Unmanned Aerial Vehicle (UAV) Derived Canopy Gaps in the Old-Growth Beech Forest of Mount Pollinello (Italy): Preliminary Results

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Abstract. Forest canopy gaps caused by natural disturbances represent the primary driver of forest regeneration dynamics, modifying several ecological factors such as the light environment within an ecosystem. Canopy openings constantly change the shape and structure of forests as well as tree species diversity. The analysis of forest canopy gap spatial patterns in old-growth forests can provide helpful information for their conservation. Moreover, it can be an important reference for outlining sustainable forest management to restore and maintain the original biodiversity and accelerate forest succession towards old-growth characteristics. The main goal of this research was to assess a first forest gap size distribution and analyze their spatial pattern in an old-growth beech (*Fagus sylvatica* L.) forest in the Pollino National Park (Italy) strict reserve, with no human influence in at least the past 70 years due to its remote location. Using an unmanned aerial vehicle (UAV)-based canopy height model (CHM), we detected and classified 196 canopy gaps ranging from 10 to 343 m^2. The gap size-frequency reflected a power-law distribution. Using second-order statistics, following the *K* and *L* Ripley's function, we found that the canopy gaps were spatially clustered distributed. These preliminary results show the predominance of small-scale disturbances, confirmed by the spatial structure analyses highlighting the single tree nature of these processes influenced by site-specific conditions.

Keywords: Canopy height model (CHM) · Old-growth beech · Forest regeneration dynamics · Forest canopy gaps · Pollino National Park (Italy)

1 Introduction

Forest structure results from the interactions between different ecological factors that affect regeneration establishment, competition, and mortality dynamics. Past disturbances often drive these dynamics. Tree-fall gaps are the most frequent small-scale

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natural disturbances in many forest ecosystems [1], playing an important role in maintaining biodiversity [2–5]. Natural disturbances can create small canopy gaps (e.g., single dead trees) or large canopy gaps, allowing different scale patterns and processes. These phenomena play an important role in many forest ecosystems and represent the dominant form of forest regeneration due to the continual reshaping of forest structure after creating canopy openings [6]. The analysis of forest canopy gaps spatial patterns can provide helpful information on these dynamics [7], playing an important role in old-growth forest conservation. It is an essential reference for delineating a sustainable management approach to restore and maintain native biodiversity and accelerate forest succession towards old-growth characteristics within managed forests [8–10]. Understanding natural patterns and processes, including forest canopy gaps, size-frequency distribution, and spatial patterns, better enables forest managers to enhance biodiversity conservation in these forests, providing insight into ecosystem-level successional processes and disturbance patterns [11]. Disturbance-driven canopy gaps need to be quantified and monitored, studying variation and size distribution in different forest types to understand the different gap dynamics and their ecological perspectives.

Remote sensing techniques allow to map entire landscapes and describe changes based on time series [12–14]. However, tiny gaps can not easily be recorded even with the latest medium resolution satellite imagery (i.e., Sentinel-2), but very high-resolution images provided by commercial satellites should be used. For small-scale forest monitoring, there is a need for a new and cost-effective survey methodology.

In recent times, several remote sensing platforms have been used for mapping canopy gaps, including multispectral satellite images [15], unmanned aerial vehicles (UAV) [16], RGB and infrared stereo aerial images [17, 18], airborne laser scanning (ALS) [19, 20] and terrestrial laser scanning data (TLS) [21]. The latter two acquisition systems use a pulsed 3D laser scanner and their reflections to measure the earth's surface. To date, despite the very high costs, ALS data provide more detailed gap characterization compared to the other sensors due to their higher accuracy. Before developing these LiDAR-based approaches, few studies had characterized canopy gaps because of the time-consuming nature of the field-based methods. These limitations can be overcome by UAVs' availability, being able to accurately map all gaps of a small forest stand at very high resolution and precision levels [22]. These UAVs represent a cost-effective solution for usual forest stand sizes because of their easy repeatability and the almost total absence of clouds in the images.

