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Spatial forest structure reconstruction as a strategy for mitigating edge-bias in circular monitoring plots

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ABSTRACT

Forest ecosystem monitoring is an important task of forest science worldwide and its outcomes have important consequences both for national forest policies and local decision making. Often forest monitoring is implemented using circular plots of limited size. Edge effects can seriously bias the results of spatially explicit analyses of circular plot data and little research has been carried out on how to mitigate this problem. In this study, we have compared the method of spatial forest structure reconstruction to traditional plus-sampling, to the reflection method and to a situation where no edge-bias mitigation method is used at all. Reconstruction is a non-parametric modelling method based on simulated annealing. In the context of this study, the arithmetic means of structural summary characteristics are used to extrapolate spatial patterns previously measured in the core area of the monitoring plots to the margins outside. The computer experiments were based on 706 circular monitoring plots of the Estonian long-term monitoring network maintained by the Estonian University of Life Sciences, Tartu. The results clearly indicate the superiority of the reconstruction method and suggest that this approach has great potential for future spatially-explicit data analyses and modelling involving circular monitoring plots. Further improvements can be expected from using density functions and histograms of structural summary characteristics instead of arithmetic means.

1. Introduction

Forest ecosystem monitoring is an important responsibility of the international forest research community (Motz et al., 2010). There are two main strategies in forest monitoring that involve either the use of **(1)** large scarcely replicated sample plots (Pretzsch, 2009, p. 112ff.) or of **(2)** small frequently replicated plots (van Laar and Akça, 2007, p. 229ff.). Whilst large plots usually have the potential of providing data for detailed analyses and basic research, small frequently replicated monitoring plots have a better coverage and representation of larger landscape entities.

A problem associated with the spatial analysis of all types and geometric shapes of monitoring and sample plots is the fact that off-plot trees can have an effect on trees inside the plots near the boundaries (Radtke and Burkhart, 1998). Ignoring these effects can therefore introduce a bias to spatial estimations. The problem of how to mitigate edge-bias effects is not a topic new or unique to forestry; one of the earliest descriptions of the issue is from Finney and Palca (1949). The various methods developed for edge-bias compensation can be subdivided into two main groups, *plus-sampling* and *minus-sampling* (see Table 1).

Plus-sampling usually implies the measurement of additional off-plot trees to correctly account for neighbourhood relationships of trees inside the plot near the boundaries (Illian et al., 2008).

By contrast, minus-sampling restricts the spatial analysis to a core area of the sample plot, in which the trees are unaffected by off-plot neighbours. Minus-sampling therefore usually leads to a loss of data, which is particularly crucial in small monitoring plots because of the unfavourable ratio of area to circumference. Pommerening and Stoyan (2006) could for example show that large 1-ha plots often do not even require an edge-bias compensation at all, as edge-effects are very small.

Over the years, various solutions for mitigating edge-bias effects have been proposed in the literature and Table 1 provides a systematic overview of the main methods (Pommerening, 2008).

Translation and *reflection* are traditional methods used in many spatial analyses. Both methods extrapolate the spatial structure from within the monitoring plot to an infinite plane and join parts of the spatial pattern that do not occur so close together in nature. This can lead to unrealistic spatial patterns near the plot boundaries. Particularly the reflection method has the reputation of often performing badly and therefore cannot be recommended (see Pommerening and Stoyan, 2006). Translation, *periodic boundary*

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Table 1
An overview of general plus- and minus-sampling methods. Explanations are provided in the text (adapted from Pommerening, 2008).

Plus-sampling	Minus-sampling
Translation (=periodic boundary conditions, toroidal wrapping, torus)	*Internal buffer* • Fixed buffer • Flexible buffer: NN1, NN2
Reflection • Across an axis (e.g. plot boundary) • Through a point (e.g. arbitrary point near plot boundary)	
External buffer • Additional measurements • Conditional simulation (=reconstruction)	

conditions or *toroidal wrapping* plays an important role in spatial simulations and can be applied to rectangular monitoring plots with little computational effort (Illian et al., 2008, p. 184).

The *external buffer* method can include the measurement of additional trees outside the monitoring plot, which might interact with those inside. Determining the optimal width of the buffer is difficult; if it is too small residual edge effects will remain; if it is too large unnecessary sampling effort is applied. However, with nearest-neighbour summary statistics (NNSS, Pommerening, 2002) in practical implementations of forest inventory, it is often sufficient to sample the nearest off-plot neighbours of trees near the plot boundaries, although this precludes retrospective analyses including changes to the number of neighbours of a structural measure.

