Individual tree crown detection and delineation across a woodland using leaf-on and leaf-off imagery from a UAV consumer-grade camera

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Abstract. Extraction of information about individual trees using remotely sensed data is essential to supporting ecological and commercial applications in forest environments. Data acquired by consumer-grade cameras onboard Unmanned Aerial Vehicles (UAV) offer an affordable option of high spatial resolution imagery that can be used to extract forest structural information at a tree level. The aim of this work is to investigate the potential and accuracy of UAV time series data to automatically detect and delineate tree crowns across an entire woodland. The workflow (presented in a step-by-step manner) involves the construction of a Canopy Height Model (CHM) based on digital elevation models derived from the UAV photogrammetric point clouds. A watershed-based approach is modified to automatically detect and delineate the tree crowns, based on the CHM and the brightness information from the UAV orthomosaics. The accuracy of the proposed method was evaluated by comparing its results against manually delineated tree crowns. The results show an overall accuracy of 63%, where conifer species were more accurately delineated (up to 80%), while broadleaf species returned lower accuracies (<50%). Continued research is necessary to improve the confidence of automated individual tree crown detection and delineation, especially over complex forest structures.

Keywords: crown delineation, drone, forest inventory, watershed algorithm, phenology, COTS.

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1 Introduction

Individual tree crowns, which are associated with the location and size of individual trees, can provide important structural information of a forest ecosystem. The automatic and accurate detection of individual tree crowns has many ecological and commercial applications, including forest planning¹, optimizing orchard management², evaluating tree growth dynamics³, improving tree species classification^{4,5}, estimating diameter at breast height and aboveground biomass⁶ and tree cover estimation⁷. Remote sensing data and techniques have been increasingly used to automatically detect and count tree crowns in substitution and/or in complement to traditional

forest inventories, which are time consuming and expensive ^{5,8}. However, the accurate identification of individual trees across diverse forest ecosystems in remote sensing data using automated methods is (still) not an easy task ⁹. Therefore, obtaining automatic identification of tree crowns, their locations and counts from remotely detected data is a useful and challenging task ¹⁰.

Aerial mapping of 3D forest structure has been largely undertaken with the aid of Airborne Laser Scanning (ALS) technology ^{11–13}, and, more recently, UAV imagery has emerged as a feasible and cost-effective local scale option for this purpose ^{14–20}. This is possible due to advances in structure-from-motion and multi-view stereo techniques, which have allowed Digital Terrain Models (DTMs) and Digital Surface Models (DSMs) to be generated out of a 3D photogrammetric point clouds ¹⁵. In a forest environment, the underlying ground topography (DTM) can be reconstructed based on points classified/selected as ground ¹⁴. A Canopy Height Model (CHM) can therefore be obtained by subtracting these two elevation models and forest attributes (e.g. total tree height, tree crown area) can potentially be derived from the CHM at an individual tree level, similarly to ALS data ¹⁶.

There are many approaches available to detect and delineate tree crowns from a CHM, with no single method performing best for all applications ^{8,21}. The accuracy of single-tree-level attributes estimation can be affected by the delineation method and data chosen but also, it can be highly dependent on the forest structure under investigation ^{10,12,22}. Individual tree level prediction accuracies of complex canopy structures (e.g. old broadleaf forest and uneven aged trees) are usually lower than those found in simpler and more homogeneous structures (e.g. conifer-dominated forests and same age plots) ^{23,24}. Therefore, there is a need for continued research in

either new algorithms or new remote sensing data sets to improve individual tree crown delineation.

Several studies have tested the potential of UAV data acquired from low-cost Red-Green-Blue (RGB) digital cameras for individual tree parameters detection^{14,16–19,25–29}, but they present a combination of methods, forest types and estimated metrics that are mostly different from the work here presented, including: i) focus on a single date acquisition^{14,16–19,25,26,29}; ii) monospecific forest plantations or crop trees^{16,25,26,28}; iv) using the spectral information (or image Digital Number - DN- values) alone²⁶; IV) -using the photogrammetric point clouds-derived products (e.g. CHM) alone^{14,16,25,28,30}. Comparatively, fewer studies used both the photogrammetric point clouds and the spectral data, but the spectral information was used to classify tree species^{15,19} and to predict forest biophysical parameters¹⁷, not being incorporated into the individual tree detection algorithm. In one study, however, Yancho et al.²⁹ combined point clouds with spectral information for individual tree crown detection but, unlike the raster-based methodology here proposed, the authors worked in the point level domain to form sub-crown clustering. Nuijten et al.³⁰ and Yancho et al.²⁹ suggested that future research should explore different ways to incorporate the spectral information into individual tree detection methods, across a diversity of forest environments.

