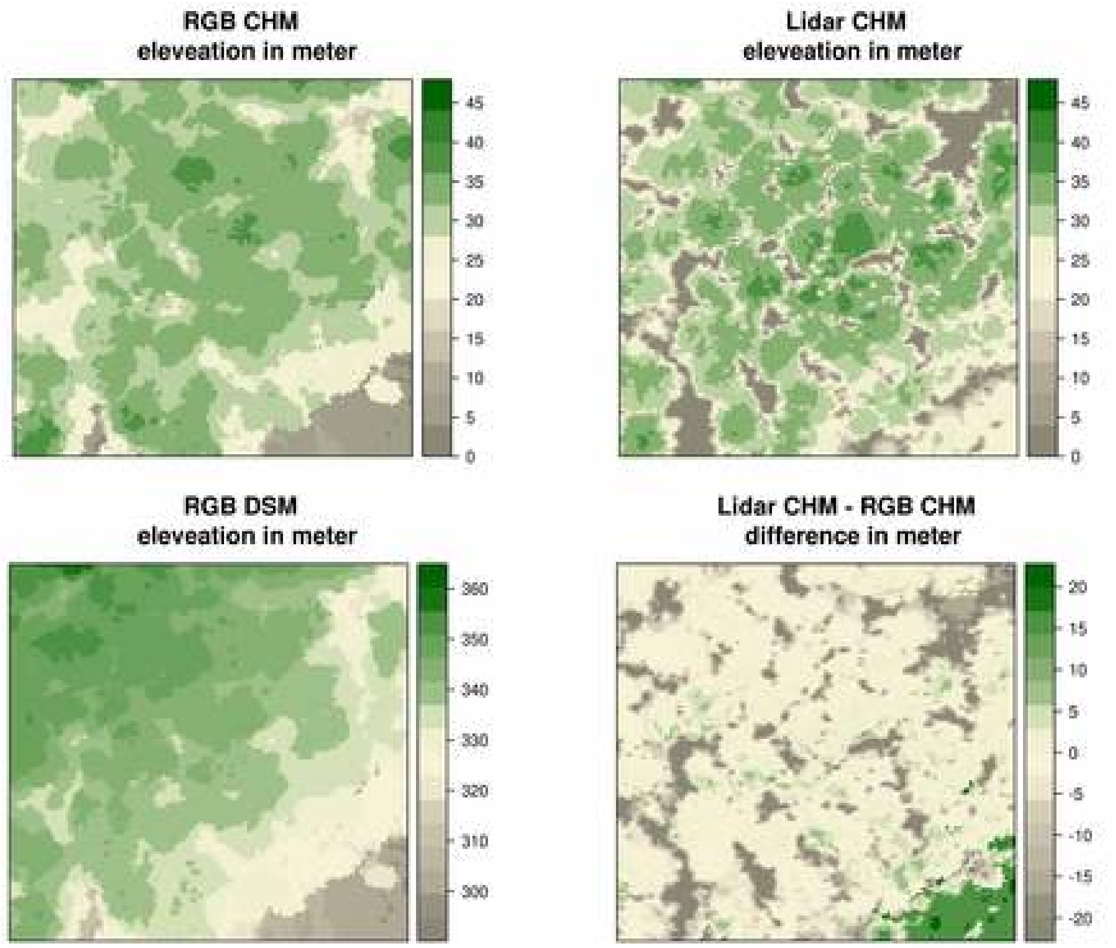
In order to verify the TFA results between the RGB imagery approach and the LiDAR approach, an adaption of the rsTree validation algorithm by C. Silva was used(Silva *et al.*, 2016). Hereby the number of trees detected (NTD) per subplot from RGB imagery were compared with LiDAR-based data and evaluated in terms of true positive (TP, correct detection, RGB LiDAR match), false negative (FN, omission error, only found in LiDAR) and false positive (FP, commission error, only found in RGB). The accuracy of the detection was further evaluated for recall (r), precision (p) and F-score (F). The algorithm originally uses two variable parameters, the maximum euclidean distance (MED) and the minimum height difference (MHD). The adapted version hereinafter is named rsTreeA. The MED was adapted so that for each found tree in the RGB CHM, not the MED, but the actual crown shape is used as a buffer around it, each representing a search window. All LiDAR-derived trees located within this search window which have a height difference (HD) to the RGB-based tree smaller than the MHD are selected. In this study a MHD of tree height / 10 meters was chosen, so that for every 10^{th} meter of tree height one meter of false estimation is allowed. If more than one RGB based tree has HD ≤ MHD, the trees are ranked by HD and the tree with the smallest HD is selected.

Regarding their similarity, the crown shapes of the TPs with an overlap of at least 33% between RGB crown and LiDAR crown were compared by the parameters length, width, calliper, area and DBH and AGB. The former are simple shape parameters calculated with the uavRst implementation of the Momocs package (Reudenbach, 2018b). The latter are calculated by the “agb” and “dbh” function of the itcSegement package which are based on allometric models determined by a study of Jucker et al. in 2017. The allometric bases on tree height and crown area and therefore are not used for the DSM approach because there the tree heights are not suitable. As a method of comparison, a Pearson Correlation was conducted between those parameters derived by the selected RGB and LiDAR crowns. Results of insignificant correlations (significance level 0.05) were not analysed.

