



Analysing changes in spatial point patterns: A proposal using data from a forest thinning experiment

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ABSTRACT

Spatial patterns reveal critical features at the individual and community levels. However, how to evaluate changes in spatial characteristics remains largely unexplored. We assess spatial changes in spatial point patterns by augmenting current statistical functions and indices. We fitted functions to describe unmarked and marked (tree size) spatial patterns using data from a large-scale silvicultural experiment in southern Chile. Furthermore, we compute the mingling index to represent spatial tree diversity. We proffer the pair correlation function difference before and after treatment to detect changes in the unmarked-point pattern of trees and the semivariogram-ratio to evaluate changes in the marked-point pattern. Our research provides a quantitative assessment of a critical aspect of forest heterogeneity: changes in spatial unmarked and marked-point patterns. The proposed approach can be a powerful tool for quantifying the impacts of disturbances and silvicultural treatments on spatial patterns in forest ecosystems.

1. Introduction

Heterogeneity of structural elements in forests is an aspect of major interest for understanding population and community ecology. Forest structural heterogeneity refers to a measure of the variety and relative abundance of different structural attributes (Pommerening, 2002). Within structural heterogeneity, the spatial component is of prime importance in the planning of any ecological study (Fortin et al., 1989; Legendre and Fortin, 1989), as well as a determinant of plant dynamics and pattern formation (Getzin et al., 2008). The spatial arrangement of trees in a forest is a key component of forest structure, accounting for the horizontal dimension of forest heterogeneity. This arrangement produces spatial patterns of trees that result from several interactions acting through forest development. Concordantly, spatial patterns of species and sizes are essential for understanding forest dynamics (Moeur, 1993; Pelissier and Goreaud, 2001; Franklin et al., 2002) because we can infer the history of a forest and estimate what could happen along successional trajectories. Besides, knowing the spatial patterns of trees in unmanaged

forests may serve as a reference for the implementation of silvicultural treatments (Pukkala, 1988; Pretzsch, 1997; Carey, 2003; Bauhus et al., 2017) or restoration efforts (Churchill et al., 2013; Larson et al., 2012). Spatial heterogeneity can be assessed by different statistical models and indices (Staudhammer and LeMay, 2001). However, we purposely avoid the computation of spatial indices because they tend to summarize complex ecological processes into a single number. Furthermore, these indices, such as those based on direct competitors (Lorimer, 1983), imply searching for different distances because they change with stand development. We instead focus on functions representing the pattern that depends on the scale of the studied phenomena.

In forest ecology, a common assumption is that small trees exhibit a clustered spatial pattern, and large trees tend to be regularly distributed. The process of change from a clustered pattern (young trees) to a regular one (adult trees), is mainly caused by mortality process associated with competition for resources (Moeur, 1993, 1997; He and Duncan, 2000; Salas et al., 2006; LeMay et al., 2009; Ledo et al., 2014) or partial overstory disturbance (Oliver and Larson, 1996). After partial overstory

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disturbance (e.g. a canopy gap), shade-tolerant species use this gap and exhibit a clustered spatial pattern (Veblen et al., 1979; Salas et al., 2006).

In a nutshell, the study of the spatial patterns of trees helps to interpret forest dynamics, where quantitative spatial analysis aims to detect and describe spatial patterns (Salas et al., 2006; Ben-Said, 2021), by accounting for the spatial structure of a population, community, or any ecological phenomenon (e.g. disturbance) in a given space (Perry et al., 2006). However, the limitation of these analyses is that they do not account for the inherent temporal dynamics of any forests. Besides, these analyses are punctual or static in time, which forbids plausible interpretations of the complex dynamics that forests may follow to reorganize following disturbance.

Analysing spatial changes in time of trees in the same forest is rarely studied in ecology and forest management. Vegetation is structurally dynamic, and dynamics are, in part, initiated by disturbances (Greig-Smith, 1979; White, 1979). Changes in spatial patterns can determine which species dominate the upper strata when interacting species have markedly different height growth patterns (Oliver and Larson, 1996); thus, detecting spatial changes is interesting in forest dynamics. Notice, though, that most of these reported changes in forest ecology rely on the assumption of substitution of space for time (Johnson and Miyanishi, 2008). Here, spatial patterns of trees in forests at different locations and distinct stages of development are studied. Nonetheless, this assumption has received significant criticism in ecology (Johnson and Miyanishi, 2008; Walker et al., 2010; Srivathsa et al., 2018). Consequently, better studying the tree spatial pattern changes requires data from a permanent sample plot. However, analysis of the change in spatial patterns based on long-term data is scarce in forest ecology (Ward et al., 1996).

Although there is a solid body of literature on spatial point pattern analysis, spatial changes have received less attention. A sound statistical theory supports spatial analyses (Ripley, 1981; Diggle, 1983; Cressie, 1993; Schabenberger and Gotway, 2005; Wiegand and Moloney, 2014); hence there are functions and indices for studying unmarked and marked-point processes. A spatial process is a stochastic model governing the location of events in a spatial domain, and a spatial pattern is a realisation of this process (Cressie, 1993). For instance, in forest ecology, trees can be understood as events in a forest. When we are interested in the solely spatial location of trees, we refer to the unmarked process; meanwhile, when we consider a covariate (e.g., species or stem diameter), we refer to the marked process (Ben-Said, 2021). While Ripley's K (Ripley, 1977) and the pair correlation (Stoyan and Stoyan, 1996) functions are quantitative alternatives usually used for assessing unmarked patterns (i.e., the realization of a process), semivariograms and correlograms are mostly used to study marked patterns. Although the literature is abundant in both analyses (i.e., unmarked/marked), to our knowledge, there are no statistical studies directly analysing changes in spatial patterns. The only somehow related work is the one by Long and Robertson (2018). They defined spatial pattern comparison as a numerical assessment of the (dis)similarity between two (or more) mapped datasets. Another topic in some manner connected could be the co-dispersion analysis between two spatial sequences (Vallejos, 2012; Vallejos et al., 2020). Comparing spatial tree patterns of forests before and after treatments by statistical functions may help elucidate the main processes governing vegetation dynamics and species richness (Franklin et al., 2002). As far as we know, little research has been devoted to developing statistical functions for analysing changes in spatial patterns and has never been attempted before in forest ecology.