The aim of this work is to investigate the potential and accuracy of leaf-on and leaf-off imagery acquired by a consumer-grade RGB camera on board a UAV to automatically detect and delineate tree crowns across a heterogeneous woodland with conifer and broadleaved species. More specifically, this manuscript assesses the effect of combining photogrammetric point cloud-derived CHM and orthomosaic brightness values (raster datasets) to detect and delineate individual tree crowns (while retrieving associated tree heights and crown diameters), adding further understanding on how spectral information may be used in individual tree detection. The work

uses UAV data acquired on two dates (leaf-on and leaf-off) in order to better reconstruct the DTM and the DSM, without intending to quantify errors associated with mapping crowns over time, as this is already done elsewhere³⁰. While the accuracy of the delineated crowns was evaluated by comparing its results against manually delineated tree crowns, the height and crown diameter were validated against ground measurements. Besides, the chosen methodology is described in a detailed, step-by-step manner (almost as a guide) to facilitate reproducibility and adoption by the community. Finally, the potential and uncertainties of the proposed method is discussed for applications in forest phenology studies.

2 Methodology

2.1 Study area and UAV data collection

The study area was previously described in Berra et al.³¹. Briefly, the study area consists of 15 ha of mixed deciduous and evergreen (conifer and broadleaf) woodland in the northeast of England (**Fig. 1**). The terrain within the woods has relatively flat topography with an altitude of approximately 75 m above sea level. A temperate climate is observed with a mean annual temperature of 8.3 °C³². Ground and UAV data were collected during the spring season of 2015, as part of an intensive field campaign to characterize the spring phenology (e.g. day of year of appearance of first leaves) of the study area³¹. Section 4.1 discusses the potential of the proposed methodology for phenology studies.

Six plots were installed in order to sample 20 individuals³³ from the main tree species within this woodland (locations are shown in **Fig. 1**). The plots' names and respective tree species are as follows:

- Larch: European larch (*Larix decidua*);

- Sycamore: Sycamore (*Acer pseudoplatanus* L.);
- Oak: Sessile oak (*Quercus petraea*);
- Sitka spruce: Sitka spruce (*Picea sitchensis*);
- Norway spruce: Norway spruce (*Picea abies*); and,
- Mix: English oak (*Quercus robur*) and Sycamore.

Fig. 1. Orthomosaic made of UAV images (visible camera) acquired on 21/04/2015. Ground validation data were acquired in six different plots (each containing 20 trees). The woodland was classified in four different land cover types. The Great Britain national outline is a product of ©Crown copyright and database rights 2016 Ordnance Survey.

Geographical coordinates of the 120 trees were surveyed with total station and Global Navigation Satellite System (GNSS). Tree height was measured using a vertex hypsometer (Vertex IV) and transponder (Transponder T3) (Haglof Sweden AB, Langsele, Sweden). The following average and variability in tree height was observed within each plot: Larch (21.3 ± 2.4 m), Sycamore (20.5 ± 1.2 m), Oak (19.6 ± 3.1 m), Sitka spruce (19.1 ± 0.8), Norway spruce (15.8 ± 0.9 m) and Mix (18.9 ± 4.5 m).

The collection, processing, calibration and validation of the series of UAV data used in this paper are described in detail in Berra et al.^{31,34}. Briefly, the study area was flown by a fixed-wing UAV (Quest300 and QPOD - QuestUAV Ltd., Amble, UK) equipped with one gimballed Panasonic DMC-LX5 digital camera (Panasonic UK Ltd., Bracknell, Berkshire, UK). The camera has 5.1 mm nominal focal length, 3648 x 2736 pixels (effective pixels 10 megapixels), CCD sensor type with a sensor size of 1/1.63" and records the visible light in the Red-Green-Blue (RGB) channels (Table 1). The Panasonic's relative spectral response functions can be seen in ³⁴.

Table 1. Spectral settings of the RGB Panasonic camera. FWHM: full width at half maximum.

Band	Band width (nm)	FWHM wavelength (nm)		Centre Wavelength (nm)
		lower	upper	
Blue	87	426	512	469
Green	121	473	595	534
Red	76	579	655	617

All UAV images were captured on manual settings (ISO-100, shutter speed 1/800 s, aperture f/2 and focus to infinity) and saved in RAW format. The RAW files were individually converted to dark- and vignetting- corrected linear TIFF images (i.e. RGB image)^{31,34}. The corrected TIFF images were thereafter mosaicked using the software Agisoft PhotoScan v.2 (Agisoft LLC, St. Petersburg, Russia). Orthomosaics were created following recommended settings³⁵, but with a key modification: the orthomosaic was constructed with blending mode deactivated in order to preserve the original (corrected) DN values. While surface reflectance was retrieved from the orthomosaic DNs in Berra et al.^{31,34}, this work uses only the orthomosaic DN values (referred to as brightness values in this manuscript) without any further correction.

The orthomosaics (10 cm spatial resolution; geolocation accuracy of ± 11 cm), and associated point clouds, were generated for two dates (Table 2): 18th March 2015 (leaf-off) and 6th August 2015 (leaf-on). This was done in order to take advantage of the: i) leaf-off phase of deciduous species as to detect a higher density of ground points for later DTM calculations; and ii) leaf-on phase to produce a higher density of tree canopy points for later DSM reconstruction. More details of the orthomosaic and digital elevation models generation are provided next.

