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# Analysing gap dynamics in forest canopies with landscape metrics based on multi-temporal airborne laser scanning surveys – A pilot study

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ABSTRACT

For a long time gaps or openings in the forest canopy have been of considerable interest to forest ecologists and to forest managers. In the context of disturbances induced by climate change, canopy gap dynamics are of particular interest, since they can indicate imminent damage to forest resources and irreversible trends such as forest decline. Here, statistical significance is crucial for establishing whether any imminent large-scale threat to the sustainability of forest resources exists. In order to be able to assess significance, we applied the Boolean model, a null or reference model from random set statistics. The Boolean model served as a theoretical benchmark for testing the significance of the observed trends in forest canopy gap dynamics. As a pilot study we analysed airborne laser scan (ALS) data collected in the Krycklan catchment area (Northern Sweden) in 2006 and 2015. The data were analysed using eight different landscape metrics. Despite the moderate resolution of our ALS data the landscape metrics have proved to be useful tools for monitoring canopy gap dynamics of forest ecosystems. The Boolean model has been successful in ascertaining statistical significance and the model parameters indicated important trends. In the Krycklan catchment area, there was no significant trend of canopy gap dynamics indicating any harmful development between 2006 and 2015. On the contrary, we found evidence for gaps closing in and gap locations becoming more random whilst the canopy cover increased between the two survey years.

## 1. Introduction

Gaps or openings in the canopies of forest stands have been of considerable interest to many ecologists studying the dynamics of forest ecosystems. A gap is created by the natural death or removal of main canopy trees and can be defined as the vertical projection downward of any canopy opening in the forest that extends through the vegetation strata down to a height of 2 m above ground (Brokaw, 1982; Kimmins, 2004; Newton, 2007). Whatever process caused them, gaps in the main canopy of forest stands markedly modify the environmental conditions of plants growing in the affected patches (Binkley, 2021). More light and precipitation reach the forest floor whilst evapotranspiration at the soil surface is also increased. Light availability depends on the ratio of canopy height to gap radius, but also on the sun elevation angle and therefore may be offset from the opening in the canopy depending on latitude (Kimmins, 2004). Canopy gaps increase the environmental heterogeneity and thus provide quite different microhabitats and consequently different opportunities for plant seedlings to colonise affected areas, whilst existing mid-storey trees can emerge into the main canopy. The response of vegetation after gap formation is closely related to gap size (Whitmore, 1989). Reflecting all this, the *gap-partitioning hypothesis* states that species with different requirements establish in different parts of the same gap (e.g. edge versus centre; Perry et al., 2008). Gaps can attract herbivores such as deer because of an increased abundance of herbaceous plants in the opening. The formation of canopy gaps of various sizes and the subsequent recruitment and growth of plants in the gaps are key processes in autogenic forest succession (Kimmins, 2004). Canopy gaps are reflected by belowground gaps that are generally much smaller than the canopy gaps because roots extend much further from the stem than branches (Lukac and Godbold, 2011).

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Multiple causes and agents can be responsible for gap formation, either in isolation or in unison. Frequent causes include wind, insect infestations, diseases, forest management, flooding, air pollution, invasive species, road construction and lightning. Repeated long-term droughts can prepare and trigger insect infestations, as can wind and fire. Dominant trees often tend to die through the natural process of senescence that leaves trees vulnerable to the aforementioned agents. Such mortality is frequently spatially aggregated thus opening relatively large gaps (Perry et al., 2008). The creation of canopy gaps usually enhances biodiversity in terms of species richness and size diversity and also results in accumulations of large quantities of dead wood. With ongoing climate change it is expected that gap-inducing causes and agents will increase, leading to a more frequent occurrence of gaps but also to steady gap enlargement and the merging of existing gaps (Nakamura et al., 2017; Senf et al., 2018). Gap formation is counteracted by the crown growth of gap-boundary trees whose crowns enlarge and close in as time goes by. At the same time tree regeneration may close some gaps and in others small existing trees may gradually claim the available space.

These dynamics are interesting in themselves, since they are the key to understanding the interactions between periodic disturbances and tree dynamics (Kimmins, 2004). For example, frequent, relatively mild disturbances create a small gap mosaic, while infrequent, more severe disturbances can initiate a large-scale successional dynamic that includes long-term changes (Perry et al., 2008). With ongoing climate change it is, however, possible that disturbances will have a much greater effect on forest ecosystems than currently observed. In that situation, monitoring gap dynamics can play a key role in determining the progress of anthropogenic impacts on our environment. Furthermore, continued canopy screening can contribute to an early-warning system that alerts forest managers to the emergence of tipping points beyond which forest restoration will be difficult or even impossible.

Remote sensing techniques and particularly airborne laser scanning (ALS) can provide opportunities for accurate and spatially explicit mapping of forest canopy gaps (Silva et al., 2019). They allow the detection and analysis of forest gap data using ALS-derived 3D point clouds or canopy height models (CHM). Up to a point, high spatial resolution reduces the uncertainty that is associated with both gap detection and gap characterisation using summary statistics. While most studies are based on high resolution ALS data, our focus is on the more common situation of being limited to the availability of existing airborne surveys to avoid additional costs.

The objectives of this paper are (1) to perform a literature review of landscape metrics in order to identify the most suitable characteristics for an effective monitoring of tree canopy gaps in airborne laser scanning (ALS) data. Furthermore we intended (2) to develop a simulation method that gives evidence whether an observed difference of a characteristic is significant or not and provides additional information assisting the interpretation of changes. Finally, (3) achievements and limitations were discussed and recommendations were made.

## 2. Materials and methods

### 2.1. Gap identification

Since the emphasis of this study is placed on quantitative gap description, we have adopted a definition of canopy gaps along the automated gap identification reported in the remote sensing literature. This definition relies on canopy height models (CHM), which are spatially explicit descriptions of the tree canopy height over a given area of forest. CHMs are commonly calculated as the difference between the canopy surface and the underlying topography (Vepakomma et al., 2011; Wöllauer et al., 2020).

We defined gaps in terms of minimum penetration rate below a 2-m height threshold. The penetration rate measures the proportion of points in a given height stratum (Takahashi et al., 2006). A gap is then defined by a penetration rate below this threshold of at least 80% which was calculated on a regular raster grid. Due to the moderate point density of the first ALS acquisition used in this study, 3.91–6.81 points/m$^2$ in 2006 compared to 30.15–46.73 points/m$^2$ in 2015, a spatial resolution of 2.5 m was chosen for the grid cell size.

Other studies filtered the identified gaps in terms of a pre-defined minimum gap size and/or a gap perimeter/area ratio (e.g. Heidrich et al., 2020; Bae et al., 2019). In general, minimum gap size is mainly a matter of research question (e.g. whether a researcher intends to focus on a certain type of gaps and only gaps are studied) and we decided that for our research topic all gaps are relevant regardless of their size and that it therefore would be better not to introduce a lower boundary. The gap perimeter/area ratio is usually applied to ensure that linear structures such as roads, rides and trenches are not included (Heidrich et al., 2020). However, our study areas do not include any forest roads and rides (see Section 2.4).