The main aim of this research was to assess a first canopy gap detection and spatial pattern distribution from a UAV-derived canopy height model (CHM) in an old-growth beech (*Fagus sylvatica* L.) forest in the Pollino National Park (southern Italy). This forest, growing on Mount Pollinello and including the upper elevation limit (2000 m a.s.l.) of beech distribution, represents a high conservation priority area and, for its ecosystem integrity, is a candidate to join the UNESCO World Natural Heritage of transboundary "Ancient and Primeval Beech Forests of the Carpathians and Other Regions of Europe" serial sites.

2 Materials and Methods

2.1 Study Area

The study area is represented by an old-growth beech (*Fagus sylvatica* L.) forest, a candidate as UNESCO World Heritage serial site for its ecosystem integrity, located in the Pollino national park, on Mount Pollinello in southern Italy (Fig. 1). The Pollino massif is the southernmost component of this UNESCO network of ancient beech forests. The old-growth forest core extends for 10.5 hectares with a perimeter of 1860 m, at an altitude between 1900–2000 m. a.s.l. The forest is characterized by a very complex structure, with no human influence in at least the past 70 years due to its remote location. It has an uneven-aged structure, and within this area, beech trees up to 620 years old are in close contact with old (800–1200 years) *Pinus heldreichii* trees [23]. It is a characteristic example of the association *Asyneumato-Fagetum sylvaticae*, a high-altitude community endemic in the Southern Apennines.

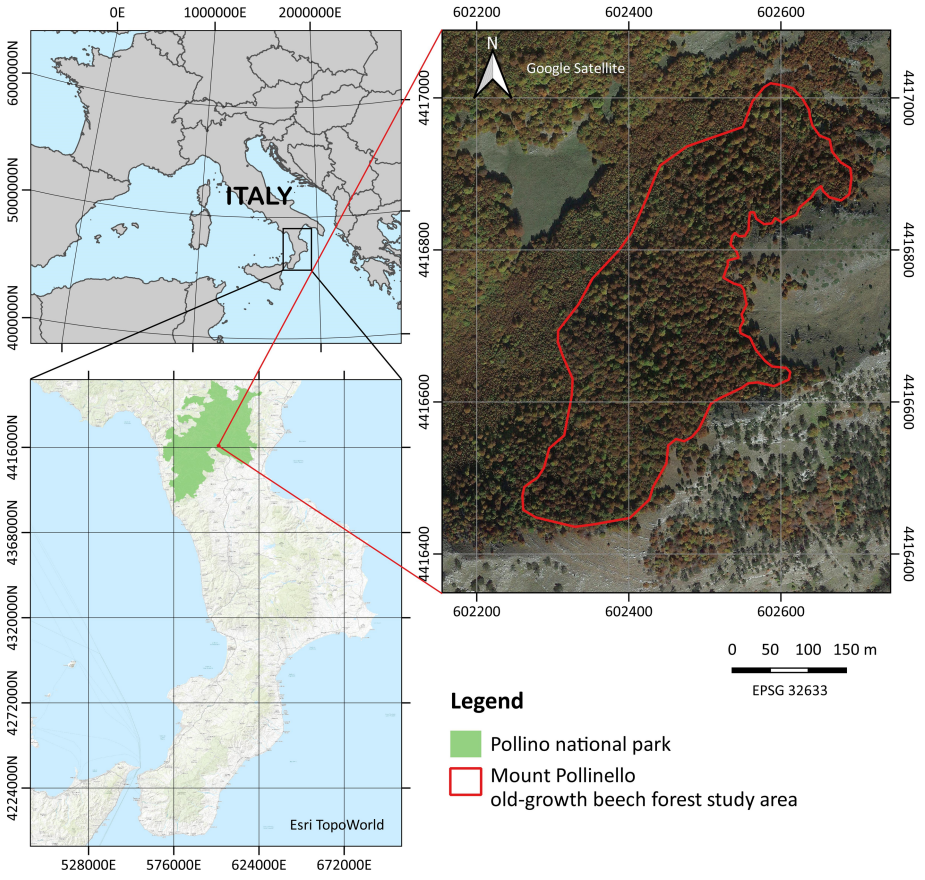

Fig. 1. Localization of the old-growth beech (*Fagus sylvatica* L.) forest of Mount Pollinello study area, within the Pollino national park (southern Italy).