Assessments of silvicultural treatments are largely non-spatial. Silvicultural treatments are usually focused upon changing the spatial configuration of forest stands in the vertical and/or the horizontal profile. Traditional appraisals of management interventions focus on comparing stand-level variables before and after the intervention has been carried out (O'Hara et al., 2015; Willis et al., 2018). These comparisons assess structure, composition, growth and regeneration afterwards, and there is an impressive amount of research in this regard. However, the traditional assessments do not consider the spatial pattern

component; therefore, we refer to them as non-spatial. In contrast, little research assesses how the spatial tree patterns are altered due to these man-created overstory disturbances. Among them, Fajardo et al. (2006) found that established *Pinus ponderosa* and *Pseudotsuga menziesii* saplings followed a cluster pattern after uneven-aged silviculture in Montana (USA). Kuehne et al. (2015) studied responses to thinning after 11 years in Oregon (USA) by focusing on computing indices to represent spatial heterogeneity. Gradel et al. (2017) compared unmarked point patterns before and after treatments in *Betula platyphylla* and *Larix sibirica* stands in Mongolia. Kuehne et al. (2018) went further and analyzed the spatial patterns at 1 and 10 years since commercial thinnings were applied in Maine (USA). In these works, directly assessing spatial changes was not a research topic, but only a description of the spatial patterns at different times. Regardless, we highlight these works to stress that studies dealing with assessing spatial tree patterns after management are scarce. Accordingly, we think much more research remains to be accomplished on this topic.

Species diversity is a keystone attribute of forest ecosystems. By analyzing tree species diversity or tree functional group diversity, we can better understand intra- and interspecific competition, a crucial aspect shaping forest dynamics because of the relation between growth, mortality and competition (Duncan, 1991; Oliver and Larson, 1996). Concordantly, several non-spatial aggregation indices had been devised for representing diversity features in ecology (Clark and Evans, 1954; Pielou, 1959). Nonetheless, spatial tree diversity is rarely studied in partial overstory disturbances. In this regard, the works of Hui et al. (2011), Pommerening et al. (2019) and Wang et al. (2021) advanced on studying several spatial functions suitable for assessing diversity, and are influential to our work.

Variable-density thinning (VDT) is a promising silvicultural alternative for forest management. VDT promotes the creation of gaps and reserves (or skips) within the thinned matrix where shade-tolerant species are preferred over pioneer shade-intolerant species (Carey, 2003; Puettmann et al., 2016; Willis et al., 2018; Donoso et al., 2020). VDT adds heterogeneity to simple forest structures (commonly found in secondary forests, Puettmann et al., 2016), enhancing the old-growth attributes of forests under management, a highly desirable feature because of their positive impacts on tree diversity and resilience (Bauhus et al., 2009). VDT has also been applied in temperate rainforests in southern Chile (Donoso et al., 2020); spatial pattern assessment in stands which were subjected to VDT remains unstudied. Thus, having mapped data of trees before and after applying a VDT, offer a remarkable opportunity to test novel and simple statistical models to assess the impact of a partial overstory disturbance on unmarked and marked-point patterns change. Owing to the identified research needs above, we used a large-scale VDT experiment in southern Chile to analyse the spatial changes of trees in two secondary forests following variable-density thinning. Based on spatial models for unmarked and marked-point processes, we proffer novel approaches for analysing spatial changes.

2. Materials and methods

2.1. Data

We used tree location data from a VDT experiment implemented at Llancahue, an experimental forest located at low-to-middle elevations in the Coastal Range of southern Chile, near the city of Valdivia (Fig. S1). The elevation in Llancahue ranges from 50 to 410 m a.s.l, with clay-silt soils of medium depth (60–100 cm), annual precipitation of 2300 mm, and mean annual temperature 12.2 °C (Donoso et al., 2014). We focused on two secondary forest types, i.e., mixed-evergreen (MSG) and a *Nothofagus dombeyi*-dominated (NSG). Following the classification of Donoso (1995), these stands belong to the evergreen and *Nothofagus obliqua*-*N. alpina*-*N. dombeyi* forest types, respectively. Six 1-ha plots were established in each type of secondary forest in 2016. Within each type of secondary forest, three randomly selected permanent sample plots (PSPs)

were subject to VDT, and the remaining were kept as controls. In the present study, we only focus on the managed plots, therefore there were three plots per forest type. The VDT was implemented by: leaving untouched large and small reserves, creating large and small gaps, and thinning the rest of the area or matrix within a restoration thinning aiming to favor, as long as possible, shade-tolerant species (Bauhus et al., 2009). Further silvicultural details are fully described in Donoso et al. (2020). It is important to point out that because the experiment was just recently applied, we are not actually assessing the response of the forests to the variable-density thinning, but only how the forest was left after of applying the VDT.

For all live and dead standing trees with diameter at breast-height (d) ≥ 5 cm, species were determined and d measured. When trees were multi-stemmed, each stem was considered as a separate tree, if the stem-division was below breast-height (1.3 m). The location of each tree was recorded, via conventional measurements of distance, slope, and azimuth, and then the position of each tree was determined on a Cartesian plane using trigonometric relationships (Salas et al., 2006). Nearly 20,000 trees were measured in the six plots. For each sample plot, we computed stand variables such as density, basal area and the diameter of the tree of average basal area (i.e., the quadratic mean d_g). Overall, the residual basal area was 42 and 51 $\text{m}^2\cdot\text{ha}^{-1}$ in the MSG and the NSG secondary stands, respectively (Table 1). The d_g was 14 and 22 cm for MSG and NSG, respectively. Meanwhile, the VDT removed between 25% and 30% of the stand basal area.