### 2.2. Characterising gaps and their dynamics

According to the results of our literature review, there are two main groups of characteristics that can be applied in the analysis of spatial canopy patterns, i.e. *indices* and *spatially explicit functions* (Chiu et al. 2013). In the context of landscape research, indices are commonly referred to as metrics (Turner and Gardner, 2015; Gergel and Turner, 2017). Both, indices and functions, quantify different aspects of the pattern under study, e.g. patchiness or shape aggregation/segregation. Dale and Fortin (2014) defined “patch” as a spatially homogeneous area where at least one variable has similar attributes either of a category (e.g. tree canopy or gap) or of a quantitative value (e.g. mean tree height). The first group of characteristics is often referred to as *landscape metrics* (Turner and Gardner, 2015; Gergel and Turner, 2017), because these characteristics were originally proposed for analysing landscape patterns in land-cover maps obtained from remote sensing images (Dale, 1999). However, they can be applied to labelled image data of different scales from microscopy to landscapes. They include a number of different measures of varying complexity, e.g. forest cover percentage, mean patch size, mean or total perimeter length, mean distance of points in forest patches to the nearest non-forest point, percentage of edge area, fractal dimension, number of forest patches, mean distance between centroids of forest patches, and spatial correlation (Kleinn, 2000; Turner and Gardner, 2015).

Spatially explicit functions by contrast are dependent on Euclidean distance and quantify the spatial relationship between pixels, cells or objects (such as gaps). Typical examples are the spherical contact distribution, also termed empty-space statistic and the variogram (Chiu et al., 2013). Spatially explicit functions are typically more exact and can provide more detailed information than indices, however, they have limitations when the geometrical resolution of the images is moderate in comparison to the investigated objects, and consequently cannot develop their full potential in such situations (Pommerening and Grabarnik, 2019).

#### 2.2.1. Landscape metrics for describing canopy gaps

From our literature review, we learned that landscape metrics can be grouped into different categories. Here we followed the classification used in the `landscapemetrics` R-package (Hesselbarth et al. 2019) including.

- aggregation metrics,
- area and edge metrics,
- complexity metrics,
- core area metrics,
- diversity metrics and
- shape metrics.

The results of the analysis crucially depend on the selection of the landscape metrics. For some applications, core sets of the most useful metrics have been defined, e.g. for landscape planning by Botequilha-Leitão and Ahern (2002) or for analysing biodiversity by Schindler et al. (2008). Cushman et al. (2008) and Riitters et al. (1995) used factor analysis to define more general recommendations for useful sets of landscape metrics. However, these recommendations apply to analysing landscapes rather than to analysing binary canopy gap maps.

Although such core sets have not been developed for binary gap maps, there are more general recommendations in the literature, which apply regardless of the application: (1) Choosing the metrics should contribute to answering the particular research question as opposed to trying to study everything. (2) The chosen landscape metrics should be able to sufficiently explain pattern variability across the landscape and redundancies should be minimized. Therefore, the chosen metrics should be relatively independent of each other. (3) Metrics should be used for which a wide range of their domain is covered by the investigated landscape (Eigenbrod et al., 2011; Turner and Gardner, 2015).

Since we were only interested in fundamental, significant changes of the gaps, most types of gap metrics were suitable for our analysis. However, advised by the literature we excluded two types of metrics from this analysis straight away: core metrics and the diversity metrics (Table 1). Core metrics do not seem to be reasonable for this application because there are hardly any core areas in our data. Core areas include all gap pixels, which are not directly connected to any canopy pixels (McGarigal, 2014). Such pixels hardly occur in the data of our study areas due to the moderate spatial resolution. Diversity metrics were not meaningful in this application either, since the gap maps were only binary, i.e. there were only two classes of patches.

Patch area (AREA) measures the area of patches, e.g. canopy gaps (Table 1). PLAND gives the proportion of gaps in the whole study area. AREAmn in our application is the mean gap area. The clumpiness index (CLUMPY) is a measure of the aggregation of gap pixels. The normalised landscape shape index (nLSI) measures gap aggregation by considering the ratio of the actual perimeter and the hypothetical range of possible perimeter lengths. The landscape division index (DIVISION) can be interpreted as the probability that two randomly selected pixels are not located in the same gap. The Euclidean nearest neighbour distance (ENN) gives the distance between a gap and its nearest neighbour gap (Jaeger, 2000). Finally, the mean fractal dimension index (FRAC) is a shape index describing gap complexity based on gap perimeter and gap area (Table 1).

Landscape metrics can be measured at patch, class or landscape level. Most landscape metrics are considered at class or landscape level. For binary landscapes, this implies that the metrics results are one or two scalars, respectively (Turner and Gardner, 2015). For this study, the scalar landscape metrics that proved useful were percentage of

**Table 1**
Overview of all landscape metrics used in this paper. There are two classes of patches $i = 1, 2$, where $i = 1$ denotes gaps and $i = 2$ denotes tree canopies. For each class, there are $n_i$ observations/patches. The area and perimeter of a patch $ij$ are given by $a_{ij}$ and $p_{ij}$, respectively. $j$ is an index denoting each patch within class $i$. The total landscape area is given by $A = \sum_{i=1}^{2}\sum_{j=1}^{n_i} a_{ij}$ and the total class area for class $i$ is given by $A_i = \sum_{j=1}^{n_i} a_{ij}$. In analogy, the total perimeter is $P = \sum_{i=1}^{2}\sum_{j=1}^{n_i} p_{ij}$ and $P_i = \sum_{j=1}^{n_i} p_{ij}$.

| Metric name and acronym | Metric type | Formula | Range | Description, details and interpretation | Reference |
|---|---|---|---|---|---|
| Patch area (AREA) | Area and Edge | $a_{ij}$ | $\mathbb{R}^+$ | Area of patch $j$ of class $i$. Measured at patch level, hence a distribution can be considered.<br><br>For $i = 1$, the characteristic represents *gap area* of gap $j$. | Turner and Gardner, 2015 |
| Percentage of landscape of class $i$ (PLAND) | Area and Edge | $100 \cdot \left(\frac{\sum_{j=1}^{n_i} a_{ij}}{A}\right)$ | [0, 100] | Percentage of patches of class $i$ in the landscape.<br><br>For $i = 1$, the characteristic represents the proportion of gaps in the whole study area and is called *gap area proportion.* | Turner and Gardner, 2015 |
| Mean of patch area (AREAmn) | Area and Edge | $\frac{1}{n_i}\sum_{j=1}^{n_i} a_{ij}$ | $\mathbb{R}^+$ | Mean area of the patches of class $i$ in the landscape.<br><br>For $i = 1$, the characteristic represents *mean gap area.* | Turner and Gardner, 2015 |
| Clumpiness index (CLUMPY) | Aggregation | $\begin{cases} \frac{G_i - P_i}{P_i} & \text{for } G_i < P_i < 0.5 \\ \frac{G_i - P_i}{1 - P_i} & \text{else} \end{cases}$ with $G_i = \frac{g_{ii}}{\sum_{k=1}^{m} g_{ik} - f_{\min}(P_i)}$ | $[-1, 1]$ | $g_{ik}$– total number of neighbouring pixels of pixels of class $i$ which belong to class $k$.<br>$g_{ii}$– total number of neighbouring pixels of pixels of class $i$, which belong to class $i$ as well.<br>$f_{\min}(P_i)$– smallest theoretically possible value of the perimeter of class $i$<br>The index equals $-1$ for maximally disaggregated, 0 for randomly distributed and 1 for maximally aggregated classes. | Hesselbarth et al. 2019; McGarigal, 2014; With, 2019; |
| Normalized landscape shape index (nLSI) | Aggregation | $\frac{P_i - f_{\min}(P_i)}{f_{\max}(P_i) - f_{\min}(P_i)}$ | $[0, 1]$ | $f_{\min}(P_i)$ and $f_{\max}(P_i)$ give the smallest/largest theoretically possible value of the perimeter of class $i$.<br>Results in the ratio of the actual perimeter and the hypothetical range of possible perimeter lengths.<br>Equals 0 when only one square patch is present, i.e. a patch with equal lengths of sides, and increases the more disaggregated patches there are. | Patton, 1975 |
| Landscape division index (DIVISION) | Aggregation | $1 - \sum_{i=1}^{2}\sum_{j=1}^{n_i}\left(\frac{a_{ij}}{A}\right)^2$ | $[0, 1]$ | Can be interpreted as the probability that two randomly selected pixels are not located in the same patch. | Jaeger, 2000 |
| Euclidean nearest-neighbour distance (ENN) | Aggregation | $h_{ij}$ | $\mathbb{R}^+$ | $h_{ij}$– Euclidean distance from patch $ij$ to the nearest patch of the same class $i$.<br>For $i = 1$, the characteristic gives the Euclidean distance from gap $j$ to the nearest distinct gap.<br>Measured at patch level, hence distribution can be considered. | Turner and Gardner, 2015 |
| Mean fractal dimension index (FRAC) | Shape | $\frac{1}{n_i}\sum_{j=1}^{n_i}\left(2 \cdot \frac{\log_e(0.25 \cdot p_{ij})}{\log_e(a_{ij})}\right)$ | $[1, 2]$ | Describes patch complexity based on patch perimeter and patch area.<br>The factor of 0.25 results from a standardisation such that the perimeter of a one-pixel patch is standardised to be 1. | With, 2019; Mandelbrot, 1977;Turner and Gardner, 2015 |

