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Adapting the pair-correlation function for analysing the spatial distribution of canopy gaps

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ABSTRACT

Forestry around the world has been experiencing a paradigm shift towards more nature-oriented forest management leading foresters to emulate natural disturbances by their silvicultural treatments. Important characteristics of all disturbances are their size, severity, temporal and spatial distribution. This study focuses on the spatial distribution of gaps in the forest canopy which are typically caused by small-scale, low intensity disturbances.

The considerable spatial extent and irregular shape of canopy gaps are obvious obstacles to the application of classical point pattern analysis. The approximation of objects by their centroids does not lead to reasonable results, since the objects are at the same scale as the expected effects. By dividing the study area in grid cells and analysing all cells covered by an object, the size and the shape of the objects is accounted for. Nevertheless, both methods show undesirable effects. Thus we propose a new approach using the boundary polygons of the objects and construct the adapted pair-correlation function from the shortest distances between polygons.

The adapted pair-correlation function is presented using simulated data and mapped canopy gaps of a near natural forest reserve. The results of our proposed method are compared to the grid-based approach and the classical point pattern analysis. The presented method provides meaningful results and even reveals the relationship of objects at short distances, which is not possible using the classical point pattern analysis or the grid-based approach. With regard to the analysis of the spatial distribution of canopy gaps, the adapted pair-correlation function proves to be a useful analytical tool.

1. Introduction

Forestry around the world has been experiencing a paradigm shift towards more nature-oriented forest management (Lähde et al., 1999; Gamborg and Larsen, 2003; Fürst et al., 2007; Puettmann and Ammer, 2007). Management objectives are changing from the mere timber production to more diverse goals, such as sustaining native biodiversity (Christensen and Emborg, 1996; Mitchell et al., 2002), providing recreational value (Nielsen et al., 2007), improving stand stability (Emborg et al., 2000) and utilisation of 'biological rationalization' (Gamborg and Larsen, 2003; Schütz, 2004). Gamborg and Larsen (2003) state that this trend can be found under various terms e.g. 'close-to-nature', 'nature-based silviculture', and 'ecosystem management' in Europe, North America, and in other forest regions of the world. But the new silvicultural approaches have been motivated and developed differently. Puettmann and Ammer (2007) for instance describe the differences between the North American and European approach. However, both have in common that they build on so-called natural forest dynamics and structure (Gamborg and Larsen, 2003). While the disparities between natural disturbance and silviculture can never be fully overcome, the more the intensity, frequency, and spatial patterns created by the silvicultural treatments resemble the characteristics of the natural disturbance regime the narrower the gap (Palik et al., 2002). To assess the size of the gap, one needs meaningful parameters to characterise managed forests as well as comparable (near-) natural forests.

This study focuses on small-scale, low intensity disturbance, which is found under two dominant conditions: (i) in climatic zones where large-scale disturbances are rare, such as in tropical or temperate forests and (ii) in dispersed areas that have escaped catastrophic disturbances, for example boreal forests which have gone undisturbed by fires, blowdowns or lethal insect outbreaks for long time periods. Nevertheless, all forests eventually undergo small-scale gap dynamics if they escape large-scale disturbance (Denslow and Diaz, 1990; Runkle, 1990; Coates and Burton, 1997). Important characteristics of all disturbances are the size, severity,

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temporal and spatial distribution (Pickett and White, 1985; Coates and Burton, 1997). The size, severity, and temporal distribution have been investigated extensively (Runkle, 1982, 1990; Canham et al., 1990; Pontailler et al., 1997; Tanaka and Nakashizuka, 1997; Denslow et al., 1998; Meyer et al., 2003; Fujita et al., 2003; Drößler and von Lüpke, 2005; Mountford et al., 2006; de Lima and de Moura, 2008), whereas the spatial distribution of canopy gaps was analysed only in few studies (Runkle and Yetter, 1987; Lawton and Putz, 1988; Runkle, 1990; Frelich and Lorimer, 1991; Poorter et al., 1994; van der Meer and Bongers, 1996; Trichon et al., 1998; Hessburg et al., 1999; Salvador-van Eysenrode et al., 2000). The wealth of studies on spatial distribution of canopy gaps was carried out in tropical forests and mostly observed clustered canopy gaps.

Various methods were suggested to capture the spatial distribution of canopy gaps. They range from landscape indices to nearest neighbour distances and point processes. Landscape indices as employed by Hessburg et al. (1999) rather measure the diversity and intermixing of patch types than solely the spatial distribution of patches. Landscape indices are, therefore, not useful for studies focused on the analysis of the spatial distribution of canopy gaps. Frelich and Lorimer (1991) investigated spatial patterns of 46 plots in the Porcupine Mountains using Moran's I to test for spatial autocorrelation. If Moran's I is calculated over a range of scales the size of influence of an ecological process can be estimated from the ranges with significant autocorrelation. Detailed information on the spatial distribution cannot be gained. Hemispherical photographs (Trichon et al., 1998) and nearest neighbour distances (Poorter et al., 1994; van der Meer and Bongers, 1996; Salvador-van Eysenrode et al., 2000) provide information only about the immediate vicinity of the considered point. Point pattern analysis in contrast provides a useful framework for investigating the pattern at multiple scales by considering the distances between all pairs of points. A set of tools for analysing the spatial distribution of discrete points is available (Ripley, 1981; Stoyan and Stoyan, 1994; Perry et al., 2002; Møller and Waagepetersen, 2007; Illian et al., 2008). Second-order statistics, such as Ripley's K function or the pair-correlation function, have proved to be particularly useful in ecological research (Perry et al., 2006; Getzin et al., 2006; Atkinson et al., 2007; Longuetaud et al., 2008; Picard et al., 2009). Lawton and Putz (1988) used canopy gap centres as points and adopted Ripley's K to examine gap dispersion. This approximation may lead to valid results if the size of objects is small in comparison with the spatial scales investigated but may obscure the real spatial relationships at scales in the same range as the size of objects (e.g. Simber-loff, 1979; Prentice and Werger, 1985). Accordingly, Lawton and Putz (1988) mention that their results "must be interpreted with an eye to the gap sizes". Furthermore, Wiegand et al. (2006) found that point approximation produces misleading results if the object size varies substantially. The size and irregular shape of canopy gaps are obvious obstacles to the application of classical point pattern analysis for exploring their spatial distribution.

