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Unveiling the complex canopy spatial structure of a Mediterranean old-growth beech (*Fagus sylvatica* L.) forest from UAV observations

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ABSTRACT

In front of climate change scenarios and global loss of biodiversity, it is essential to monitor the structure of old-growth forests to study ecosystem status and dynamics to inform future conservation and restoration programmes. We propose an Unmanned Aerial Vehicle (UAV)-based framework to monitor fine-grained forest top canopy structure in a primary old-growth beech (*Fagus sylvatica* L.) forest in Pollino National Park, Italy, which belongs to the UNESCO World Heritage (UNESCO WH) serial site "Ancient and Primeval beech forests of the Carpathians and other regions of Europe". Canopy profile, gap properties and their spatial distribution patterns were analysed using the canopy height model (CHM) derived from UAV surveys. Very high-resolution orthomosaic images coupled with direct field measurement data were used to assess gap detection accuracy and CHM validation. Forest canopy properties along with the vertical layering of the canopy were further explored using second-order statistics. The reconstructed canopy profile revealed a bimodal top height frequency distribution. The upper canopy layer (h > 14 m) was the most represented canopy height, with the remaining 50% split between the medium and lowest layer; 551 gaps were identified within 11.5 ha. Gap size varied between 2 m^2 and 353 m^2, and 19 $m^2$was the mean gap size; the gap size-frequency relationship reflected a power-law probability distribution. About 97 % of the gaps were <100 m^2 in size, showing a significant tendency to cluster. Most gaps were located in the upper and medium canopy layers; however, the highest relative gap area was found in the lowest layer. These results confirmed the high natural integrity of the ecosystem processes that distinguish the old-growth beech stands in respect to managed woodlands. Our findings demonstrate that the low-cost UAV-DAP (Digital Aerial Photogrammetry) workflow has the potential to generate realistic old-growth forest canopy attributes at a very fine scale. The proposed protocol can be adopted for monitoring the structural dynamics of high-value natural forest ecosystems as in the case of UNESCO WH sites or other old-growth stands. This approach is also helpful for mapping and deriving spatially explicit canopy structure information over confined forest areas and determining where conservation actions should be directed to preserve or restore natural ecosystem function.

1. Introduction

As climate change intensifies and biodiversity loss accelerates (Erb et al., 2018; García-Vega & Newbold, 2020), understanding primeval and old-growth forests' structural dynamics is of great importance from both a conservation and management perspective (Feldmann et al., 2018, 2020). Actually, old growth structure and dynamics constitute a benchmark for evaluating the impacts of man-induced disturbances, e.g.

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how close-to-nature is the forestry at work. Such close-to-nature forestry can therefore contribute to the mitigation of the effects of climate change and reaching biodiversity conservation targets. Stand structure is a direct result of long-term, interacting ecological factors that can affect tree mortality, regeneration and growth dynamics. Natural disturbances can create openings in the forest canopy (i.e., gaps), initiating different growth patterns and processes, dependent on disturbance ecology. Gaps generated by tree falls are the dominant disturbance regime in many forest ecosystems, driving the composition and abundance of stand regeneration (Runkle, 1981; Brokaw, 1982). The derived structural complexity found in forests are essential predictors of biodiversity (Lindenmayer et al., 2000; Oettel & Lapin, 2021). Thus, understanding the vertical variation of canopy height (Müller & Brandl, 2009), canopy cover (Smith et al., 2008), and forest gaps (Zellweger et al., 2013, 2019) provide essential information on forest dynamics in secondary old-growth forests. Furthermore, gap dynamics in old-growth stands represents an important benchmark for defining nature-driven management to restore native biodiversity by emulating old-growth properties within human-influenced or traditionally managed forests (Seymour et al., 2002; Solano et al., 2021a).

European beech (*Fagus sylvatica* L.) forests represent one of the most prevalent forest types in Europe (Packham et al., 2012). Due to anthropogenetic pressure thousands of years ago (Munteanu et al., 2015; Parviainen, 2005), the dynamics of primeval beech forests in western Europe have been overlooked, and few scattered relicts of natural beech forests remain (Hobi et al., 2015a). Thus, it becomes increasingly important to monitor old-growth beech ecosystem integrity and functionality especially as climate change intensifies. Assessing the structural properties of old-growth beech forests can provide critical information for managing beech forests sustainably at the landscape level and for detecting and mapping potential primeval beech forests (Chiarucci & Piovesan, 2020).

However, despite a wide range of studies about disturbances in beech-dominated forests (Asenova et al., 2019; Bagaram et al., 2018; Di Filippo et al., 2017; Feldmann et al., 2018; Kenderes et al., 2008; Khodaverdi et al., 2019; Petritan et al., 2013; Pie & Schreiber, 2016), it is challenging to compare results and draw conclusions because of varying methodologies. The development of a translatable method based on a technologically advanced approach to monitor structural dynamics is needed.

Gap size and spatial distribution are the most frequently mapped parameters across various terrestrial (Hobi et al., 2015b; Stepper et al., 2014) and remote sensing surveys (Getzin et al., 2014). Between these two approaches remote sensing analyses enable the user to map larger landscapes and describe change over time (Praticò et al., 2021; White et al., 2018). The tools to map canopy gaps vary and include: multispectral satellite images (Hobi et al., 2015b), unmanned aerial vehicles (UAV) (Getzin et al., 2012, 2014), RGB and infrared stereo aerial images (Nuske, 2006), airborne laser scanning (ALS) (Koukoulas & Blackburn, 2004; Vepakomma et al., 2012), and terrestrial laser scanning (TLS) (Seidel et al., 2015). Before LiDAR-based methods had been developed, few studies focused on canopy gaps because field methods were time consuming. However, the usage of UAVs can allow accurate mapping of canopy gaps within a small forested stand at high resolution and quality (Getzin et al., 2012). UAVs are cost effective because they allow for easy replicability and minimize cloud cover in imagery compared to aerial or satellite one. Advances in the field of digital photogrammetry indicate great potential for deriving digital surface models (DSMs) and canopy height models (CHMs), allowing for accurate representations of forest canopy structure (Miranda et al., 2021; Straub et al., 2013) and gap detection. Despite the increasing number of applications and approaches, few studies have used these techniques in complex old-growth forests in mountaneous environments of the Mediterranean basin.

The primary goal of the present study was to design a UAV-based forest canopy survey capable of capturing the fine properties of the canopy gaps and their spatial distribution, as well as the vertical layering of the forest canopy. The research was carried out and validated in Pollino National Park (South Italy) in a primary old-growth beech forest (*Fagus sylvatica* L.) located at the upper altitudinal limit of beech distribution (Piovesan et al., 2019). Because of its exceptional ecological value, this area is a conservation priority and it was recently included in the UNESCO World Natural Heritage (UNESCO WH) of serial sites' "Ancient and Primeval beech forests of the Carpathians and other regions of Europe" (https://whc.unesco.org/en/list/1133/). Considering the capabilities provided by the adopted technology and the now widespread availability of these products, we suggest a UAV monitoring framework for describing and tracking canopy and gap patterns and processes in high-natural forest stands such as site with the UNESCO WH network.

2. Materials and methods

2.1. Study area

The research area is located on Mount Pollinello, within Pollino National Park (Fig. 1). This beech forest is a strong representative of old growth, growing at an altitude ranging from 1900 to 2000 m a.s.l. within a strict reserve area. Due to its remote location, we selected only the core of the old growth forest which has not had human influence for at least 70 years. With assistance from park staff, we determined that the perimeter of the ancient forest was 11.5 ha.

This forest is characterized by the *Asyneumato-fagetum sylvaticae* association, a community endemic to high-altitude areas in the Southern Italian Apennines, characterized by an uneven-aged structure. Beech trees can grow up to 620 years old and grow in proximity to old (800–1200 years) *Pinus heldreichii* trees (Piovesan et al., 2019).

The proposed method to monitor fine-grained forest canopy structure in primary old-growth forests is outlined in Fig. 2 and described below.

2.2. Aerial image acquisition and processing

Digital imagery of the study area was acquired using the DJI Phantom 4Pro + quadcopter at the end of August 2020. Four different flight missions were carried out based on the UAV technical characteristics, extension, and morphology of the study area, with 80% of mean overlap, ensuring the maximum coverage and mean altitude across the study area (Supplementary material S1). The main processing steps included camera alignment, georeferencing, building a dense 3D point cloud using a structure from motion (SfM) algorithm (Solano et al., 2021b), generating a digital terrain model (DTM), a digital surface model (DSM), and mosaicked orthofotos. The following data were obtained from the SfM photogrammetric workflow: a raster grid orthomosaic with a ground sample distance (GSD) of 3 cm, a DSM and a DTM with 15 cm of GSD. Finally, the DTM was resampled to 3 cm for further analysis.