Results

The results of each site are displayed and described in three figures per site. One for a CHM and DSM compare, one with the findings for the CHM approach and one for the DSM approach.
The CHM validation results are presented in the first figure as a panel of four plots. Plot one and two show the generated CHMs, three a RGB derived DSM raster and four a LiDAR CHM – RGB CHM raster. Plot three is able to show structural similarities between the RGB DSM and the LiDAR CHM. Plot four gives a good overview of LiDAR CHM and RGB CHM similarities and deviations.
The crown segmentation and tree finding results are shown in the second figure, in a comparison panel containing all three algorithms. The first row shows all tree positions (TPs, FPs, FNs) and the corresponding RGB image derived crown shapes within the plot (blue) and thereof the crowns, which are suitable for a comparison (red). The second row shows the same tree positions but with the LiDAR-derived crown shapes. Subsequently follows the correlation matrix which shows correlation values between all chosen parameters with a significant p-value. The direct diagonal comparison is of special interest because it offers a direct measurement of equality between selected RGB crowns and LiDAR crowns. The last row consists of a data table giving an overview of the different tree numbers, the results of the rsTreeA and the amount of compared crowns.

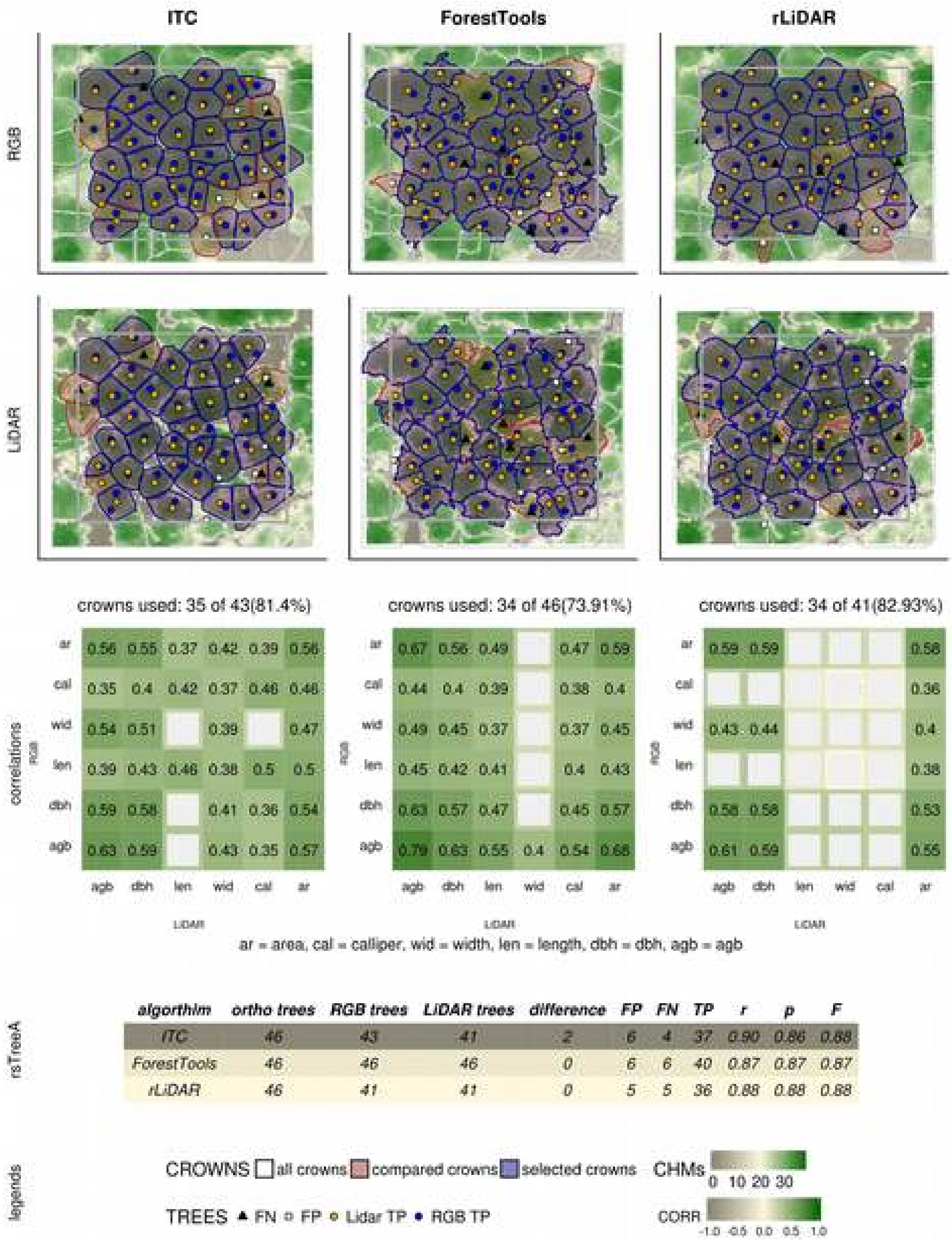
Site one



range	-Inf -20	-20 -10	-10 -5	-5 -2.5	-2.5 -1.5	-1.5 -0.5	-0.5 0.5	0.5 1.5	1.5 2.5	2.5 5	5 10	10 20	20 Inf
pixel in %	9.01	8.14	8.03	10.26	8.13	13.08	14.35	12.19	6.11	4.96	1.82	3.6	0.32