A first approach to account for the size of objects while investigating their spatial distribution was introduced by Simberloff (1979). He approximated the objects by circles and proposed corrected statistics for nearest neighbour methods. Additionally, two different approaches for extending the classical point process analysis for objects of finite size were proposed. Prentice and Werger (1985) suggested adapting the null model used for hypothesis testing instead of the pattern itself in order to account for the average size of the objects. Using non-overlapping circles instead of points in the null models prevents from the false conclusion objects are a minimum distance apart. This approach corresponds to models with no or less than expected short distances, meaning with a strict or soft minimum distance between points, namely hard- and soft-core models (e.g. Cressie, 1991; Matérn, 1986). Wiegand et al. (2006) suggested a grid-based approach to not only account for the size but also the shape of the objects in the pattern. Following this approach, objects are approximated by groups of cells in a categorical raster map. Single objects may occupy several adjacent cells depending on their size and shape. The resulting point pattern comprises all cell centres being part of an object. The number of points is, therefore, much higher than the number of objects. Null models for complete spatial randomness are constructed by rotating and shifting the objects in the raster map. Wiegand et al. (2006) found that their approach does not produce undesirable and misleading pseudo hard- and soft-core distances caused by the size and shape of the objects. However, the approximation of the object's size and shape by a group of points makes it hard to interpret the pair-correlation function at small scale. The distance between two objects is no longer one discrete value but a distribution of distances measured between all cells of one object and all cells of the other object. Furthermore, even the distances between all cells belonging to one object are counted. This leads to a huge number of small distances masking the real interaction effect in this range. The range of scales affected is controlled by the object sizes.

Therefore, we propose a new extension of the classical point pattern analysis for objects of finite size and irregular shape. In our approach, objects are characterised by their boundary polygon instead of groups of cells in a categorical raster map or their centroid. Only one distance is considered for each pair of objects and calculated as the shortest distance between the borders of the objects. This approach avoids pseudo hard- and soft-core effects and is able to describe the real interaction effect at small scales. For the construction of null models we also resort to random rotation and positioning within the study area.

We chose the pair-correlation function, which has become a popular tool for analysing mapped point patterns (e.g. Schurr et al., 2004; Getzin et al., 2006; Perry et al., 2006; Li and Zhang, 2007). The pair-correlation function $g(r)$ is related to the derivative of the widely used K-function (Ripley, 1976, 1981) and can be interpreted as the expected number of points per unit area (intensity) at a given distance r of an arbitrary point, divided by the intensity λ of the pattern (Stoyan and Stoyan, 1994). The pair-correlation function is considered to be more powerful in detecting spatial patterns across scales, because it indicates precisely the spatial scales at which the null model is violated (Wiegand and Moloney, 2004; Perry et al., 2006). The pair-correlation function thus correctly identifies the length of the interval, where the function deviates from the null model, in contrast to Ripley's K, which confounds the effect at large distances with the effect of small distances (memory effect) complicating its interpretation (Condit et al., 2000; Schurr et al., 2004).

We first introduce our proposed adaptation of the classical point pattern analysis and subsequently compare it to the pair-correlation functions calculated using the point approximation and the grid-based approach suggested by Wiegand et al. (2006). For the comparison, a suite of three simulated datasets having a regular, random, and clustered pattern, respectively, will be used. A case study with data from a near natural beech forest demonstrates the suitability of the proposed adaptation of the pair-correlation function for the analysis of the spatial distribution of canopy gaps.

2. Material and methods

2.1. Simulated data

To compare our proposed adaptation of the pair-correlation function with the point approximation and the grid-based approach, we generated three datasets with different spatial

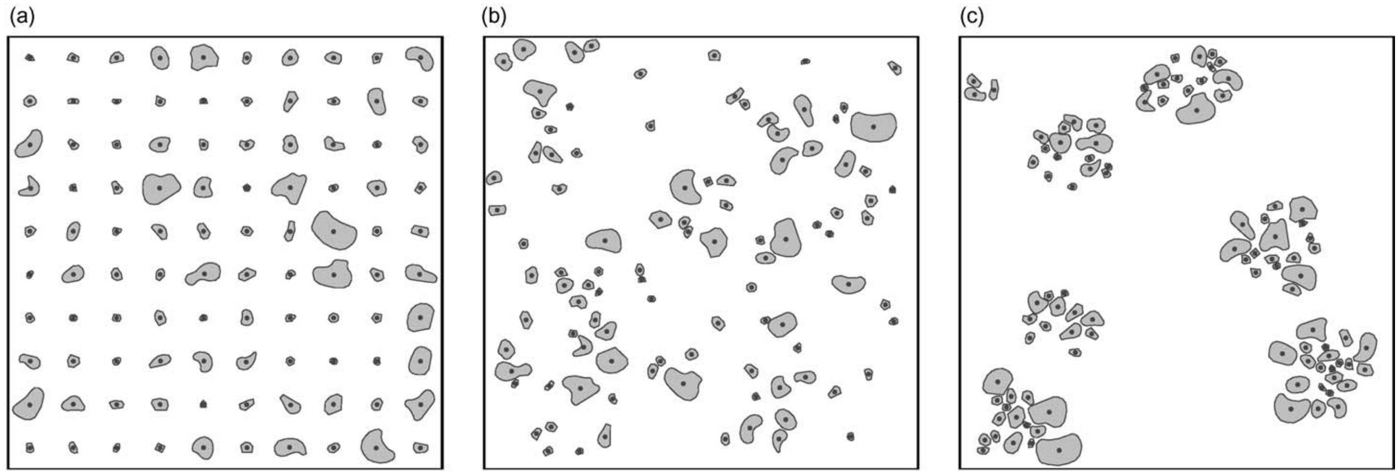

Fig. 1. Simulated datasets: Within the 100 × 100 m study area the same set of polygons is laid out in a (a) regular, (b) random and (c) clustered arrangement. Placement of the objects is based on (a) a regular pattern with 10 m spacing, (b) a Binomial process with intensity 0.01 m^{-2} and (c) a Matérn process with parameters ω = 0.0006 m^{-2}, R = 10 m and γ = 16.6. The centroids of the objects are marked with small dots.

distributions. The spatial distribution of the objects should be as different as possible to test the proposed method. Thus we chose a strictly regular, a random, and a clustered distribution of objects. The study area is in all three cases 100 m × 100 m. Since the object area percentage, the size distribution, and the shapes of the objects have a strong influence on the performance of the methods, we first generated a set of n = 100 objects and placed the identical set of objects subsequently according to the designated spatial distribution. The size distribution and shapes of the objects are inspired by measurements of canopy gaps. The areas of the objects range from 1.6 m^2 to 57.7 m^2 with an arithmetic mean of 9.7 m^2 and a median of 5.5 m^2. The total area of all objects is 969.7 m^2, meaning 9.7% of the study area is covered by objects.