Table 2. Characteristics of the UAV imagery acquisition, derived products and from which date each product was extracted.

Acquisition date	Season	Images	Flight height (m)	Elevation model	Points per m ²	RGB Brightness
March 18, 2015	Winter (leaf-off)	499	122	DTM	122	No
August 6, 2015	Summer (leaf-on)	429	122	DSM	110	Yes

2.2 Automatic tree crown delineation based on CHM

In this paper, the automatic tree crown delineation across the entire study area was achieved by using a watershed-based approach, as proposed by ¹⁴, who used very high resolution UAV imagery, similar to the imagery available in this study, as input data to delineate tree crowns. Because watershed algorithm is easy to be implemented and improved, well developed ^{8,10} and is commonly available in GIS software, watershed is frequently used to perform crown delineation from a CHM ^{1,2,10,14,22,36–38}. ¹⁴'s original workflow, which used only 3D data, was modified in this study to also include the orthomosaic's RGB brightness information in the processing chain (**Fig. 2**) in order to test whether this would increase the delineation accuracy.

Fig. 2. Flowchart of the UAV data processing for automatic delineation of tree crowns. Modified from ¹⁴.

UAV images from two dates were used as input to generate a CHM (Table 2). On each date, the study area was flown twice in order to have a higher rate of image overlapping, which in turn can produce a denser point cloud, resulting in a more detailed 3D model and potentially minimizing occlusion problems ^{15,19}. The DTM was derived from a UAV acquisition date corresponding to deciduous leaf-off phase (DOY 77, 18th March 2015) in order to have a higher density of points representing the ground, at least over deciduous covers. UAV images acquired during a deciduous leaf-on phase were used to derive a DSM (DOY 218, 06th August 2015) as the canopy foliage was fully developed at this date.

After image alignment within PhotoScan (498 out of 499 aligned on DOY 77 and 429 out of 429 on DOY 218), the resulting sparse point cloud was georeferenced by using 13 Ground Control Points (GCPs). Thereafter, the camera parameters were optimized and a denser point cloud was

generated using a high quality reconstruction setting within PhotoScan³⁵. From the dense point cloud of DOY 77 (122 points/m²), an automatic classification (within PhotoScan) detected points associated with the ground. This classification is based on three user-defined parameters (maximum angle = 15°, maximum distance = 1 m, and cell size = 150 m), values which were determined based on a trial and error approach. The point cloud is firstly divided into the chosen cell size (150 m represents the approximate size of the largest evergreen stand (closed canopy; Sitka spruce in **Fig. 1**), where fewer ground points are likely to be present), and the lowest point within each cell is detected. An initial terrain model is triangulated from these points. Afterwards, the remaining points are iteratively checked and added to the ground class if they satisfy the specified angle and distance (in relation to the terrain model)^{35,39}. A DTM is then build based on the selected ground points employing the “Enabled (default)” interpolation option within PhotoScan. The DSM was constructed using the entire dense point cloud from DOY 218 (110 points/m²), using the same interpolation option. The DSM and DTM were exported as raster files (10 cm spatial resolution) to be used as input in ArcGIS 10.3.1 (ESRI©).

ArcGIS`s model builder was used to automate the tree crown delineation (**Fig. 2**). Firstly, a normalized CHM (nCHM) was calculated by subtracting the DTM from the DSM. The nCHM was then inverted to allow the Inverse Watershed Segmentation (IWS) method^{2,36} to be applied, whereby each segment is considered as an individual hydrologic drainage basin. Besides the inverted surface, a watershed approach also needs markers or ‘ponds’ (tree peaks in this case), which was achieved using the following three steps:

- 1) Determination of local minima by focal flow statistics. This step returned many tree peaks, not only over crown areas but also on the ground, so a cleaning and selection was applied.