Fig. 4: Raster images of site one

The generated CHMs of site one match relatively good as to see in Fig. 4. Main differences are to find in the ground area pixel caused by LiDARs capability to penetrate the canopy. The DSM raster shows structural similarities, but with a descending gradient from south-east to north-west. The classified CHM-CHM subtraction image shows that 39.67 % of the pixels indicate a deviation of -1.5 to 1.5 meters between RGB CHM and LiDAR CHM. 43.67 % of the pixel lay under -1.5 meters and 16.66 % above 1.5 meters (Fig. 4).

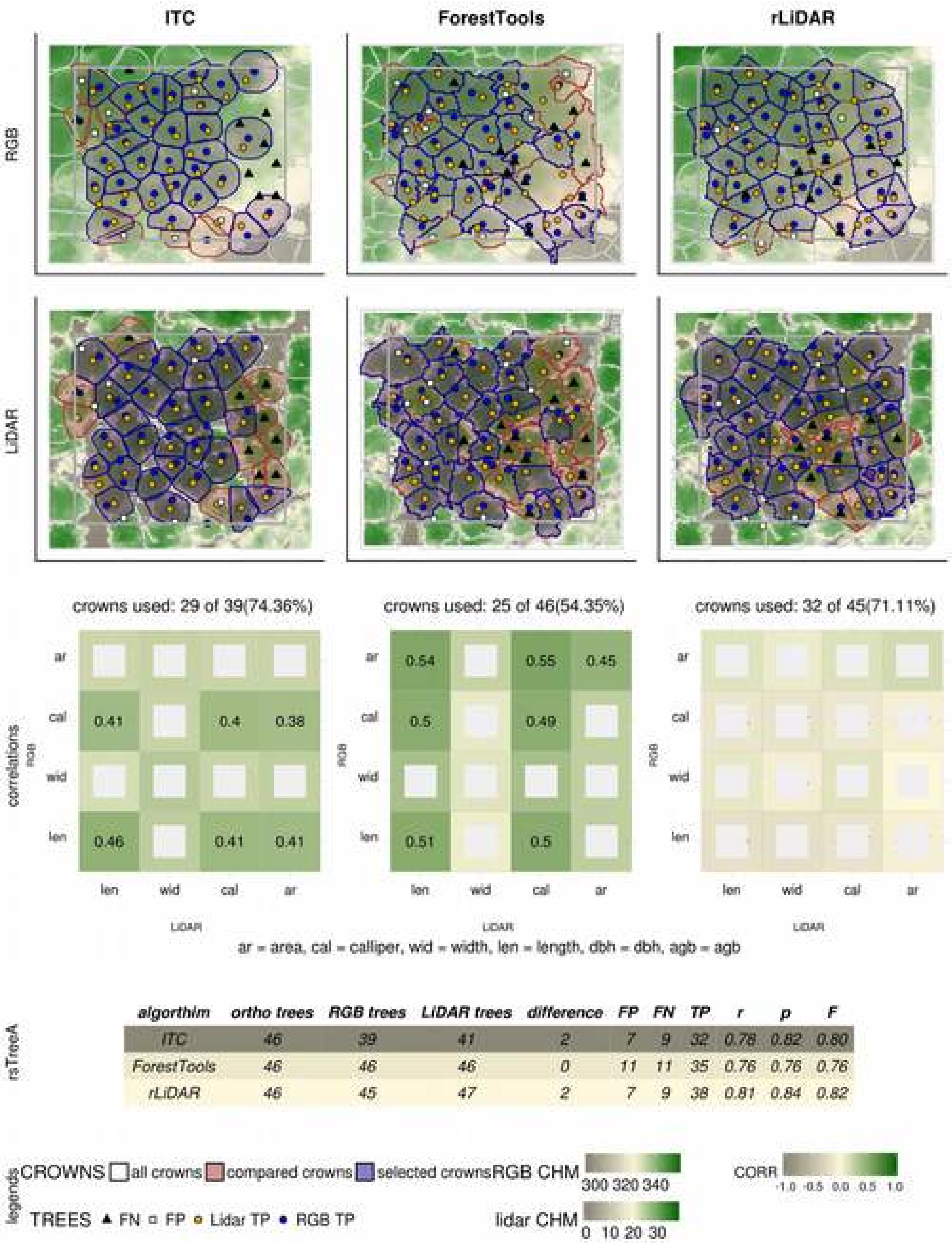


algorthim	ortho trees	RGB trees	LiDAR trees	difference	FP	FN	TP	r	p	F
ITC	46	43	41	2	6	4	37	0.90	0.86	0.88
ForestTools	46	46	46	0	6	6	40	0.87	0.87	0.87
rLiDAR	46	41	41	0	5	5	36	0.88	0.88	0.88

Fig. 5: CHM approach panel site one

Crown segmentation and tree finding results on the normalised RGB CHM of site one show rsTreeA F-Scores of: ITC 0.88; FT 0.87; rLiDAR 0.88 and a number of comparable crowns of: ITC 81.4%; FT 73.3591 rLiDAR 82.93%. Despite a good F-Score, the rLiDAR approach generated few significant correlations which are mostly area related. The ITC and the FT algorithm on the other hand show only a few insignificances. The correlations are mostly positive. Only the ITC algorithm shows trees which are located close to each other but are not matched. This indicates a height difference greater than the allowed MED (RGB tree height/ 10). All other FNs or FPs are not matched due to different amounts of crowns and different shapes. It is observable that all three approaches show susceptibility to errors in similar areas (Fig. 5).