2.3. Mapping forest canopy gaps

Across remote sensing canopy gap research, fixed and variable height thresholds are the most frequent methods for gap detection. However, disagreement on the definition of gap closure is ongoing. Several studies considered different regeneration height thresholds between 2 m and 20 m (Asner et al., 2013; Blackburn et al., 2014; Gaulton & Malthus, 2010; Kenderes et al., 2008; Nuske et al., 2009; Petritan et al., 2013; White et al., 2018) depending on the biogeographical context, forest composition, and the purpose of the research together with the accuracy of the data to detect those gaps (Bagaram et al., 2018; Zielewska-Büttner et al., 2016). The same disagreements can be found regarding the accepted minimum gap dimensions, varying from 1 to 1000 m^2 (Bonnet et al., 2015; Garbarino et al., 2012; Getzin et al., 2014; Hobi et al., 2015a; Vepakomma et al., 2008). Based on these statements, we chose to adopt a fixed height threshold approach, determined by

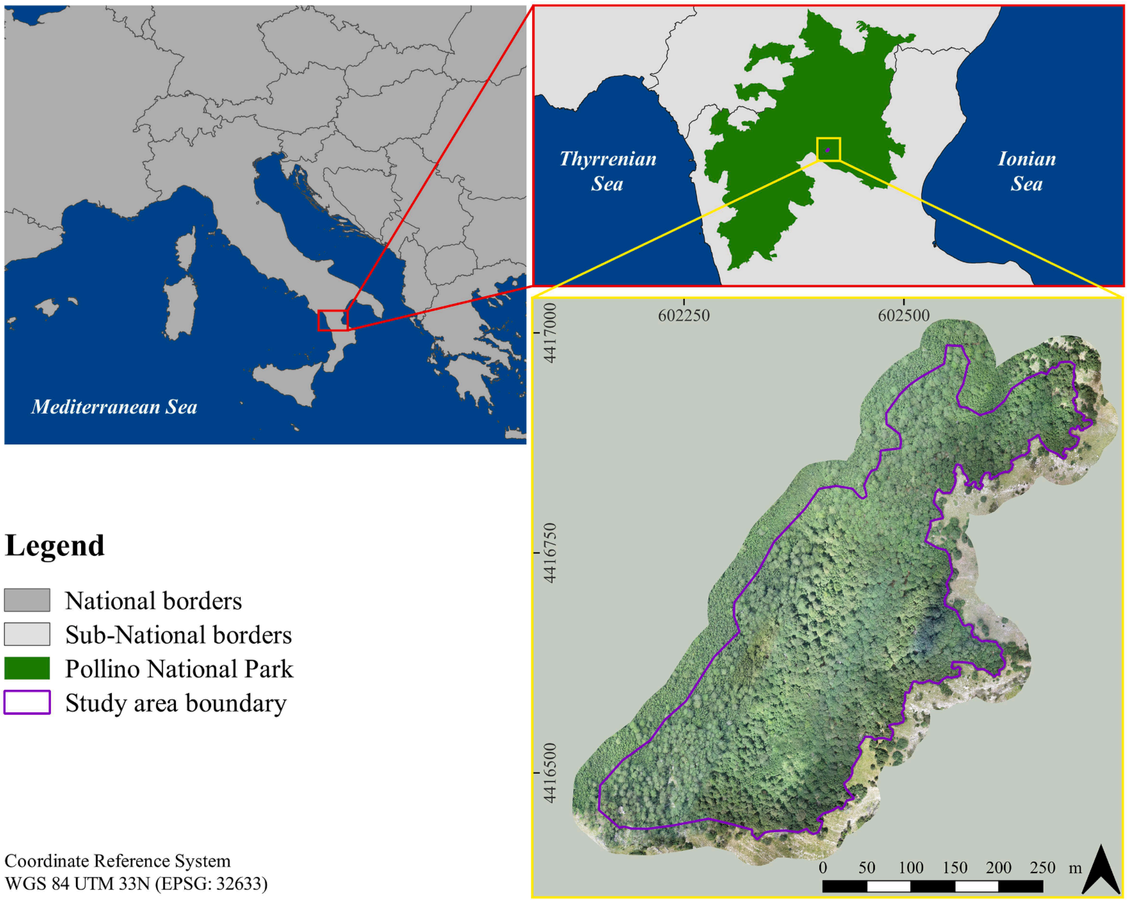

Fig. 1. Study area localization and UAV-derived very high-resolution orthomosaic image.

previous studies in the area and the ecological conditions of the beech forest ecosystem (Piovesan et al., 2019). We considered a gap as a canopy opening defined by the vertical crown projection of the bordering trees, reaching the ground through all strata to 2 m vegetation height and a minimum of at least 2 m^2. The vertical difference measurement between DTM and DSM (i.e., CHM) was then used to evaluate the height of the forest canopy above the ground, covering all the study area at 3 cm of spatial resolution. We used the R package ForestGapR (Silva et al., 2019) to detect canopy gaps across the CHM, allowing us to locate contiguous areas consistent with our gap definition.

2.4. Forest canopy height and vertical structure

Height variation between the canopy layers were considered indicative of different stages of development. Maximum canopy height has often been used to describe a forest stand (Gaulton & Malthus, 2010; Hobi et al., 2015b; Rehush & Waser, 2017; Roşca et al., 2018), and because height is strongly correlated with stem diameter, we used the 100 tallest trees per hectare to estimate the max height (Koch et al., 2009). We first resampled the original CHM of the entire study area to 0.5 m resolution ($CHM_{0.5}$) and then divided it into subareas of approximately 1 ha. Within each subarea, we applied a maximum local moving filter in a 5 × 5 window to generate an area representing the maximum height of the forest canopy. We chose this filter size to prevent the top of the canopy from overlapping smaller gaps (<3 m^2), thus preserving the height variation in the study area (Gaulton & Malthus, 2010; White et al., 2018). The greatest 100 height values were collected and averaged to estimate the top height of each subarea. The average value between the 12 subareas was used to separate the canopy layers of the beech forest, corresponding to the IUFRO classification (Leibundgut, 1956): upper layer > 2/3 of the $CHM_{0.5}$ max height, medium layer > 1/3 and ≤2/3 of the $CHM_{0.5}$ max height and lower canopy layer ≤ 1/3 of the $CHM_{0.5}$ max height. The gap layer was considered below the lower area (Fig. 3). Finally, we reclassified the $CHM_{0.5}$ with each height layer value obtained.

We used the Rumple index to estimate canopy surface roughness (Parker et al., 2004). Following Kane et al. (2008), we computed the ratio between the 3D CHM surface area and its 2D ground projection surface area using the lidR package (Roussel et al., 2020) with $CHM_{0.5}$ as the input raster data.

2.5. Accuracy assessment and data validation

Forty-two tree heights, diameters at DBH and geographic coordinates were measured in-situ to validate CHM across various canopy layers using a Vertex IV hypsometer and transponder (Haglöf, Sweden). We then used ordinary least square (OLS) regression to fit a linear model between measured and estimated heights from the CHM, using the adjusted determinant coefficient ($_{adj}R^2$) and the root mean square error (RMSE) to evaluate model accuracy and therefore the reliability of the CHM. Statistical analysis was performed in R (4.1.0) statistical software (R Core Team, 2021).

Gap validation data were derived from both field surveys (geographic coordinates of 25 sample gaps), and visual interpretation of the UAV derived very high-resolution outputs. First, we superimposed a 25 m × 25 m grid (sample cell of 625 m^2) over the study area (Fig. 4). Then, we randomly selected 60 sample cells within the grid, covering 1/3 of the total study area. Inside each sample cell, all visually detectable gaps were manually digitized as vector polygons, representing the reference gap boundaries, using the orthomosaic and the CHM as base

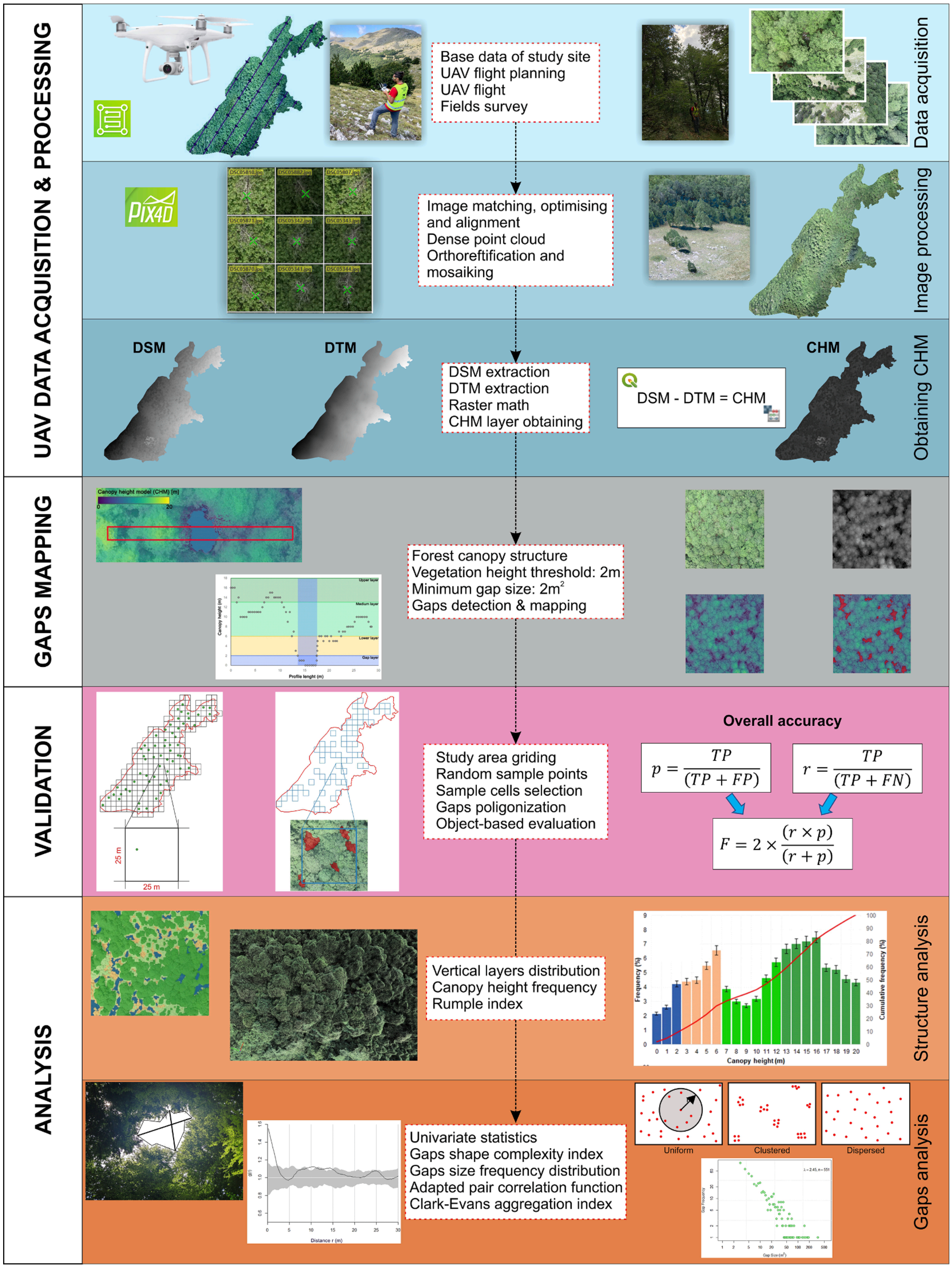

Fig. 2. Workflow of the presented methods for monitoring primary old-growth forest canopy structure.

layers (Fig. 4).