- 203 2) Selection of the highest peak within a defined circular radius (focal statistics). The
204 optimal radius was determined per woodland type, based on a trial and error approach
205 (Larch = 2 m; Sycamore = 2.2 m; Oak = 2.7 m; Sitka spruce = 1.5 m; Norway spruce
206 = 0.9 m, and Mix = 2.4 m).
- 207 3) Removal of peaks by testing two methods:
- 208 3.1) “CHM only”, by using only the CHM data (similarly to ¹⁴): Removal of peaks with
209 low height (below the average CHM value of a 5x5 m window);
- 210 3.2) “CHM + Brightness”, by combining CHM and the orthomosaic’s brightness
211 values: Removal of peaks with low height (as above) and low brightness. This later
212 step was added into the ¹⁴’s workflow by defining a brightness threshold (either 20%
213 or 30% percentiles, dependent on woodland type) from the Green band of the
214 orthomosaic of DOY 218. The green band was chosen as it has the highest signal-to-
215 noise ratio (Table 1). This was undertaken in order to eliminate peaks located either on
216 the edge of crowns or very close to the crown (peaks which were not eliminated by the
217 height threshold alone), as illustrated in **Fig. 3**. Low brightness areas are expected to
218 detect canopy shadows which are related to canopy gaps among the tree crowns (**Fig.**
219 **3**); vegetation indices (instead of individual bands) were not used as they tend to
220 minimize shadowing effects⁴⁰, outcome which was not desired for this study.
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Fig. 3. Example of tree crowns and peaks extracted over the Larch dominated area. Tree peaks extracted by both the “CHM only” (yellow circle) and the “CHM + brightness” (pink X) methods are shown. The white arrow indicates a tree peak that was incorrectly detected when using the CHM data alone. On the other hand, by incorporating the orthomosaic values into the workflow (“CHM + brightness”), the candidate tree peak was excluded (filtered out) as it falls into a low brightness area.

Watershed segmentation was then applied by using both the selected tree peaks (imitating ponds) and the nCHM-derived flow direction as inputs (**Fig. 2**). The later raster was created using the ‘Flow direction’ tool within ArcMap, where each output cell represents the direction of flow from the elevation surface (nCHM). Since the segmentation results in a continuous raster, segments falling into areas of either low height (“CHM only” method) or low brightness and low brightness (“CHM + brightness” method) were removed using the same thresholds mentioned above.

Finally, the resulting watersheds were converted to polygons. Any hole inside a polygon was filled and polygons with small areas (1-3 m², dependent on woodland type as seen in **Fig. 2**) were either merged with adjacent ones or eliminated. The remaining polygons represent the tree crowns

(as seen in **Fig. 6**) and they were exported as a shapefile in order to allow for accuracy checks across the whole study area.

2.3 Automatic tree crown delineation: Accuracy assessment

The validation/reference data consisted of manually delineated crowns, a common approach when high or very high resolution imagery is available^{21,22,41}. Considering the very high spatial resolution of the UAV orthomosaics (10 cm), tree crowns were extracted by a manual delineation approach in ArcGIS. Firstly, a point data set containing the location and identification of each sampled tree (surveyed in the field) was overlain on the UAV orthomosaics. Each crown boundary was thereafter drawn based on leaf-on orthomosaics, but both orthomosaics (Table 2) were used to aid the image interpretation, allowing individual crowns to be resolved with confidence. Besides the 20 trees within each plot (**Fig. 1**), 20 more tree crowns (surrounding these plots) were manually delineated on the UAV orthomosaics, resulting in 40 crowns per woodland type (Larch, Sycamore, Oak, Sitka spruce, Norway spruce and Mixed); increasing the statistical representativeness.

The watershed-derived tree crowns were quantitatively evaluated at both plot and individual tree level, following the method proposed by²². Plot level assessment consisted of quantifying the tree count errors, i.e., comparing the crown count estimation against the number of reference crowns. However, this analysis, does not quantify wrongly/correctly delineated crowns and²² proposed a confusion table in order to evaluate individual tree level accuracy from both a reference crown and delineated crown perspective. The method is illustrated in **Fig. 4** with an interpretation provided in **Table 3**. In summary, the approach quantifies correctly detected tree crowns, and errors due to omission, commission and under- and over-segmentation.

Fig. 4. Detection scenarios from (a) reference and (b) crown perspectives with reference crowns shown as circular polygons and delineated crowns as filled polygons (Adapted from ²²). An interpretation of these five cases (i-v) is given in **Table 3**.

Table 3. Interpretation of the detection scenarios showed in **Fig. 4**. Adapted from ²².

Case	Interpretation
(i)	Simple omission (0 delineated: 1 reference).
(ii)	Simple commission (1 delineated: 0 reference).
(iii)	Perfect match, i.e., correctly delineated tree (1 delineated: 1 reference) in both perspectives.
(iv)	Commission from over-segmentation. One reference crown is delineated as two crowns, so a '2 delineated: 1 reference' ratio from a reference perspective. However, from the delineated crown perspective, each delineated crown sees only one reference crown (1 delineated: 1 reference).
(v)	Omission due to under-segmentation. A group of reference trees is delineated as a single one, resulting in a '1 delineated: 3 reference' ratio under the delineated perspective. From a reference crown perspective, however, each reference tree sees only one delineated polygon, so the '1 delineated: 1 reference' ratio.

The results from this confusion matrix are thereafter translated in terms of producer's (PA) and user's (UA) accuracy. PA calculates the probability of a reference tree being correctly delineated (Eq. 1) and UA represents the probability that a delineated tree will correctly represent a reference tree (Eq. 2) ²²:

$$PA = \frac{N_p}{N_r} \quad (1)$$

$$UA = \frac{N_p}{N_d} \quad (2)$$

where N_p is the number of correctly delineated trees; N_r is the number of reference trees and N_d is the number of delineated trees.