2.2. Statistical analyses

2.2.1. Unmarked spatial patterns

Many spatial analyses based on mapped-data in forest ecology (e.g., Moeur, 1993; Haase et al., 1996; Perry et al., 2006; Getzin et al., 2008) have been carried out by fitting the Ripley's K function (Ripley, 1977). This function models the expected number of trees within distance r of an arbitrary tree (Moeur, 1993), and an unbiased estimate of K is expressed as follows

$$\hat{K}(r) = \frac{A}{n^2} \sum_{i=1}^n \sum_{j=1}^n \frac{1}{w_{ij}} I_r(u_{ij}), \quad (1)$$

where: A is the plot size (m^2), n is the number of trees measured in the plot, u_{ij} is the distance (m) between the i -th subject tree and the j -th tree, I_r is a counter, equal to 1 if $u_{ij} \leq r$ (the tree is within the circular plot of radius r) or zero otherwise, and w_{ij} is an edge correction factor, such as the isotropic one implemented in the geoR package (Ribeiro and Diggle, 2001). The edge effect arises from the unobservability of points outside the sample plot. Regardless, large plot sizes are preferred for analysing spatial patterns of forest trees, otherwise, the expected pattern is rather limited to a small number of points. One of the key features of Eq. 1, is that values are computed both from the i -th to the j -th tree and vice versa.

Some criticism had been raised on the use of $K(r)$, and alternative functions have been proposed (details are given in Wiegand and Moloney, 2014), whose the most used by ecologists is the pair correlation function $g(r)$ (Ben-Said, 2021), which avoids the cumulative nature of the $K(r)$ (Stoyan and Stoyan, 1996; Law et al., 2009), and is as follows,

$$\hat{g}(r) = \frac{d\hat{K}(r)}{dr} / 2\pi r, \quad (2)$$

where the first term of the function is the derivative of the estimated Ripley's function on the distance r . Concordantly, the $\hat{g}(r)$ computes the estimated value of $g(\cdot)$ for rings around the tree of interest, but not in a cumulative sense as in $\hat{K}(r)$. We used 0.5 m as the interval for incrementing r , starting with $r = 0.5$, and ending with a maximum value of $r = 50$ m, following the recommendation of Haase (1995), to minimize edge problems and approximation errors in the location measurement of trees. Also, beyond 50 m, interactions between trees are expected to be minimal (Moeur, 1993; Salas et al., 2006). As explained by Law et al. (2009), the $\hat{g}(r)$ function represents how on average a plant perceives the density of other plants.

Monte Carlo simulations were conducted to test the null hypothesis of a Poisson process, the one describing complete randomness on point patterns (Besag and Diggle, 1977). For each simulation, each tree was randomly relocated over the permanent sample plot, then the $\hat{g}(r)$ was computed for each r . We later computed an empirical 95% confidence envelope over r from the simulated distributions of $\hat{g}(r)$. This envelope, or interval, defined the variability of the estimator $\hat{g}(r)$ under a random spatial process. Thus, if the values of $\hat{g}(r)$ lies within the confidence envelope, the observed spatial distribution is likely random. Meanwhile, if $\hat{g}(r)$ is larger than the upper values of the confidence envelope, the pattern is aggregated or clustered. Finally, if $\hat{g}(r)$ is smaller than the lower limit of the confidence envelope, the spatial pattern is likely uniform or regular.

We fit the $\hat{g}(r)$ function using data before and after variable-density thinning was applied to the secondary forests. We randomly choose a single permanent sample plot for each forest type as the data for the spatial analyses presented here (Fig. S1). All the spatial pattern analyses were carried out for: all species and by functional groups (short-lived pioneer, long-lived pioneer, and late successional) based upon Donoso (2006).

2.2.2. Marked spatial patterns

A marked-point process comprises a stochastic model of the location of events and an associated mark or covariate. The marks can be either categorical (e.g., species) or continuous variables (e.g., diameter, biomass, carbon). We can study the spatial correlation of marks by studying its variation depending on the distance. In a forest ecosystem, the points or events are tree locations and the marks are tree characteristics (Gavrikov and Stoyan, 1995; Stoyan and Penttinen, 2000). The

Table 1

Descriptive statistics for stand level variables by type of secondary forest before and after the variable-density thinnings were applied. These values were obtained based on three 1-ha permanent sample plots in each type of forest. The % column represents the rate of removal for density and basal area, and the rate of change for the average diameter. CV stands for the coefficient of variation.

Type of secondary forest	Statistics	Density(trees·ha ⁻¹)				Basal area(m ² ·ha ⁻¹)				Diameter of the average basal area tree (cm)			
		Before	Thinned	%	After	Before	Thinned	%	After	Before	Thinned	%	After
Mixed-evergreen (MSG)	Minimum	3907.0	1297.0	33.2	2610.0	56.6	14.8	26.1	41.0	13.2	12.0	88.6	13.4
	Mean	4154.7	1437.0	34.5	2717.7	59.7	18.3	30.5	41.4	13.5	12.7	93.8	13.9
	Median	4031.0	1417.0	35.2	2614.0	60.5	19.2	31.8	41.3	13.6	12.9	95.1	14.2
	Maximum	4526.0	1597.0	35.3	2929.0	61.9	20.9	33.8	41.8	13.8	13.1	97.8	14.3
	CV (%)	7.9	10.5	3.4	6.7	4.6	17.3	13.0	1.0	2.3	4.6	5.0	3.7
<i>N. dombeyi</i> (NSG)	Minimum	1540.0	610.0	33.1	930.0	65.5	14.1	21.5	50.3	19.5	16.2	77.5	20.8
	Mean	1966.3	701.0	36.0	1265.3	66.8	16.0	23.9	50.8	21.0	17.1	81.5	23.0
	Median	2061.0	683.0	35.2	1378.0	66.0	15.7	23.8	50.7	20.1	16.9	80.6	21.8
	Maximum	2298.0	810.0	39.6	1488.0	68.8	18.1	26.4	51.4	23.4	18.1	86.5	26.2
	CV (%)	19.7	14.4	9.2	23.4	2.7	12.8	10.2	1.1	9.8	5.6	5.6	12.6

spatial variation of a random variable Z can be represented by the semivariogram (Schabenberger and Gotway, 2005), as follows,

$$\frac{1}{2} \text{Var}[Z(s_i) - Z(s_j)], \quad (3)$$

where: $Z(s_i)$ and $Z(s_j)$ are the random variable Z at spatial position i and j , respectively; and Var is the variance operator. Our continuous variable was tree diameter (d) because it is easy to measure and is a good proxy for tree sizes, and ultimately for ecological understanding of forest dynamics. Further applied details on marked-point process in plant communities can be found in Pommerening and Särkkä (2013) and Stoyan et al. (2017).