For the first dataset, the objects were arranged in a strict regular manner. A centric systematic grid was constructed, and the objects of the set were then randomly rotated and randomly placed by locating the centroids of the objects exactly on the matching randomly numbered grid points, resulting in a regular arrangement of objects with a constant distance of the centroids of 10 m (Fig. 1a). For the second dataset with randomly distributed objects, we generated a realisation of the Binomial process with intensity 0.01 m^{-2}, meaning one point per 100 m^2. The objects were again randomly rotated and numbered and objects put on matching points with their centroid as close to the point as possible without overlapping other objects (Fig. 1b). The third dataset represents a clustered configuration. Again, we first created a point pattern with 100 points and then put the randomly numbered objects on the points. The point pattern was a realisation of Matérn's cluster process with $\omega = 0.0006\,m^{-2}$ or 6 cluster centres per ha, a dispersion radius of R = 10 m and on average γ = 16.6 points per cluster (Fig. 1c). We used the R-package spatstat (Baddeley and Turner, 2005) for simulating the Binomial process and Matérn's cluster process. The polygon datasets were finally converted to categorical raster maps and the centroids of the polygons to points for the purpose of the grid-based and the centroid-based point pattern analysis, respectively.

2.2. Case study

The case study is based on data from the forest nature reserve "Wiegelskammer", which has been unmanaged for almost 40 years and is now part of the National Park Eifel (Schulte, 2003). The forest is located in the south-west of North Rhine-Westphalia (Germany) on a north-facing slope at an altitude of about 400 m. The subatlantic climate of the area is characterised by 750 mm precipitation per year and an annual average temperature of 7.3 °C. (LÖLF, 1975). The bedrock of the region is mainly sandstone with additional colluvial layers resulting in a skeletal and well ventilated cambisol with a mull-like mor. (LÖLF, 1975). The forest is made up of 150–175-year-old beech (*Fagus sylvatica*) with a few sessile oaks (*Quercus petraea*) and is classified as a nutrient-poor beech forest (*Luzulo-Fagetum*) (Schulte, 2003). The forest has one dense main canopy layer with a height of about 30 m containing a number of gaps, some of them with already established regeneration.

The canopy gaps of the central 8 ha of the nature reserve were mapped using aerial photographs and a digital stereoplotter. The photographs were taken in summer 2001 with sufficient overlap to provide a stereoscopic view of the canopy surface. We followed Runkle's (1992) gap definition and mapped all areas not covered by trees of the main canopy layer as gaps (Fig. 2). Vegetation within the gap was regarded as belonging to the main canopy if it was higher than 2/3 of the stand height. The size of mapped canopy gaps ranges from 5 to 650 m^2, the lower limit being set as the

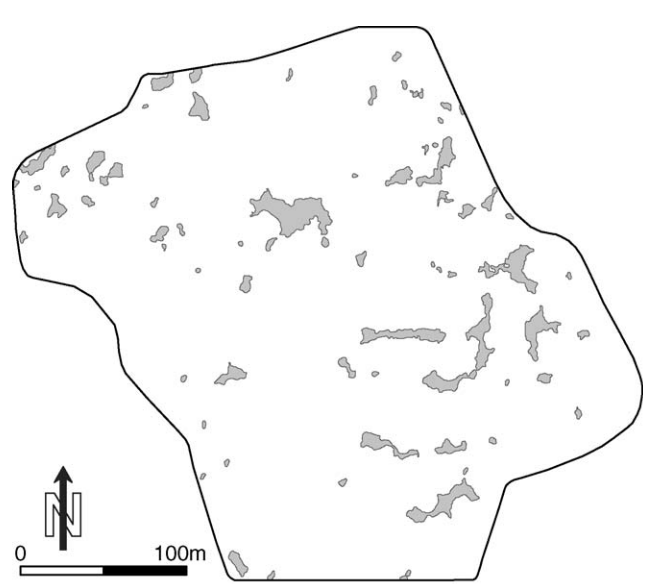

Fig. 2. Canopy gaps of the core area of the forest nature reserve "Wiegelskammer" mapped from aerial photographs taken in summer 2001.

minimum gap size for mapping. A total of $n = 72$ gaps were found, which cover 5.5% of the study area.

Before performing a spatial analysis of this dataset, the fundamental assumption of stationarity must be addressed. Illian et al. (2008) recommend justifying stationarity based on non-statistical arguments, since it is impossible to prove rigorously that a specific point pattern is a sample from a stationary point process. The study site is the core area of a forest nature reserve and thus not influenced by silvicultural treatment or edge effects. The trees of the main canopy layer are about the same height throughout the study area. The study site being quite small is under the same climatic conditions, and the soil does not vary considerably within the area. Moreover, the pair-correlation function of this dataset approaches one for larger distances (cf. Fig. 5), a typical property of stationary point processes. Although natural environments are rarely totally homogeneous, we consider the assumption as met.

2.3. Adaptation of the pair-correlation function

The pair-correlation function $g(r)$ is based on object-to-object distances and describes regularity and aggregation at a given radius r. For a completely random point process (i.e. a homogeneous Poisson process), $g(r)$ is equal to 1. If $g(r) > 1$, the inter-object distances around r are relatively more frequent than they would be under complete spatial randomness; if this is the case for small values of r, it suggests clustering. Values of $g(r) < 1$ indicate that the corresponding inter-object distances are relatively rare, which suggests regularity. The pair-correlation function can take any value between zero and infinity; as r increases, $g(r)$ typically approaches 1 (Stoyan and Stoyan, 1994).

We adapted the pair-correlation function, basically, by describing the objects by their boundary polygons instead of their centroids. Accordingly, the distances between objects are calculated as length of the shortest straight line between polygons. This new distance concept implies that the estimation of the pair-correlation function can no longer be based on the well-known estimator

$$\hat{g}(r) = \sum_{i=1}^{n} \sum_{j=1, i \neq j}^{n} \frac{\omega(r_{ij} - r)}{\hat{\lambda}^2 2\pi r\, s(r)}, \quad r > 0 \tag{1}$$

suggested by Penttinen et al. (1992), as it is the case for the point approximation. Therefore, that estimator has to be appropriately adapted to the modified distance concept. In Eq. (1) r_{ij} is the distance between points i and j of the point pattern, $\hat{\lambda}$ the estimated point intensity, $s(r)$ an edge correction, and $\omega(\cdot)$ a kernel function. The kernel function weights point pairs according to the deviation of their inter-point distance r_{ij} from r. That way not only point pairs with exactly $r_{ij} = r$ are counted but also those with r_{ij} close to r, leading to a smoother pair-correlation function.