The interpreter was not aware of the CHM-derived gap to ensure independence (White et al., 2018). Gap detection accuracy was determined via object-based evaluation (Solano et al., 2021b) by comparing the total number of true gaps as identified from the CHM with the validation data. This process was performed using an independent sample for recall (r) and precision (p), both used to calculate the F-score (Modica et al., 2021; Sokolova et al., 2006) for the overall accuracy (equation (1)):

$$F = 2 \times \frac{(r \times p)}{(r + p)} \tag{1}$$

where

$$r = \frac{TP}{(TP + FN)} \tag{2}$$

$$p = \frac{TP}{(TP + FP)} \tag{3}$$

The omission error is related to r (equation (2)), while the commission error to p (equation (3)). These performance indicators consider correctly detected gaps (true positives-TP), erroneously detected gaps (false positives-FP), and gaps not detected (false negatives-FN). The ratio between TP and the total number of gaps was used as a gap

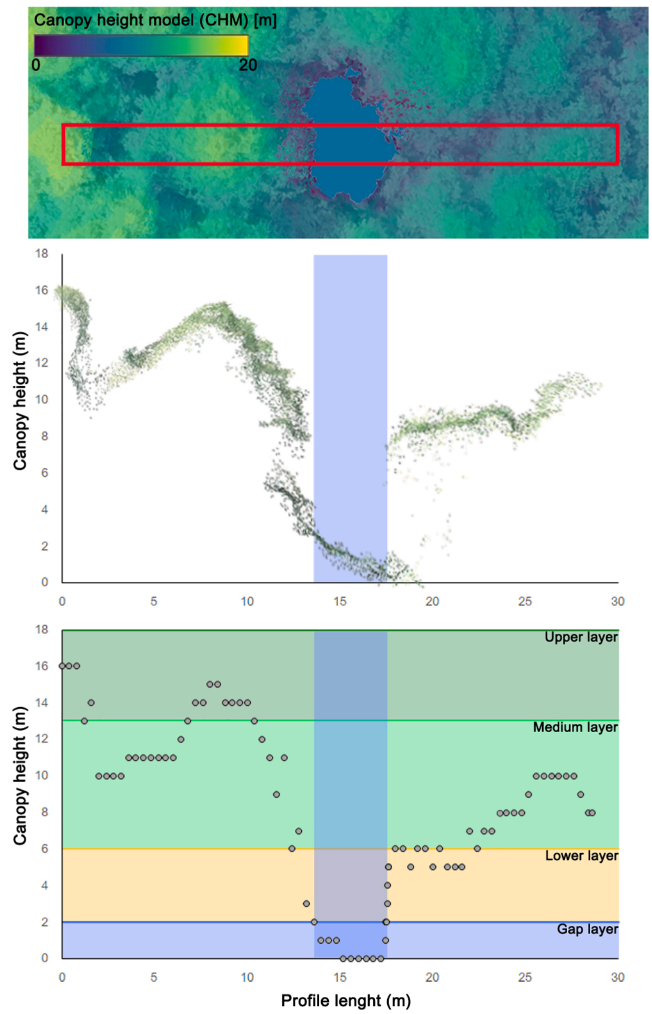

Fig. 3. Results of canopy gap detection and layers stratification.

detection rate indicator. Validation data acquisition and accuracy assessment were performed using QGIS (ver. 3.16 LTR) (QGIS.org, 2021).

2.6. Forest canopy gaps and spatial pattern analysis

After the CHM-derived gaps were analyzed, they were extracted and converted to vector polygons before calculating statistics to determine structural properties: i) gap area; ii) maximum, minimum, and mean canopy height; iii) the standard deviation of canopy height; and iv) Gini coefficient of canopy height. Statistical analysis was performed using the ForestGapR R package (Silva et al., 2019). To analyze the geometrical properties of each gap, we explored the area-perimeter relationship (Khodaverdi et al., 2019) and calculated the gap shape complexity index (GSCI). This index is frequently used forest gap metric (Koukoulas & Blackburn, 2004), representing the ratio of a gap's perimeter (P) to the perimeter of a circular gap of the same area (A) (equation (4)).

$$\mathrm{GSCI} = \frac{P}{\sqrt{4\pi A}} \tag{4}$$

When GCSI is equal to 1, the gap is a circle, and increasing values correspond to more compelx shapes.

To quantify the size-frequency distribution of forest canopy gaps, we used the Zeta distribution function from the R package ForestGapR. This distrubition is characterized by the exponent (λ), representing the discrete power-law probability density, also known as the Pareto distribution (White et al., 2008). For the Zeta distribution with parameter λ, the probability that the gap size takes the integer value k is:

$$f(k) = \frac{k^{-\lambda}}{\zeta(\lambda)} \tag{5}$$

We used the calculation method proposed Hanel et al. (2017) to determine the estimates of maximum likelihood values for λ by utlizing the negative log-likelihood function (Asner et al., 2013). In this equation, the exponent (λ) is represented by a negative slope on a log–log scale of the relationship between gap size and frequency. Results are reported in a log–log plot depicting λ and possible minimum likelihood values. Asner et al. (2013) reported values of $\lambda > 2.0$ (steeper slope) which suggests that the prominence of smaller gaps in a forest could be indicative of high-growth, low-mortality dynamics. Values of $\lambda < 2.0$ indicate the prevalence of larger canopy gaps associated with large canopy mortality or high disturbance rates to whole stands.

The mapped forest gaps were further analysed exploring their spatial pattern, using second-order statistics. Because our gap sizes are variable and the centroid of the gap could be far from the edges, we could not use point-pattern analysis (Picard et al., 2009; Silva et al., 2019). Therefore, we used an adapted version of the pair correlation function (PCF) to adequately consider the irregular shapes and sizes of gaps (Nuske et al., 2009; Wiegand et al., 2006). The PCF g(r) is often defined as the predicted number of gaps (points) per unit area (intensity) at a set distance (r) from a random point, divided by the intensity of λ (Stoyan & Stoyan, 1994). The method involves three fundamental steps: (i) computing null models to test for deviations from the Complete Spatial Randomness (CSR) by randomizing areas of the initial pattern within the study area, (ii) determinig the buffer area and correcting edge boundaries, and (iii) calculating the minimal distance between patches (Nuske et al., 2009). As proposed by Stoyan & Stoyan (1994), we set the bandwidth parameter of the smoothing kernel to $0.15/\sqrt{\lambda}$ (with λ representing pattern intensity). Using the PCF from the null model a pointwise critical envelope was derived. Confidence envelopes (95%) were computed using 199 Monte Carlo simulations. The artithmentic mean of all PCFs of the null models were then used to correct for bias in the empirical PCF and of the extreme bounds of the envelope. The output is the resulting g(r) function that, under CSR condition, is equal to 1. Values less than 1 [$g(r) < 1$] indicate regularity and values greater than 1 [$g(r) > 1$] indicate aggregation Nuske et al. (2009). Polygon-based PCF calculation was performed with the apfc R package (Nuske et al., 2009), using GDAL 2.2.3 (https://gdal.org/) and GEOS 3.6.1 (https://trac.osgeo.org/geos) libraries.

The value of the Clark-Evans (Clark & Evans, 1954) aggregation index R was used to test for clustering or ordering of the gap pattern, with a two-sided alternative hypothesis and the Z-test for statistical significance. When $R < 1$ the pattern is clustered and when $R > 1$ the pattern is uniform (Law et al., 2009). The R package ForestGapR was used to perform this analysis.

Finally, to infer the occurrence of the gap position related to vertical layering, the gap polygons and the canopy height distribution map were used to analyze the neighborhood relationship between the gap boundaries and the forest height layers.

3. Results

3.1. CHM and gap detection validation

The results of the CHM validation assessment were statistically significant, with ${}_{\mathrm{adj}}R^2 > 0.95$ and an RMSE value < 1 m (Fig. 5).

The interpreter detected 294 randomly distributed gaps throughout the study area upon inspection. Of the 294 gaps, 280 were correctly extracted, and 14 were not detected. There were no falsely detected gaps. The recall (r) performance metricwas 0.95, and the precision (p) value was 1. The F-score (0.98) determined the overall accuracy, thus

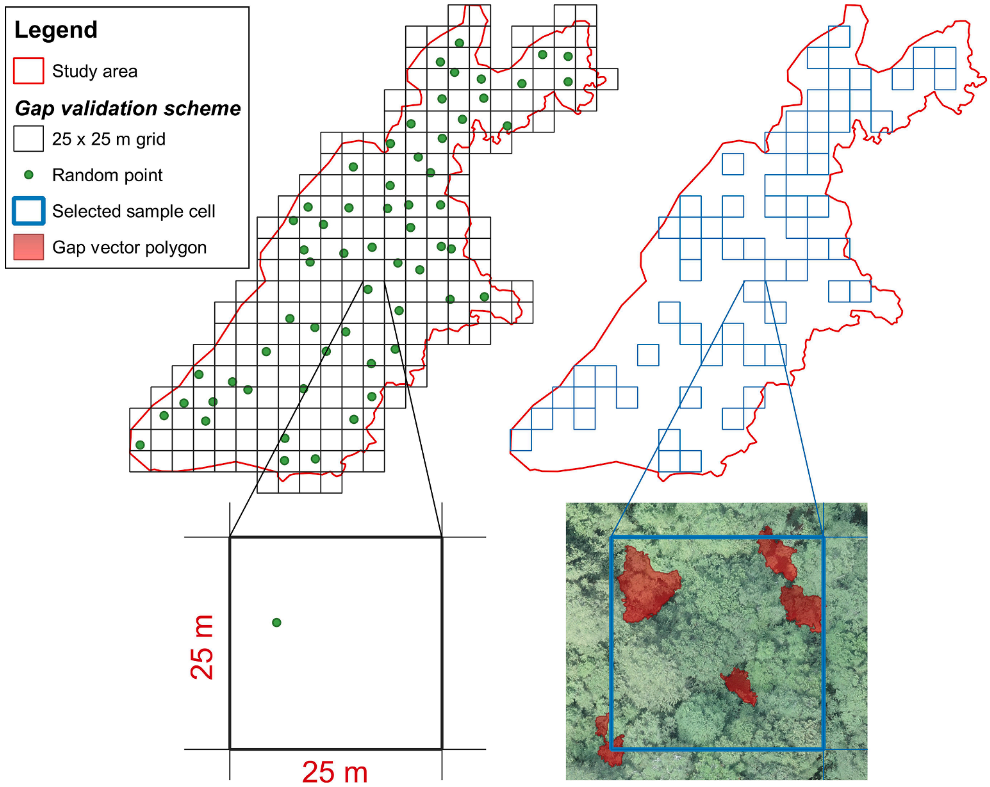

Fig. 4. Data validation scheme for gaps accuracy assessment.