landscape of class, mean of patch area, clumpiness index, normalized landscape shape index, landscape division index, contiguity index and mean fractal dimension index (Hesselbarth et al., 2019; With, 2019; Turner and Gardner, 2015; McGarigal, 2014; Jaeger, 2000; LaGro, 1991; Mandelbrot, 1977, Patton, 1975), see Table 1.

In addition to the scalar landscape metrics, we considered two landscape metrics which are measured at patch level, i.e. patch area and Euclidean nearest-neighbour distance (Turner and Gardner, 2015). In the context of our study, the gaps are the patches of interest. These landscape metrics are not observed as scalars but their distribution in the whole study area is of interest. As these metrics do not take values smaller than 0, the analysis is carried out using kernel density estimation with a log-transformed kernel density estimator (Charpentie and Flachaire, 2015).

In the context of climate change and potential forest damage, it is crucial to establish whether any canopy gap pattern and particular the changes in gap patterns over time are statistically significant. Significant differences in landscape metrics values between years can alert to trends that may lead to a gradual climate-induced dissolution of forest canopy or to a recovery. In our analysis, we compared gap maps observed at two points in time with simulated gap maps resulting from a theoretical spatial model, the *Boolean model*, see Section 2.2.2. Apart from the direct comparison of metrics values, we also used the parameters of the theoretical model for characterising and testing the changes that occurred between the two observation dates.

### 2.2.2. The theoretical benchmark: The Boolean model

The germ-grain model is the most important model in random set statistics and its most basic variant is the Boolean model (Chiu et al., 2013). The germs of this model result from a Poisson point process which implies *complete spatial randomness* (CSR), i.e. there is no correlation between point locations in a Poisson paint pattern. Complete spatial randomness often serves as a *reference model* in spatial statistics. Other, synonymous terms include *benchmark* or *null model*. Using CSR as a reference is very common in point process and random set statistics (Illian et al., 2008). Any significant deviation from CSR cannot be explained by chance alone and therefore constitutes a statistically important observation.

There are several possibilities for constructing the grains of Boolean models (e.g. circles with constant radius, circles with random radii, polygons etc.) and we focussed on the standard model of circular grains with constant radius. As a consequence, the grains in our case are discs with a constant radius $R$ around each germ. Therefore, the Boolean model can be uniquely specified by only two parameters: the intensity of the underlying Poisson point process $\lambda$ and grain radius $R$ (Pommerening and Grabarnik, 2019; Stoyan et al., 1995). The union of grains simulates the random pixel set formed by the tree canopies in our data. As a consequence, canopy gaps are modelled by the complement of the Boolean model, i.e. the area not covered by grains.

Although it seems to be an intuitive choice to make germs coincide with individual tree locations so that the corresponding grains represent their crowns, there is no theoretical justification for such a modelling strategy. In fact, in any model the germs can flexibly represent parts of trees, whole trees or clusters of several trees. This is the modelling strategy we adopted in our study and the germs can be interpreted as ***auxiliary points*** that help construct overall forest canopy structure. Therefore in our study, the *number of auxiliary points* is based on the *intensity rate*.

For simulating the Boolean model we used the `spatstat` R package (Baddeley et al., 2016; Baddeley and Turner, 2005). The simulations were carried out in two steps: (1) A Poisson process with intensity $\lambda$ was simulated using the function `runifpoint()`. The intensity was specified in points per hectare to ensure scale invariance. (2) The grains were added as circles around the germs using the function discs. This second step was performed pixel by pixel following the 2.5 m × 2.5 m raster of the CHM derived from the ALS data (see Fig. 1).

To take into account that the edges of the study areas are not the edges of the forest a buffer method was applied, i.e. the Boolean models were first simulated in a larger area and then an area matching the size of the study area was extracted from the centre of the simulated area.

In theory, model parameters $\lambda$ and $R$ are continuous, i.e. $\lambda, R \in \mathbb{R}^+$. However, for our application we needed to choose a grid of values, which could be simulated in a reasonable amount of time. We decided to use 1 m steps from 1 m to 7 m for $R$ and a step width of 50 $\mathrm{ha}^{-1}$ within a range from 50 $\mathrm{ha}^{-1}$ to 1200 $\mathrm{ha}^{-1}$ for $\lambda$. Therefore, there are several possible combinations of model parameters not explicitly considered by our grid values. In some cases, as shown in our results, none of the estimated models coincides with the observed values, however, theoretically a model matching the observations might exist for some values lying between two values of our grid. In such cases, we often provided intervals in which these values might lie. To do so we applied the usual notation based on using "(" for an open interval and "[" for a closed one (e.g. $50\ \mathrm{ha}^{-1} < \lambda \leq 150\ \mathrm{ha}^{-1}$ was denoted as

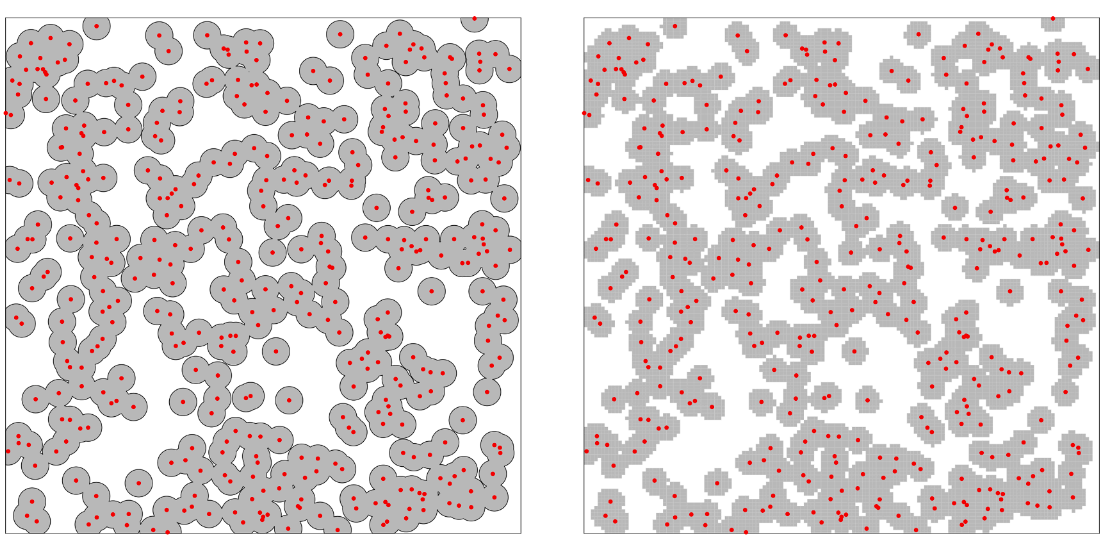

**Fig. 1.** Left: Realisation of a Boolean model with $R = 8$ m and $\lambda = 30\ \mathrm{ha}^{-1}$. Right: The same realisation is fitted into the 2.5 m × 2.5 m raster. The germs are shown in red. Window size is 375 m × 375 m, which is equivalent to 150 × 150 pixels. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