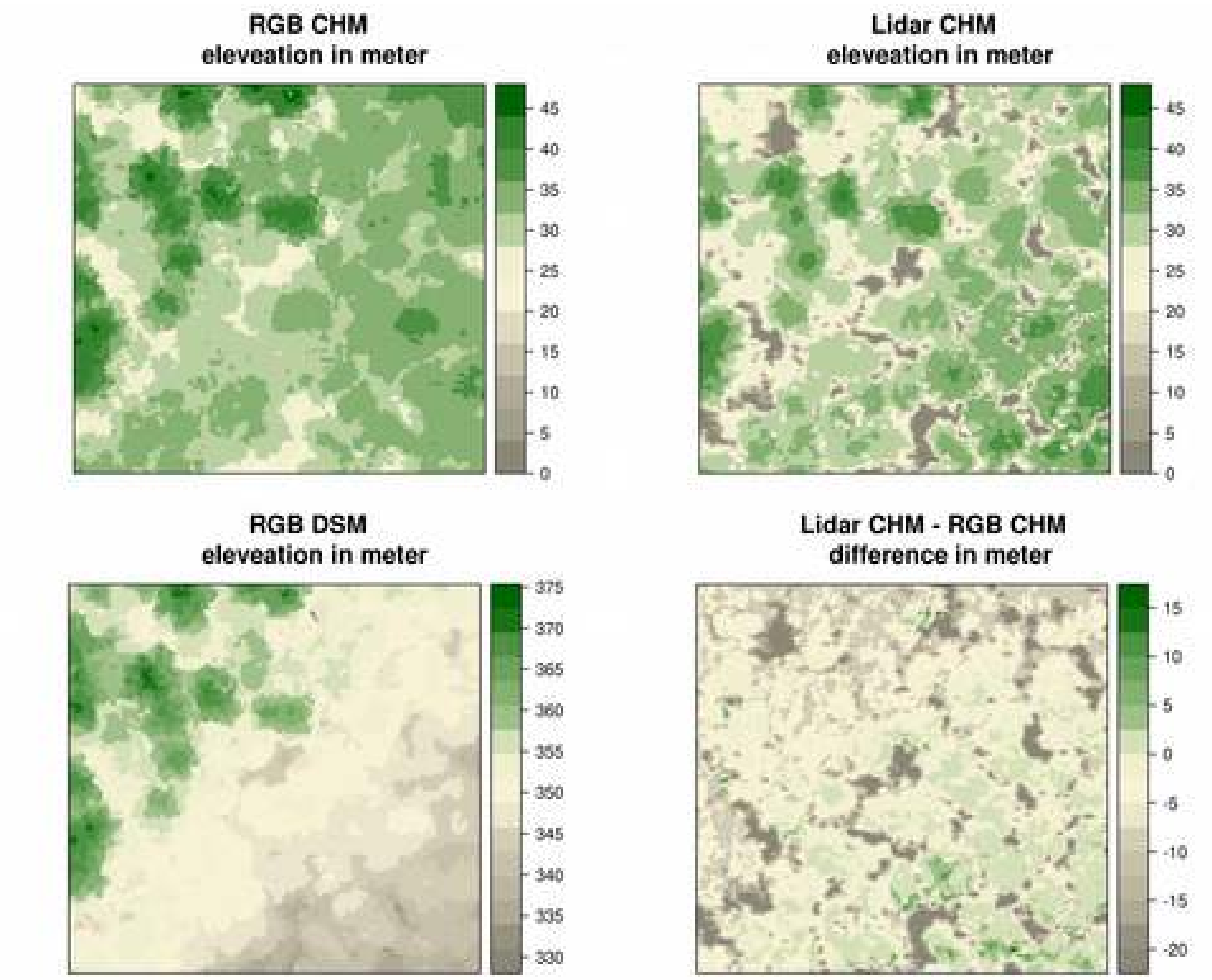
In direct comparison to the results with an underlying DTM the F-Scores of the DSM approach for site one (ITC 0.80; FT 0.76; rLiDAR 0.82), the number of comparable crowns (ITC 74.36%; FT 54.35% rLiDAR 71.11%), as well as the correlations are worse. The correlations show no significance for the rLiDAR algorithm, only two direct significances (len:len; cal:cal) for the ITC algorithm, and less than the half for the FT algorithm (again missing width:width). In addition, the sole positive correlation values are still worse than the ones with a DTM. It is notable that again all three show errors in similar areas, mainly due to the fact that the crowns shapes seem to be distorted or do not exist in the RGB derived results. Especially on the eastern side, the LiDAR approach produces more but smaller crowns (Fig. 6).