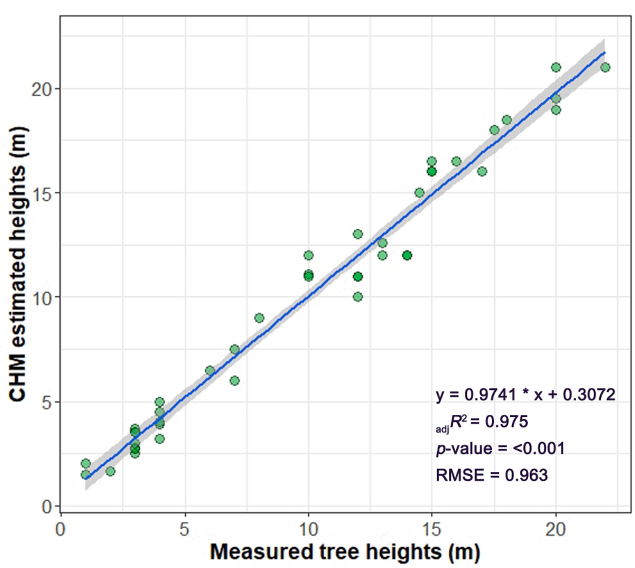

Fig. 5. Scatter plot of the CHM validation results, obtained by comparing tree heights measured in-situ in the different canopy layers with the height recovered from CHM. The solid blue line represents the fitted linear model and the grey area its 95% confidence interval.. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

achieving an overall gap detection rate value of 95%.

3.2. Forest canopy height distribution

The most representative forest canopy height was the upper layer ($13 \geq h \geq 20$), mainly found in the central and southern areas (Fig. 6). Approximately 50% of the remaining canopy layer is the lower and medium layers (Fig. 7) with a clustered pattern distribution. The average Rumple index of the canopy reached a value of 3.32.

3.3. Canopy gap properties

In total, 551 gaps were identified, representing 9% of the total study area. The mean gap size was 19.16 m^2, varying considerably from 2 m^2 (i.e., the fixed minimum threshold) to 353.42 m^2 (Table 1). There was a significant difference between the perimeter-area relationship especially as gap size increased (Supplementary material S2). The P/A ratio ranged from 1.0 to 8.93, with a mean value of 3.22 (Table 1). The average GSCI was 2.83 (183% gap shape complexity) with a max value of 9.94 (594% complexity) (Table 1).

The vegetation height range varied from 0.15 m to 2 m within the canopy gaps (Fig. 8), with a mean height of 1.3 m (±0.5). The mean Gini coefficient of the height of the gap vegetation is 0.26. About 97% of the gaps were <100 m^2 in size. The 90% was smaller than 50 m^2, and the 52% was <10 m^2 of area (Fig. 8).

Small gaps (area < 100 m2) were most prevalent, accounting for 81% of the overall gap area and were primarily located in the upper and medium canopy layer, while the lower layer had the highest gap area per canopy layer ratio (Fig. 9).

Gap-size frequency distribution of all 551 detected gaps followed a power-law distribution. The observed distribution has a negative slope characterized by a λ-value of 2.45 (Supplementary material S3).

The spatial pattern distribution of the canopy gaps did not digress greatly from the confidence envelopes of the CSR null model (Fig. 10). The PCF deviates significantly from the confidence envelope more clearly at the smaller scales (1–3.5 m) and less pronounced at greater scales (9–11) and from 13.5 to 15 m, suggesting the amassing of values at these distances. The PCF showed an overall soft-core effect without significant differences. These distances are more frequent than expected under CSR and suggest a trend towards clustering. According to the aggregation index ($R = 0.71$, p-value < 0.001), the distances between

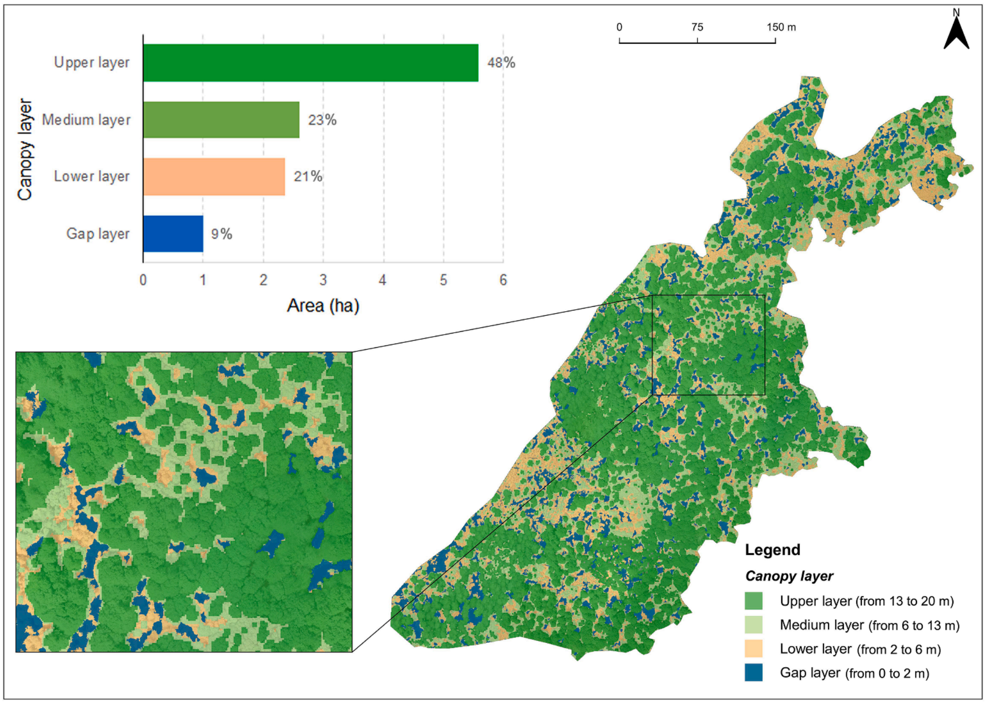

Fig. 6. Vertical layer distribution map Mount Pollinello's old-growth forest according to the canopy height classification scheme, estimated from $CHM_{0.5}$.

the neighboring gaps showed a significant tendency to cluster.

4. Discussion

4.1. Mapping complex forest canopy structure

The UAV digital aerial photogrammetry (DAP) approach provided consistent data regarding tree canopies by obtaining 3D point clouds from images with high overlap (>80% overlap), which made the stitching process more efficient (Mohan et al., 2017). We showed that the UAV-DAP workflow has the potential to generate realistic CHM (RMSE $<$ 1 m) in an old-growth forest characterized by a very complex structure and achieve similar accuracy to LiDAR products (Iglhaut et al., 2019;Krause et al., 2019; Roşca et al., 2018; White et al., 2018).

However, our study identified and dealt with some critical limitations about understory vegetation and the overall forest vertical structure that were not easily detectable. This is directly due to the usage of a UAV-DAP approach, as photogrammetry is limited to reconstructing surfaces visible from above in the image data (Iglhaut et al., 2019). To overcome these issues, pre-existing ground data derived from LiDAR or TLS can be merged with photogrammetric data (Blanchette et al., 2015; Seidel et al., 2015) to achieve better accuracy in particular in old-growth forests. Moreover, recent developments in processing algorithms can better detect local minima in 3D point clouds (Zhang et al., 2021) and may improve the generation of DTM under dense canopy cover without external datasets. This enables quick, accurate estimation and monitoring of valuable characteristics at the stand level, facilitating the upscaling at a larger scale.

Gap mapping produced very promising results, with a detection rate of 95%. However, the omission error is likely due to the fact that the spaces in between tree crowns, as detected by the orthomosaic, had vegetation above the defined height threshold. Likewise, the spaces covered by small branches resulted in a greater height of vegetation along the edge of the gap, which reduced the overall width of the gap, leading to the absence of misidentified gaps. Considering the complex forest structure and the geomorphology of the study area, the results confirm the potential of the proposed approach, in agreement with similar studies (Getzin et al., 2012, 2014; Kent et al., 2015; J. C. White et al., 2018).

4.2. Old-growth beech forest canopy structure

The reconstructed canopy profile revealed a bimodal top height frequency distribution (Fig. 6) as reported in other studies (Harding et al., 2001; Maltamo et al., 2005). In our approach, the forest vertical canopy structure was subdivided into three non overlapping layers and canopy height analysis indicated that the middle layer (7–12 m) was less represented than the upper layer (13–20 m). Such bimodality could result from the merging of tree canopies alongside the pole stage and regeneration processes in gaps. Moreover, once released, beech trees can "grow fast" through the medium-diameter classes (Hobi et al., 2015a), forming a wide canopy height distribution up to reach the top canopy layer (20 m), as seen in other old-growth European beech forests (Hobi et al., 2015b; Rugani et al., 2013).

The forest canopy heterogeneity found in our study area reflects the relatively high mean canopy Rumple index value. This complexity seems to result from the fine-scale canopy gap pattern and the vertical variability among individual trees (Blanchette et al., 2015). To the best of our knowledge, there are very few applications of this "roughness" index in old-growth broadleaved forests to compare our results. We found variation between 0 and 5 in tropical forests (Fagua et al., 2021) to 12 in conifer stands in North America (Lesmeister et al., 2019; Parker et al., 2004; Seidl et al., 2012). The variability of Rumple index is closely related to different tree dimensions and crown architectural properties, dependent on species composition, different top heights and development stages. The rugosity of stands increased with vertical complexity (Kane et al., 2010) and tree crown architecture, and the mean value of 3.32 for a pure forest with a dominant height of 20 m indicates a very complex outer canopy surface (Kane et al., 2008; Parker et al., 2004).