An alternative to measuring additional trees as part of the external buffer method is *conditional simulation* outside the monitoring plot. This method involves a structural analysis of the spatial pattern inside the plot and a simulation of this pattern outside the plot based on the results of the structural analysis. "Conditional" in this context means that the simulation does not modify the spatial pattern within the monitoring plot but only generates new patterns outside, which are statistically similar to those inside and have statistically correct ties to inner trees (see Biber, 1999; Illian et al., 2008).

The *internal buffer* or *guard* method is a minus-sampling method. Like all minus-sampling methods the *fixed-buffer* method only uses a subset of the trees in the monitoring plot. Again the choice of the buffer width is difficult (see Diggle, 2003, p. 5) and refined versions have been developed which create a *flexible buffer* by addressing each tree's potential relation to off-plot neighbours individually. These methods are known as nearest-neighbour edge mitigation methods and have been proposed and investigated as NN1 and NN2 methods in Pommerening and Stoyan (2006), where a detailed description can be found. The NN1 method was identified as a very reliable and robust option.

In forest monitoring, the second strategy of using small, frequently replicated sample units is mostly implemented with *circular plot designs*. Whilst circular plot shapes can markedly ease mensuration effort (van Laar and Akça, 2007), edge-bias compensation for the data involved is less straightforward. Most edge-bias mitigation methods have been developed for rectangular plots (see Radtke and Burkhart, 1998; Pommerening and Stoyan, 2006) because the necessary mathematics are less complex for this plot shape. One of the few methods that are applicable to circular plots is the transformation of circular plots to square ones followed by the torus edge-correction as suggested by Williams et al. (2001). Windhager (1997) reflects neighbouring trees through points of the circular plot boundaries defined by lines parallel to the line connecting the subject tree and the plot centre. In general, reflection and translation methods are difficult to apply to circular sample plots because of a lack of common reflection axes in the first case and because of disjoint boundaries in the latter. Inspired by edge-correction methods in forest inventory (Schmid, 1969), Sims et al. (2009) developed a reflection method replacing missing off-plot neighbours by trees from inside the plot (see Fig. 1).

Edge-correction methods for circular monitoring plots have been proposed only on rare occasions and yet this plot design finds considerable application in forest monitoring and inventory. There is clearly a need for developing suitable compensation methods for data gathered in circular plots and we address the question in this paper.

The original idea of plus-sampling is based on the measurement of additional off-plot trees. In this paper, however, we follow suggestions by Illian et al. (2008, p. 185) to simulate plus-sampling instead by using the reconstruction method. This is a useful approach because often additional measurements are not feasible or the data used in current analysis have been collected in the past. Reconstruction in this context can be considered as a spatial extrapolation of forest structure from inside the research plot to an area outside the plot. To our knowledge this is the first time that a study of simulated plus-sampling has been published.

The objective of this paper is therefore to present and to test this new method of edge-bias mitigation for circular monitoring plots based on the reconstruction technique (Yeong and Torquato, 1998; Torquato, 2002, p. 294ff.; Tscheschel and Stoyan, 2006; Pommerening and Stoyan, 2008; Nothdurft et al., 2010).

2. Materials and methods

2.1. The reconstruction method

The reconstruction of forest structure from a knowledge of limited structural information (e.g. NNSS and second-order characteristics) is an intriguing inverse problem (Yeong and Torquato, 1998). It is based on the idea that meaningful summary characteristics should allow the analysis of forest structure to be reversed and thus enable the simulation of spatial patterns from estimated summary statistics (Pommerening, 2006). Therefore reconstruction is a non-parametric modelling method that is independent of model assumptions and empirical model parameters. An effective reconstruction based on summary characteristics enables one to synthesise accurate structures at will (Yeong and Torquato, 1998) which can be used for multiple analyses. Such reconstructions are of great value in a wide variety of fields including materials science, geology and biology.

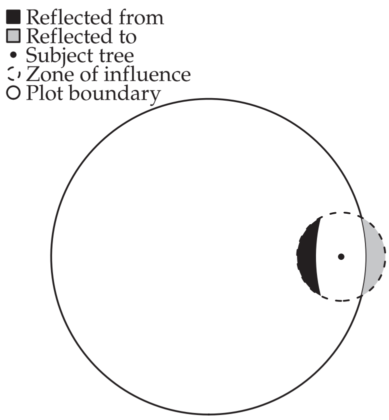

Fig. 1. The principle of the reflection method for edge-bias mitigation. The area highlighted in black is reflected across the plot boundary to provide off-plot tree neighbours in the grey area to compensate for the loss of original tree neighbours.