algorthim	ortho trees	RGB trees	LiDAR trees	difference	FP	FN	TP	r	p	F
ITC	46	39	41	2	7	9	32	0.78	0.82	0.80
ForestTools	46	46	46	0	11	11	35	0.76	0.76	0.76
rLiDAR	46	45	47	2	7	9	38	0.81	0.84	0.82

Fig. 6: DSM approach panel site one

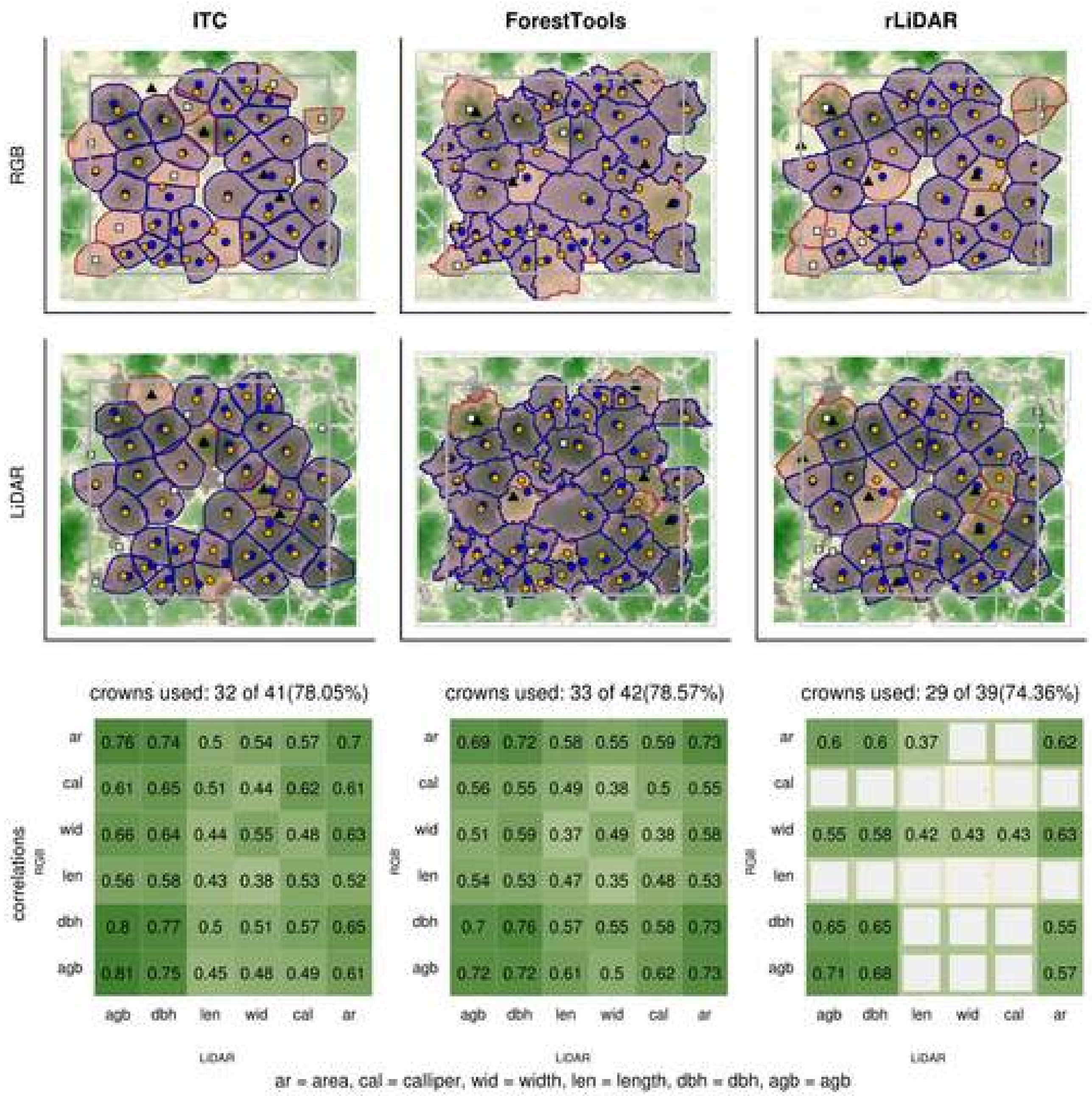
Site two



range	-Inf -20	-20 -10	-10 -5	-5 -2.5	-2.5 -1.5	-1.5 -0.5	-0.5 0.5	0.5 1.5	1.5 2.5	2.5 5	5 10	10 20	20 Inf
pixel in %	6.39	7.9	18.18	23.78	11.55	12.33	9.13	5.56	2.78	1.94	0.44	0.01	0

Fig. 7: Raster images of site two

On the first view, a visual comparison of the CHMs and the RGB DSM of site two indicates structural similarities. Again the LiDAR CHM is able to show ground area while the RGB CHM shows nearly no elevation pixel underneath a hight of 20 meters. The RGB CHM tends to be of higher elevation in the upper left corner where coniferous are to find (Fig. 2) while the bottom right corner shows lower results. The RGB DSM has structural similarities as well but shows an ascending gradient from south-east to north-west in terms of elevation. In the classified CHM CHM subtraction image 27.02% of the pixels lay between -1.5 to 1.5, while 67.8% of the pixels are below -1.5 and thereby indicate a generally higher elevation of the RGB CHM (Fig. 7).