The horizontal complexity observed in our study area could result from a long-term fine-scale disturbance regime as expected in a primary forest (Franklin et al., 2002). Small-scale disturbances, like single gap maker tree, can stimulate structural complexity through the creating of favorable conditions for massive beech regeneration as well as the

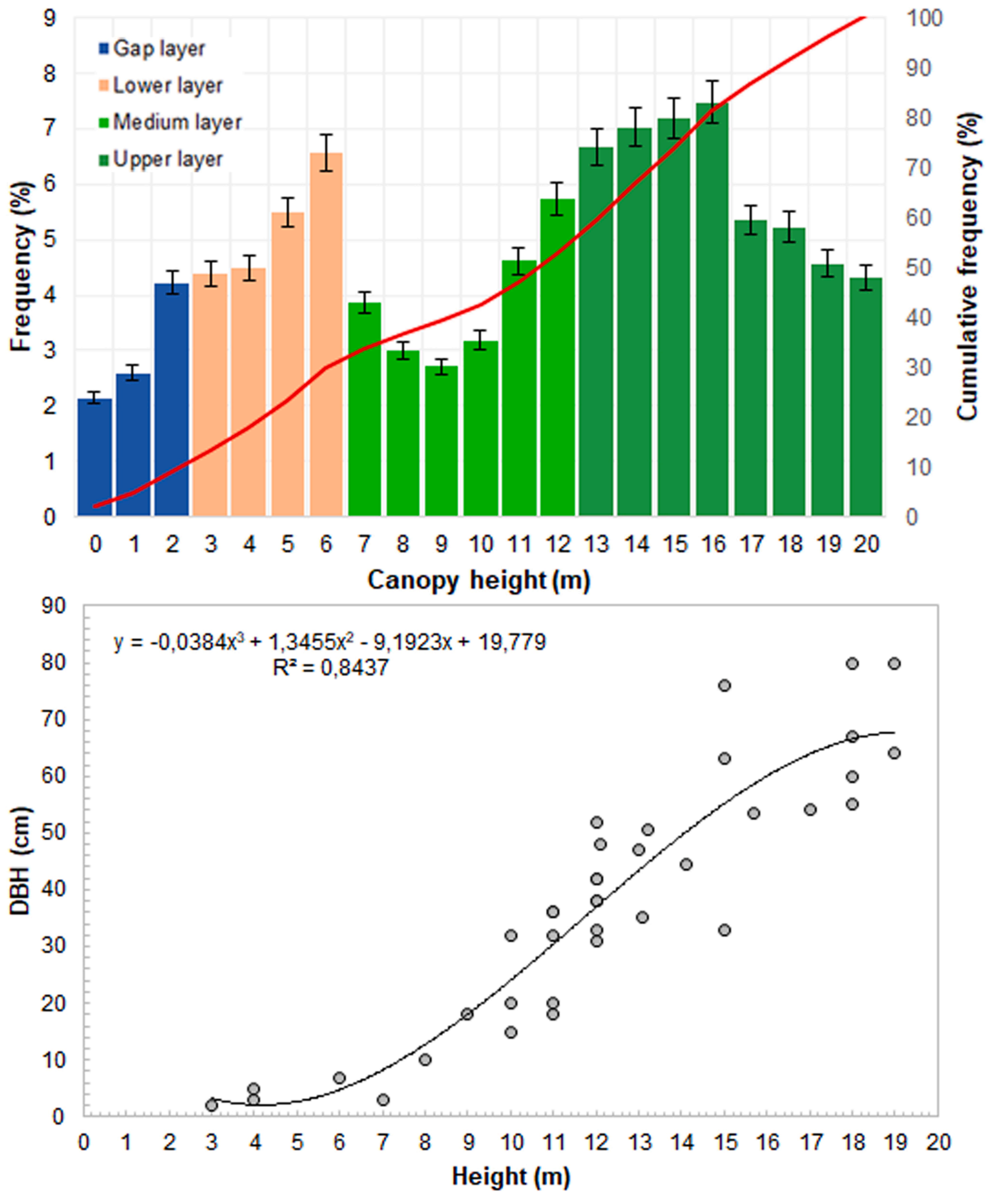

Fig. 7. Forest canopy structure defined by the frequency distribution of the upper canopy heights derived from the $CHM_{0.5}$. Error bars indicate ± standard error. The continuous red line refers to the cumulative frequencies reported in the secondary axes. Height curve derived from the trees measured in the field modeled using a third-order polynomial function. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Principal gap geometric properties of Mount Pollinello's old-growth beech forest. (P): perimeter; (A): area; (GSCI): gap shape complexity index; (±st.dv): standard deviation.

	Area (m^2)	Perimeter (m)	P/A	GSCI
mean	19.16	42.45	3.22	2.83
min	2.03	7.40	1.00	1.42
max	353.42	390.63	8.93	6.94
± st.dv	28.6	42.6	1.33	0.91

growth of understory trees (Willim et al., 2019; Ziaco et al., 2012).

The mean gap size and fraction found is comparable to other European old-growth beech forests (Getzin et al., 2014; Kenderes et al., 2008), confirming the important role of small-scale disturbances in stand dynamics. As suggested by the Gini coefficient, it seems that these events do not cause considerable alterations to the light environment in the forest (Valbuena et al., 2016) because the beech crown architecture enabled rapid horizontal growth into gaps so the smallest one could persist only for a few years (Madsen & Hahn, 2008). Our maximum gap shape complexity of 6.94 indicates a high complexity of canopy gaps, while other studies had values of 2.64 for a deciduous woodland and 2.3 for unmanaged beech (Getzin et al., 2014; Koukoulas & Blackburn, 2005). Higher values of GSCI are strongly correlated with species richness (Getzin et al., 2012), and this result highlights the key role that old-growth forests have in maintaing biodiversity.

The observed gap-size frequency distribution follows a similar trend reported in tropical (Brokaw, 1982) and boreal forests (Goodbody et al., 2020). The obtained value (>2) suggests that the forest is characterized by small openings in the canopy, indicative of sustained growth, and low mortality dynamics (Fisher et al., 2008). Our results differ from those reported in other old-growth forests (Goulamoussène et al., 2017; Kent et al., 2015) which could be a result of the size of the study area, which could influence gap are fraction and result in systematically biased estimates of λ (Lobo and Dalling, 2014). It may also be a result due to the

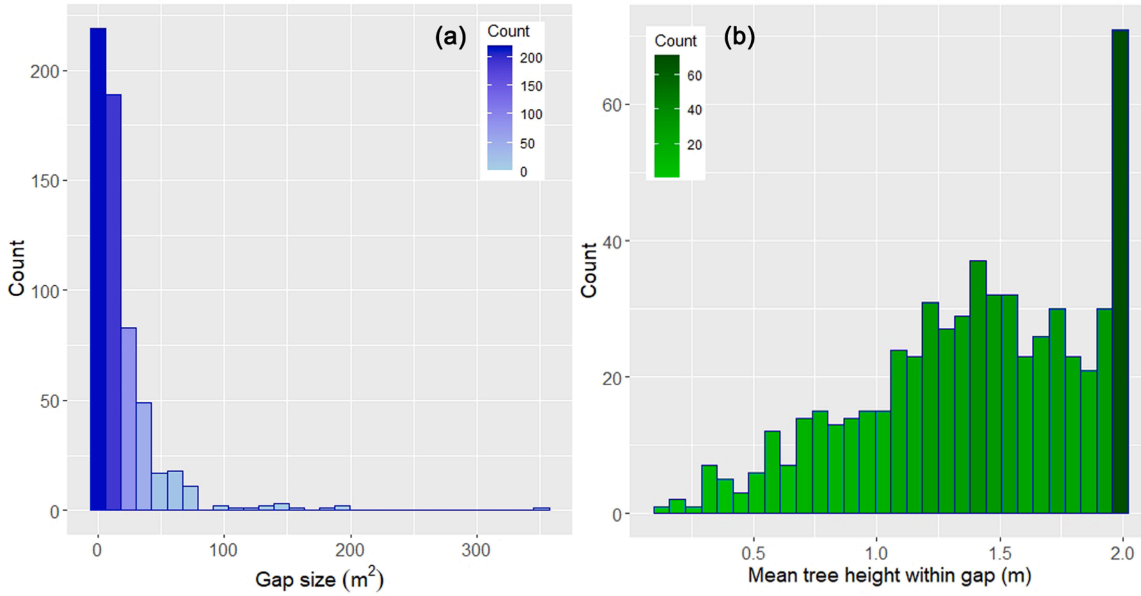

Fig. 8. Distribution of the canopy gap size of the detected gaps (a); distribution of the mean vegetation height within the detected gaps (b) of the beech forest of Mount Pollinello (Italy).

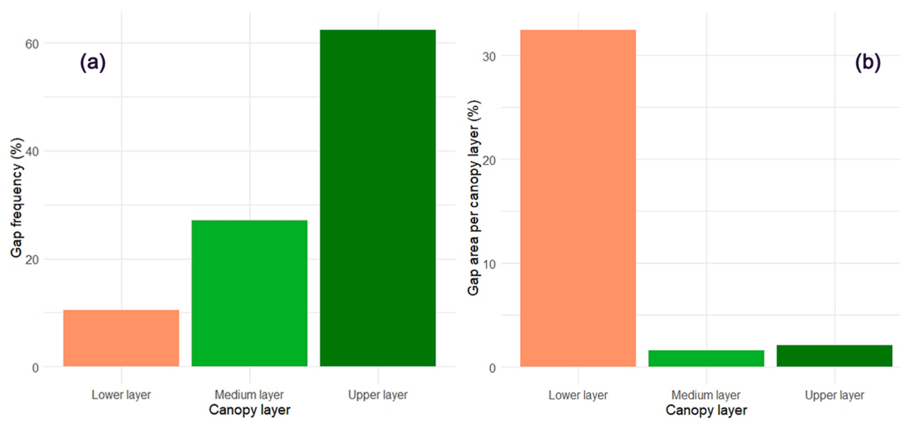

Fig. 9. Canopy gap frequency for each canopy layer (a); gap area percentage per canopy layer total extension (b) of the old-growth beech forest of Mount Pollinello (Italy).