Because of the scope of our study, we favor to use a function being able to predict the semivariogram of the marks (Eq. 3). Duly, we fit semivariogram functions based on our spatial data, represented by

$$\hat{\gamma}(s, r, \theta) = f(Z(s), r, \theta), \quad (4)$$

where $f(\cdot)$ is a non-linear function for the semivariogram; r is the lag distance use for the s position, and θ is a vector of parameters of the function. As pointed out by Schabenberger and Gotway (2005), Eq. 4 is defined by choosing: a functional form for the semivariogram, a distance type, and whether a nugget effect is added. We fitted different functional forms for the semivariogram function, such as exponential, spherical, and Gaussian (Schabenberger and Gotway, 2005).

For all spatial point pattern analyses, the maximum distance was set to 50 m. In addition, we assessed tree distance types: Euclidean, maximum, and Manhattan. Finally, we added a nugget effect. Therefore, we had different semivariogram model-variants depending on the definition used for the above explained tree components. These model-variants were fitted by maximum likelihood, and comparisons among them were based on the Akaike's Information Criterion. All the analyses were carried out in the *geoR* package implemented in R (R Core Team, 2022). All the semivariograms were fitted using the same functional groups of species as explained above (all species and by successional stage).

2.2.3. Tree species diversity

Temperate forests in southern Chile are species-rich ecosystems (Donoso, 1995; Veblen, 2007), and as a consequence they are a particular challenge for spatially explicit species diversity monitoring (Pommerening et al., 2019). Several indices and functions are available (e.g., Ferrier and Guisan, 2006; Wiegand and Moloney, 2014; Brown et al., 2016; Pommerening et al., 2019; Zhang et al., 2021) to represent spatial tree diversity. For this purpose, we used the mingling index for assessing spatial changes in species diversity $\bar{M}_k$ (Lewandowski and Pommerening, 2006) before and after the VDT was applied. The mingling index was the mean fraction among the k -nearest-neighbours of a given tree that belonged to a different species than the given tree (Wiegand and Moloney, 2014). To compute this index, we needed first to estimate the constructed mark $\bar{M}_k(x_i)$, representing for a given i -th tree the fraction of the k -nearest neighbours that belong to a different species than the individual x_i . Later, we averaged the mark for all the N points x_i within the plot as follows

$$\bar{M}_k = \frac{1}{N} \sum_{i=1}^N \bar{M}_k(x_i). \quad (5)$$

Lewandowski and Pommerening (2006) proposed edge-correction alternatives for computing a single index for a given plot, and the index was applied with success elsewhere (Lewandowski and Pommerening, 1997; Hui et al., 2011). We computed Eq. 5 for different ranks (k) from 1 to 10, thus, allowing us to build a graph of $\bar{M}_k$ against k , which helps to represent the relationship between species diversity and distance. Wiegand and Moloney (2014) discussed the relationship of the mingling index with other spatial-diversity indices.

2.2.4. Changes in spatial patterns

How to analyse the change in spatial patterns is understudied. A researcher might be interested in studying how two population patterns change rather than in describing them separately. An impressive amount of literature provides analytical tools for analysing spatial data, such as spatial point patterns (Ripley, 1981; Cressie, 1993; Schabenberger and Gotway, 2005). Despite that, how to analyse spatial pattern changes is an unfathomable subject. Concordantly, we proffer to use the difference in the estimated values of the pair correlation function for any given distance as a proxy for detecting spatial pattern differences. Hence we suggest the following expression

$$\Delta[\hat{g}(r)] = \hat{g}_{(r,B)} - \hat{g}_{(r,A)}, \quad (6)$$

where: $\hat{g}_{(r,B)}$ and $\hat{g}_{(r,A)}$ are the estimated value of the $g(\cdot)$ function (Eq. 2) at the r -th radius before and after the disturbance, respectively. If the values of $\Delta[\hat{g}(r)]$ are equal to 0, there is no change in the spatial pattern. Any other interpretation depends on the value of $\hat{g}_{(r,B)}$. For instance, when $\hat{g}_{(r,B)} > 0$, two alternatives can occur: (i) If the values of $\Delta[\hat{g}(r)]$ fall under 0, the pattern changes towards a more clustered distribution than before; and (ii) if $\Delta[\hat{g}(r)]$ is larger than 0, the distribution moves towards a less clustered pattern. The reasoning in other conditions is similar (§A.4). As far as we are aware, this is the first study on proposing a mathematical expression for assessing spatial point pattern changes.

In the same vein, but now to assess the changes in the marked-point pattern, we propose to compute the ratio between the fitted semivariogram for the corresponding forest before and after the intervention, as follows

$$\phi[\hat{\gamma}(r)] = \frac{\hat{\gamma}_{(r,A)}}{\hat{\gamma}_{(r,B)}}, \quad (7)$$

where: $\hat{\gamma}_{(r,A)}$ and $\hat{\gamma}_{(r,B)}$ are the fitted value of the semivariogram γ at the r -th radius after and before the disturbance, respectively. The outcomes of Eq. 7 are interpreted as follows (§A.4): if the values of $\phi[\hat{\gamma}(r)]$ are equal to 1, there is no change in the marked-point pattern (i.e., no spatial size variation). If the values of $\phi[\hat{\gamma}(r)]$ fall under 1, the spatial variation of the covariate decreases after the disturbance. Finally, if $\phi[\hat{\gamma}(r)]$ is larger than 1, the spatial variation of the covariate increases after the disturbance. To our knowledge, this is the first study proposing a mathematical expression for assessing changes in the spatial variation of a marked-point pattern.

3. Results

VDT modified the diameter distribution of the secondary forests and produced a platykurtic distribution of tree sizes. Within the functional groups, the diameter structure of the short-lived pioneer species was more altered (Fig. S2). The application of the partial disturbance shows a noticeable reduction in tree density for both forest types (Table 1) by creating small gaps (Fig. S3). The estimated values for the pair correlation function before and after the partial disturbance show an intensification of the clustered pattern for both forest types and functional groups (Figs. 1a and 2a). It is essential to notice that tree clustering is more prominent at small scales; thus, the VDT mimics this trend and intensifies it. The long-lived and the short-lived pioneer species strongly affected this pattern in the MSG and the NSG forests, respectively. The fitted semivariograms show that spatial variation of tree sizes (i.e., stem diameter) increased right after applying the VDT for both forest types (Figs. 1b and 2b). This trend is more noticeable in the NSG forest than in the MSG. The tree size spatial variability is stronger at small distances for the MSG than for the NSG and the late-successional species in both forests. Besides, this functional group's variability was increased more in the NSG than in MSG. Overall, the range (i.e., the distance at which the asymptote is reach) of the semivariogram differs among the functional groups too.