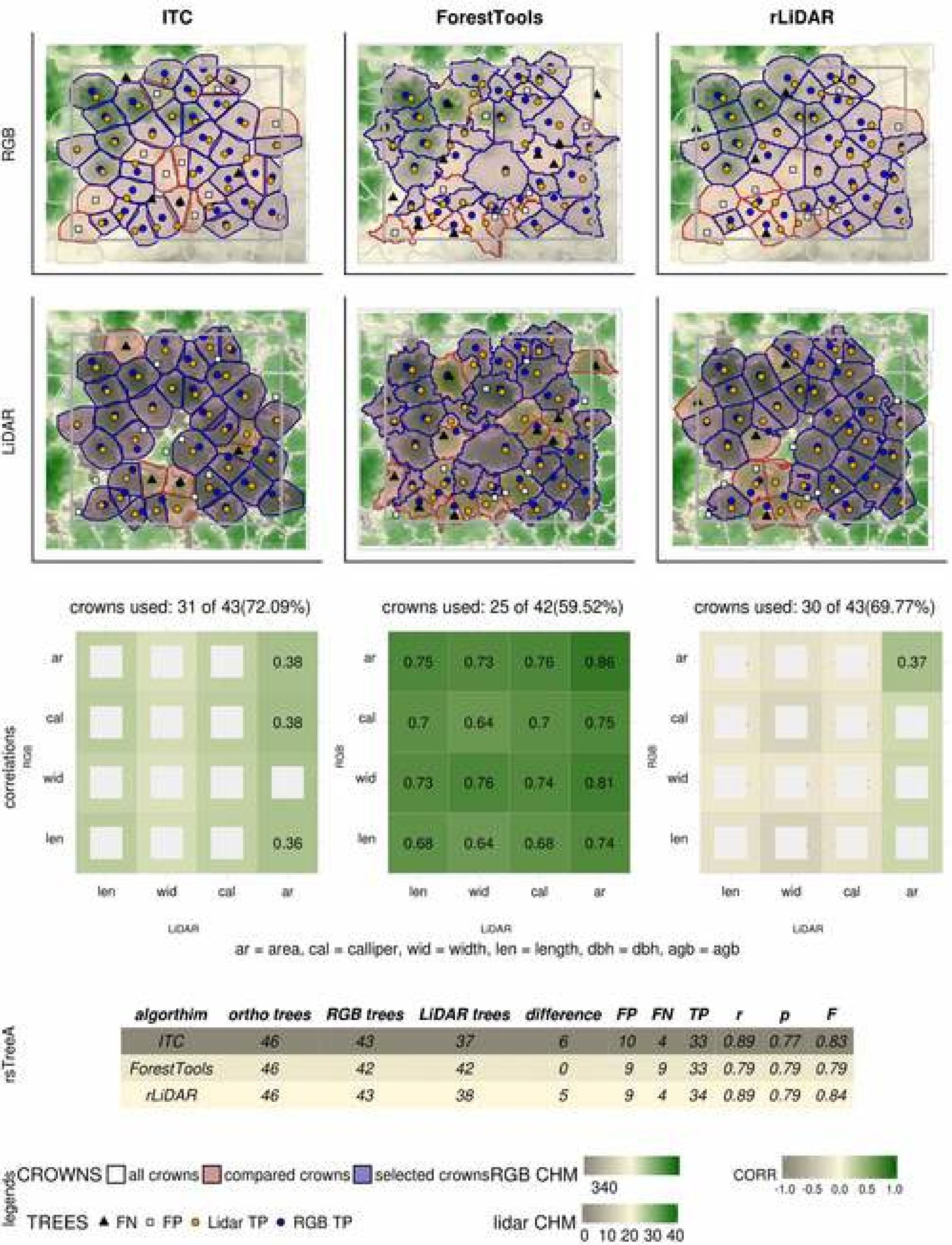
rsTreeA

algorthim	ortho trees	RGB trees	LiDAR trees	difference	FP	FN	TP	r	p	F
ITC	46	41	37	4	8	4	33	0.89	0.80	0.84
ForestTools	46	42	42	0	5	5	37	0.88	0.88	0.88
rLiDAR	46	39	38	1	7	6	32	0.84	0.82	0.83

Fig. 8: CHM approach panel site two

In this case, the CSAs and TFAs generated the following results on the normalized RGB CHM of site two. The rsTreeA validation detected F-Scores of: ITC 0.84; FT 0.88 rLiDAR 0.83 and thereby percentages of comparable crowns of: ITC 78.05%; FT 78.57%; rLiDAR 74.36%. The correlation results of the ITC and ForestTools algorithm pair show sole significant results with positive correlation values and notable worse results for the rLiDAR algorithm with fewer significances by few positive correlations. Here again area related parameter and additionally the width parameter show significances for the rLiDAR approach. One notable source of error is that the missing ground areas in the RGB CHM lead to FPs where the LiDAR CHM shows ground area. Furthermore, the rLiDAR CSA and the ForestTools CSA produce the same tree pair in the north-western corner which can not be matched due to Height difference problems. Again all other FNs and FPs occur due to different amounts of crowns and different shapes. An overview over all three CSAs shows difficulties in similar areas spread over the whole plot (Fig. 8).