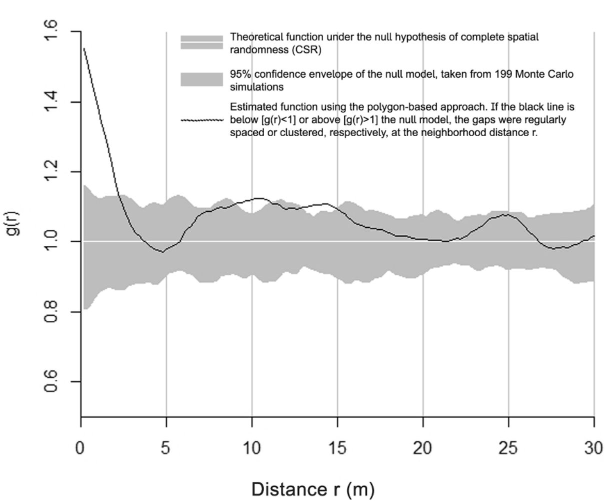

Fig. 10. Adapted pair-correlation function (PCF) of the gaps of the old-growth beech forest of Mount Pollinello (Italy).

frequency of tree sizes (Asner et al., 2013), such as the spatial configuration of tree canopies within and among canopy layers and disturbance regimes across forested environments. The peaks of the PCF showed that most gaps are approximately 1 to 13 m apart, the latter is about the diamter of the crown of a large beech tree in the study area. Our findings suggest an uneven recruitment as a result of the gap creation dynamics, which could be influenced also by soils and slopes characteristics (Aldrich et al., 2003). The death of a single gap maker tree with a large crown appears to be the primary driver of gap opening, while the partial destruction of large branches at gap edges can cause lateral gap expansion. The tendency of gaps to cluster at larger distances could be a result of several topographical factors including slope or aspect, which are also related to gap area formation in this ecosystem, as other studies have reported. (Splechtna & Gratzer, 2005). However, the clustered distribution that we found differs from other studies in European temperate forests (Torimaru et al., 2012) and North America (Spies et al., 1990). Where the PCF showed no significant deviation from the CSR model indicated that the gaps are approximately randomly distributed,in agreement with other studies in temperate forests (Nuske et al., 2009).

5. Conclusions

In our study, we used a CHM approach derived from UAV-SfM to measure old-growth forest attributes of the canopy, including vertical layering of canopy top heights and gap detection. Cost-effective UAV surveys and the combined use of Rumple Index (as a proxy for canopy roughness), P/A relationship, GSCI and second-order statistics for canopy gap spatial pattern characterization proved to supply basic and applicable information about forest structure. Differences found in canopy profile and spatial pattern distribution are also linked to local topographic or edaphic factors and tree growth rates, but these assumptions need further research. The proposed approach could be used as a standard monitoring protocol for gathering reliable canopy estimates that can be used to improve reference knowledge for site conditions, forest conservation issues, and restoration planning purposes. This protocol could be extended to natural forests (old-growth stand, UNESCO WH forests) for monitoring the preservation of ecological integrity and functioning in the face of global changes. This study confirms its suitability in providing detailed canopy data that can also be integrated with dendroecological and floristic-vegetational surveys to understand better gap ecology concerning the disturbance regime and global changes.

CRediT authorship contribution statement

Francesco Solano: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Giuseppe Modica:** Data curation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Salvatore Praticò:** Data curation, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Olivia F. Box:** Writing – review & editing. **Gianluca Piovesan:** Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2022.108807.

References

Aldrich, P.R., Parker, G.R., Ward, J.S., Michler, C.H., 2003. Spatial dispersion of trees in an old-growth temperate hardwood forest over 60 years of succession. For. Ecol. Manage. 180 (1–3), 475–491. https://doi.org/10.1016/S0378-1127(02)00612-6.

Asenova, M., Panayotov, M., Tsvetanov, N., 2019. Measuring the stand parameters of old-growth beech and fir-spruce-beech forests using orthoimages, satellite data and terrain data analysis. Silva Balcanica 20 (3), 5–17. https://www.researchgate.net/publication/339663397.

Asner, G.P., Kellner, J.R., Kennedy-Bowdoin, T.y., Knapp, D.E., Anderson, C., Martin, R. E., Chen, H.YH., 2013. Forest canopy gap distributions in the Southern Peruvian Amazon. PLoS ONE 8 (4), e60875.

Bagaram, M.B., Giuliarelli, D., Chirici, G., Giannetti, F., Barbati, A., 2018. UAV remote sensing for biodiversity monitoring: Are forest canopy gaps good covariates? Remote Sensing 10 (9), 1–28. https://doi.org/10.3390/rs10091397.

Blackburn, G.A., Abd Latif, Z., Boyd, D.S., Nakashizuka, T., 2014. Forest disturbance and regeneration: a mosaic of discrete gap dynamics and open matrix regimes? J. Veg. Sci. 25 (6), 1341–1354.

Blanchette, D., Fournier, R.A., Luther, J.E., Côté, J.F., 2015. Predicting wood fiber attributes using local-scale metrics from terrestrial LiDAR data: A case study of Newfoundland conifer species. For. Ecol. Manage. 347, 116–129. https://doi.org/10.1016/j.foreco.2015.03.013.

Bonnet, S., Gaulton, R., Lehaire, F., Lejeune, P., 2015. Canopy gap mapping from airborne laser scanning: an assessment of the positional and geometrical accuracy. Remote Sensing 7 (9), 11267–11294. https://doi.org/10.3390/rs70911267.

Brokaw, N.V.L., 1982. The definition of treefall gap and its effect on measures of forest dynamics. Biotropica 14 (2), 158. https://doi.org/10.2307/2387750.

Chiarucci, A., Piovesan, G., 2020. Need for a global map of forest naturalness for a sustainable future. Conserv. Biol. 34 (2), 368–372. https://doi.org/10.1111/cobi.13408.

Clark, P.J., Evans, F.C., 1954. Distance to nearest neighbor as a measure of spatial relationships in populations. Ecology 35 (4), 445–453. https://doi.org/10.2307/1931034.

Di Filippo, A., Biondi, F., Piovesan, G., Ziaco, E., Butt, N., 2017. Tree ring-based metrics for assessing old-growth forest naturalness. J. Appl. Ecol. 54 (3), 737–749.

Erb, K.-H., Kastner, T., Plutzar, C., Bais, A.L.S., Carvalhais, N., Fetzel, T., Gingrich, S., Haberl, H., Lauk, C., Niedertscheider, M., Pongratz, J., Thurner, M., Luyssaert, S., 2018. Unexpectedly large impact of forest management and grazing on global vegetation biomass. Nature 553 (7686), 73–76. https://doi.org/10.1038/nature25138.

Fagua, J.C., Jantz, P., Burns, P., Massey, R., Buitrago, J.Y., Saatchi, S., Hakkenberg, C., Goetz, S.J., 2021. Mapping tree diversity in the tropical forest region of Chocó-Colombia. Environ. Res. Lett. 16 (5), 054024.

Feldmann, E., Drößler, L., Hauck, M., Kucbel, S., Pichler, V., Leuschner, C., 2018. Canopy gap dynamics and tree understory release in a virgin beech forest, Slovakian Carpathians. For. Ecol. Manage. 415-416, 38–46.

Feldmann, E., Glatthorn, J., Ammer, C., Leuschner, C., 2020. Regeneration dynamics following the formation of understory gaps in a Slovakian beech virgin forest. Forests 11 (5). https://doi.org/10.3390/F11050585.

Fisher, J.I., Hurtt, G.C., Thomas, R.Q., Chambers, J.Q., 2008. Clustered disturbances lead to bias in large-scale estimates based on forest sample plots. Ecol. Lett. 11 (6), 554–563. https://doi.org/10.1111/j.1461-0248.2008.01169.x.

Franklin, J.F., Spies, T.A., Pelt, R.V., Carey, A.B., Thornburgh, D.A., Berg, D.R., Lindenmayer, D.B., Harmon, M.E., Keeton, W.S., Shaw, D.C., Bible, K., Chen, J., 2002. Disturbances and structural development of natural forest ecosystems with silvicultural implications, using Douglas-fir forests as an example. For. Ecol. Manage. 155 (1–3), 399–423. https://doi.org/10.1016/S0378-1127(01)00575-8.

Garbarino, M., Mondino, E.B., Lingua, E., Nagel, T.A., Dukić, V., Govedar, Z., Motta, R., 2012. Gap disturbances and regeneration patterns in a Bosnian old-growth forest: A multispectral remote sensing and ground-based approach. Ann. Forest Sci. 69 (5), 617–625. https://doi.org/10.1007/s13595-011-0177-9.

García-Vega, D., Newbold, T., 2020. Assessing the effects of land use on biodiversity in the world's drylands and Mediterranean environments. Biodivers. Conserv. 29 (2), 393–408. https://doi.org/10.1007/s10531-019-01888-4.

Gaulton, R., Malthus, T.J., 2010. LiDAR mapping of canopy gaps in continuous cover forests: A comparison of canopy height model and point cloud based techniques. Int. J. Remote Sens. 31 (5), 1193–1211. https://doi.org/10.1080/01431160903380565.

Getzin, S., Nuske, R.S., Wiegand, K., 2014. Using unmanned aerial vehicles (UAV) to quantify spatial gap patterns in forests. Remote Sensing 6 (8), 6988–7004. https://doi.org/10.3390/rs6086988.

Getzin, S., Wiegand, K., Schöning, I., 2012. Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. Methods Ecol. Evol. 3 (2), 397–404. https://doi.org/10.1111/j.2041-210X.2011.00158.x.

Goodbody, T.R.H., Tompalski, P., Coops, N.C., White, J.C., Wulder, M.A., Sanelli, M., 2020. Uncovering spatial and ecological variability in gap size frequency distributions in the Canadian boreal forest. Sci. Rep. 10 (1), 1–12. https://doi.org/10.1038/s41598-020-62878-z.