2.2 UAV Data Acquisition and Processing

The UAV survey was conducted using the quadricopter DJI Phantom 4Pro +. This UAV has an integrated RGB sensor with a 20 megapixel 1" CMOS. The field of view (FOV) is 84° (https://www.dji.com/it/phantom-4-pro/info#specs – last access 23/03/2021). To ensure the same mean altitude above ground level for the entire study area, four different flights have been carried on. Each flight was conducted in a semi-automatic mode. The pilot's take-off and landing phases were handled manually, while the photogrammetric flight was carried out under autopilot using the flight planning app Pix4Dcapture (https://www.pix4d.com/product/pix4dcapture - last access: 23/03/2021). Each flight was georeferenced using the GPS mounted on board the vehicle. Once surveyed the aerial images, the entire photogrammetric process to obtain the needed output data of the whole study area was conducted in Pix4Dmapper Pro 4.3 (Pix4D SA, Switzerland). First, a 3D points cloud was reconstructed by a structure from motion (SfM) process as described in Modica et al. [24], and then the orthomosaic (see Fig. 2), digital surface model (DSM), and digital terrain model (DTM) were produced. The final resolution of the orthomosaic reached 3 cm/px.

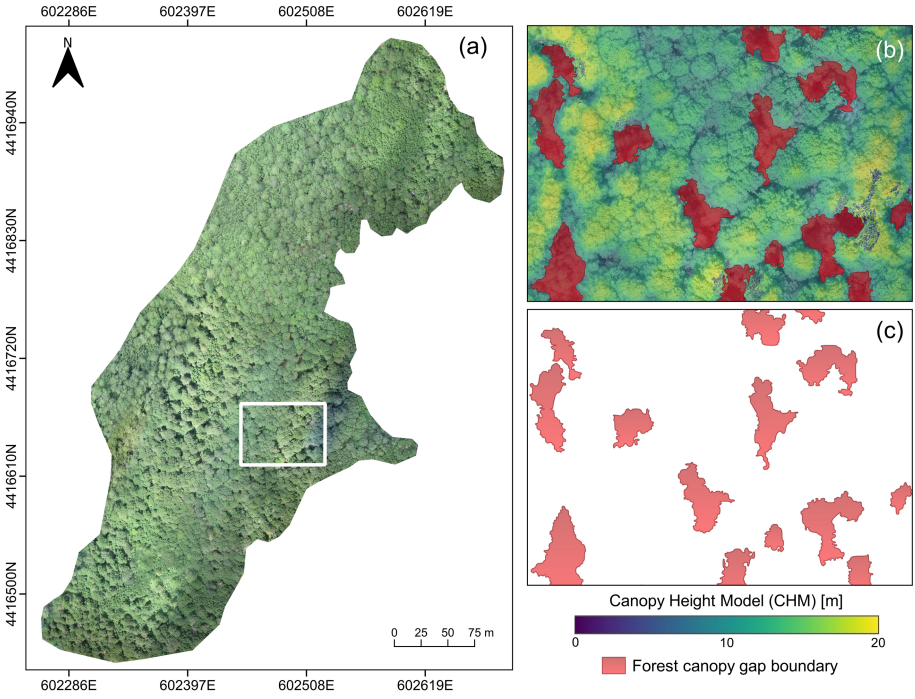

Fig. 2. Canopy gap distribution in the old-growth beech forest of mount Pollinello study area. (a): UAV-derived orthomosaic overview, (b): detail of gap boundaries superimposed on the UAV-derived canopy height model (CHM), (c): canopy gap vector polygons derived from canopy height model (CHM). Coordinates reference system UTM 33N, Datum WGS84 (EPSG 32633).

2.3 Mapping Forest Canopy Gaps

To estimate forest canopy height, the vertical difference between the DSM and DTM was used to obtain the canopy height model (CHM). The CHM raster layer was then resampled at 0.5 m spatial resolution. The R package ForestGapR [25] was used to locate canopy gaps across the CHM and generate metrics on gap extent. The algorithm implemented in the package, developed by Asner et al. [26], defines forest canopy gaps as contiguous areas where the vegetation height is minus or equal to a defined height threshold and between a minimum and maximum gap size (area in m^2) to be detected.