$\lambda \in \left(50\ \mathrm{ha}^{-1}, 150\ \mathrm{ha}^{-1}\right]$). This should not be confused with sets of values of $\lambda$ denoted by "{" (e.g. $\lambda \in \{50\ \mathrm{ha}^{-1}, 150\ \mathrm{ha}^{-1}\}$ or $\lambda \in \left\{950\ \mathrm{ha}^{-1}, 1000\ \mathrm{ha}^{-1}, 1050\ \mathrm{ha}^{-1}\right\}$).

### 2.3. *Methods for simulating envelopes and tests*

When comparing the values of the landscape metrics of the study area to those of the theoretical model, i.e. the Boolean model, the aim was to identify significant differences, as described in Section 2.2.2. However, since most landscape metrics have an unknown distribution, envelopes or regions of trust cannot be derived theoretically (Myllymäki et al., 2017; Turner and Gardner, 2015; Remmel and Csillag, 2003). Therefore, for each model parameter combination approximate envelopes were generated by drawing 2500 independent samples from the Boolean model and calculating the 2.5% and 97.5% quantiles of the landscape metrics of these samples (Turner and Gardner, 2015; Fortin et al., 2003; Remmel and Csillag, 2003).

For scalar landscape metrics, a difference between the value observed in the study area and the Boolean model is considered significant, if the observed value is not included in the simulated envelopes (Remmel and Csillag, 2003). Regarding the comparison of the observed values of the two study years with the simulated ones, there are three possible cases: (1) Both observed values are not significantly different from the simulated one resulting from a single Boolean model, i.e. one envelope covers both observed values. (2) None of the model parameter combinations of $\lambda$ and $R$ included in our grid leads to such an envelope but due to the size of the other envelopes, such a model configuration most likely exists for some value between the grid values. (3) The difference between the study years is larger than the envelopes and, therefore, the two observed values are not significantly different from the ones resulting from distinctly different Boolean models. In the latter case, we were mostly interested in which of the observed values coincided with the model with the higher number of auxiliary points since this gives an indication of canopy regrowth or forest decline.

Boolean model simulations of non-scalar landscape metrics lead to pointwise envelopes of the corresponding estimated densities. For determining whether the density of observed values differs significantly from the corresponding one of the theoretical model we applied the global envelope test (Myllymäki et al., 2018).

### 2.4. *Krycklan study area*

Krycklan is a watershed located in the boreal region of Northern Sweden in the county of Västerbotten. The area is located approximately 50 km northwest of the city of Umeå (64°, 14′N, 19° 46′ E). The Krycklan river is a tributary to the river Vindelälven which starts in the mountain range, crosses Sweden and enters the Baltic Sea near Umeå. Krycklan is a 6790 ha water catchment running through a mosaic of forests, wetlands and lakes that are interspersed throughout the forest landscape (Fig. 2). The catchment area is partly located within the Svartberget experimental forest which is managed by the Swedish University of Agricultural Sciences (Laudon et al., 2013). Krycklan ranges in elevation from 114 to 405 m a.s.l. Forests cover 87% of the catchment followed by mires (9%), shallow soils (7%) and rocky outcrops (1%). The land use is dominated by rotation forest management and 25% of Krycklan has been protected since 1922. In terms of abundance, the main tree species include Scots pine (*Pinus sylvestris* L.; 63%) and Norway spruce (*Picea abies* (L.) H. Karst., 26%) and mostly grow on postglacial sedimentary deposits. The climate can be characterised as cold temperate humid with persistent snow cover during the winter season. Mean annual temperature is 1.8 °C (-9.5 °C in January and +14.7 °C in July). Mean annual precipitation is 614 mm. We selected two test sites in the catchment areas that were comparatively little affected by forest management operations to be able to focus on natural tree crown development.

For selecting appropriate study regions for our analysis we mainly considered areas which

- were located completely inside the Svartberget experimental forest,
- were not involved in ongoing field trials,
- did not include any forest roads or rides (except for small footpaths or minor extraction racks),
- were larger than 5 ha, and
- were relatively dissimilar and not in direct proximity of each other.

The final selection was mostly based on high-resolution aerial photos, road maps and the Silvaboreal database (https://www.silvaboreal.com), which includes all field trials in the Svartberget experimental forest and historical information about the vegetation structure. Taking these criteria into consideration two suitable study areas were identified (Fig. 2).

The first area spreads over approximately 14 ha and the trees are on average 96–109 years old, the second one has a total size of approximately 16 ha and an average stand age of 122–139 years.

## 3. Results

The gap area proportion (PLAND) in the first study area (Fig. 3, PLAND) is smaller than in the second (Fig. 4, 12.7% versus 15.1% in 2006), particularly in 2015 (7.1% versus 12.8%). However, the differences between the years are not too dissimilar for the two areas and the trend of declining gap area proportion between 2006 and 2015 is the same. The envelopes produced by the simulations with the Boolean models in both study areas are relatively narrow compared to the difference between the study years. In both study areas, for $R = 3$ m there is no Boolean model leading to a gap area proportion value which is not significantly different from the values observed in 2006, but it can be concluded from Figs. 3 and 4 that such a model exists for some intensity

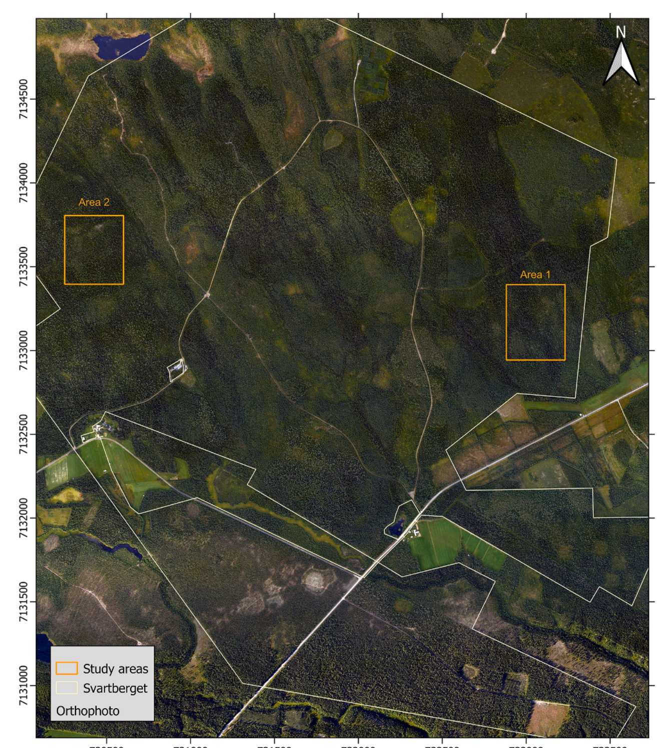


**Fig. 2.** Overview of the locations of the two study areas within the Svartberget experimental forest. Data source: SLU Field-based Forest Research Unit. (For interpretation of the references to colour in the figure legend, the reader is referred to the web version of this article.)