The CHM approach to DSM approach compare shows that a crown segmentation based on a RGB DSM is able to detect nearly the same amount of TPs (ITC 33 to 33; ForestTools 37 to 33; rLiDAR 32 to 34) by only leading to relatively low percentages of comparable crowns: ITC 72.09%; FT 59.52%, rLiDAR 69.77%. Except for the ForestTools algorithm, the correlations show few significant results, while area derived parameter tend to be significant. Significant correlations are positive. A visual comparison between all three results again shows similarities in term of problematic areas. Notable is that the bottom left area has many not matched trees, mainly due to dissimilar crown shapes and amounts (Fig. 9).



algorthim	*ortho trees*	*RGB trees*	*LiDAR trees*	*difference*	*FP*	*FN*	*TP*	*r*	*p*	*F*
ITC	*46*	*43*	*37*	*6*	*10*	*4*	*33*	*0.89*	*0.77*	*0.83*
ForestTools	*46*	*42*	*42*	*0*	*9*	*9*	*33*	*0.79*	*0.79*	*0.79*
rLiDAR	*46*	*43*	*38*	*5*	*9*	*4*	*34*	*0.89*	*0.79*	*0.84*

Fig. 9: DSM approach panel site two

The rsTreeA outcomes show good results for the CHM approach (mean F-Score: 0,86) and slightly worse results for the DSM approach (mean F-Score: 0,81). One notable source of errors is the lack of ground areas in the RGB CHM, due to which the minimal tree altitude of the algorithms cannot be used properly and therefore the RGB approach produces trees where LiDAR detects ground area (Fig. 8). It is observable, that the rsTreeA in some cases selects a crown as a usable crown on one approach while a similar crown is not selected because it exceeds the plot limits a little bit too much (Fig. 8 rLiDAR upper left corner). This could lead to a distortion of the results. Within the CHM approaches, a few trees cannot be matched, although they are located next to each other because the height difference is too big (Fig. 8 ForestTools upper right corner). All other unmatched trees can be traced back to different amounts of crowns or different shapes produced by the algorithms.

Main differences between the chosen CSAs are detectable in the correlation results. In all cases, the ForestTools crowns show many significant correlations and mostly positive correlation values in all four approaches. Similar results are produced by the ITC CSA, which shows few insignificances and slightly better correlation values for the CHM approach but only a few significances on the DTM approach. In the case of the rLiDAR algorithm, both approaches show very few significant correlations and these nearly solely in area-based parameters (Fig. 5, Fig. 6, Fig. 8, Fig. 9).

A comparison between the percentages of compared crowns shows that the ITC findings are the best on both DTM approaches (Fig. 6, Fig. 9), while ForestTools has the highest percentage in the CHM approach for site two (Fig. 8) and rLiDAR for site one (Fig. 5).

A direct F-Score comparison between the CSAs shows that the rLiDAR values are the highest in both DSM approaches (Fig. 6 Fig. 9) and one of the highest in one case (Fig. 5). The ForestTools algorithm only has the highest score in the CHM approach on site two (Fig. 8) and the worst in all other cases. The ITC approaches only share the highest score one time (Fig. 5), but in two cases the findings are just slightly worse than the rLiDAR algorithm scores.

Discussion

The results show that a RGB derived CHM creation is possible and moreover contains elevations close to the LiDAR findings. However, the fact, that the RGB CHM does not show ground area remains a significant disadvantage (Fig. 4, Fig. 7).

Overall each TFA and CSA performed well referring to the operability. The rsTreeA validation outcomes show good results for the CHM approach (mean F-Score: 0,86)(Fig. 5, Fig. 8) and little worse results for the DSM approach (mean F-Score: 0,81)(Fig. 6, Fig. 9). One source of errors is the lack of ground areas in the RGB CHM, and the resulting malfunction of the minimal tree altitude parameter (Silva *et al.,* 2018; Plowright, 2018; Dalponte, 2018a). As mentioned in the results other errors are to find in the adapted rsTreeA itself.

Referring to the crown segmentation validation correlations between suitable crowns were conducted based on different shape parameters. Despite the fact that the determined tree heights and positions of all algorithms show similarly good rsTreeA validation results, the crown segmentation results show notable differences. The rLiDAR algorithm leads to the worst overall results regarding the correlations with few significant correlations and therefore should not be used for researches, as long as other tested algorithms can be used instead. Especially the ITC algorithm is a possible alternative choice because it has a similar grade of generalisation. Additionally, it tries to generate overlaps of crowns.

Since rLiDAR shows best results for the DSM approaches, it certainly could be used for these. Due to the fact that crown segmentation overall shows bad results on DSM, the approach, in general, is questionable. Therefore the following discussions concentrate on the other two CSAs.