For this study, a value of 5 m was set as the vegetation height threshold [27] and 10 m^2 as the minimum gap size. After identifying the grid cells with height values $\leq$ than the defined threshold and assigning a unique label to them, the algorithm evaluates the 8 neighbors of the grid cells identified. If they are part of the same canopy gap, the same forest canopy gap label is assigned, iterating the process until there are no unlabeled CHM grid cells.

2.4 Data Validation and Accuracy Assessment

To assess the gap detection accuracy, the UAV-based very high-resolution orthomosaic was used as a reference layer for manual digitization of the gap boundaries. Preliminarily, we built a 25 × 25 m grid over the study area in a GIS environment. Then, we randomly distributed 10 sample points within the grid. Inside each cell, where the sample point fell, all gaps present have been manually digitized within this area of 625 m^2, obtaining a total of 58 vector polygons representing the gap boundaries, randomly distributed all over the study area. The accuracy of gap detection was assessed as object-based evaluation [28] by comparing the correctly detected gaps derived from the CHM, with the digitized reference data. The assessment was performed by counting gaps correctly detected or missing, based on an independent sample for recall (r) and another for precision (p). The overall accuracy was obtained by the F-score (Eq. 1):

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

where

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

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

Recall indicates the omission error, while precision indicates the commission error [29], and the *F-score* represents their harmonic mean [30]. These performance indicators were evaluated considering: true positives (TP), representing correctly detected gaps; false positives (FP), which are the erroneously detected gaps; and false negatives (FN), i.e., not detected gaps. The F-score value ranges from 1.0, indicating perfect precision and recall, to 0, if either the precision or the recall is zero.

2.5 Forest Canopy Gap Analysis

Once all boundaries of the forest canopy gaps were extracted and converted as vector polygons, several gap statistics were calculated to define structural gap properties such as i) area of gap (m^2) (gap_area); ii) maximum canopy height (m) (ch_max); iii) minimum canopy height (m) (ch_min); iv) mean canopy height (m) (ch_mean); v) standard deviation of canopy height (m) (ch_sd); vi) Gini coefficient of canopy height (m) (ch_gini); and vii) range of canopy height (m) (ch_range). Moreover, we analyzed the geometrical properties of each gap by exploring the perimeter-area relationship and calculating the gap shape complexity index (GSCI) metric. The GSCI is widely used as a forest gap measure [19] and is a measure of the complexity of gap shape compared to a circular shape of the same size (Eq. 4).

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

Where P is the perimeter and A is the area. A value of 1.0 describes a circle while increasing values indicate increasing shape complexity.

The Zeta distribution function was used to quantify the size-frequency distribution of forest canopy gaps as it is a discrete power-law probability density [26]. For the Zeta distribution with parameter λ, the probability that the gap size takes the integer value k is:

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

where the denominator is the Riemann zeta function, being the sum of all terms $k^{-\lambda}$ for positive integer k, and is undefined for $\lambda = 1$. The function calculates the maximum likelihood estimates of λ by minimizing a negative log-likelihood function [26]. The negative slope of the relationship between gap sizes and their frequency (on a log-log scale) is the exponent (λ). As a result, a log-log plot of gap-size frequency distributions and a vector containing λ and the minimum value of the likelihood were obtained. According to [26, 31], values of λ higher than 2.0 suggest a forest with many small gaps that might indicate high growth-low mortality dynamics. In comparison, values of λ smaller than 2.0 indicate the prevalence of larger canopy gaps that might be associated with considerable canopy mortality or emergent trees.

Through the use of second-order statistics, we finally investigate the spatial pattern of the detected forest gaps, calculating the position of each gap, analyzing whether they are significantly distributed in clusters or uniformly, with the null hypothesis being a random distribution (Poisson process). The output is the resulting Ripley's $K(r)$ function [32], showing the number of gaps located at a distance lower than r, and its $L(r)$ function transformation, which enhances visual interpretation. Results also return the value of the Clark and Evans [33] aggregation index R. Values for $R < 1$ suggest a clustered pattern, while values for $R > 1$ suggest a uniformly ordered pattern [34]. All statistical analyses were performed with the R package ForestGapR [25, 35].