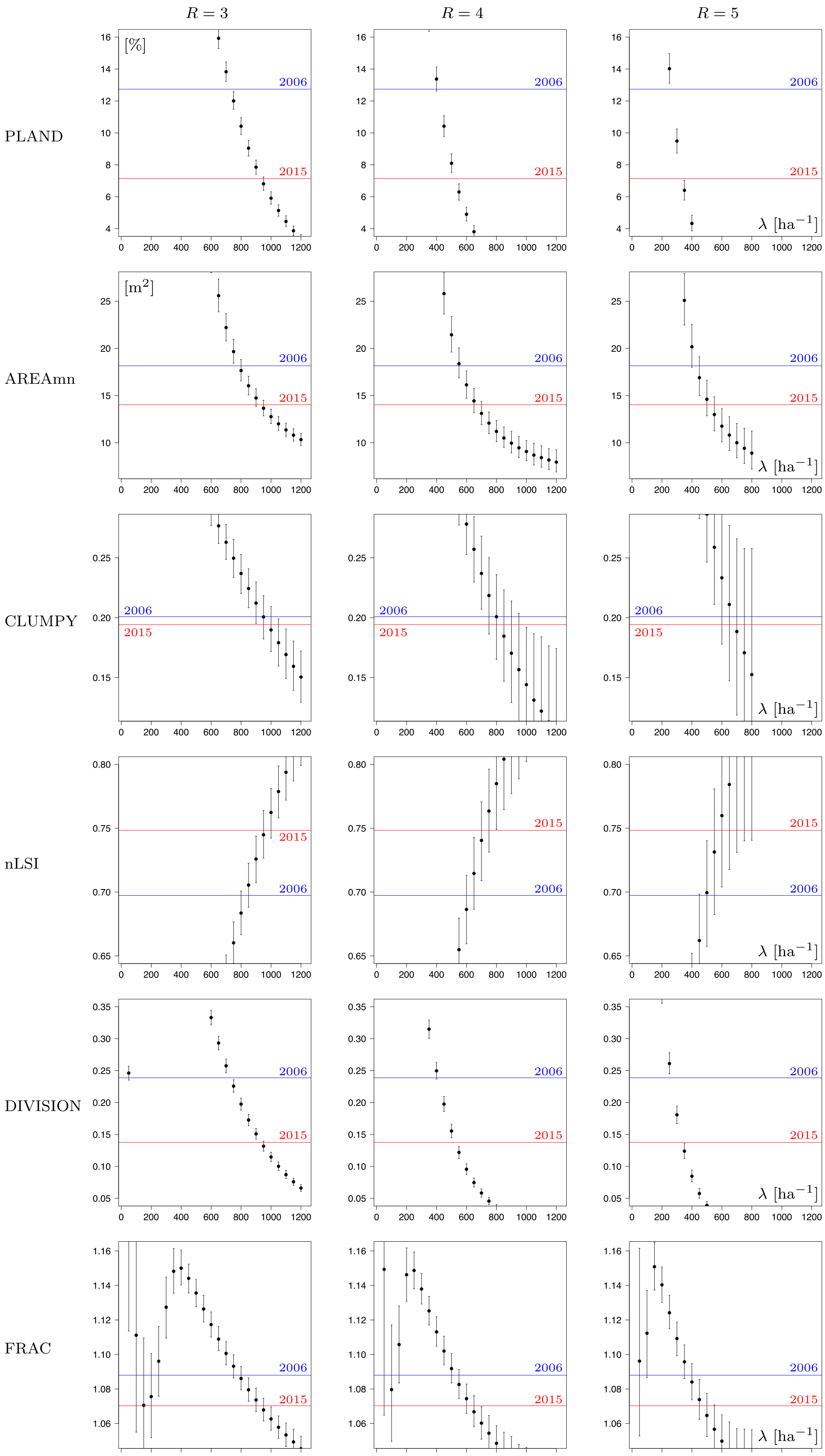


**Fig. 3.** Results of the class and landscape level metrics for the first study area. The means resulting from the simulation of the Boolean model are shown as black dots and their 95% envelopes as black bars. The observed values are shown in red for 2015 and in blue for 2006. The *x*-axis gives the intensity of the auxiliary points per hectare of the Boolean models and the *y*-axis shows the value of the corresponding metric. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

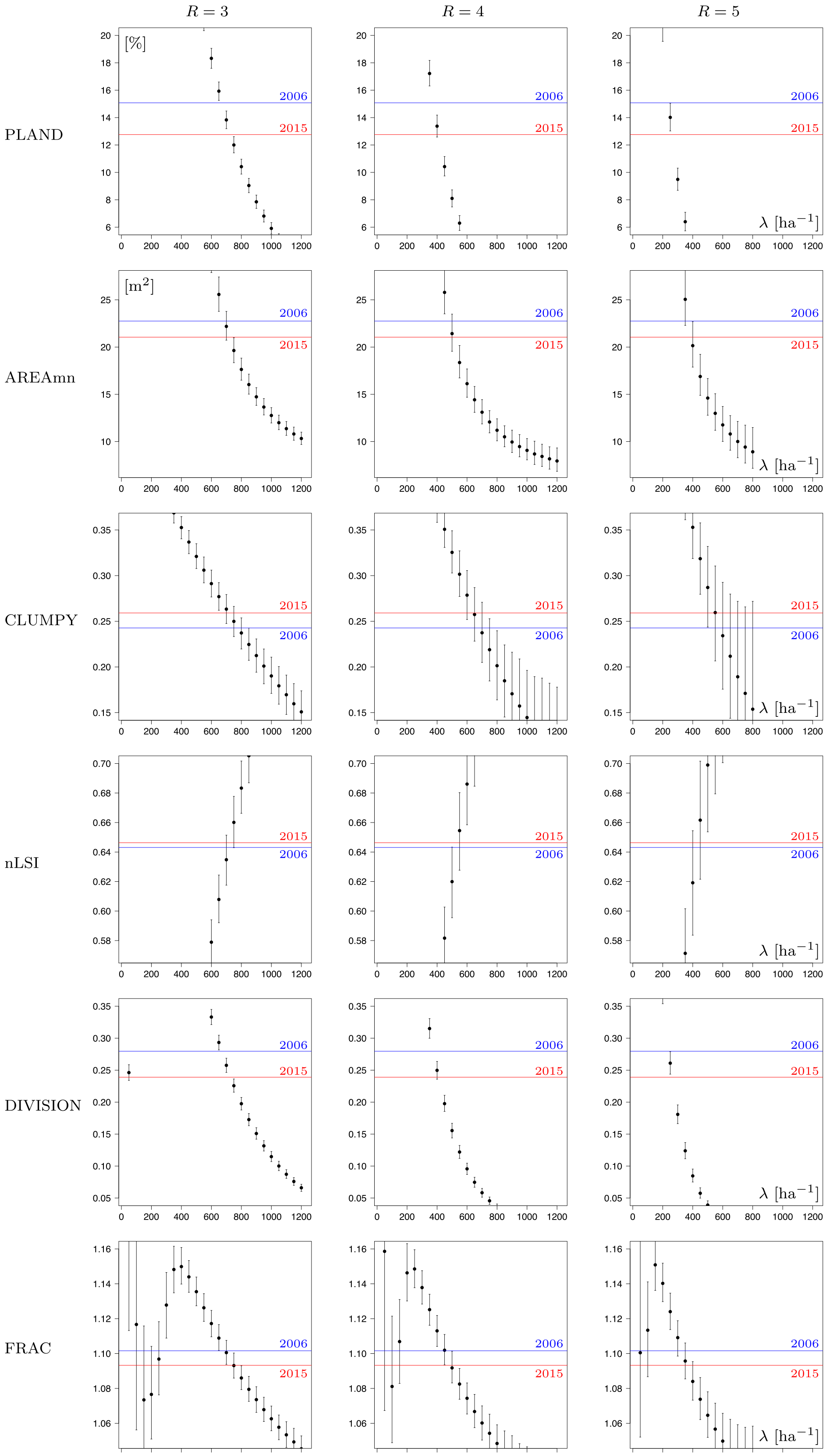


**Fig. 4.** Results of the class and landscape level metrics for the second study area. The means resulting from the simulation of the Boolean model are shown as black dots and their 95% envelopes as black bars. The observed values are given in red for 2015 and in blue for 2006. The *x*-axis gives the intensity of the auxiliary points per hectare of the Boolean models and the *y*-axis shows the value of the corresponding metric. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