A direct F-Score comparison between the ITC algorithm and the ForestTools algorithm, the latter is worse in 3 of 4 cases even though the difference between the amount of RGB trees and LiDAR trees is zero in all cases. Considering the fact that the search window of the ForestTools TFA is able to be set very precise (Plowright, A. 2018, it could be assumed that it is set too precisely and accordingly generates forced results. This again leads to the assumption that the ITC algorithm produces more reliable results because it produces better F-Scores without the risk of over tuning.

Also, a comparison between the percentages of comparable crowns shows that the ITC findings are better in 3 of 4 cases. In the CHM approach, the correlation results between both CSAs are similarly satisfying.

Regarding their shape, the ForestTools findings are more detailed, and the ITC shapes are generalized with the possibility to generate overlaps. In sum, it can be said that both approaches are satisfying and should be used depending on the research field.

During a testing of the used DTM algorithm, a susceptibility to low noise within the generated point cloud was ascertainable, leading to the assumption that the point cloud creation and preprocessing should be improved to ensure that the DTMs are as correct as possible. In a case where it is not possible to generate a proper DTM, and the DSM approach is the only choice, it could bring improvement when the full potential, in terms of high resolution, of the imagery is used. This possibly leads to more suitable elevation structures within the DSM.

For this thesis aim, many algorithm parameters are not changed due to comparability reasons. It is possible that a fine-tuning of parameter settings could lead to even better results. In order to test the reliability of the chosen CSAs, no fine tuning was conducted. Gaining the mentioned results by just changing the search window size to fit an visually counted amount of trees, allows the assumption that the CSAs can be transposed on RGB CHMs without risking irresponsible accuracy loss,

Referring to the results of this study it can be stated, that the RGB imagery derived CHMs are an affordable and suitable alternative for crown segmentation processes, leading to estimations which are comparable to LiDAR results. Further investigations with more fine tuning could encourage this conclusion.

Even though the results can compete with those of Mohan et al from 2017, at least in a LiDAR to RGB comparison, some improvements could be made. Mainly the ground area problem should be approached. Certainly, imagery will not be able to penetrate the canopy but one main advantage of the high-resolution imagery, the RGB values, are unused in the chosen CSAs. It is conceivable that RGB values could be used to improve crown segmentation itself or could be used to detect treeless areas in the CHM creation process. Certainly, the rsTreeA algorithm could be improved. One conceivable idea would be to implement a weighted "distance to tree height difference" index.

Due to the fact that the used methods are found to be reliable, usable with little expertise and most importantly affordable, it is conceivable that the spectrum of users could increase over the coming years, at least in disciplines and for problems where a very good estimation and no particularly high accuracy is needed. The high temporal resolution could accelerate decision findings in forest management, detect forest damages faster, describe seasonal growth behaviour etc. The capability to fly underneath the crown cover could improve forest monitoring in cloudy and foggy areas. Of course, this advantages can be reached by UAV derived LiDAR data as well, but not on a consumer grade base and therefore only for few users. The low costs could lead to a more detailed forest monitoring because even small managed areas can be monitored or even private areas. Hereby the fact that the AGB, DBH and area parameter values show positive correlation values in all cases for the CHM approach could allow further applications with more focus on the use of such parameters.

Even if this is not the aim of this study it would be of high interest to expand the tests with a field-based reference. In this study, it is assumed that the LiDAR findings are close to the reality because it is a very established method and all used single steps proved their capability. It is to be mentioned that the amount of visually counted trees is hard to validate and therefore the LiDAR search window size settings cannot be validated as well. A validation and/or changing of the LiDAR findings is not of high importance in terms of the comparability but could lead to different and probably better results for both, LiDAR and RGB imagery findings. Furthermore, this study should be expanded by a larger number of more diverse study sites, ideally with a field-based reference to validate the made findings of this study. In this study, this was not possible due to a lack of suitable sites. Furthermore, the effect of the leaf status could be tested. Due to the fact that no exact date of record for the LiDAR data is available, it is possible that data was obtained with a leaf-off condition. Even if Brandtberg et al. (2003) stated that a leaf-off condition produces sufficient segmentation results it is of interest which effect the leaf status has. It is conceivable that especially the areas which are close to clearings with finer branches are harder to detect by LiDAR. This could lead to smaller crowns or rather to more ground areas. In addition, the difference of 7 years between the dates of record could have effects on the tree crowns. Due to the fact that most of the detected trees are higher than 20 meters a timespan of 7 years should not produce too much difference in terms of tree information. But it can be assumed that the results improve if the dates of record are in the same season of the same year.

Conclusion

In conclusion, this study shows that it is possible to generate RGB imagery derived CHMs which can lead to sufficient tree crown segmentation results. The DSM approach leads to such bad correlations results that it is to say, that this approach is not suitable for further studies. All compared CSAs can be conducted and are leading to usable results. The direct comparison indicates that the rLiDAR algorithm pair should not be the first choice, while the ITC and ForestTools approach compete with each other and should be selected depending on the research aim.

Although the results are satisfying improvements can be made to gain even more accuracy and reliability especially in terms of ground detection on the CHM approach.

To ensure that the found results describe realistic forest inventories a comparison with field-based references and more study sites should be conducted.

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Hiermit versichere ich, dass ich die vorliegende Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.
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