In order to quantify the effect of adding the orthomosaic brightness values into the original workflow that used only CHM data, the above-mentioned accuracy checks were carried out for both methods: “CHM only” and “CHM + brightness”. Accuracy checks for crown diameter and tree height estimates (next) were performed only for the data coming from the method with the least uncertainties.

A final accuracy assessment (for the crown delineation) was undertaken by comparing the delineated crown diameter against the reference diameters, but considering only the correctly delineated tree crowns (case (iii), **Fig. 4**). This involved calculation of mean error, absolute error and RMSE values.

Tree heights derived from the CHM (‘tree peaks’, **Fig. 2**) were linearly regressed against observed tree heights (hypsoneter) in order to quantify the accuracy of the UAV-derived CHM. An intersection test selected the observed vs estimated pairs of data; if the geolocation of an observed height (point) intersects an automatic delineated crown (polygon), then the observed tree height value is associated with the polygon’s tree peak value.

Lastly, it was tested whether decreasing image resolution would affect the tree crown delineation error. The spatial resolution of the UAV-derived CHM and orthomosaics were degraded in a 10 cm step up to 50 cm (i.e. 10-20-30-40-50 cm). The PA (Eq. 1) and UA (Eq. 2) of tree crown delineated at each of these five spatial scales were compared across the six different test sites.

3 Results

3.1 Accuracy of the automatic tree crown delineation

For the “CHM + Brightness” method, no difference was detected between the number of observed and detected trees in the Larch and Mix plots, whilst underestimation of the number of trees was observed for Sycamore, Sitka spruce and Norway spruce, contrary to overestimation for the Oak plot (**Table 4**). On the other hand, the “CHM only” method detected, on average, 5% more trees (**Table 4**). However, this tree counting does not provide the proportion of correctly delineated trees, information that is given by the reference/crown perspective confusion matrix (**Table 5**, **Table 6**).

Table 4. Tree count estimation error at plot level, comparing results achieved using the “CHM only” vs. “CHM + brightness” methods. Every automatically delineated crown (Estimated) represents one tree.

Plot	Reference	CHM + Brightness		CHM only	
		Estimated	Difference (%)	Estimated	Difference (%)
Larch	40	40	0	41	3
Sycamore	40	35	-13	38	-5
Oak	41	51	24	56	37
Sitka spruce	40	39	-3	44	10
Norway spruce	40	36	-10	32	-20
Mix	40	40	0	42	5
Total	241	241	0	253	5

Considering the “CHM + Brightness” method, an overall accuracy of 63% was detected across all woodland types, as given by the PA and UA (**Table 5**). Conifer species were more accurately delineated with PA ranging from 73% to 80% (UA from 78% to 82%), whilst broadleaf species achieved lower PAs (43% to 57%, with UA from 43% to 63%). Only 1 tree (out of 240) was omitted and no simple commission errors were observed. Over-segmentation affected mainly the Oak and Mix plots, predominantly with 2 segments (2:1 in the reference crown perspective) and

not more than 3 segments per tree. These two plots were also the most affected by under-segmentation (1:2 and 1:3 in the delineated crown perspective). Examples of the results are showed in **Fig. 5**, where manual and automatic delineated polygons are overlaid on the UAV orthomosaic (all the automatic delineated crowns can be seen in **Fig. 6**).

Table 5. Accuracy assessment of automatically delineated tree crowns for “CHM + Brightness”. “1:1” shows the correctly delineated trees, or perfect matches. 40 reference trees were sampled in each plot, totalling 240 reference trees.

Plot	Reference crown perspective				Delineated crown perspective				1:1	PA ¹ (%)	UA ² (%)
	0:1	1:1	2:1	3:1	1:0	1:1	1:2	1:3			
A	0	34	6	0	0	39	1	0	31	78	78
B	0	32	8	0	0	29	6	0	23	57	66
C	1	29	10	1	0	44	5	2	21	51	41
D	0	36	4	0	0	35	3	1	32	80	82
E	0	35	5	0	0	33	3	0	29	73	81
F	0	26	12	2	0	33	5	2	17	43	43
All	1	192	45	3	0	213	23	5	153	63	63

¹Producer`s accuracy; <sup>2</sup>User`s accuracy; A=Larch; B=Sycamore; C=Oak; D=Sitka spruce; E=Norway spruce; F=Mix. A, D and E are conifers; the others are broadleaf species.

As for the “CHM only” method, an overall accuracy of 53% and 51% was detected across all woodland types, as given by the PA and UA, respectively (**Table 6**). This indicates that the “CHM only” method produced poorer results by ~10%, indicating that the inclusion of brightness data is beneficial for individual tree detection approaches. Despite such differences in magnitude, the “CHM only” method returned similar tendencies, with conifer species being more accurately delineated (PA = 50 to 65%; UA = 59 to 61%) than broadleaved species (PA = 35 to 55%; UA = 33 to 58%) (**Table 6**). Due to this overall better performance of the “CHM + brightness” method, only the heights and crown diameters derived from this method are compared against ground measurements.