Goulamoussène, Y., Bedeau, C., Descroix, L., Linguet, L., Hérault, B., 2017. Environmental control of natural gap size distribution in tropical forests. Biogeosciences 14 (2), 353–364. https://doi.org/10.5194/bg-14-353-2017.

Hanel, R., Corominas-Murtra, B., Liu, B., & Thurner, S. (2017). Fitting power-laws in empirical data with estimators that work for all exponents. *PLOS ONE*, *12*(2), e0170920. doi: 10.1371/journal.pone.0170920.

Harding, D.J., Lefsky, M.A., Parker, G.G., Blair, J.B., 2001. Laser altimeter canopy height profiles methods and validation for closed-canopy, broadleaf forests. Remote Sens. Environ. 76 (3), 283–297. https://doi.org/10.1016/S0034-4257(00)00210-8.

Hobi, M.L., Commarmot, B., Bugmann, H., Woods, K., 2015a. Pattern and process in the largest primeval beech forest of Europe (Ukrainian Carpathians). J. Veg. Sci. 26 (2), 323–336.

Hobi, M.L., Ginzler, C., Commarmot, B., Bugmann, H., 2015b. Gap pattern of the largest primeval beech forest of Europe revealed by remote sensing. Ecosphere 6 (5), art76.

Iglhaut, J., Cabo, C., Puliti, S., Piermattei, L., O'Connor, J., Rosette, J., 2019. Structure from Motion Photogrammetry in Forestry: a Review. Current Forestry Reports 5 (3), 155–168. https://doi.org/10.1007/s40725-019-00094-3.

Kane, V.R., Bakker, J.D., McGaughey, R.J., Lutz, J.A., Gersonde, R.F., Franklin, J.F., 2010. Examining conifer canopy structural complexity across forest ages and elevations with LiDAR data. Can. J. For. Res. 40 (4), 774–787. https://doi.org/10.1139/X10-064.

Kane, V.R., Gillespie, A.R., McGaughey, R., Lutz, J.A., Ceder, K., Franklin, J.F., 2008. Interpretation and topographic compensation of conifer canopy self-shadowing. Remote Sens. Environ. 112 (10), 3820–3832. https://doi.org/10.1016/j.rse.2008.06.001.

Kenderes, K., Mihók, B., Standovár, T., 2008. Thirty years of gap dynamics in a central European beech forest reserve. Forestry 81 (1), 111–123. https://doi.org/10.1093/forestry/cpn001.

Kent, R., Lindsell, J., Laurin, G., Valentini, R., Coomes, D., 2015. Airborne LiDAR detects selectively logged tropical forest even in an advanced stage of recovery. Remote Sensing 7 (7), 8348–8367. https://doi.org/10.3390/rs70708348.

Khodaverdi, S., Amiri, M., Kartoolinejad, D., Mohammadi, J., 2019. Canopy gaps characteristics of pure and mixed stands in the Hyrcanian forests of north Iran. Ann. Silvicultural Res. 43 (2), 62–70. https://doi.org/10.12899/asr-1882.

Koch, B., Straub, C., Dees, M., Wang, Y., Weinacker, H., 2009. Airborne laser data for stand delineation and information extraction. Int. J. Remote Sens. 30 (4), 935–963. https://doi.org/10.1080/01431160802395284.

Koukoulas, S., Blackburn, G.A., 2004. Quantifying the spatial properties of forest canopy gaps using LiDAR imagery and GIS. Int. J. Remote Sens. 25 (15), 3049–3072. https://doi.org/10.1080/01431160310001657786.

Koukoulas, S., Blackburn, G.A., 2005. Spatial relationships between tree species and gap characteristics in broad-leaved deciduous woodland. J. Veg. Sci. 16 (5), 587–596. http://www.jstor.org/stable/4096798.

Krause, S., Sanders, T.G.M., Mund, J.P., Greve, K., 2019. UAV-based photogrammetric tree height measurement for intensive forest monitoring. Remote Sensing 11 (7). https://doi.org/10.3390/rs11070758.

Law, R., Illian, J., Burslem, D.F.R.P., Gratzer, G., Gunatilleke, C.V.S., Gunatilleke, I.A.U. N., 2009. Ecological information from spatial patterns of plants: insights from point process theory. J. Ecol. 97 (4), 616–628. https://doi.org/10.1111/j.1365-2745.2009.01510.x.

Leibundgut, H., 1956. Empfehlungen für die Baumklassenbildung und Methodik bei Versuchen über die Wirkung von Waldpflegemaßnahmen. Mitteilungen IUFRO Sektion, Article 23.

Lesmeister, D.B., Sovern, S.G., Davis, R.J., Bell, D.M., Gregory, M.J., Vogeler, J.C., 2019. Mixed-severity wildfire and habitat of an old-forest obligate. Ecosphere 10 (4). https://doi.org/10.1002/ecs2.2696.

Lindenmayer, D.B., Margules, C.R., Botkin, D.B., 2000. Indicators of biodiversity for ecologically sustainable forest management. Conserv. Biol. 14 (4), 941–950. http://www.jstor.org/stable/2641993.

Lobo, E., Dalling, J.W., 2014. Spatial scale and sampling resolution affect measures of gap disturbance in a lowland tropical forest: implications for understanding forest regeneration and carbon storage. Proc. R. Soc. B: Biol. Sci. 281 (1778), 20133218. https://doi.org/10.1098/rspb.2013.3218.

Madsen, P., Hahn, K., 2008. Natural regeneration in a beech-dominated forest managed by close-to-nature principles — a gap cutting based experiment. Can. J. For. Res. 38 (7), 1716–1729. https://doi.org/10.1139/X08-026.

Maltamo, M., Packalén, P., Yu, X., Eerikäinen, K., Hyyppä, J., Pitkänen, J., 2005. Identifying and quantifying structural characteristics of heterogeneous boreal forests using laser scanner data. For. Ecol. Manage. 216 (1–3), 41–50. https://doi.org/10.1016/j.foreco.2005.05.034.

Miranda, A., Catalán, G., Altamirano, A., Zamorano-Elgueta, C., Cavieres, M., Guerra, J., Mola-Yudego, B., 2021. How much can we see from a uav-mounted regular camera? Remote sensing-based estimation of forest attributes in south american native forests. Remote Sensing 13 (11). https://doi.org/10.3390/rs13112151.

Modica, G., De Luca, G., Messina, G., Praticò, S., 2021. Comparison and assessment of different object-based classifications using machine learning algorithms and UAVs multispectral imagery: a case study in a citrus orchard and an onion crop. Eur. J. Remote Sensing 54 (1), 431–460. https://doi.org/10.1080/22797254.2021.1951623.

Mohan, M., Silva, C.A., Klauberg, C., Jat, P., Catts, G., Cardil, A., Hudak, A.T., Dia, M., 2017. Individual tree detection from unmanned aerial vehicle (UAV) derived canopy height model in an open canopy mixed conifer forest. Forests 8 (9), 1–17. https://doi.org/10.3390/f8090340.

Müller, J., Brandl, R., 2009. Assessing biodiversity by remote sensing in mountainous terrain: the potential of LiDAR to predict forest beetle assemblages. J. Appl. Ecol. 46 (4), 897–905. https://doi.org/10.1111/j.1365-2664.2009.01677.x.

Munteanu, C., Kuemmerle, T., Keuler, N.S., Müller, D., Balázs, P., Dobosz, M., Griffiths, P., Halada, L., Kaim, D., Király, G., Konkoly-Gyuró, É., Kozak, J., Lieskovsky, J., Ostafin, K., Ostapowicz, K., Shandra, O., Radeloff, V.C., 2015. Legacies of 19th century land use shape contemporary forest cover. Global Environ. Change 34, 83–94. https://doi.org/10.1016/j.gloenvcha.2015.06.015.

Nuske, R.S., 2006. A retrospective study of canopy gap dynamics of a european beech stand. In T. Koukal & W. Schneider (Eds.), International Workshop "3D Remote Sensing in Forestry" (pp. 40–44).

Nuske, R.S., Sprauer, S., Saborowski, J., 2009. Adapting the pair-correlation function for analysing the spatial distribution of canopy gaps. For. Ecol. Manage. 259 (1), 107–116. https://doi.org/10.1016/j.foreco.2009.09.050.

Oettel, J., Lapin, K., 2021. Linking forest management and biodiversity indicators to strengthen sustainable forest management in Europe. Ecol. Ind. 122, 107275 https://doi.org/10.1016/j.ecolind.2020.107275.

Packham, J.R., Thomas, P.A., Atkinson, M.D., Degen, T., 2012. Biological flora of the British Isles: Fagus sylvatica. J. Ecol. 100 (6), 1557–1608. https://doi.org/10.1111/j.1365-2745.2012.02017.x.

Parker, G.G., Harmon, M.E., Lefsky, M.A., Chen, J., Van Pelt, R., Weiss, S.B., Thomas, S. C., Winner, W.E., Shaw, D.C., Franklin, J.F., 2004. Three-dimensional structure of an old-growth Pseudotsuga-tsuga canopy and its implications for radiation balance, microclimate, and gas exchange. Ecosystems 7 (5), 440–453. https://doi.org/10.1007/s10021-004-0136-5.

Parviainen, J., 2005. Virgin and natural forests in the temperate zone of Europe. Forest Snow and Landscape Research 79 (1–2), 9–18.

Petritan, A.M., Nuske, R.S., Petritan, I.C., Tudose, N.C., 2013. Gap disturbance patterns in an old-growth sessile oak (Quercus petraea L.)–European beech (Fagus sylvatica L.) forest remnant in the Carpathian Mountains, Romania. Forest Ecol. Manage. 308, 67–75. https://doi.org/10.1016/j.foreco.2013.07.045.

Picard, N., Bar-Hen, A., Mortier, F., Chadoeuf, J., 2009. Understanding the dynamics of an undisturbed tropical rain forest from the spatial pattern of trees. J. Ecol. 97 (1), 97–108. https://doi.org/10.1111/j.1365-2745.2008.01445.x.