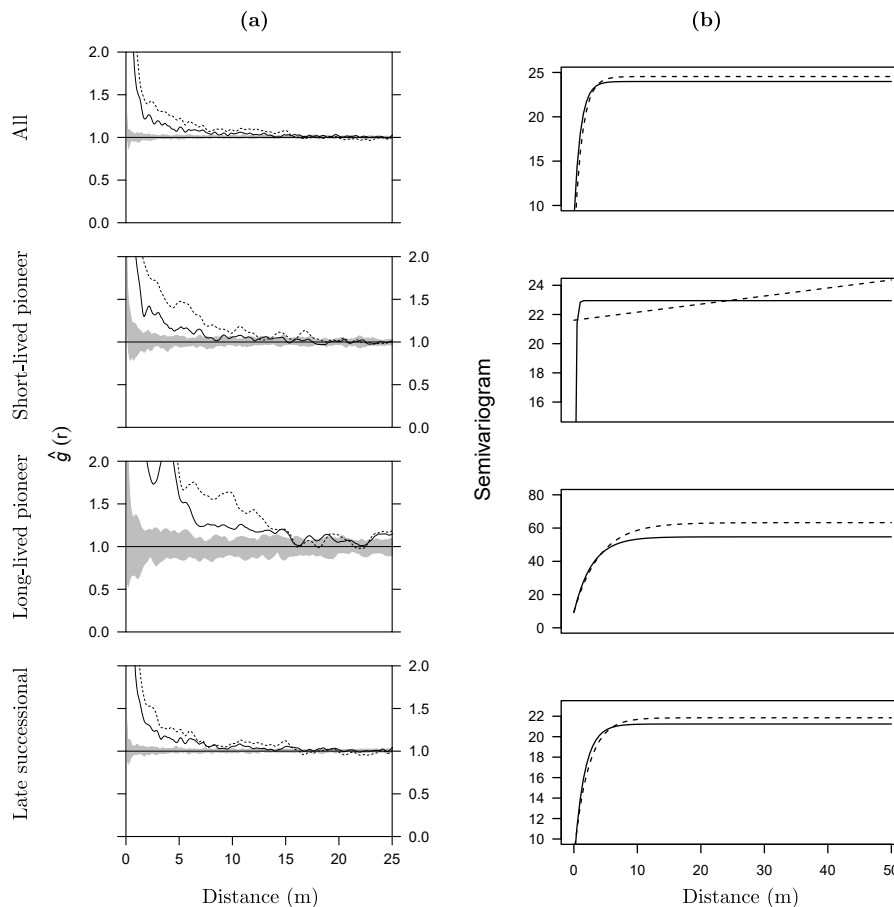


Fig. 1. Spatial results of the experiment for the mixed-evergreen secondary forest before and after the thinning for each functional group. (a) Estimated value for the pair correlation function before (solid line) and after (dashed line) with the 95% confidence envelope for a completely random point process; and (b) the semivariogram fit for the tree diameters before (solid line) and after (dashed line).

The mingling index as a function of the number of neighbours depicted the proportion of heterospecific individuals in space, i.e., the larger the mingling value, the larger the tree diversity. In this context, the number of neighbours can be used as a proxy for distance. The mingling value asymptotically increases as the number of neighbours taking into account increases (Fig. 3). Therefore, the larger the distance from a random tree, the proportion of finding neighbours of different species and the three functional groups increases. Overarching, the spatial tree diversity is greater for the NSG than for the MSG; however, this feature segregated by functional groups enormously varied among forest types. Besides, the spatial tree diversity among functional groups is more similar in the NSG than in the MSG. We found a decline in mingling after the human-induced partial disturbance across all distances but this is especially notable in the MSG forest. The exceptions to this trend are for the functional groups of short-lived pioneer species in the NSG forest and long-lived pioneer species in the MSG forest. Overall, the immediate application of the VDT reduced spatial diversity for both forest types, but especially for the MSG forest.

To assess the spatial changes, we first compared the unmarked patterns and later the marked-point patterns. Firstly, the statistics $\Delta[\hat{g}(r)]$ highlights that most of the difference between the forest before and right after the human-induced partial disturbance was up to 20 m of distance (first-row of Fig. 4). Given that before the VDT, $\hat{g}(r) > 0$, the sign of the statistics $\Delta[\hat{g}(r)]$ suggests that the pattern changed towards a more clustered distribution than before for both forests. The only exception to this trend is found for the short-lived pioneer species in the NSG forests, where the change was less clustered. Furthermore, the spatial changes fell off rapidly above 15–20 m of distance, but not for the long-lived

pioneer species, for which the unmarked pattern keep changed after 35 m in both forests. Overall, with the exception mentioned about, the two forest types have no major differences in the trend of $\Delta[\hat{g}(r)]$, our proxy for assessing spatial pattern changes. The more considerable spatial changes occur for the long-lived pioneer species and the short-lived ones at small scales. Secondly, the statistics $\phi[\hat{\gamma}(r)]$, the semivariogram-ratio, highlights the differences in the spatial variability of tree sizes (second-row of Fig. 4). Overall, the spatial variability of tree sizes was increased after the thinning. However, this trend is more prominent in the NSG than in the MSG forest. For instance, the variability increased around 20% for all species in the NSG forest but only about 3% for MSG. The changes in the spatial variability of tree diameters among functional groups were invariant for the MSG but were dissimilar for the NSG. The most noticeable changes in the semivariogram-ratio occur for the late-successional group in the NSG forest.