$\lambda \in \left(700\ \mathrm{ha}^{-1},\ 750\ \mathrm{ha}^{-1}\right)$. For $R = 4$ m and study area 1, such a model is given for $\lambda = 450\ \mathrm{ha}^{-1}$, whilst in study area 2 such a model exists for some intensity $\lambda \in \left(400\ \mathrm{ha}^{-1},\ 450\ \mathrm{ha}^{-1}\right)$. For study area 1 (Fig. 3, PLAND), the gap area proportion observed in 2015 was not significantly different from the one resulting from Boolean models with $R = 3$ m and $\lambda = 950\ \mathrm{ha}^{-1}$. For $R = 4$ m and study area 1, none of the estimated models coincided with the observed value of 2015, but such a model exists for some intensity $\lambda \in \left(500\ \mathrm{ha}^{-1},\ 550\ \mathrm{ha}^{-1}\right)$ whilst for study area 2 (Fig. 4, PLAND) the gap area proportion observed in 2015 was not significantly different from the corresponding one resulting from Boolean models with $R = 4$ m and $\lambda = 400\ \mathrm{ha}^{-1}$.

Similar to PLAND, the mean gap area (AREAmn) of study area 1 is smaller than that of area 2 (approximately 18.0 $m^2$ versus 22.8 $m^2$ in 2006 and 14.0 $m^2$ versus 21.0 $m^2$ in 2015). However, the difference between the two survey years is greater in study area 1 (Fig. 3, AREAmn). As with PLAND there is a trend of declining mean gap area from 2006 to 2015. For study area 1, the gap area proportion observed in 2006 was not significantly different from the one resulting from Boolean models with $R = 3$ m and $\lambda = 800\ \mathrm{ha}^{-1}$, $R = 4$ m and $\lambda = 550\ \mathrm{ha}^{-1}$ or $R = 5$ m and $\lambda \in \left(400\ \mathrm{ha}^{-1},\ 450\ \mathrm{ha}^{-1}\right)$, whilst with $R = 3$ m and $\lambda \in (900\ \mathrm{ha}^{-1},\ 950\ \mathrm{ha}^{-1})$, $R = 4$ m and $\lambda \in (650\ \mathrm{ha}^{-1},\ 700\ \mathrm{ha}^{-1})$ and $R = 5$ m and $\lambda \in (500\ \mathrm{ha}^{-1},\ 550\ \mathrm{ha}^{-1})$ models exist that lead to values not significantly different from those observed in 2015. For study area 2 (Fig. 4, AREAmn), there are even single Boolean models explaining the observed values in both years, i.e. with $R = 3$ m and $\lambda = 700\ \mathrm{ha}^{-1}$, $R = 4$ m and $\lambda = 500\ \mathrm{ha}^{-1}$ or $R = 5$ m and some $\lambda \in (350\ \mathrm{ha}^{-1},\ 400\ \mathrm{ha}^{-1})$.

The clumpiness index (CLUMPY) values for the two study areas are positive and closer to zero than to one. For study area 1 (Fig. 3, CLUMPY), they are approximately 0.20 and 0.19, respectively, while for study area 2 the index values are approximately 0.24 and 0.26 in 2006 and 2015 (Fig. 4, CLUMPY). These numbers indicate that the observed canopy gaps are slightly more clustered than randomly distributed, which is a result intuitively expected from a visual inspection of the canopy-gap maps. In study area 2 (Fig. 4, CLUMPY), the gaps are slightly more aggregated than in study area 1 (Fig. 3, CLUMPY). In both study areas, the difference in the clumpiness index between 2006 and 2015 is very small compared to the average size of the relevant envelopes of the simulated Boolean models. From 2006 to 2015 gap pixels became more aggregated in study area 2 and more random in study area 1. For study area 1, both observed values were not significantly different from those resulting from the same Boolean models (e.g. $R = 3$ m and $\lambda \in \{950\ \mathrm{ha}^{-1},\ 1000\ \mathrm{ha}^{-1}\}$ or $R = 4$ m and $\lambda \in \{750\ \mathrm{ha}^{-1},\ \cdots,\ 950\ \mathrm{ha}^{-1}\}$ or $R = 5$ m and $\lambda \in \{600\ \mathrm{ha}^{-1},\ \cdots,\ 800\ \mathrm{ha}^{-1}\}$). The observed clumpiness index values of both years in study area 2 (Fig. 4, CLUMPY) correspond to the envelopes resulting from the same Boolean models with $R = 3$ m and $\lambda = 750\ \mathrm{ha}^{-1}$, $R = 4$ m and $\lambda \in \{650\ \mathrm{ha}^{-1},\ 700\ \mathrm{ha}^{-1}\}$ or $R = 5$ m and $\lambda \in \{500\ \mathrm{ha}^{-1},\ \cdots,\ 800\ \mathrm{ha}^{-1}\}$.

For both study areas the values of the normalised landscape shape index (nLSI) are in the upper half of the index range (between 0.75 and 0.70 in area 1 and around 0.65 in area 2) which indicates that the gaps tend to be more aggregated than disaggregated and this outcome matches the results of the clumpiness index. However, nLSI indicates a greater aggregation of gaps in study area 1 (Fig. 3, nLSI). In both areas, aggregation increases from 2006 to 2015 and the difference is markedly larger in area 1. In study area 1, the observed values in 2006 and 2015 can be explained with models based on parameters for $R = 3$ m and $\lambda \in \{800\ \mathrm{ha}^{-1},\ 850\ \mathrm{ha}^{-1}\}$ and $R = 3$ m and $\lambda \in \{950\ \mathrm{ha}^{-1},\ 900\ \mathrm{ha}^{-1}\}$, respectively. Alternatives are $R = 4$ m and $\lambda \in \{600\ \mathrm{ha}^{-1},\ 650\ \mathrm{ha}^{-1}\}$ and $R = 4$ m and $\lambda = \in \{750\ \mathrm{ha}^{-1},\ 800\ \mathrm{ha}^{-1}\}$, respectively. For $R = 5$ m and $\lambda = 550\ \mathrm{ha}^{-1}$ the envelope simulated from the Boolean model covers both observed values. The observed values of the normalised landscape shape index in study area 2 (Fig. 4, nLSI) and in both survey years are not significantly different from those resulting from Boolean models with $R = 3$ m and $\lambda \in \{700\ \mathrm{ha}^{-1},\ 750\ \mathrm{ha}^{-1}\}$, $R = 4$ m and $\lambda = 550\ \mathrm{ha}^{-1}$ or $R = 5$ m and $\lambda \in \{400\ \mathrm{ha}^{-1},\ 450\ \mathrm{ha}^{-1}\}$.