In order to explain the implications of the polygon approach, we first simplify (1) by ignoring the edge correction factor, that is replacing $s(r)$ by the area A of the study region, and using the simple rectangular kernel function

$$\omega(x) = \begin{cases} \dfrac{1}{2\Delta}, & \text{if } -\Delta \le x \le \Delta \\ 0, & \text{otherwise} \end{cases}$$

putting equal weights of $1/(2\Delta)$ on all point pairs, whose inter-point distance deviates not more than Δ from r. Using $\hat{\lambda} = n/A$ as an estimate of the overall intensity, we obtain the intuitive estimator for point patterns

$$\hat{g}(r) = \frac{1}{n} \sum_{i=1}^{n} \frac{\#\{j : r - \Delta \le r_{ij} \le r + \Delta\}}{\hat{\lambda}\, 2\pi r\, 2\Delta}, \quad r > 0,$$

where the function $\#\{j\!: r - \Delta \le r_{ij} \le r + \Delta\}$ counts the objects j within the given distance interval. It shows that the estimated pair-correlation function can simply be interpreted as the mean ratio of the number of points observed within a small distance interval $[r - \Delta,\ r + \Delta]$ related to a given point i of the pattern (numerator) and of the expected number of points within that interval in case of a homogeneous Poisson pattern (denominator).

In the new polygon approach, we replace the numerator by the number of polygons within the distance interval using the polygon distance defined above. Accordingly, we should also replace the denominator by the expected number of polygons within that distance interval under a completely random process, but the latter can no longer be estimated by $2\pi r 2\Delta$ times the number of objects (polygons) per unit area, $\hat{\lambda}$, as it is done for the point approximation. The expected number of polygons is difficult to determine in a closed form and even distance dependent as will be shown later by simulation of completely random polygon patterns. It means that, under the polygon approach, the intuitive estimator, as well as (1), yields a biased estimator $\hat{g}_{\text{biased}}(r)$ of the pair-correlation function, which has to be corrected by a distance dependent correction factor. The latter will be derived by Monte Carlo simulation of the null model.

Since the pair-correlation function is a density function, we return to estimator (1) together with the frequently used and more efficient Epanechnikov kernel (Silverman, 1986; Stoyan and Stoyan, 1994)

$$\omega_{\text{E}}(x) = \begin{cases} \dfrac{3}{4\delta}\left(1 - \dfrac{x^2}{\delta^2}\right), & \text{if } -\delta < x < \delta \\ 0, & \text{otherwise} \end{cases}$$

and an appropriate edge correction, instead of using the intuitive estimator. The Epanechnikov kernel is a weight function putting maximal weight to point pairs with distance exactly equal to r but also incorporating point pairs only roughly at distance r with reduced weight. This weight falls to zero if the actual distance between the points differs from r by at least δ, the so-called bandwidth parameter, which determines the degree of smoothness of the function. We set δ between $0.1/\sqrt{\lambda}$ and $0.2/\sqrt{\lambda}$ as suggested by Penttinen et al. (1992) and Stoyan and Stoyan (1994). Then the adapted pair-correlation function can be estimated as

$$\hat{g}(r) = \sum_{i=1}^{n} \sum_{j=1, i \neq j}^{n} \frac{\omega_{\text{E}}(r_{ij} - r)}{\hat{\lambda}^2 2\pi r\ p_{ij}}, \quad r > 0 \tag{2}$$

with p_{ij} being the edge correction replacing $s(r)$ based on suggestions by Ripley (1981). For each pair of objects i and j, a buffer with buffer distance r_{ij} is constructed around the object i. The object j is then weighted by the inverse of the proportion p_{ij} of the buffer perimeter being within the study area. That way we account for the reduced probability of finding objects close to the edge of the study area. We emphasize that (2) is still biased for the polygon approach if the kernel function is evaluated using the polygon distance and $\hat{\lambda}$ estimated by the number of polygons per unit area as described above. Before we will develop the bias-correction factor, we describe the Monte Carlo method for the simulation of the null model and the construction of confidence envelopes.

To test for the significance of regularity or clustering within a point process, as expressed by the $g(r)$ function, it is necessary to compare the results to an appropriate null model. Complete spatial randomness usually serves as the null hypothesis for a univariate point process. Confidence envelopes are computed using Monte Carlo simulation. Each simulation generates an estimation of the pair-correlation function. Approximate confidence envelopes to the significance level α are calculated from the $(k+1)\alpha/2$ and $k - ((k+1)\alpha)/(2) + 1$ lowest value of $\hat{g}(r)$ taken from k simulations of the null model (Besag and Diggle, 1977; Stoyan and Stoyan, 1994).

In this case, the 5th smallest and the 5th largest values of 199 randomisations provide a 95% confidence envelope. If the