3 Results and Discussions

3.1 CHM Derived Gaps Accuracy

The total number of gaps in the 10 plots, derived from the manual digitization, was 58, while those from the CHM were 56. This was because of the very high resolution of the orthomosaic, thanks to which it was possible to manually digitize 2 gaps that were lower than the pre-established threshold size of 10m^2. Therefore, these 2 gaps were not considered in the accuracy assessment. Out of the 56 gaps, 50 were correctly extracted, 4 were missing, and 2 were falsely detected. The *r* (omission error) value resulted in 0.93 while *p* value (commission error) was 0.96. The F-score, which considers both *r* and *p*, was 0.94. The overall detection rate has reached a value of 89%. This result can be explained by assuming that in-between tree crown spaces intercepted by the orthomosaic were actually occupied by vegetation with height above the defined threshold, which can only be deduced through the CHM. Likewise, the four gaps erroneously identified are spaces where the tree branches fall back inside them, causing the increase in vegetation height along the inner gap edge, reducing the minimum gap width considered in the CHM. Considering the study area's imperviousness and the complex forest structure, the results obtained can be regarded as more than satisfactory if compared with other similar studies [12, 16, 22, 36].

3.2 Canopy Gap Detection, Distribution and Structural Property

Within the whole study area, we were able to detect 196 gaps, primarily located in the forest's central and southern parts. The mean canopy gap fraction was 10% of the total forest extension (1.05 ha). Gaps were highly variable in size, ranging from 10 m^2 to a maximum value of 343 m^2 with a mean value of 64 m^2 (Table 1). The data are in line with other Italian old-growth beech forests, as stated by Piovesan et al. [23], and other European old-growth forests [16, 37]. Similar values are also found in tropical rain forests, ranging from tiny size to 500 m^2 [38, 39] and temperate rain forests [40, 41].

Differences in vegetation heights inside canopy gaps, ranging from 1 m up to 4 m, show how the underway renewal processes are due to disturbance events differentiated over time (Table 1). The Gini coefficient's low values (Table 1) indicate that such events have not caused major disturbances in the forest ecosystem's light environment [42].

Table 1. Forest canopy gap statistics. Area of gap (m^2) (gap_area); maximum canopy height (ch_max); minimum canopy height (ch_min); mean canopy height (ch_mean); standard deviation of canopy height (ch_sd); Gini coefficient of canopy height (ch_gini); range of canopy height (ch_range); gap shape complexity index (GSCI); standard deviation (±.).

gap_area (m^2)	ch_max (m)	ch_min (m)	ch_mean (m)	ch_sd (m)	ch_gini	ch_range (m)	GSCI min (mean) max
64 (±52)	4	0.95	2.89	0.95	0.19	3	1.2 (2.1) 4.1

Our results showed that the gap area-perimeter relationship differed markedly from circular reference gaps as the canopy gap size increased, indicating that the gap geometry became more complex with gap size (see Fig. 3). The perimeter-area ratio for all gaps ranged from 0.5 to 2.5, and the mean perimeter-to-area ratio was 1.2 (± 0.38 standard deviation). This result is also consistent with the mean GSCI value, meaning that the gap shape reached 110% complexity (Table 1) with a maximum of 310% complexity. This condition points out the vital role of old-growth forests in conserving biodiversity as higher values of GSCI are strictly correlated with species richness [22].