The landscape division index (DIVISION) has higher values for the second study area than for the first. In both areas, the probability that two randomly selected pixels are not located in the same patch decreased from 2006 to 2015. This difference was much larger than for the two other aggregation indices. The decrease was larger in study area 1 (Fig. 3, DIVISION). Most likely this is much related to the decrease in mean gap area (AREAmn). In study area 1, the envelopes were so small that there was no Boolean model for any $R$, which could explain the observed division index values in both survey years 2006 and 2015. The Boolean model, which led to values that were not significantly different from the observed values in 2015, had a larger intensity (e.g. $R = 3$ m and $\lambda = 950\ \mathrm{ha}^{-1}$, $R = 4$ m and $\lambda \in \{500\ \mathrm{ha}^{-1},\ 550\ \mathrm{ha}^{-1}\}$) than those that were not significantly different from the observed values in 2006 (e.g. $R = 3$ m and $\lambda \in \{700\ \mathrm{ha}^{-1},\ 750\ \mathrm{ha}^{-1}\}$, $R = 4$ m and $\lambda = 400\ \mathrm{ha}^{-1}$). A similar trend with only slightly different values was obtained for study area 2 (Fig. 4, DIVISION).

For the mean fractional dimension index (FRAC) we observed values close to 1 which indicated that most canopy gaps had a shape of low complexity (e.g. rectangles) in both years. This outcome is highly influenced by the moderate resolution and our gap definition (see Section 2.1) which tends to lead to many one- and two-pixel gaps. Complexity of gap size appears to be slightly higher in study area 2 compared to study area 1. In both areas, complexity of gap size decreases from 2006 to 2015, where the difference is greater in study area 1. For both study years the size of the envelopes produced by the Boolean models vary with $\lambda$. Generally a higher intensity is needed to simulate a model leading to a mean fractal dimension index which is not significantly different from the observed one in 2015 compared to 2006. The mean fractal dimension index (Fig. 4, FRAC) observed in in study area 2 in both survey years is covered by the envelopes simulated by Boolean models with $R = 3$ m and some $\lambda \in (250\ \mathrm{ha}^{-1},\ 700\ \mathrm{ha}^{-1})$, $R = 4$ m and some $\lambda \in (100\ \mathrm{ha}^{-1},\ 150\ \mathrm{ha}^{-1}) \cup (450\ \mathrm{ha}^{-1},\ 500\ \mathrm{ha}^{-1})$ or $R = 5$ m and $\lambda \in (50\ \mathrm{ha}^{-1},\ 100\,\mathrm{ha}^{-1}) \cup \{350\ \mathrm{ha}^{-1}\}$. In study area 1, the trends are similar, but the envelopes simulated by Boolean models usually do not cover both observed values except for very small $\lambda$ (Fig. 3, FRAC).

For study areas 1 and 2, the estimated distributions of the observed Euclidean nearest neighbour distance (ENN) are very similar (Figs. 5 and 6, ENN). The maximum of the 2015 curves are always lower than those of the 2006 curves whilst the right tails of the 2015 curves are above those of the 2006 curves. This indicates that as a result of canopy growth the distances between gap pixels have increased from 2006 to 2015 and are consistent with the results of the other indices. For both study areas, some of the density distributions resulting from Boolean models were partly similar to the distributions of observed ENN distance values, e.g. for model parameters $R = 3$ m and $\lambda \in \{700\ \mathrm{ha}^{-1},\ 750\ \mathrm{ha}^{-1}\}$, $R = 4$ m and $\lambda = 350\ \mathrm{ha}^{-1}$ for 2006 and $R = 3$ m and $\lambda = 900\ \mathrm{ha}^{-1}$, $R = 4$ m and $\lambda = 450\ \mathrm{ha}^{-1}$ for 2015 (Figs. 5 and 6, ENN). The curves simulated from the Boolean model, however, differed especially at their right tail from those estimated for the observed values. Therefore, according to the global envelope test, the empirical distributions differ significantly from the theoretical ones resulting from the Boolean models.

The patch-area curves generally decrease with increasing metrics value. Due to the small average gap size, there is hardly any difference between the 2006 and 2015 patch-area curves (AREA), but it is possible to see also here that the gap size decreases from 2006 and 2015. For study area 1, this reduction appears to be larger than for study area 2 (Figs. 5 and 6, AREA). The gap area distribution estimates for the two survey years showed small differences relative to the width of the

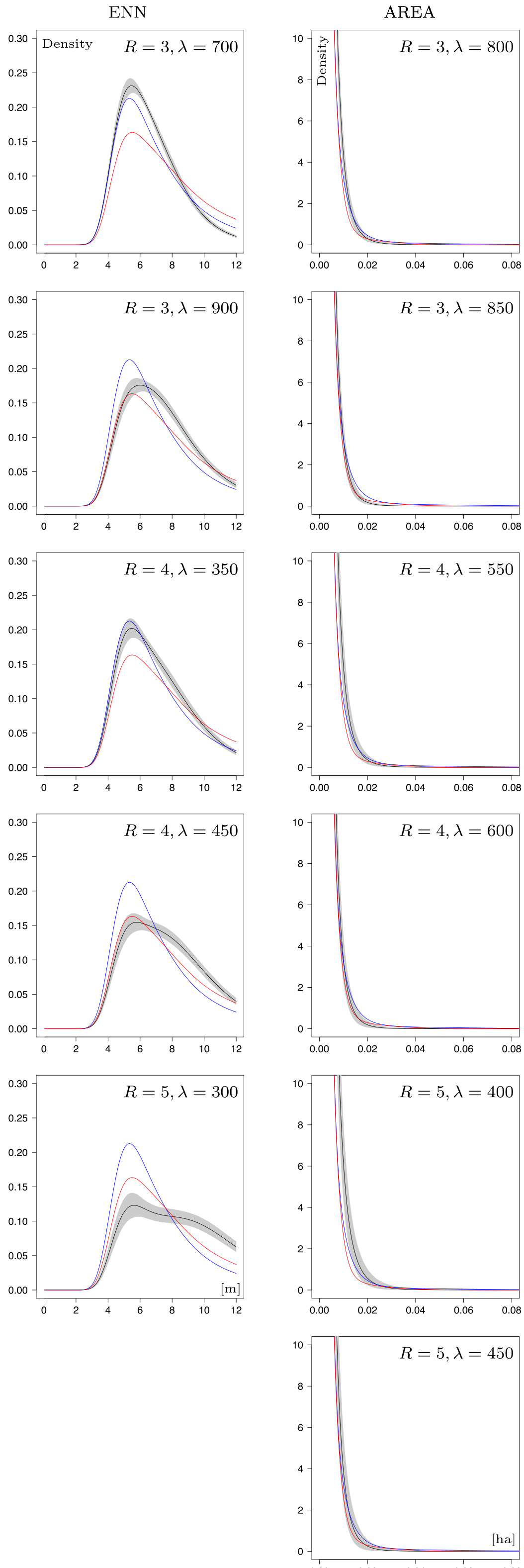


**Fig. 5.** Kernel density estimates of the patch level metrics for the first study area. The mean kernel density estimate resulting from the simulation of the Boolean model is shown as black lines and their 95% envelopes as grey area. The kernel density estimates based on the observed values are given in red for 2015 and blue for 2006. The *x*-axis shows the values of the corresponding metric. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