4. Discussion

The intervention (VDT) induced a clustered spatial pattern of trees due to small canopy openings (Figs. 1a and 2a). In that way, Franklin et al. (2002) pointed out that one of the structural development phases in forest dynamics is the horizontal diversification stage, where spatial heterogeneity is achieved. The functional groups of short-lived pioneer and late-successional species shape the spatial arrangement in the mixed-evergreen secondary forest, while the long-lived pioneer and late-successional species shape it in the *Nothofagus*-dominated forest (Fig. S3). The VDT aims to accelerate forest dynamics by enabling the recruitment of more shade-tolerant species into the forest. These species

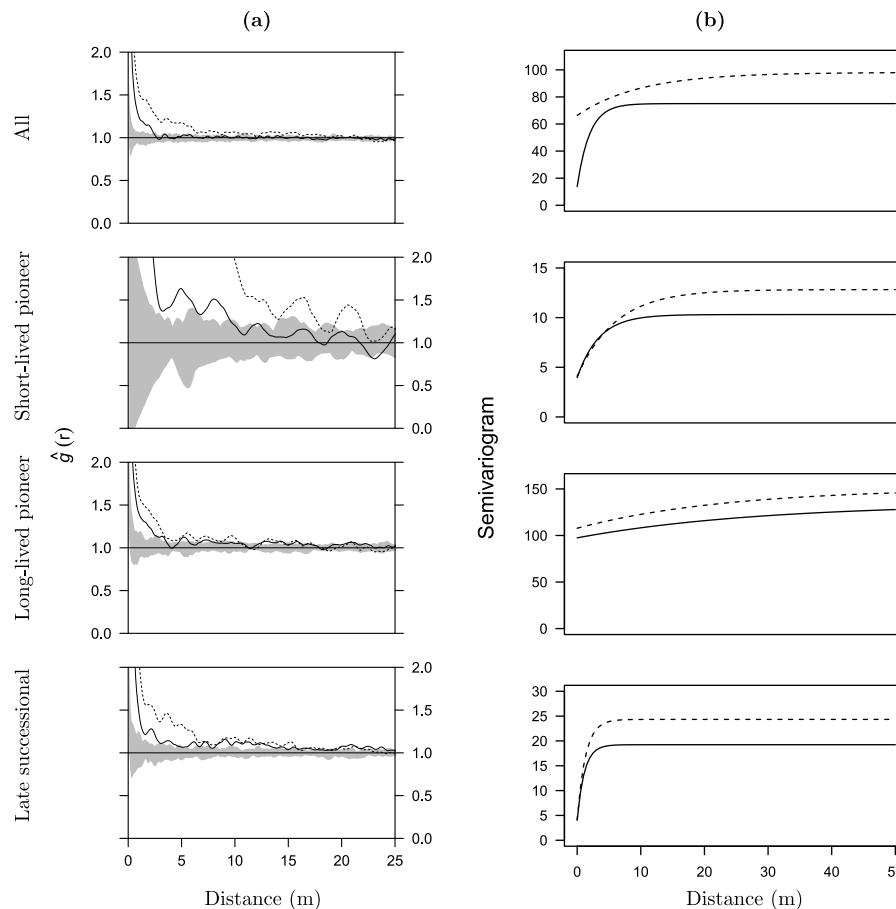


Fig. 2. Spatial results of the experiment for the *Nothofagus*-dominated secondary forest before and after the thinning for each functional group. (a) Estimated value for the pair correlation function before (solid line) and after (dashed line) with the 95% confidence envelope for a completely random point process; and (b) the semivariogram fit for the tree diameters before (solid line) and after (dashed line).

follow the gap-phase and the continuous regeneration modes (Veblen, 1992) and develop better in the sheltered environmental conditions under the dominant forest canopy (Gutiérrez et al., 2004; Pollmann and Veblen, 2004). These species need small canopy openings to establish and grow well under partially shaded conditions (Oliver and Larson, 1996). The spatial clustering of trees at small scales is a natural pattern reported in several studies (Moeur, 1997; Woods, 2000; Salas et al., 2006; Soto et al., 2010). After applying the VDT, we have observed that spatial heterogeneity has been promoted by intensifying the trees' clustered distribution and increasing the variability of tree sizes (Figs. 1b and 2b).

The shape of the mingling curve shows that with increasing distance, mingling increases as well. That is to say, the probability of finding neighbours of another species increases (Fig. 3). A similar pattern was also described by Pommerening et al. (2019) in China's various species-rich temperate forest ecosystems. In general, the mingling curve proved that trees are surrounded by more heterospecific neighbouring trees at larger scales. This finding agrees with the results of Wang et al. (2018) in Korean forests. The greater spatial tree diversity found in the NSG forests than in MSG forests may be due to the former being at more advanced stage of development, which enables the recruitment of semi shade-tolerant and shade-tolerant species. In the same vein, the median stand basal area for the NSG is 66 versus 61 m²·ha⁻¹ for the MSG, while the median stand density for the NSG forest is remarkably lower than for the MSG: 2061 vs 4031 trees·ha⁻¹ (Table 1). Although we reported that spatial diversity was slightly decreased by the thinning, we expect in time to see a remarkable change in this feature because one of the objectives of the VDT is to promote conditions for the establishment of

late-successional species in the long term. Along this vein, it is helpful to distinguish between the immediate effects of species richness on ecosystems and those that become apparent on a more extended scale (Grime, 2002). How similar plant species coexist is a puzzle (Lusk, 2003). In this regard, the change in the proportion of conspecific neighbours, as expressed by the mingling index, is a practical and easy quantitative tool to represent the coexistence of species in space. This spatial analysis of tree diversity could provide insightful thoughts on intra- and interspecific competition, a crucial aspect shaping forest dynamics (Duncan, 1991). Furthermore, understanding how the functional groups interact following a partial overstory disturbance can provide insights into species assemblages of these functional groups in space and time. Besides, the response in tree diversity (of functional groups) offer us a way to understand the coexistence of the groups and stand dynamics.