The reconstruction algorithm is based on a variant of the simulated annealing method (Kirkpatrick et al., 1983). It originates from physics where it was used to describe and to model how metals and other heterogeneous materials anneal (Yeong and Torquato, 1998; Torquato, 2002). The method can be considered as an application of the so-called Joshi–Quiblier–Adler (JQA) device, which has originally been applied in physics for heterogeneous microstructures (Rice, 1945).

In our context, the objective is to simulate off-plot neighbours of plot trees in such a way that the whole point pattern has NNSS as close as possible to those estimated from the core area of the research plot. A suitable choice of the initial configuration is a completely random point pattern with species and diameter marks copied randomly following the bootstrap method and sampling with replacement described by Schreuder et al. (1993, p. 143) and Krebs (1999). The total number of trees in the initial configuration of the simulation corresponds to the density estimated from the original research plot. The initial configuration of off-plot trees is then subsequently improved by stochastic optimisation and we selected the following algorithm:

(1) A given spatial tree configuration is characterised by an energy function E_{old}, which quantifies the difference between the NNSS estimated from the plot core area and the reconstructed pattern including the off-plot neighbours.
(2) To improve the reconstructed tree pattern, one of the following actions is carried out: Either (**a**) a randomly selected tree is moved to a new random candidate location or (**b**) a randomly selected pair of trees with the same species is selected and their stem diameters are swapped (Lewandowski and Gadow, 1997) or (**c**) a new tree with corresponding species and stem diameter randomly selected from the original data is added to the point pattern or finally (**d**) a randomly selected tree is deleted from the point pattern.
(3) If $E_{\text{new}} < E_{\text{old}}$, the action randomly selected from (a)–(d) in (2) is accepted and finally implemented. E_{new} is then set as E_{old}. Otherwise the action randomly selected from (a)–(d) in (2) is rejected.
(4) Steps 2 and 3 are repeated until (**a**) a maximum number of $50z$ (with z – initial number of trees in the reconstruction area) is exceeded or (**b**) the current energy function measure E_{old} falls below a pre-set energy level of $E_{\text{old}} = 10^{-6}$. Alternatively (b) has a further option, i.e. a reconstruction simulation is re-started if the number of current iterations exceeds 10,000. This alternative helps to save computation time.

The procedure as described above is the so-called *improvements-only* algorithm (Tscheschel and Stoyan, 2006), which has proved to be efficient and faster than the original simulated annealing algorithm. However, it is also possible to adhere more closely to the original simulated annealing procedure, which is said to have better convergence properties.[1] Interestingly, there are parallels between this non-parametric reconstruction algorithm and that of Gibbs processes (Tscheschel and Stoyan, 2006).

The reconstruction method mainly depends on the choice of the *energy function*, E (also referred to as *contrast measure*), which controls the simulation process. E is usually defined as least-squares error function (see Torquato, 2002), which can be written as:

$$E = \sum_{i=1}^{k} \left(\hat{f}(x_m) - f(x_m) \right)^2 \cdot w_m \tag{1}$$

where k is the number of NNSS used in the reconstruction, $\hat{f}(x_m)$ is arithmetic mean of NNSS m of the reconstruction, $f(x_m)$ is the arithmetic mean of NNSS m of the research plot centre, w_m is the specific weight corresponding to the importance of NNSS m for the given tree pattern.

A free example implementation of a reconstruction algorithm in R and C++ can be found on http://www.crancod.org.

2.1.1. Application to circular monitoring plots

For reconstructing off-plot trees and for the purpose of the computer experiment described in the following section each plot was subdivided into three concentric areas (see Fig. 2): the trees in the core area unaffected by edge bias were used together with their nearest neighbours in the zone between core area and plot boundary (outer zone) to calculate the arithmetic means of the NNSS given in Eqs. (2)–(4). Individually for each plot the radius of the core area was defined by 5 m subtracted from the plot radius. In the outer area beyond the boundaries of the original plot we reconstructed the unrecorded nearest neighbours of the trees in the outer area as described above.

We selected four NNSS in an attempt to cover the whole range of structural aspects of a forest, i.e. the *diversity of tree locations*, *species* and *size diversity* (Pommerening, 2006). For this purpose and in contrast to Pommerening and Stoyan (2008), in the energy function (Eq. (1)) we used the arithmetic means of the mean directional index, $\bar{R}$ (Corral-Rivas, 2006), of species mingling, $\bar{M}$ (Gadow, 1993), of diameter differentiation, $\bar{T}$ (Gadow, 1993), and of distance to nearest neighbour, $\bar{D}$. The individual-tree structural measures are provided in Eqs. (2)–(4).

$$R_i = \sqrt{\left(\sum_{j=1}^{n} \cos \alpha_{ij} \right)^2 + \left(\sum_{j=1}^{n} \sin \alpha_{ij} \right)^2} \tag{2}$$

where α_{ij} is the angles measured clockwise between a line connecting the location of tree i and a nearest neighbour j and a reference bearing (e.g. due north or line between tree i and the 1st nearest neighbour), n is the number of neighbours, in our study $n = 4$.

$$M_i = \frac{1}{n} \sum_{j=1}^{n} \mathbf{1}(species_i \neq species_j) \tag{3}$$

$\mathbf{1}(\cdot)$ is an indicator function that returns the value of 1 if the condition in the brackets is fulfilled, otherwise it returns the value of 0.