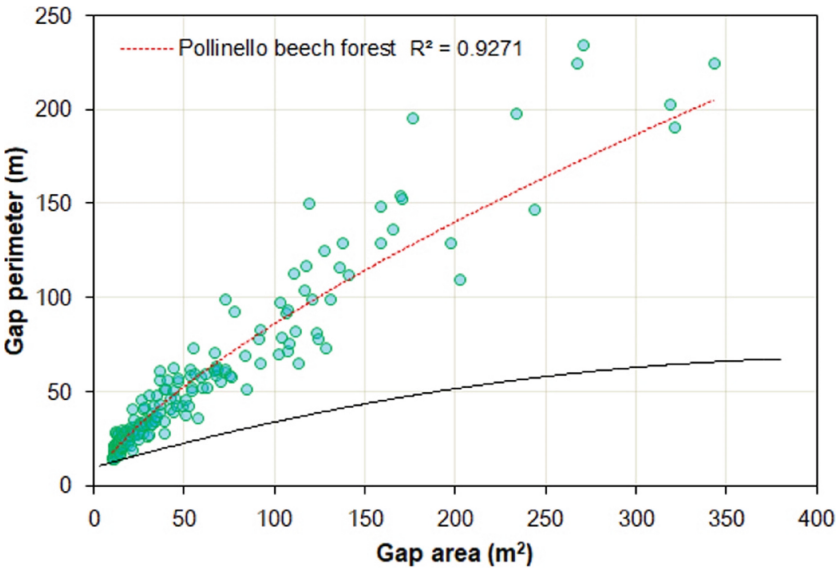

Fig. 3. The gap area–perimeter relationship for the old-growth beech forest of mount Pollinello. The dashed black line indicates the area-perimeter ratio for a circle.

According to results reported in tropical [2] and boreal forests [11], we found that the gap size frequency in a representative Mediterranean forest followed a power-law distribution. The observed gap size distribution (see Fig. 4) has a negative slope. Thanks to its size frequency, plotted on a logarithmic scale, we infer the scaling parameter $\lambda = 1.95$. The obtained value close to 2 means that the forest is dominated by small canopy openings, indicating high growth and low mortality dynamics. In contrast, smaller values of λ indicate an increased frequency of large gap events [43]. Our results are slightly different from those reported in other studies on old-growth forests in different environments [36, 44].

On the one hand, this may be due to the smaller size of the study area, which may produce systematically biased estimates of λ or the gap area fraction [45]. Other factors affecting the frequency distribution of gaps are related to the frequency distribution of tree sizes [46, 47], comprising the tree canopies spatial configuration within and among canopy strata and disturbance regime [48] of different forest environments.

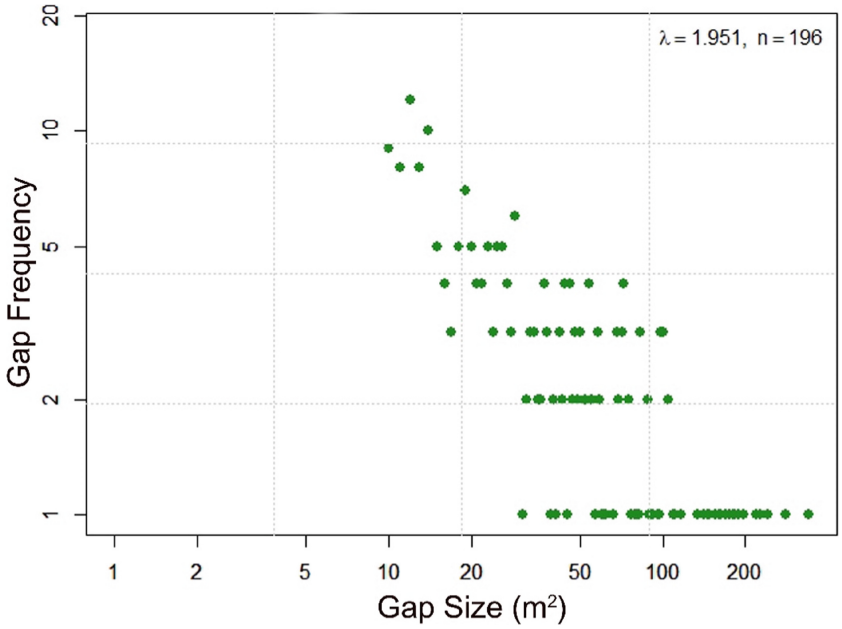

Fig. 4. Size frequency distribution of forest canopy gaps log-log plot. Power-low exponent (λ) and the number of mapped gaps (n) are provided.

The study of second-order statistics of the spatial gap patterns showed a predominantly clustered pattern in the old-growth forest canopy gaps (see Fig. 5). In detail, the observed $K(r)$ value is higher than the expected one for a certain distance so that the distribution is more clustered than randomized at that distance (scale of analysis). Moreover, the spatial clustering for that distance is statistically significant because the observed K value was larger than the upper confidence envelope value. The same pattern was observed considering the K-function modification Ripley's $L(r)$ that showed statistically significant dispersion only for a smaller distance within 15 m.