We found that most of the spatial changes occur at small distances. These changes, induced by the VDT, represents a strong trend towards clustering (first-row of Fig. 4). The clustering occurs at a distance lower than 10 m but around 20 m for long-lived pioneer species. The spatial variability of tree sizes primarily increased at small scales for the NSG forest (second-row of Fig. 4). This information can be instrumental for future management interventions. Nonetheless, the intervention little influenced the spatial variability of tree diameter in the MSG forest. The latter indicates that the partial disturbance was lightly applied, and another VDT must be carried out soon in this forest. Willis et al. (2018) discussed the periodicity of VDTs when analyzing a 14-year VDT experiment in the Pacific Northwest of the USA. They brought to attention the use of diameter growth rates of individual trees. The increase in tree size spatial variability mainly occurs at small scales, being less than

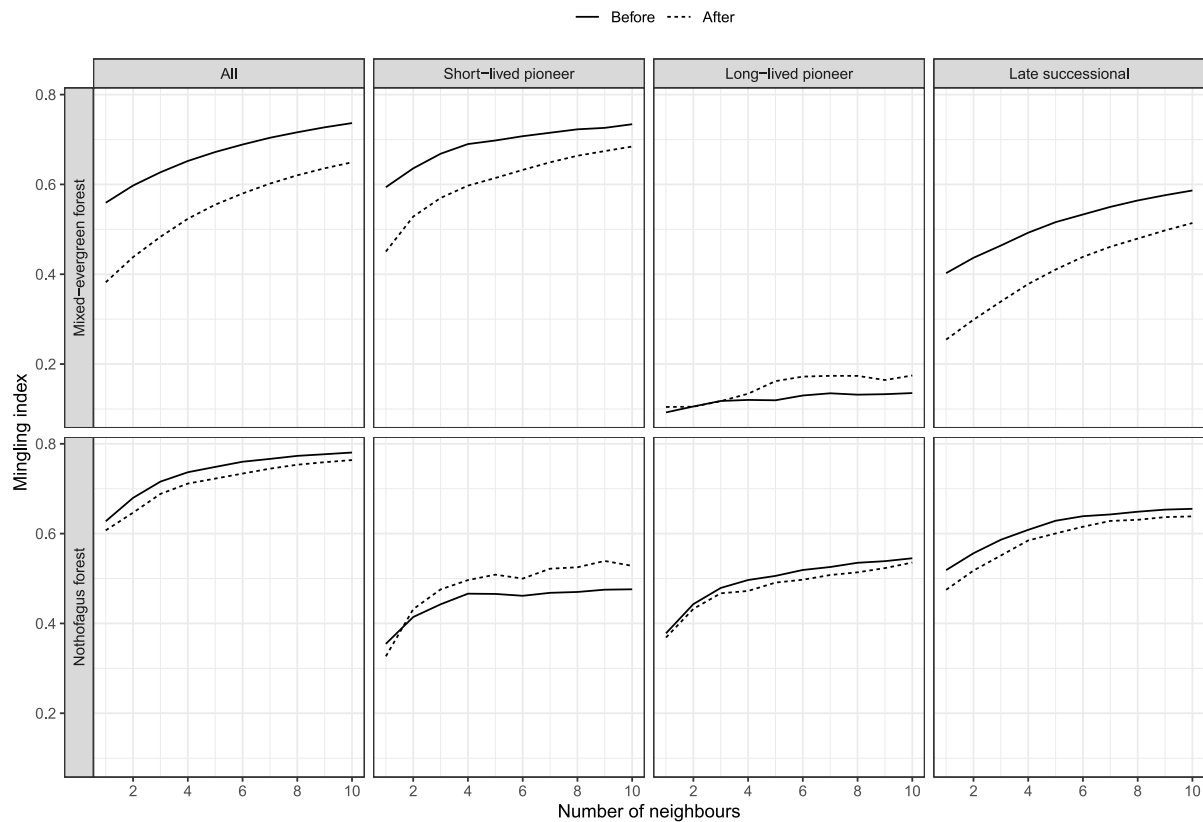


Fig. 3. Spatial tree diversity results of the variable-density experiment for each functional group. The first-row panel is for the mixed-evergreen forest, while the second-row for the *Nothofagus*-dominated. The solid line is before the thinning and the dashed line after.

10 m for both forests, but changes depending upon the functional group. A widespread practice in most statistical analyses, which we dislike, is to reduce extensive analyses only to compute *P*-values or detect a significant difference (Breiman, 2001; Goodman, 2008, 2019; Ellison and Dennis, 1996; Fanelli et al., 2017; Ioannidis, 2019). Regardless, a rule of thumb is that a semivariogram-ratio larger than five could be considered statistically significant from one (i.e., no difference) at a *P*-value of 5%. By studying the change in spatial features of trees in such experiments, we firmly think that we advanced our scientific understanding of partial disturbance by adding quantitative models that rely upon a solid statistical theory.

The sort of spatial analyses showed here can be used in marteloscope research. Tree selection for removal is one of the most complex tasks in forest management because it determines the outcome of the current harvest and certainly influences future harvests through its effects on regeneration, available growing space, vigour, and composition of the residual stand (Soucy et al., 2016). Marteloscopes are multifunctional training permanent sample plots developed as didactic tools for virtual tree selections (Bruciamacchie, 2006), to better understand forest management. The ability to analyse the implementation of a management strategy by spatial statistics functions and indices allows us to correct unseen potential problems (Pommerening and Grabarnik, 2019). For instance, if we noticed that the thinnings largely seem to reduce diversity, we could calculate the person-specific tree marking rate to detect the responsible for this reduction. Pommerening et al. (2018) studied 36 silvicultural training sites throughout Britain and highlighted that the variability of selecting individual trees for forest management operations is considerable. Moreover, evaluating the spatial differences before and after disturbances can also be helpful for an array of purposes. For instance, whether experimental plots received the same treatment

homogeneously can be assessed by computing spatial pattern differences as shown in the present study. Ergo, aside from checking that the state variables (e.g., density and basal area) do not broadly vary among plots subjected to the same experimental treatment, our proposed statistics provide another dimension to be considered when rating the fairness of treatments among sample units.

Variable-density thinning (VDT) is a suitable alternative for promoting ecological silviculture (Palik et al., 2021). It contributes to creating old-growth attributes in second-growth forests characterized by complexity in tree species composition and structure (vertical and horizontal). The creation of gaps or patches (Fig. S3) within managed stands mimics small-scale disturbances common in old-growth forests (Veblen et al., 1980; Veblen, 1985). In the present study, VDT mimics partial overstory disturbance to add heterogeneity to forest ecosystems.