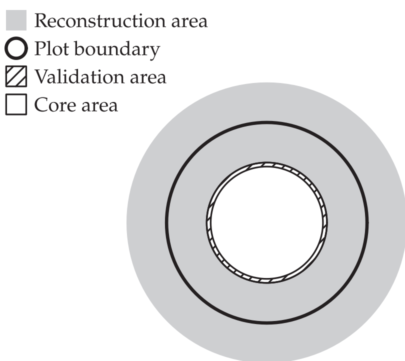

Fig. 2. The reconstruction and experimental design applied to the circular monitoring plots used in this study. The areas shown in grey were reconstructed and trees in the thin hatched orbit were used for validation. The white core area was not modified.

[1] To avoid getting caught up in a local optimum, a change with an inferior E_{new} ($E_{\text{new}} > E_{\text{old}}$) is accepted when a random number in the interval [0,1] is less than the so-called Metropolis probability $P(E) = e^{(-\Delta E/T)}$ with $\Delta E = E_{new} - E_{old} > 0$. In each iteration the temperature T is reduced by a cooling factor. The higher the temperature T, the greater the value of $P(E)$, i.e. the greater the probability that an inferior energy value will be accepted.

$$T_i = 1 - \frac{1}{n}\sum_{j=1}^{n}\frac{\min(dbh_i, dbh_j)}{\max(dbh_i, dbh_j)} \tag{4}$$

where dbh is the stem diameter at breast height (1.3 m above root collar).

In preliminary test simulations, we established the following weights (w_m) for the structural characteristics used in the energy function (Eq. (1)): 0.2 with $\bar{R}$, 0.1 with $\bar{M}$, 0.4 with $\bar{T}$ and 0.3 with $\bar{D}$.

2.1.2. Experiment and validation

The reconstructed plots were analysed to identify possible bias trends in the point patterns. This was accomplished by using the successful and widely applied Hegyi (1974) competition index as an independent validation measure. This measure has not previously been involved in the reconstruction procedure. Hegyi's competition index (Eq. (5)) was calculated for all trees within a range of 1 m from the boundaries of the core area of each research plot (see Fig. 2). 1 m was selected to perform the validation on trees with a maximum of nearest neighbours outside the core area whilst retaining sufficient data at the same time.

$$C_i = \sum_{j=1}^{n}\frac{dbh_j}{dbh_i}\cdot\frac{1}{dist_{ij}} \tag{5}$$

where $dist_{ij}$ is the Euclidean distance between the locations of tree i and a nearest neighbour j.

Like most spatial indices of plant competition the Hegyi index requires the definition of a zone of influence (ZOI), which is the assumed area around a tree in which it predominantly draws on resources like light, water and nutrients (Berger and Hildenbrandt, 2000). All other trees that happen to exist inside this influence zone are likely to compete with the subject tree for resources (Burkhart and Tomé, 2012, p. 204). Irrespective of the edge-mitigation method we deliberately used the same simple method of defining ZOI, i.e. each tree is surrounded by a circular zone defined by a 5-m radius, to make results easier to interpret.

For establishing the advantages and disadvantages of the new edge-mitigation method based on reconstruction we additionally applied three alternatives **(1)** using the real neighbour trees that originally occurred in the vicinity of every tree regardless of their location inside or outside the core area as the main control, **(2)** reflecting trees of the core area to replace the original trees in the outer areas (Sims et al., 2009) and **(3)** no edge correction as another control.

The results of using four different edge-bias mitigation methods were compared to each other based on linear models and scatterplots. We used the slope values obtained from the linear models to indicate the performance of the edge-correction methods.

2.2. Study data

The data used in this study were taken from Estonian long-term forest monitoring plots, which are part of a nation-wide network established and maintained by the Estonian University of Life Sciences, EMÜ, since 1995. The monitoring network predominantly uses circular sample plots with plot radii ranging from 15 to 30 m depending on tree density and environmental factors. Among other characteristics stem diameter at breast height, dbh, was measured for all sample trees. In addition tree locations were recorded and transformed to Cartesian coordinates.