The value of the Clark and Evans index R of 0.81 ($p\text{-}value < 0.001$) confirms a cluster aggregation. However, suggesting a tendency towards randomness. Our results reflect the possibly patchy recruitment on these particular soils and slopes [49]. Gaps clustering at greater distances could be caused by factors related to the site's nature, such as slope or aspect, which may influence the formation of gaps in the study area, as reported in other studies [50]. The clustered distribution of natural canopy gaps differs from other studies dealing with temperate forests in Europe [51] and North America [7]. This could be due to the dynamics that generate the gaps in this forest. The death of single big trees with large crowns appears to be primarily responsible for gap opening phenomena next to the edges of other gaps and a lateral expansion of branches and their following destruction [52].

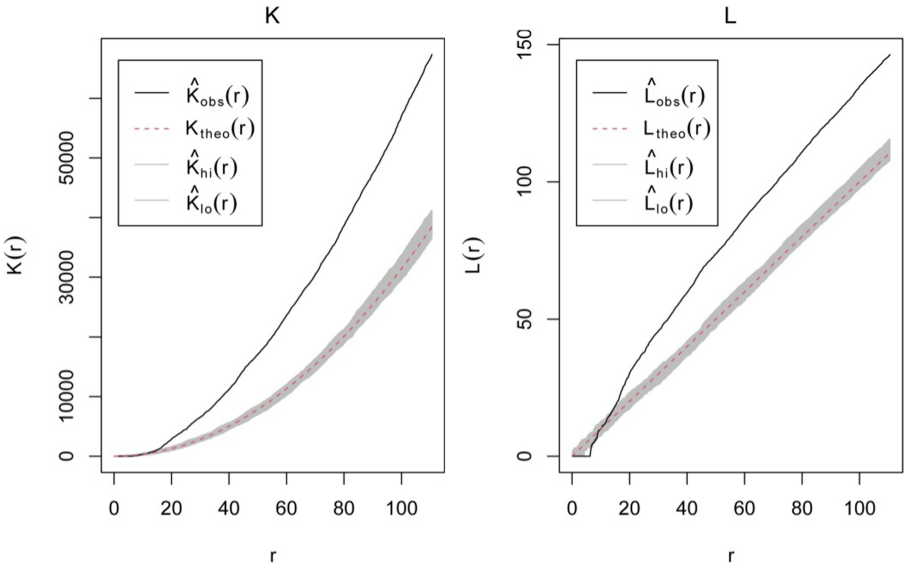

Fig. 5. Spatial pattern analysis for the old-growth forest of mount Pollinello. Ripley's *K* and *L* function (black line); theoretical random distribution function (red dashed line); higher and lower confidence interval (grey line) (Color figure online).

4 Conclusions

The analysis of forest canopy gaps, size, and spatial pattern distribution in an old-growth forest are parameters to be considered. They provide helpful information for conservation and sustainability to restore and maintain biodiversity and accelerate forest succession towards old-growth characteristics within managed ones. Using advanced geomatic techniques, as a low-cost effective UAV survey, we were able to derive very high-resolution CHM of the old-growth beech forest of Mount Pollinello in a strict reserve in the Pollino National Park, obtaining consistent results in detecting canopy gaps. First of all, these preliminary results showed the potential reliability of a CHM-based gap automatic extraction procedure. Moreover, it showed the nature of gap opening processes, such as tree mortality and local stand-level disturbance. At the local scale, the prevalence of small-scale processes was confirmed by spatial structure analyses highlighting the absence of major and intermediate disturbances due to the absence of human pressure and its remote location. Further studies will be needed to increase the accuracy of the survey adopted to ensure reliable ground truth to better understand the ongoing ecological processes. Furthermore, establishing a continuous monitoring system of the disturbance dynamics will allow to better reconstruct these ecological processes, also allowing the sharing of data through the creation of dedicated web map tools [53, 54]. Canopy gap disturbance dynamics, coupled with forest complexity metrics, could then be used to evaluate forest ecosystems naturality [55]. Finally, UAV-based CHM extraction could be a helpful tool to derive tree height for carbon stock management, also in other contexts, like urban green [56].

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