In this study, we have presented pleasingly simple novel alternatives for assessing changes in spatial point patterns. Using the sound and well-established statistical theory that supports most spatial analyses in forest ecology, we have assessed spatial changes by proposing simple indices for unmarked and marked-point patterns using pre- and post-disturbed secondary forests. We propose the $\hat{g}(r)$ difference to evaluate changes among two spatial patterns quantitatively. Furthermore, we proffer the semivariogram-ratio to assess how variability in tree sizes is altered by disturbance. These new approaches give easy-to-interpret results, and thus they may be useful for ecologists to evaluate spatial changes through time. Finally, although we have shown the application of these approaches in a forest thinning experiment, they can be applied to any partial disturbances, such as forest fires, to assess the level of damage and forest degradation to support restoration projects. Concordantly, we foresee a tremendous use for them to elucidate spatial changes in a plethora of ecological situations.

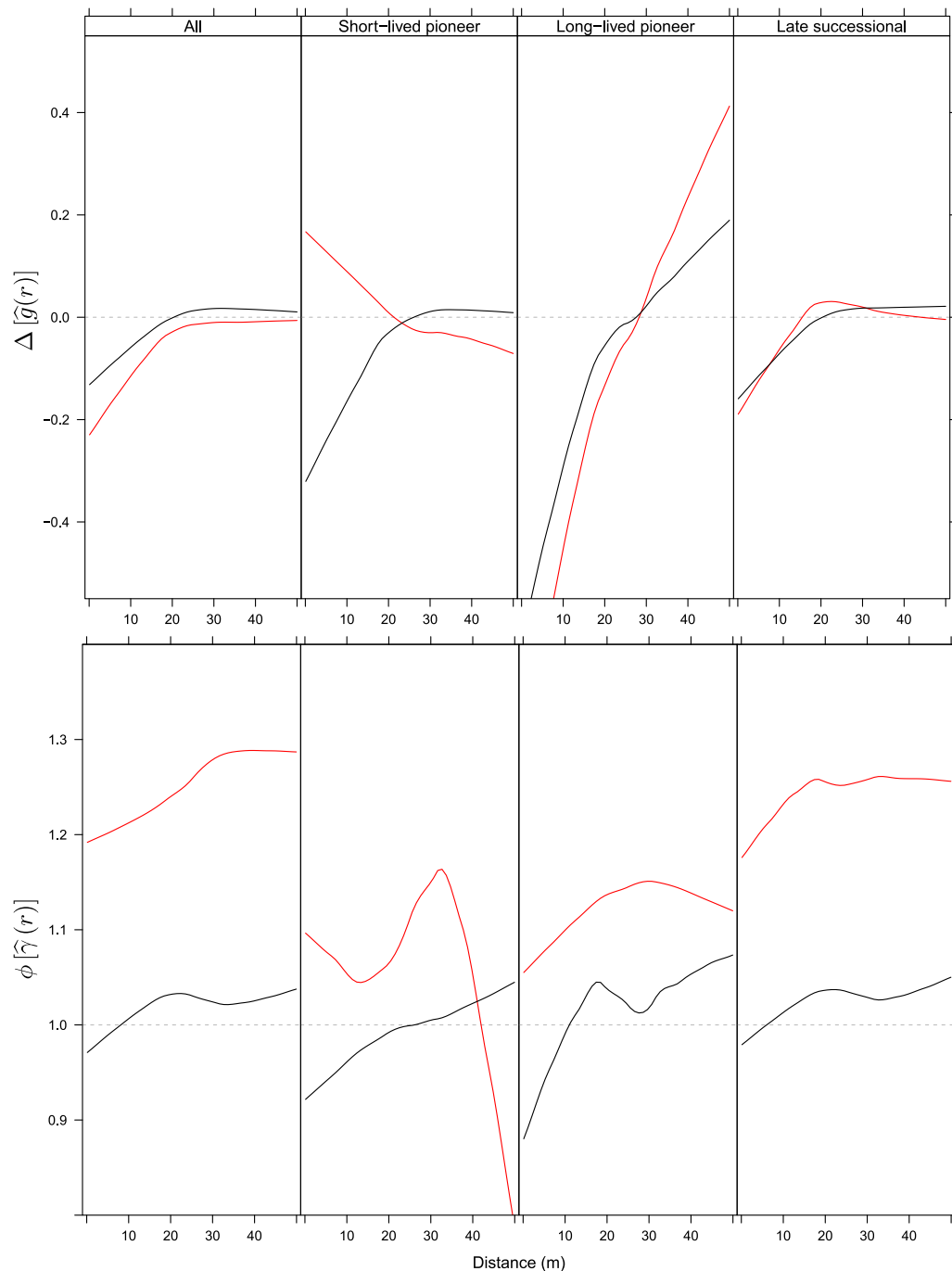


Fig. 4. Spatial changes before and after the thinning by functional group. The first row-panel shows the difference between the estimated value for the pair correlation function before and after the partial disturbance (Eq. 6) for the mixed-evergreen (black) and *Nothofagus*-dominated (red) forest types. The second row-panel shows the semivariogram-ratio between after and before thinning (Eq. 7).

5. Concluding remarks

We proffer novel and straightforward approaches to evaluate changes in the spatial patterns: the difference in the pair correlation function and the semivariogram-ratio, respectively. We assessed the usefulness of these approaches using a controlled partial overstory disturbance conducted through variable-density thinning (VDT) in two contrasting secondary temperate forests in south-central Chile. We have shown the applicability and interpretation of both approaches when considering

changes pre- and post-disturbance. Besides, we also computed changes in tree diversity with the mingling index, depicting the distinct response of functional groups. Overall, the proposed spatial statistical approaches should have broad application given the prevalence of mapped forest tree data. We think that our quantitative analyses to assess changes in unmarked and marked-point patterns helps understand the spatial tree dynamics in forest ecosystems. Finally, we showed that VDT effectively promoted variability and added features contributing to spatial heterogeneity of forests.

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Availability of data and material

The data are available upon request, and enquiries should be directed to Christian Salas-Eljatib at cseljatib@gmail.com. Sample data relating to this study is available in the datana (Salas-Eljatib, 2021) R package at <https://cran.r-project.org/package=datana>.

Authors contribution

CS-E conceived and designed this research and led the writing and the quantitative approaches supporting the manuscript; CS-E and JR conducted the analyses; PJD conceived and designed the thinning experiment; DP collected the data; DPS and PJD helped with the writing. All authors have seen and approved the submitted version of the manuscript.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pablo J. Donoso reports financial support was provided by the Chilean National Fund for Scientific and Technological Development.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.fecs.2022.100081>.

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