We decided to restrict the plots included in this study to a minimum radius of 20 m in order to have a sufficient number of trees unaffected by edge effects. This resulted in a total of 706 (which also includes re-measurements) amounting to a total number of 93,326 tree measurements, of which 6904 were located in the validation area (see Fig. 2). Fig. 3 shows the locations of the selected plots in Estonia.

The stands represented by the selected monitoring plots mainly included Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) KARST.) and silver birch (*Betula pendula* ROTH.). The main summary statistics of the dataset are presented in Table 2.

The forestry summary characteristics in the upper half of Table 2 reveal the great variety of forest stand types that are represented by the monitoring plots selected for this study: Stand age ranges from 12 to 235 years, mean diameter from 8.3 to 52.5 cm and basal area per hectare from almost 0–51 m^2. Site index is an indicator of environmental conditions in relation to forest growth (Philip, 1994) and the corresponding values in Table 2 also show a wide range of growing conditions.

We also calculated the structural characteristics that have been used in the computation of the energy function (see Section 2.2). This calculation was limited to the trees in the plot core areas to avoid edge-bias effects in the same way as for the computation of the energy function. The mean directional index, $\bar{R}$, reveals patterns that range from slightly regular to clustered tree locations with the mean near complete spatial randomness. The mean mingling index, $\bar{M}$, suggests that the data contain those that reflect pure species stands and others with intimate individual-tree mixture among the nearest four neighbours. The majority of data, however, show moderate mingling. The range of diameter differentiation, $\bar{T}$, is comparatively narrow with a maximum value of 0.51, i.e. the tree data used are fairly homogeneous in terms of tree size – a reflection of forest management practices in Estonia. Finally distances between any tree and its first nearest neighbour can markedly range between a little less than a metre and 3 m.

3. Results

Fig. 4 shows the scatterplot matrix for all four Hegyi index calculation methods. In the ideal case, the edge mitigation methods would produce the same Hegyi index values as were calculated using the original off-plot neighbours, resulting in a slope value of 1 and all the data points would align on the diagonal of the corresponding scatterplot.

The reconstruction method produced the best results with the model slope value of 1.028 and both observed and reconstructed data are symmetrically distributed along the diagonal. Reconstructing off-plot neighbours with the reflection technique

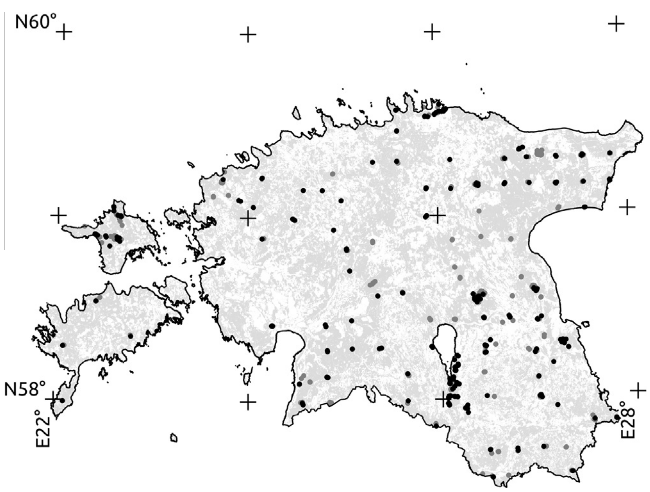

Fig. 3. Map showing the Estonian long-term forest monitoring plots established between 1995 and 2003. In black those plots have been highlighted that were used in this study.

Table 2
Forestry and structural summary characteristics of the 706 Estonian long-term forest monitoring plots used in this study.

Characteristic	Minimum	Mean	Maximum
Stand age (years)	12	53	235
Mean height (m)	10.3	23.8	42.5
Mean diameter (cm)	8.3	25.7	52.5
Basal area (m^2/ha)	0.3	17.4	50.9
Trees/ha	138	660	2570
Standing volume (m^3/ha)	44	312	800
Site index (m)	10.7	28.5	37.7
Mean directional index	1.08	1.60	2.22
Species mingling	0.00	0.36	0.76
Diameter differentiation	0.14	0.31	0.51
Distance to nearest neighbour (m)	0.95	1.95	3.22

produced inferior results as the slope values and the corresponding standard errors (*SE*) indicate a significant difference. However, it must be noted that the reflection method shows the smallest residual mean standard deviation (*RMSD*) and has the lowest bias. On the other hand, the reconstruction method is not affected by a significant bias throughout the range of the Hegyi index values as can be seen from the data points (solid line) in Fig. 4. The reflection method is clearly associated with a positive bias for small Hegyi index values, i.e. for little competition pressure, and with a negative bias for large competition index values. Using no edge-correction leads to a large positive bias throughout the range of the Hegyi index values (note the asymmetrical point cloud in Fig. 4 and the large slope value for the corresponding model).