Table 6. Accuracy assessment of automatically delineated tree crowns for “CHM only”. “1:1” shows the correctly delineated trees, or perfect matches. 40 reference trees were sampled in each plot, totalling 240 reference trees.

Plot	Reference crown perspective				Delineated crown perspective				1:1	PA ¹ (%)	UA ² (%)
	0:1	1:1	2:1	3:1	1:0	1:1	1:2	1:3			
A	0	35	5	0	0	38	3	0	25	63	61
B	0	30	9	1	0	32	6	0	22	55	58
C	1	29	8	3	0	48	6	2	21	51	38
D	0	31	8	1	0	40	4	0	26	65	59
E	3	30	7	0	0	28	4	0	20	50	63
F	0	26	12	2	0	32	9	1	14	35	33
All	4	181	49	7	0	218	32	3	128	53	51

¹Producer's accuracy; ²User's accuracy; A=Larch; B=Sycamore; C=Oak; D=Sitka spruce; E=Norway spruce; F=Mix. A, D and E are conifers; the others are broadleaf species.

Fig. 5. Examples comparing manual vs automatic delineation of oak tree crowns for three cases: correct detection, under segmentation and over segmentation. The background orthomosaic is made of visible camera UAV images, acquired on 25/06/2015.

Fig. 6. 4354 tree crowns were automatically detected across the study area. Orthomosaic made of RGB UAV images acquired on 21/04/2015.

For correctly delineated crowns, crown diameters were underestimated by around 21 cm (absolute error of 42 cm and RMSE of 11%) across the six plots, with the best match occurring for the Oak plot (RMSE = 6%) and the largest mismatch for Sitka spruce (RMSE = 19%) (**Table 7**). This underestimation tendency means that the automatically delineated crown area is smaller than the reference crown, and this can be due to: 1) generalization of the crown shape during manual delineation, i.e., not cutting into the crown between branches when drawing crown boundaries; and 2) to the exclusion of areas with low brightness and low height during the automatic delineation (**Fig. 2**), which can favour the upper canopy.

Table 7. Summary statistics of crown diameter from correctly delineated tree crowns (Perfect 1:1, Table 5, “CHM + Brightness” method). Each plot has 40 reference tree crowns. Bias is calculated as reference less delineated crowns, so a negative bias indicates underestimation of tree crown diameter. RMSE is shown as a percentage of the mean measured diameter⁴¹.

Plot	Tree crowns (Perfect matches)	Mean reference diameter (m)	Bias (m)	Absolute error (m)	RMSE (%)
Larch	31	5.3	-0.08	0.41	10
Sycamore	23	6.2	-0.34	0.45	9
Oak	21	7.9	-0.08	0.34	6
Sitka spruce	32	4.0	-0.47	0.57	19
Norway spruce	29	2.3	-0.18	0.26	13
Mix	17	6.3	-0.13	0.49	10
Total	153	5.3	-0.21	0.42	11

Fig. 7. Tree heights estimated from a UAV-derived Canopy Height Model (CHM) (“CHM + Brightness” method) are validated against ground measured tree heights (hypsometer + transponder), across six woodland plots. The dashed line represents the 1:1 line and the solid line a linear regression model.

Tree heights derived from the UAV CHM were underestimated by ~1 m (**Fig. 7**), with taller trees (Larch and Sycamore) contributing the most for this tendency, as indicated by the slope (<1) of the linear equation. This underestimation could be due to the spatial smoothing applied on the original CHM, as it tends to flatten the CHM surface. Generally, tree heights could be estimated from the UAV CHM with an uncertainty of ~1.5 m, as given by the RMSE value (**Fig. 7**).

Decreasing image resolution, in general, increased delineation error (**Fig. 8**), agreeing with⁴¹. An exception was detected with Oak trees, which could be due to their larger crowns (diameter of

~8 m). In this case, the spatial degradation can smooth out large gaps within a tree crown, reducing over-segmentation. The highest spatial resolution data (10 cm) were therefore used for the automatic tree crown delineation.

Fig. 8. Effects of spatial resolution degradation (UAV-derived CHM and orthomosaics) in the Producer's (PA) and User's (UA) accuracy assessment of tree crown delineation across six different test sites. 40 reference tree crowns were considered in each test site.