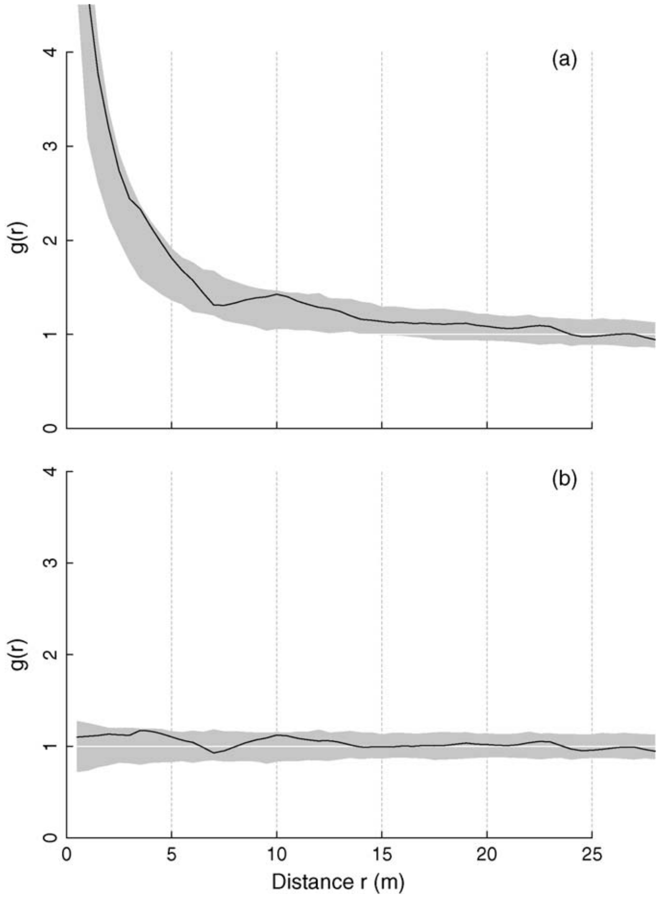

Fig. 3. Pair-correlation functions of the simulated dataset with randomly distributed objects (cf. Fig. 1a) in (a) uncorrected and (b) corrected form. Black line: estimated function; white line: theoretical value of the function under the null hypothesis of complete spatial randomness; grey area: 95% confidence envelope under the null hypothesis, computed by Monte Carlo simulation using 199 replicates. Values $g(r) < 1$ suggest inhibition between points and values $g(r) > 1$ suggest clustering.

estimated pair-correlation function of the investigated pattern has some part outside of that envelope, it is judged to be a significant deviation from the null model.

Following Wiegand et al. (2006), we constructed the null model for complete spatial randomness by random rotation and positioning of the original objects. Beginning with the largest object, all randomly rotated objects are placed randomly inside the study area until the smallest object is set. If the current object overlaps with already placed objects, another attempt at placing the object is made.

The simulation of the null model allows for the estimation of a correction factor which removes the bias inherent in (2). If the uncorrected estimator $\hat{g}_{\text{biased}}(r)$ were unbiased for each distance r, the mean of all simulated realisations of $\hat{g}_{\text{biased}}(r)$ under the null model would be close to one. Instead, according to Fig. 3a depicting the 95% confidence envelope of $\hat{g}_{\text{biased}}(r)$ under the null hypothesis, we found that it is mostly above one and increases monotonously for $r \to 0$. This means that the expected number of polygons having distance r to a given polygon i under the null model is larger than for point patterns, where it can unbiasedly be estimated by $2\pi r 2\Delta\hat{\lambda}$. This can be explained by the size of the given polygon: the closed curve connecting all points of distance r to that polygon is longer than the circumference $2\pi r$ of a circle with radius r around its centre point and increases the probability of encountering another polygon with distance r to the centre polygon. This effect obviously becomes weaker for larger r, since the ratio of the length of that curve and $2\pi r$ decreases.

The mean $c(r) = \bar{\hat{g}}_{\text{biased}}(r)$ of the simulated realisations of $\hat{g}_{\text{biased}}(r)$ under the null model is, by definition of $\hat{g}_{\text{biased}}(r)$, an appropriate Monte Carlo estimator for the ratio

$$\frac{\text{expected number of polyggons having distance } r \text{ to a given object under the null model}}{2\pi r 2\Delta\hat{\lambda}}$$

and serves as a bias correction factor in the final estimator

$$\hat{g}(r) = c^{-1}(r)\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n}\frac{\omega_{\mathrm{E}}(r_{ij}-r)}{\hat{\lambda}^2 2\pi r\, p_{ij}}, \quad r>0 \tag{3}$$

for the pair-correlation function $g(r)$ of the polygon approach. The corrected pair-correlation function and its confidence envelope are shown in Fig. 3b.

The calculation of the distances and the creation of the null models were carried out using functionality of GEOS (Geometry Engine Open Source) within PostGIS, which adds support for geographic objects to the PostgreSQL database (PostGIS Development Team, 2008). The calculation of the pair-correlation function and the confidence envelopes were done with the statistical software R (R Development Core Team, 2008).

The grid-based estimation of the pair-correlation function was carried out using the software Programita developed by Wiegand et al. (2006). This estimation of the pair-correlation function faces the same problem as the polygon approach. The expected number of cells having distance r to a given cell can also not be estimated simply via the overall density $\hat{\lambda}$. Therefore, we applied here as well the previously described correction by a distance dependent factor derived from Monte Carlo simulation of the null model.

The estimation of the pair-correlation function based on the point approximation was done with the R-package spatstat (Baddeley and Turner, 2005).

3. Results

3.1. Simulated data

The estimated pair-correlation functions of the simulated datasets show the typical shapes of random, regular, and clustered distributions of objects (cf. Fig. 4). The pair-correlation function of the randomly distributed objects estimated by means of the polygon-based approach is, as expected, over all scales close to one and thus indicates a random pattern (Fig. 4b). The grid-based pair-correlation function does not deviate from the confidence envelopes either. Only the centroid-based pair-correlation function shows a typical soft-core effect caused by the object sizes and departs from the confidence envelopes up to 2.5 m.

The regular pattern is picked up very well by all three methods (Fig. 4a) and the pair-correlation functions show accumulations of certain distances while other distances have obviously less counts than expected under complete spatial randomness. The pair-correlation function using the centroids shows a first maximum at approximately 10 m. This is caused by the distance between centroids of two adjacent objects, which is exactly 10 m. The next peak is at 14 m reflecting the distance to the nearest neighbours in diagonal direction in the square grid. The last maximum with a double peak has its highest point at 21.5 m and represents the next but one object in a straight line and the next object in a diagonal direction with a more acute angle. The pair-correlation functions of the other two methods display accumulations at corresponding scales but with lower and wider peaks. The polygon-based pair-correlation function also shows a shift of the peaks towards smaller scales.