All options of modifying and optimising the tree patterns in the reconstruction that are listed in Section 2.1 under **(2)** (a)–(d) and their combinations have performed successfully and effective.

We also studied the efficiency of the reconstruction method: When the number of iterations was restricted to 50*z* (see Section 2.1), the range of final energy values was between $10^{-2.8}$ and $10^{-10.1}$. 525 plot reconstructions (74%) had energy values smaller than 10^{-6}.

The alternative included setting an energy limit of 10^{-6} and restarting the reconstruction if the number of iterations were in access of 10,000 (see Section 2.1). It turned out that only in 39 cases (5.5%) the reconstruction simulations had to be re-set and started again. The range of final energy values of the 5.5% re-started reconstruction simulations was between $10^{-4.6}$ and $10^{-5.9}$, i.e. some of those were close to acceptance in the first simulation.

Interestingly the correlations between observed and reconstructed structural summary characteristics vary considerably. The mean directional index has a correlation coefficient of 0.23, the diameter differentiation one of 0.64, and the correlation coefficients of the distance to the nearest neighbour and mingling are 0.66 and 0.83, respectively. These values disagree with the weights of the energy function specified in Section 2.1.1. With a *F* value of 1.17 the highest ratio of variance exists between observed and reconstructed nearest neighbour distance.

4. Discussion

The objective of this paper has been to present a new method for edge-bias mitigation and to validate it using Estonian monitoring plots.

As expected the results of our study show a considerable bias in the calculated competition index values when no edge correction is applied. Both the reconstruction and reflection methods significantly help to reduce this bias. Reconstructing off-plot neighbours

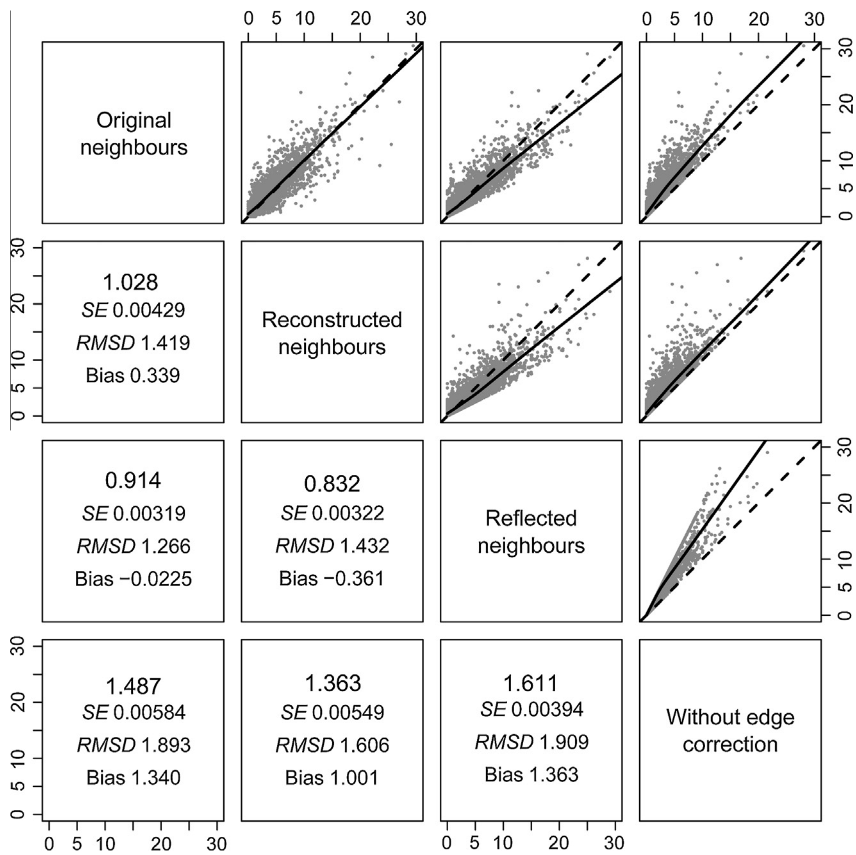

Fig. 4. The scatter plot matrix (upper panel above diagonal) and the corresponding fit statistics (lower panel below diagonal) of edge-mitigation methods used to calculate Hegyi's index.

with the reconstruction method clearly results in a more realistic point pattern than the reflection method is able to produce. This is most likely because the reflection method copies all the irregularities present near the plot boundary to the artificial buffer zone thus creating unrealistic periodicity in the simulated stand structure.