4 Discussion

Tree crowns and tree peaks were automatically detected from high resolution photogrammetric point clouds, alongside orthomosaic brightness information from UAV data, allowing tree crown and peaks estimation across the entire extent of the aerial survey. Combining elevation with brightness data ("CHM + brightness" method) improved the tree crown and tree count detection accuracy by around 10% and 5%, respectively; UAV spectral data combined with UAV point cloud data (but at the point level) was also proven to be positively influential in the accurate detection of individual trees (~6.3%) across a conifer-dominated temperate forest²⁹. Because the

upper canopy is usually brighter than the background cover, the brightness information showed to be particularly useful to eliminate those watershed areas and tree peak candidates not belonging to tree crowns (i.e., darkest areas), therefore improving the crown's limits detection. This is in accordance with St-Onge et al.¹⁵, who found that the crown outline boundaries detected from UAV photogrammetric point clouds-derived CHM tend to be less reliable (compared to Lidar) due to smoothing effects and occlusion problems. Furthermore, strong shadows, which can cause occlusions and lead to local inaccuracies in the 3D point cloud and CHM reconstruction¹⁹, can be easily classified on RGB orthomosaics (e.g. **Fig. 3**) and used to improve crown boundary delineation.

The delineation accuracy found in this research (40-80%) is within the range reported in the literature for heterogeneous environments^{14,18,24,42}. Similarly to this work, Nuijten et al.³⁰ applied a watershed segmentation onto UAV-derived CHM to delineate individual tree crowns across a deciduous-dominated temperate forest, achieving accuracies between 55% and 77%, depending on the dates on which the UAV images were acquired. Yancho et al.²⁹ also combined spectral and point cloud UAV data (but using a subcrown point clustering approach), where 48% of the individual tree crown were correctly detected and segmented across a complex forest ecosystem. Across a boreal forest, Nevalainen et al.¹⁹ found the accuracy of individual tree identification from the UAV photogrammetric point clouds varying between 26% and 96%, depending on the characteristics of the different test sites. These results confirm that heterogeneous forest structures (such as the Oak and Mix plots in this study) are challenging targets for automated individual tree crown detection and delineation using remotely sensed data^{21,23}. On the other hand, an accuracy of >90% in delineated tree crowns from UAV-derived 3D point clouds data was reported by

Sanchez et al.²⁸, which is likely due to the simpler structure of the study area (an almond tree plantation).

Likewise, the uncertainties found in this study for crown diameter (absolute error of 42 cm and RMSE of 11%) and dominant height (RMSE = 1.47 m) are within the range reported in the literature for mixed, complex forest environments^{14,15}. These results are similar to those achieved by St-Onge et al.¹⁵ who used an airborne multispectral metric camera to estimate tree height, yielding $0.53 \leq r^2 \leq 0.93$ and $1.35 \text{ m} \leq \text{RMSE} \leq 2.4 \text{ m}$ (depending on forest type and structure), confirming the potential of low-cost non-metric UAV cameras for individual tree detection applications. Unlike this study, crown diameters were overestimated by ~50 cm (absolute error of ~75 cm and RMSE of ~16%) in the CHM-based method of Panagiotidis et al.¹⁴, which can be partially explained by the combination of pixels from gap areas being counted as crown area; this problem could potentially be minimized by applying a brightness threshold to filter out such gap areas, as proposed in this study and illustrated in **Fig. 3**.

Studies retrieving canopy biophysical parameters of individual trees with UAV RGB imagery across discontinuous (open) canopies achieved better results than this study, as it could be expected. Sánchez et al.²⁸ estimated almond tree heights with an RMSE = 0.39 m. Zarco-Tejada et al.²⁵ found a similar error of RMSE = 0.35 m in the estimation of tree heights across an olive orchard, using a UAV-derived digital surface model. Across a pine forest plantation, linear fits of the field and UAV image-measured height showed an $R^2 = 0.81$ (RMSE = 0.45 m), while in crown diameter an $R^2 = 0.95$ (RMSE = 0.63 m) was achieved¹⁶. In conifer-dominated boreal forests, Puliti et al.¹⁷ predicted the dominant height with an accuracy of 0.7 m. These relatively good agreements are likely due to typically more simple forest types, in terms of species composition, and/or higher

values of canopy gap fractions (usually sparsely distributed trees), characteristics which can make it easier for the algorithm to resolve the individual trees at both the spectral and 3D domain.

The method may be applied to other forest areas where UAV optical data are available. The proposed workflow is based on RGB imagery from a consumer off-the-shelf (COTS) digital camera onboard on a UAV, making it an affordable aerial remote sensing platform. Nevertheless, because UAV data from two acquisition dates and at an individual tree level are needed, an accurate georeferencing approach should be utilised to minimize registration errors by using either GCPs surveyed with Differential GPS (as in this study) or geotags from the original images (direct georeferencing) if a high accuracy GNSS receiver is available on-board the UAV; however, over areas with a high degree of canopy openness throughout the year (e.g. orchards²⁵), UAV images acquired on a single date could be enough to satisfactorily reconstruct both the DTM and the DSM, as the proportions of canopy and background covers on the images are expected to be similar, reducing UAV acquisition costs and simplifying the methodology. Regarding the transferability of methodology to different forest structure (dense vs. open canopies) and composition (deciduous vs. conifers), different optimal parameter values within the workflow (e.g. search radius, brightness thresholds) may need to be identified and validated (sensitivity analysis).