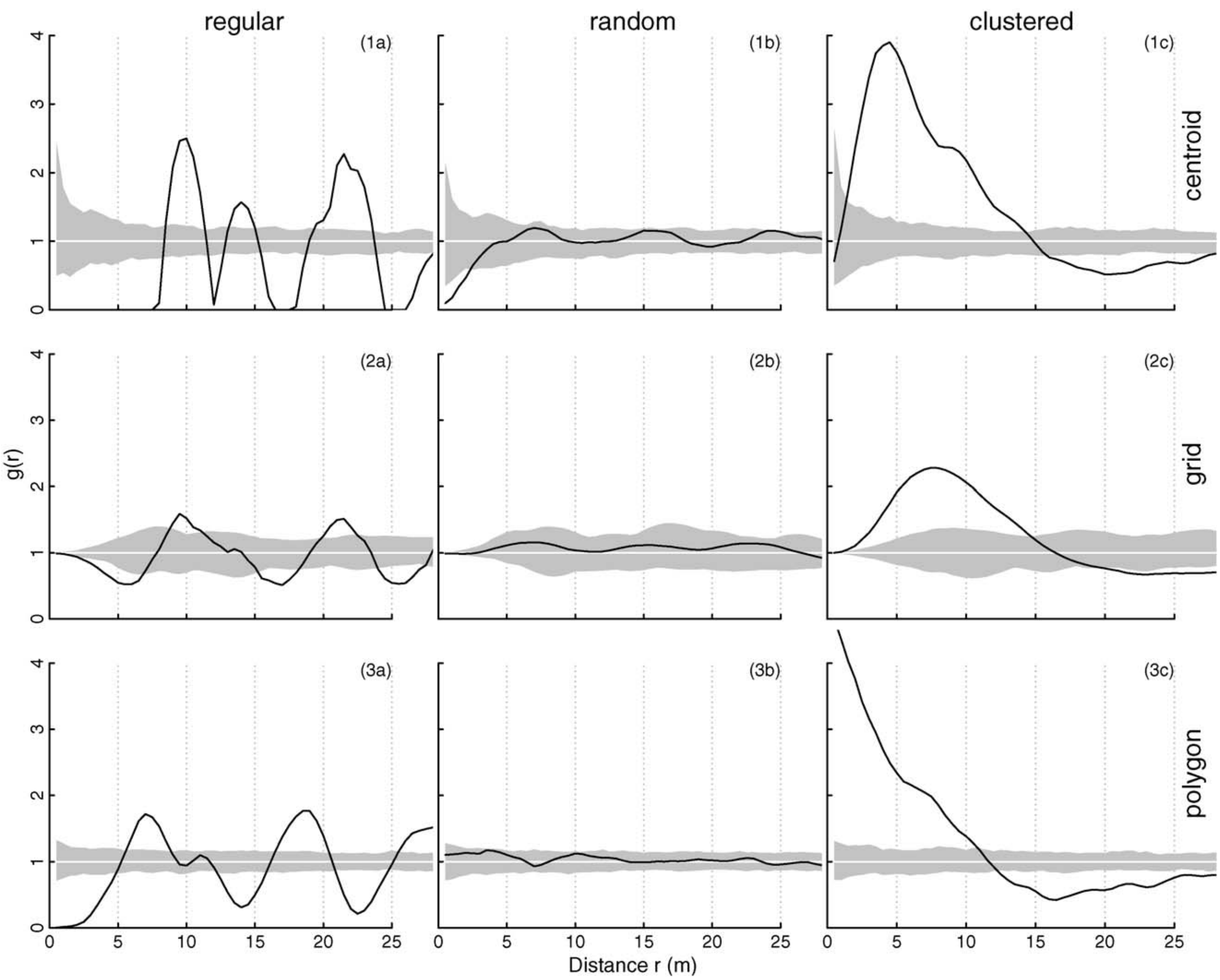

Fig. 4. Pair-correlation function of the simulated datasets having (a) regular, (b) random, and (c) clustered objects using the (1) point approximation, (2) grid-based and (3) polygon-based approach. Black line: estimated function; white line: theoretical value of the function under the null hypothesis of complete spatial randomness; grey area: 95% confidence envelope under the null hypothesis, computed by Monte Carlo simulation using 199 replicates. Values $g(r) < 1$ suggest inhibition between points and values $g(r) > 1$ suggest clustering.

In Fig. 4c, the pair-correlation functions of all three methods display an accumulation of short distances, while long distances are rare, as expected for a clustered configuration. Only the centroid-based estimation of the pair-correlation function starts with less distances than expected under complete spatial randomness, which is again a depiction of a soft-core effect. The positive deviation from the confidence envelopes reaches up to one and a half times the cluster radius for the centroid- and grid-based estimation of the pair-correlation function, whereas the polygon-based estimation deviates only up to the order of the cluster radius from the confidence envelope.

The differences arising from the different approaches to calculate the pair-correlation function can be clearly seen in Fig. 4. The pair-correlation function based on the point approximation suggests a soft-core distance of 4.5 m (Fig. 4, 1b and c) which is not pointed out by the other two methods. The grid-based approach produces empirical pair-correlation functions close to one for very small scales for all three simulated datasets. The interaction effect at small scales, inhibition for the regular and attraction for the aggregated pattern, becomes only visible in the further shape of the curve, thus obscuring the real small-scale effect. The peaks in the pair-correlation function of the regularly distributed objects are varyingly distinct in the different methods and, with the polygon approach, shifted towards smaller scales.

3.2. Case study

The spatial distribution of the canopy gaps of the forest nature reserve "Wiegelskammer" shows no large deviations from the confidence envelopes and thus from complete spatial randomness (Fig. 5). The grid-based estimator does not show any deviations from the confidence envelopes and the point approximation and the polygon-based approach have only two minor deviations. Those small but nominally significant departures from a random distribution occur in the polygon-based approach at the scales from 9.8 to 12.3 m and less pronounced from 15.7 to 18.2 m. The pair-correlation function using the point approximation deviates from the confidence envelopes at the scales from 16.1 to 17.8 m and more clearly from 25.3 to 32.2 m indicating an accumulation of the corresponding distances. The function values of the grid-based estimator stay very close to the reference value one for scales up to 23 m. The curve then stays above the reference line for the range from 23 to 46 m having a peak at 30 m. The pair-correlation function using the point approximation shows a soft-core effect, whereas the function values of the polygon-based estimator are