In contrast to Pommerening and Stoyan (2008) the application of the reconstruction method was based only on mean spatial summary statistics and only on a fixed number of nearest neighbours for their calculation (Tscheschel and Stoyan, 2006; Pommerening and Stoyan, 2008). Considering the success of this application further improvements can be expected if histograms and density distributions of structural measures and varying numbers of nearest neighbours are simultaneously used in future applications. The correlation analyses of observed and reconstructed structural summary characteristics clearly show that the use of distributional summary characteristics and of several numbers of neighbours at the same time can help to reduce the large amount of still existing variation. Also the relationship between these correlations and the weights in the energy function are not entirely clear and merit further investigation.

Yeong and Torquato (1998) mention the problem of nonuniqueness, i.e. the fact that even if the summary characteristics used in the energy function are in good agreement this does not necessarily fully ensure that reconstruction and original structures match very well. To decrease the chances of such discrepancies it can be recommended to include a good number of summary characteristics in the energy function.

In future applications, we also plan to expand the number of competition indices and, of course, to refine the definition of ZOI by making its radius dependent on tree size.

It is important to bear in mind that the performance of the reconstruction method depends on the spatial measures used in the energy function and the pattern of tree locations in the plot. In some cases, hastily chosen or unchecked edge-correction methods can introduce more error than ignoring edge bias altogether (Pommerening and Stoyan, 2006). Reconstruction thus also sheds light on the nature of the information contained in structural summary characteristics that are used in the energy function (Yeong and Torquato, 1998) and can help to identify the merits relative to other measures.

It has also been interesting to study the efficiency of the reconstruction method. In most circular sample plots the energy target could be met by using a comparatively low number of iterations, i.e. $50 \times$ initial number of trees (z). For those simulations that exceeded 10,000 iterations a re-set clearly led to a situation where the energy threshold could be met faster. However, this only affected a comparatively small number of reconstructions.

The successful application of reconstruction allows us to use the full potential of all trees in circular monitoring plots for estimating measures of competition and structure. Until now predominantly either minus-sampling or the reflection method have been used. As part of the latter some trees in the grey area of Fig. 2 are considered twice in the analysis (Sims et al., 2009).

Reconstruction turned out to be the best method for edge-bias mitigation and it is suitable for plots of any shape. Unlike translation and reflection the method does not result in periodicities. Also, reconstruction is capable of correctly extrapolating macro-structures from inside the plot, such as mixtures of different tree species, beyond the plot boundary (Pommerening and Stoyan, 2008). In addition, the reconstruction algorithm can be used to harmonise previous measurements with new data for plots where the radius has been increased retrospectively. In these cases, plot size can be unified by generating data for the outer plot areas where in previous surveys no measurements were recorded. Finally, reconstruction can also be used to convert circular monitoring plots to rectangular ones.

For practical use in model-based growth projections, off-plot neighbour trees would be independently reconstructed in every growth simulation run. The competition indices can then be estimated without bias leading to better growth projections.

Once again the study also highlighted the close relationships of forest inventory and spatial statistics that have become already apparent in other work (Pommerening and Stoyan, 2008; Motz et al., 2010; Nothdurft et al., 2010).

5. Conclusions

In this study, we explored the use of the reconstruction method for edge-bias mitigation. Stand structure reconstruction has turned out to be the best and most versatile tool for this purpose and has great potential in applications of forest monitoring. Our analysis indicated a statistically good reconstruction of nearest off-plot neighbours based on a modified simulated annealing algorithm. This substantially improved the estimations of Hegyi's competition index and provided more realistic point patterns compared to those produced by the reflection method.

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References

Berger, U., Hildenbrandt, H., 2000. A new approach to spatially explicit modelling of forest dynamics: spacing, ageing and neighbourhood competition of mangrove trees. Ecological Modelling 132, 287–302.

Biber, P., 1999. Ein Verfahren zum Ausgleich von Randeffekten bei der Berechnung von Konkurrenzindizes [A method for edge-bias compensation when calculating competition indices]. In: Kenk, G. (Ed.), Deutscher Verband Forstlicher Versuchsanstalten. Sektion Ertragskunde. Proceedings of the Jahrestagung 1999, Freiburg, Germany. Forest Research Institute, Freiburg, Germany, pp. 189–202 (in German).

Burkhart, H.E., Tomé, M., 2012. Modeling Forest Trees and Stands. Springer, Dordrecht, pp. 457.

Corral-Rivas, J.J., 2006. Models of tree growth and spatial structure for multi-species uneven-aged forests in Durango (Mexico), PhD thesis, Göttingen University, pp. 135.

Diggle, P.J., 2003. Statistical Analysis of Spatial Point Patterns, second ed. Arnold, London, pp. 159.