Future studies in this research field, could take advantage of the high temporal and spatial resolution of UAV imageries to iteratively improve the delineation accuracy (especially across complex forest ecosystems) by exploiting the phenological variability of individual plants growing adjacent to each other or other ecological processes such as competition among trees. Such approaches would, in fact, take full advantage of the information contained within time series of remotely sensed data. Measurements of individual tree crowns that is so aptly captured in field surveys, but is lost in satellite pixel-based studies, can potentially be achieved by sensors on board

a UAV. Contrary to field surveys which have to sample an ecosystem due to costs constraints or natural limitations, the approach proposed in this study offers the chance to potentially measure all the trees in the forest upper stratum within a small area, i.e., it is possible to census the plants within this area; however, complex forest structures, such as from old broadleaved species, can make it challenging to accurately detect tree crowns, as shown here and elsewhere^{22,29,30}. Bearing in mind such limitations, this approach can be extremely useful in ecological studies as it allows researchers to analyse a forest in its primary element, the tree⁵. This could be useful for many ecological applications, such as tree species or plant communities mapping^{43,44}, forest phenology³¹, predicting bird phenology⁴⁵ and can aid in understanding processes occurring at very fine scales.

4.1 Considerations in forest phenology applications

It is commented above that one potential application of delineated tree crowns is the ability to monitor the life cycle development of forests (phenology) at an individual tree level. However, consideration is needed regarding the uncertainties of this watershed-based method for individual tree-level phenology estimates more generally. Trees with multiple segments (over-segmentation) will be considered multiple trees, but the multiple segments should return very similar estimates of phenological events dates (assuming budburst occurs evenly within a same crown). On the other hand, trees clustered under one segment (under-segmentation) will be treated as a single tree and the estimated phenological events should: 1) reproduce the average behaviour of the cluster, if the individuals start the growing season on similar dates, or 2) if the clustered trees leaf out on very different dates, the estimated start of spring date may be more closely associated with the first tree to leaf out within the cluster.

The latter case may have implications on estimating phenological behaviour at large scales. For example, if phenological event dates of such clusters are aggregated up to a moderate/coarse spatial resolution satellite pixel area, the UAV-derived canopy phenology may be biased earlier, i.e. the aggregated leaf out date will be estimated earlier in the year.

5 Conclusions

A detailed, step-by-step, watershed-based approach was proposed to automatically detect and delineate tree crowns using UAV remote sensing data (from a cheap camera) and a popular GIS software. This can allow mapping of overstorey vegetation at a detailed biological scale and across local spatial extents and could be a useful tool for precision forestry. The proposed method can be used to detect the position, the size, and the shape of individual tree crowns from UAV-derived products (point clouds and orthomosaics).

Nevertheless, complex forest structures (due to, for example, heterogeneity in tree species composition and differences in age) are still very challenging environments to achieve accurate automatic delineation of tree crowns. Therefore, it is important to continuously test new algorithms and new remote sensing data sets to improve results, mainly over heterogeneous forests.

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Professional Biography

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List of Figure Captions

Fig. 1. Orthomosaic made of UAV images (visible camera) acquired on 21/04/2015. Ground validation data were acquired in six different plots (each containing 20 trees). The woodland was classified in four different land cover types. The Great Britain national outline is a product of ©Crown copyright and database rights 2016 Ordnance Survey.

Fig. 2. Flowchart of the UAV data processing for automatic delineation of tree crowns. Modified from 14.

Fig. 3. Example of tree crowns and peaks extracted over the Larch dominated area. Tree peaks extracted by both the “CHM only” (yellow circle) and the “CHM + brightness” (pink X) methods are shown. The white arrow indicates a tree peak that was incorrectly detected when using the CHM data alone. On the other hand, by incorporating the orthomosaic values into the workflow (“CHM + brightness”), the candidate tree peak was excluded (filtered out) as it falls into a low brightness area.

Fig. 4. Detection scenarios from (a) reference and (b) crown perspectives with reference crowns shown as circular polygons and delineated crowns as filled polygons (Adapted from 22). An interpretation of these five cases (i-v) is given in Table 3.

Fig. 5. Examples comparing manual vs automatic delineation of oak tree crowns for three cases: correct detection, under segmentation and over segmentation. The background orthomosaic is made of visible camera UAV images, acquired on 25/06/2015.

Fig. 6. 4354 tree crowns were automatically detected across the study area. Orthomosaic made of RGB UAV images acquired on 21/04/2015.

Fig. 7. Tree heights estimated from a UAV-derived Canopy Height Model (CHM) (“CHM + Brightness” method) are validated against ground measured tree heights (hypsometer + transponder), across six woodland plots. The dashed line represents the 1:1 line and the solid line a linear regression model.

Fig. 8. Effects of spatial resolution degradation (UAV-derived CHM and orthomosaics) in the Producer’s (PA) and User’s (UA) accuracy assessment of tree crown delineation across six different test sites. 40 reference tree crowns were considered in each test site.

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