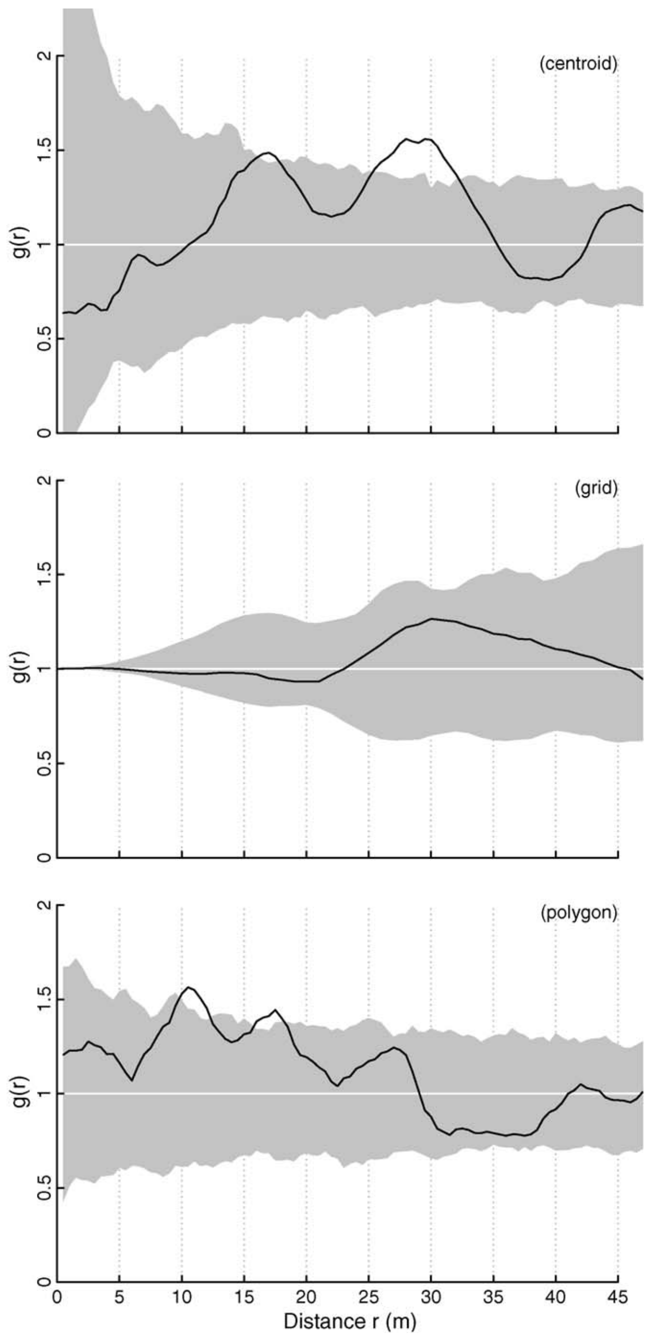

Fig. 5. Pair-correlation function of the canopy gaps of the forest nature reserve "Wiegelskammer" using the point approximation (centroid), the grid-based (grid) and the polygon-based approach (polygon). Black line: estimated function; white line: theoretical value of the function under the null hypothesis of complete spatial randomness; grey area: 95% confidence envelope under the null hypothesis, computed by Monte Carlo simulation using 199 replicates. Values $g(r) < 1$ suggest inhibition between points and values $g(r) > 1$ suggest clustering.

continuously larger than one for distances up to 29 m but mostly without significant differences. These distances are more frequent than expected under complete spatial randomness and suggest a trend towards clustering.

4. Discussion

First we cover the influence of the different methods on the pair-correlation function using simulated data with a random, regular, or clustered distribution. Subsequently, we address the suitability of the methods presented for analysing the spatial distribution of canopy gaps.

4.1. Comparison of methods

The different representation of objects implies different approaches to the estimation of the pair-correlation function. The pair-correlation function based on the point approximation describes the distribution of distances between the centroids of the considered objects. The grid approach dissects the objects in individual cells and calculates the distances between all cells of the objects. The pair-correlation function estimated with the polygon-based approach provides information about the distribution of distances from the boundary of one object to the boundary of another object and hence information about the space between the objects. The different approaches affect the shape of the pair-correlation function considerably as can be seen in Fig. 4.

The grid-based estimation of the pair-correlation function has a lower amplitude, deviates less but still clearly from the confidence envelopes and peaks are spread out over a larger range. This is because the distance of two objects is measured between the individual cells of the two objects. These distances are scattered around the corresponding distance between the centroids. Therefore, the range where distances are more frequent than under complete spatial randomness is not as sharply delimited as with the centroid-based distance measure. Thus, the effect of the spatial configuration of the objects is less clearly visible.

The differences between the three approaches are particularly recognisable at small scales. The grid-based approach produces function values close to one at very small scales and approaches one for $r \to 0$. The length of this effect is about the same size as the diameter of the larger objects of the simulated patterns, which is about 7 m. The function values close to reference value one at small scales are caused by the cell representation of objects. Since both the null models and the original data have a nearly equal large number of short distances, the pair-correlation function takes values close to one. The large numbers of short distances are mainly caused by distances between cells of the same object, since the grid-based approach considers distances between all cells. These distances are obviously short and range between the size of a cell and the maximum extension of the objects. The obfuscating effect of this behaviour is obvious in the regular and the aggregated patterns (cf. Fig. 4a and c).

The pair-correlation functions estimated based on the centroids of the objects have at small scales usually function values considerably below the confidence envelopes. These low values are caused by the fact that objects do not overlap, so that their centroids have a minimum distance according to the size of the two objects. This is the so-called soft-core distance, which should not be detected in the simulated data, since there is no such effect at the scale of the objects in the simulated dataset. The point approximation as well as the grid-based approach is affected by the size of the objects, although in different ways. If the size of the objects has no meaning in the research question at hand, the size effect leads to difficulties while interpreting the pair-correlation function, because the effect caused by object sizes interferes with the effect of the spatial distribution of the objects of interest.

Using the adapted pair-correlation function of the polygon approach, no specific function values are expected at small scales. There can be high values in case of clustered objects as well as very small values or zero detecting a segregation effect at small scales.

Each pair of objects has the same influence on the pair-correlation function in the point- and polygon-based pattern analysis, since there is only one unambiguously identifiable distance. But the grid-based estimation of the pair-correlation function takes several distances into account for every pair of objects. Hence, large objects contribute more distances to the estimation of the pair-correlation function than smaller objects. The influence of the individual objects on the pair-correlation function is not the same but rather weighted by their sizes. This is the so-called weighting effect (cf. Wiegand et al., 2006). As a consequence, a few large, regularly distributed objects can for example overpower the effect of a large number of smaller, clustered objects resulting in a pair-correlation function showing, unexpectedly, a regular pattern.