Finney, D., Palca, H., 1949. The elimination of bias due to edge-effects in forest sampling. Forestry 23, 31–47.

Gadow, K.v., 1993. Zur Bestandesbeschreibung in der Forsteinrichtung [New variables for describing stands of trees]. Forst und Holz 48, 602–606 (in German).

Hegyi, F., 1974. A simulation model for managing jack-pine stands. In: Fries, J. (Ed.), Growth models for tree and stand simulation. Proc. IUFRO meeting S4.01.04, Royal College of Forestry, Stockholm, pp. 74–90.

Illian, J., Penttinen, A., Stoyan, H., Stoyan, D., 2008. Statistical Analysis and Modelling of Spatial Point Patterns. John Wiley & Sons, Chichester, pp. 534.

Kirkpatrick, S., Gelatt Jr., C.D., Vecchi, M.P., 1983. Optimization by simulated annealing. Science 220, 671–680.

Krebs, C.J., 1999. Ecological Methodology, second ed. Benjamin Cummings, pp. 620.

Lewandowski, A., Gadow, K.v., 1997. Ein heuristischer Ansatz zur Reproduktion von Waldbeständen [A heuristic method for reproducing forest stands]. Allgemeine Forst-und Jagdzeitung 168, 170–174.

Motz, K., Sterba, H., Pommerening, A., 2010. Sampling measures of tree diversity. Forest Ecology and Management 260, 1985–1996.

Nothdurft, A., Saborowski, J., Nuske, R., Stoyan, D., 2010. Density estimation based on *k*-tree sampling and point pattern reconstruction. Canadian Journal of Forest Research 40, 953–967.

Philip, M.S., 1994. Measuring Trees and Forests, second ed. CABI Publishing, Wallingford, pp. 310.
Pommerening, A., 2002. Approaches to quantifying forest structures. Forestry 75, 305–324.
Pommerening, A., 2006. Evaluating structural indices by reversing forest structural analysis. Forest Ecology and Management 224, 266–277.
Pommerening, A., 2008. Analysing and modelling spatial woodland structure. Habilitationsschrift (DSc dissertation), University of Natural Resources and Applied Life Sciences, Vienna, Austria, pp. 145.
Pommerening, A., Stoyan, D., 2006. Edge-correction needs in estimating indices of spatial forest structure. Canadian Journal of Forest Research 36, 1723–1739.
Pommerening, A., Stoyan, D., 2008. Reconstructing spatial tree point patterns from nearest neighbour summary statistics measured in small subwindows. Canadian Journal of Forest Research 38, 1110–1122.
Pretzsch, H., 2009. Forest Dynamics, Growth and Yield: from Measurement to Model. Springer-Verlag, Berlin, pp. 664.
Radtke, P.J., Burkhart, H.E., 1998. A comparison of methods for edge-bias compensation. Canadian Journal of Forest Research 28, 942–945.
Rice, S.O., 1945. Mathematical analysis of random noise. Bell System Technical Journal 24, 46–156.
Schmid, P., 1969. Stichproben am Waldrand [Sample plots at forest margins]. Mitteilungen der Schweizerischen Anstalt für das Forstliche Versuchswesen 45, 234–303.
Schreuder, H.T., Gregoire, T.G., Wood, G.B., 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley & Sons, New York.
Sims, A., Kiviste, A., Hordo, M., Laarmann, D., Gadow, K., 2009. Estimating tree survival: a study based on the Estonian forest research plots network. Annales Botanici Fennici 46, 336–352.
Torquato, S., 2002. Random Heterogeneous Materials: Microstructure and Macroscopic Properties. Springer-Verlag, New York, pp. 701.
Tscheschel, A., Stoyan, D., 2006. Statistical reconstruction of random point patterns. Computational Statistics and Data Analysis 51, 859–871.
van Laar, A., Akça, A., 2007. Forest mensuration. Managing Forest Ecosystems 13, 383.
Williams, M.S., Williams, M.T., Mowrer, H.T., 2001. A boundary reconstruction method for circular fixed-area plots in environmental survey. Journal of Agricultural, Biological, and Environmental Statistics 6, 479–494.
Windhager, M., 1997. Die Berechnung des Ek und Monserud (1974) Konkurrenzindex für Randbäume nach unterschiedlichen Berechnungsmethoden [Calculation of the Ek and Monserud (1974) competition index for edge trees using alternative computing methods]. In: Kenk, G. (Ed.), Deutscher Verband Forstlicher Versuchsanstalten, Sektion Ertragskunde, Proceedings of the Jahrestagung 1997, Freiburg, Germany. pp. 74–86 (in German).
Yeong, C.L.Y., Torquato, S., 1998. Reconstructing random media. Physical Review E 57, 495–506.