Pie, F., Schreiber, T., 2016. Assessing the structure of primeval and managed beech forests in the Ukrainian Carpathians using remote sensing. Systems Biology January, 1–3.

Piovesan, G., Biondi, F., Baliva, M., De Vivo, G., Marchianò, V., Schettino, A., Di Filippo, A., 2019. Lessons from the wild: slow but increasing long-term growth allows for maximum longevity in European beech. Ecology 100 (9). https://doi.org/10.1002/ecy.2737.

Praticò, S., Solano, F., Di Fazio, S., Modica, G., 2021. Machine learning classification of mediterranean forest habitats in google earth engine based on seasonal Sentinel-2 time-series and input image composition optimisation. Remote Sensing 13 (4), 586. https://doi.org/10.3390/rs13040586.

QGIS.org. (2021). QGIS Geographic Information System. QGIS Association. http://qgis.osgeo.org.

R Core Team. (2021). A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.r-project.org/.

Rehush, N., Waser, L.T., 2017. Assessing the structure of primeval and managed beech forests in the Ukrainian carpathians using remote sensing. Can. J. For. Res. 47 (1), 63–72. https://doi.org/10.1139/cjfr-2016-0253.

Roşca, S., Suomalainen, J., Bartholomeus, H., Herold, M., 2018. Comparing terrestrial laser scanning and unmanned aerial vehicle structure from motion to assess top of canopy structure in tropical forests. Interface Focus 8 (2), 20170038.

Roussel, J.R., Auty, D., Coops, N.C., Tompalski, P., Goodbody, T.R.H., Meador, A.S., Bourdon, J.F., de Boissieu, F., Achim, A., 2020. lidR: an R package for analysis of Airborne Laser Scanning (ALS) data. Remote Sens. Environ. 251 (August), 112061 https://doi.org/10.1016/j.rse.2020.112061.

Rugani, T., Diaci, J., Hladnik, D., Bond-Lamberty, B., 2013. Gap dynamics and structure of two old-growth beech forest remnants in Slovenia. PLoS ONE 8 (1), e52641.

Runkle, J.R., 1981. Gap regeneration in some old-growth forests of the Eastern United States. Ecology 62 (4), 1041–1051. https://doi.org/10.2307/1937003.

Seidel, D., Ammer, C., Puettmann, K., 2015. Describing forest canopy gaps efficiently, accurately, and objectively: new prospects through the use of terrestrial laser scanning. Agric. For. Meteorol. 213, 23–32. https://doi.org/10.1016/j.agrformet.2015.06.006.

Seidl, R., Spies, T.A., Rammer, W., Steel, E.A., Pabst, R.J., Olsen, K., 2012. Multi-scale drivers of spatial variation in old-growth forest carbon density disentangled with lidar and an individual-based landscape model. Ecosystems 15 (8), 1321–1335. https://doi.org/10.1007/s10021-012-9587-2.

Seymour, R.S., White, A.S., DeMaynadier, P.G., 2002. Natural disturbance regimes in northeastern North America—evaluating silvicultural systems using natural scales and frequencies. For. Ecol. Manage. 155 (1–3), 357–367. https://doi.org/10.1016/S0378-1127(01)00572-2.

Silva, C.A., Valbuena, R., Pinagé, E.R., Mohan, M., de Almeida, D.R.A., North Broadbent, E., Jaafar, W.S.W.M., de Almeida Papa, D., Cardil, A., Klauberg, C., 2019a. ForestGapR: An r Package for forest gap analysis from canopy height models. Methods Ecol. Evol. 10 (8), 1347–1356. https://doi.org/10.1111/2041-210X.13211.

Silva, Carlos Alberto, Pinagé, E. R., Mohan, M., de Almeida, D. R. A., Broadbent, E. N., de Almeida Papa, D., Cardil, A., Valbuena, R., & Klauberg, C. (2019). ForestGapR. 1, 14.

Smith, G.F., Gittings, T., Wilson, M., French, L., Oxbrough, A., O'Donoghue, S., O'Halloran, J., Kelly, D.L., Mitchell, F.J.G., Kelly, T., Iremonger, S., McKee, A.-M., Giller, P., 2008. Identifying practical indicators of biodiversity for stand-level management of plantation forests. Biodivers. Conserv. 17 (5), 991–1015. https://doi.org/10.1007/s10531-007-9274-3.

Sokolova, M., Japkowicz, N., & Szpakowicz, S. (2006). Beyond Accuracy, F-Score and ROC: A Family of Discriminant Measures for Performance Evaluation (pp. 1015–1021). doi: 10.1007/11941439_114.

Solano, F., Praticò, S., Piovesan, G., Chiarucci, A., Argentieri, A., Modica, G., 2021a. Characterizing historical transformation trajectories of the forest landscape in Rome's metropolitan area (Italy) for effective planning of sustainability goals. Land Degrad. Dev. 32 (16), 4708–4726. https://doi.org/10.1002/ldr.4072.

Solano, F., Praticò, S., Piovesan, G., Modica, G., 2021. Unmanned Aerial Vehicle (UAV) Derived Canopy Gaps in the Old-Growth Beech Forest of Mount Pollinello (Italy): Preliminary Results. In O. et al. Gervasi (Ed.), Lecture Notes in Computer Science (Computatio, pp. 126–138). Springer. doi: 10.1007/978-3-030-87007-2_10.

Spies, T.A., Franklin, J.F., Klopsch, M., 1990. Canopy gaps in Douglas-fir forests of the Cascade Mountains. Can. J. For. Res. 20 (5), 649–658. https://doi.org/10.1139/x90-087.

Splechtna, B.E., Gratzer, G., 2005. Natural disturbances in Central European forests: approaches and preliminary results from Rothwald, Austria. Forest Snow Landscape Res. 79 (1–2), 57–67.

Stepper, C., Straub, C., Pretzsch, H., 2014. Assessing height changes in a highly structured forest using regularly acquired aerial image data. Forestry 88 (3), 304–316. https://doi.org/10.1093/forestry/cpu050.

Stoyan, D., Stoyan, H., 1994. Fractals, Random Shapes and Point Fields: Methods of Geometrical Statistics. John Wiley & Sons.

Straub, C., Stepper, C., Seitz, R., Waser, L.T., 2013. Potential of UltraCamX stereo images for estimating timber volume and basal area at the plot level in mixed European forests. Can. J. For. Res. 43 (8), 731–741. https://doi.org/10.1139/cjfr-2013-0125.

Torimaru, T., Itaya, A., Yamamoto, S.-I., 2012. Quantification of repeated gap formation events and their spatial patterns in three types of old-growth forests: Analysis of long-term canopy dynamics using aerial photographs and digital surface models. For. Ecol. Manage. 284, 1–11. https://doi.org/10.1016/j.foreco.2012.07.044.

Valbuena, R., Eerikäinen, K., Packalen, P., Maltamo, M., 2016. Gini coefficient predictions from airborne lidar remote sensing display the effect of management intensity on forest structure. Ecol. Ind. 60, 574–585. https://doi.org/10.1016/j.ecolind.2015.08.001.

Vepakomma, U., Kneeshaw, D., Fortin, M.-J., 2012. Spatial contiguity and continuity of canopy gaps in mixed wood boreal forests: persistence, expansion, shrinkage and displacement. J. Ecol. 100 (5), 1257–1268. https://doi.org/10.1111/j.1365-2745.2012.01996.x.

Vepakomma, U., St-Onge, B., Kneeshaw, D., 2008. Spatially explicit characterization of boreal forest gap dynamics using multi-temporal lidar data. Remote Sens. Environ. 112 (5), 2326–2340. https://doi.org/10.1016/j.rse.2007.10.001.

White, E.P., Enquist, B.J., Green, J.L., 2008. On estimating the exponent of power-law frequency distributions. Ecology 89 (4), 905–912. https://doi.org/10.1890/07-1288.1.

White, J.C., Tompalski, P., Coops, N.C., Wulder, M.A., 2018. Comparison of airborne laser scanning and digital stereo imagery for characterizing forest canopy gaps in coastal temperate rainforests. Remote Sens. Environ. 208, 1–14.

Wiegand, T., Kissling, W.D., Cipriotti, P.A., Aguiar, M.R., 2006. Extending point pattern analysis for objects of finite size and irregular shape. J. Ecol. 94 (4), 825–837. https://doi.org/10.1111/j.1365-2745.2006.01113.x.

Willim, K., Stiers, M., Annighöfer, P., Ammer, C., Ehbrecht, M., Kabal, M., Stillhard, J., Seidel, D., 2019. Assessing understory complexity in beech-dominated forests (Fagus sylvatica L.) in Central Europe—from managed to primary forests. Sensors 19 (7), 1684. https://doi.org/10.3390/s19071684.

Zellweger, F., Braunisch, V., Baltensweiler, A., Bollmann, K., 2013. Remotely sensed forest structural complexity predicts multi species occurrence at the landscape scale. For. Ecol. Manage. 307, 303–312. https://doi.org/10.1016/j.foreco.2013.07.023.

Zellweger, F., Baltensweiler, A., Schleppi, P., Huber, M., Küchler, M., Ginzler, C., Jonas, T., 2019. Estimating below-canopy light regimes using airborne laser scanning: an application to plant community analysis. Ecol. Evol. 9 (16), 9149–9159. https://doi.org/10.1002/ece3.5462.

Zhang, H., Bauters, M., Boeckx, P., Van Oost, K., 2021. Mapping canopy heights in dense tropical forests using low-cost UAV-derived photogrammetric point clouds and machine learning approaches. Remote Sensing 13 (18), 3777. https://doi.org/10.3390/rs13183777.

Ziaco, E., Biondi, F., Di Filippo, A., Piovesan, G., 2012. Biogeoclimatic influences on tree growth releases identified by the boundary line method in beech (Fagus sylvatica L.) populations of southern Europe. For. Ecol. Manage. 286, 28–37. https://doi.org/10.1016/j.foreco.2012.09.005.

Zielewska-Büttner, K., Adler, P., Ehmann, M., Braunisch, V., 2016. Automated detection of forest gaps in spruce dominated stands using canopy height models derived from stereo aerial imagery. Remote Sensing 8 (3), 1–21. https://doi.org/10.3390/rs8030175.