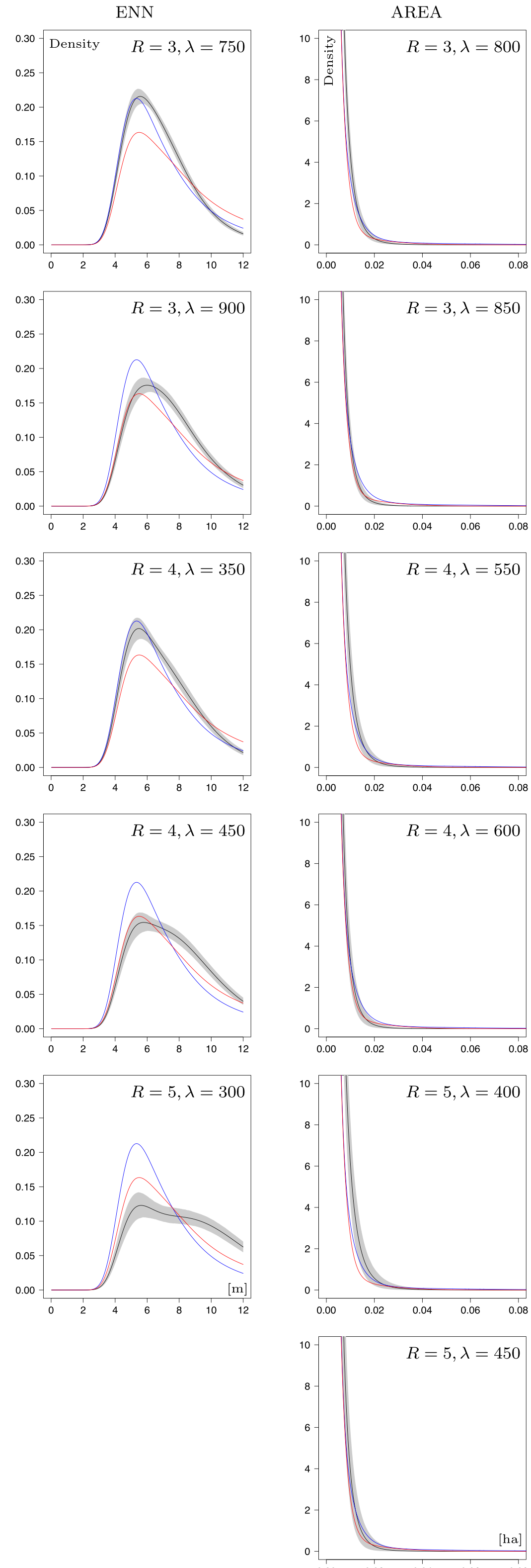


**Fig. 6.** Kernel density estimates of the patch level metrics for the second study area. The mean kernel density estimate resulting from of the simulation of the Boolean model is shown as black lines and their 95% envelopes as grey area. The kernel density estimates based on the observed values are presented in red for 2015 and blue for 2006. The *x*-axis shows the values of the corresponding metric. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

envelopes resulting from the corresponding Boolean model. This meets the expectation we developed from the analysis of the mean value. None of the density distribution curves generated by the Boolean model fully matched the curves estimated from the observed data, although there is more of a trend here than for ENN that the curves for both survey years are covered by one and the same Boolean model. Thus the global envelope test indicated significant differences.

## 4. Discussion

Considering the results from the selected eight landscape metrics simultaneously has proven useful for monitoring canopy gap patterns, since they complemented each other and highlighted different aspects of canopy gap patterns.

We applied a new method combining landscape metrics values with statistical tests that were based on a model from random set statistics, the Boolean model. As a result we obtained three types of information, i. e. the metrics values, test results and additionally information on the parameters of the Boolean model ($\lambda$, $R$) as well as on the magnitude of the envelopes relative to the differences in the metrics values from the two survey years. The model information has proved particularly valuable, as it characterises the observed differences in the metrics values between the survey years. These differences and associated characteristics are of primary interest when monitoring gap dynamics.

The landscape metrics convey the impression of a landscape with a gap proportion of 7–15% where the gaps are in the process of closing in rather than expanding. Accordingly, it can be concluded that there is no imminent danger of large-scale forest damage resulting from canopy collapse in the Krycklan catchment. In both study areas, the change between survey years is towards a decreasing number of canopy gaps and decreasing canopy gap areas. The gap dynamics in study area 1 apparently changed more during the observed nine years than in study area 2. There is also a change towards greater randomness of gaps in study area 1. This was indicated by the size of the changes in time compared to the size of the envelopes resulting from the Boolean model. Judging by the CLUMPY and DIVISION statistics in study area 2, the canopy gaps are also slightly more clustered than in study area 1. There is a tendency towards increasing randomisation of canopy caps in both study areas, which can also be a consequence of gaps gradually closing in again. Study area 2 had more complex gap shapes than study area 1, however this landscape trait declined from 2006 to 2015. The increasing randomisation of gaps and decreasing complexity of shape also suggest that the threat of forest damage is decreasing.

Nearly all observed values of landscape metrics can be explained by simple Boolean models with varying values of parameters $\lambda$ and $R$. This implies that both the current values of 2006 and 2015 and the differences between them were not significantly different from randomly generated gap structures with the same intensity. Whilst an increase in $\lambda$ implies an increase in the number of tree canopy pixels, an increase of $R$ additionally increases the size of the auxiliary points used for modelling the gap patterns and ultimately leads to larger, more aggregated gaps. Judging by Fig. 3 und 4, the envelopes appear to increase in size with increasing $R$.

The question of significance of the differences was even more clearly answered in those cases, where both current values could be explained by just one Boolean model with fixed parameters. This occurred in the case of metrics CLUMPY (for all $R$ in study area 1, $R \in \{4\,\mathrm{m}\,,5\,\mathrm{m}\}$ in study area 2), nLSI ($R = 5$ m in study area 1, all $R$ in study area 2) and FRAC (all $R$). With these indices it is highly unlikely that the index changes between survey years are significant.

There is an overall trend that in those cases, where the values of the metrics of the two study years were not covered by the same envelopes, the values observed in 2015 are without any exception always related to the model parameters leading to a higher number of auxiliary points. This confirms that in the nine years between the two study years there was most likely more gap filling than canopy decline. The result matches the descriptive, straightforward interpretation of the change in gap area proportion and mean gap area between the study years.

Using landscape metrics in conjunction with a model from random set statistics apparently is an effective way to ascertain the nature of changes in forest gap dynamics. We have considered this new methodology in the context of climate change and forest decline, however, forest gap dynamics are of general interest. Therefore the methodology used can also be applied to general ecological monitoring and to forest management. In the latter case information on decreasing gap size and spatial dispersal of gaps can be very informative for deciding when to plan the next intervention so that regeneration processes are supported and maintained.

## 5. Conclusions

Landscape metrics have proved to be useful tools for monitoring canopy gap dynamics of forest ecosystems. The statistical significance of these characteristics and particularly of their changes can be ascertained by simulating canopy gap patterns from the Boolean model. The parameters of this model, particularly intensity parameter $\lambda$, were helpful in establishing the trends of the canopy dynamics. Overall in the studied Krycklan catchment there was no evidence suggesting any unusual, harmful canopy gap development between 2006 and 2015. Instead, there was evidence for gaps closing in and gap locations becoming more random. In addition tree canopy pixels clearly increased between the two survey years.

## 6. Authors' contributions

All authors analysed the data, carried out the analyses and substantially contributed to the text. All persons entitled to co-authorships have been included in this paper. All authors have seen and approved the submitted version of the manuscript.

## 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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*Data availability and accessibility statement*

Sample R code used in this study is available at https://zenodo.org/record/7274422 or using DOI doi.org/10.5281/zenodo.7274422. The ALS data are accessible from https://www.slu.se/en/departments/field-based-forest-research/experimental-forests/vindeln-experimental-forests/krycklan/.

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