Besides the estimation of the pair-correlation function, it is important to choose an appropriate null model for hypotheses testing. Therefore, null models representing completely randomly distributed objects are generated for each approach. A comparison of these null models is not easily available, since they are constructed differently. The null models for the grid- and polygon-based approach are generated by relocation of the original objects, whereas for the centroid-based analysis a homogeneous Poisson process was used to generate null models. Strictly speaking, the usage of a Poisson process for objects approximated by points gives a wrong impression of the distribution of the objects, since the Poisson process allows points to be arbitrarily close to each other, which should not be possible, if the represented objects are not allowed to overlap. This leads to deviations from the confidence envelopes at small scales showing an undesirable soft-core effect which is only caused by the size of the objects. A way to account for this effect would be to use soft-core models (cf. Matérn, 1986; Prentice and Werger, 1985; Cressie, 1991) as null models or to construct null models with circular objects of the same size, although these methods do not allow for irregular shapes of the objects. The grid- and the polygon-based approach on the other hand consider the soft-core effect implicitly.

The polygon approach as well as the grid-based approach are applicable only together with the Monte Carlo simulation of the null model, needed to construct the distant dependent correction factors for the inappropriate estimation of the expected number of objects under complete spatial randomness in a distance interval via the intensity of object centroids, $\hat{\lambda}$. That way the expected number of polygons under complete spatial randomness within a distance interval can be estimated in accordance with the intuitive estimator of the pair-correlation function and the pair-correlation function in its original definition in the theory of point processes.

All three approaches show the essential characteristics of the simulated patterns. Thus, they are all capable of describing the main trend of the pattern. Nevertheless, the issues described above, which are particularly noticeable at small scales, have to be considered while choosing an appropriate method and interpreting the results. While analysing patterns with small objects and large distances the differences between the methods are less pronounced, but the differences have a noticeable impact on the outcome of the analysis if patterns of large objects with small inter-object distances are studied. In the former case, it might be advisable to use the point approximation, since the method is less computationally intensive and implemented in common statistical software. However, the bigger the objects in relation to the inter-object distances the more inappropriate is the point approximation. Even in the extreme case where objects are almost touching, the pair-correlation function using the point approximation would still report almost exclusively soft-core distances. This becomes even more problematic if the pattern has a large range of object sizes causing the soft-core distances and spatial effects to become indistinct.

To avoid the above mentioned issues arising from the use of classical point pattern analysis, one should revert to other methods to analyse patterns of large objects with an irregular shape and small inter-object distances. Since the grid-based approach considers distances for all cells of an object and even distances between cells of the same object, it emphasises large objects. Thus larger objects have a greater influence on the corresponding pair-correlation function. If this weighting effect is not wanted, it poses an obstacle to the interpretation of the pair-correlation function, because it hides spatial effects occurring at small scales and blurs the true range of effects. Furthermore, the size and interaction influences are difficult to separate while interpreting the pair-correlation function. Particularly problematic are long and small objects, because they influence a large range of scales. The polygon-based method eliminates the size of objects, so that the pair-correlation function for small scales is only influenced by the spatial distribution of objects. Using the polygon-based method is recommendable for patterns with a large range of object sizes or if one is interested in effects at scales smaller than the average diameter of the objects.

4.2. Case study

The fall of a tree generates a gap of at least the size of its crown, which, for old beech trees, is about 12 m in diameter (Nagel, 1999). Furthermore, the investigated forest has also canopy gaps with a length of up to 50 m, while the distances between the gaps measure sometimes just a few meters. Thus, canopy gaps are large objects in comparison to the inter-object distances and the considered scales. Considering this constellation, the point approximation would be an oversimplification having the already discussed issues. The two main effects, the shift of the peaks towards larger scales and the soft-core effect, can clearly be seen in Fig. 5. The grid-based estimator is, at small scales, affected by the large number of small distances caused by the cell representation of the objects. Since canopy gaps are relatively large and irregularly shaped objects, this effect influences a range of scales up to 20 m. For the same reason the weighting effect leads to a very wide peak instead of number of narrow ones. Since effects in the magnitude of the size of gaps must be expected, the application of the grid approach is not advisable in this case. Thus, the estimation of the pair-correlation function using the polygon-based approach seems to be the appropriate choice for analysing the distribution of canopy gaps of the natural forest reserve "Wiegelskammer".

The canopy layer is made up of the crowns of individual trees and gaps in the canopy arise through the death or fall of a tree or major parts of a tree crown. Canopy gaps, therefore, can only be bordered by tree crowns or parts thereof (e.g. a large branch). Since crowns have a non-negligible diameter, we would have expected to find this distance as a soft-core effect in the pair-correlation function. But this is not the case; the pair-correlation function shows rather an accumulation of short distances. This suggests that canopy gaps are often separated by single large branches or by trees with elongated and very narrow crowns. The peak of the pair-correlation function at 11 m represents a large number of distances of this magnitude meaning many gaps are about 11 m apart, which is about the crown diameter of a large beech tree (Nagel, 1999).

The pair-correlation function showing no considerable deviation from the confidence envelopes suggests that the canopy gaps of the researched forest are at least approximately randomly distributed. This agrees with other studies in temperate forests (Runkle and Yetter, 1987; Runkle, 1990; Frelich and Lorimer, 1991). Tropical forests in contrast seem to show mostly clustered canopy gap patterns. Whether these most different patterns are caused by different single tree stability or topographic or edaphic factors needs further research (Fujita et al., 2003; de Lima and de Moura, 2008).

5. Conclusions

The comparison of the methods to estimate a pair-correlation function using simulated datasets shows that all three methods have the ability to show the most important characteristics of the spatial distribution of objects of finite size and irregular shape. However, the pair-correlation functions estimated by the different methods vary considerably in their explanatory power and suitability. The differences between the methods we pointed out are caused by the different construction of the estimators, namely the dissimilar distance concepts. The shift of peaks or the distracting shape of the curves at small scales may be of varying size depending on the object sizes but will nevertheless remain. The choice of an appropriate approach should be based on the characteristics of the investigated pattern, particularly the size of the objects in relation to the inter-object distances, the object shapes and the present research question.

Depending on the question at hand a weighting of the objects by their size might be needed or obstructive. The grid-based approach does weight objects by their size, larger objects, thus, have more influence on the pair-correlation function. The polygon-based pair-correlation function, in contrast, describes the spatial distribution of objects without being influenced by their size. This facilitates the investigation of the space between the objects without mixing size and interaction effects. According to that characterization, a final and generally valid ranking of the three approaches is not possible.

With regard to the analysis of the spatial distribution of canopy gaps, where no weighting is wanted, the polygon-based approach provides meaningful results and even reveals the interaction of objects at small scales, which was not possible using the point approximation or the grid-based approach. Hence, the adapted pair-correlation function proves to be a useful analytical tool for analysing the spatial distribution of canopy gaps.

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