Forest Systems
25(1), e056, 9 pages (2016)
eISSN: 2171-9845
http://dx.doi.org/10.5424/fs/2016251-07968
Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria (INIA)

RESEARCH ARTICLE

OPEN ACCESS

The influence of sampling unit size and spatial arrangement patterns on neighborhood-based spatial structure analyses of forest stands

Hongxiang Wang[1], Gongqiao Zhang[1], Gangying Hui[1], Yuanfa Li[2], Yanbo Hu[1]*, Zhonghua Zhao[1]

[1] *Research Institute of Forestry, Chinese Academy of Forestry; Key Laboratory of Tree Breeding and Cultivation, State Forestry Administration, Beijing 100091.* [2] *College of Forestry, Guangxi University, Xixiangtang district, Nanning, Guangxi province, 530004*

Abstract

Aim of the study: Neighborhood-based stand spatial structure parameters can quantify and characterize forest spatial structure effectively. How these neighborhood-based structure parameters are influenced by the selection of different numbers of nearest-neighbor trees is unclear, and there is some disagreement in the literature regarding the appropriate number of nearest-neighbor trees to sample around reference trees. Understanding how to efficiently characterize forest structure is critical for forest management.

Area of study: Multi-species uneven-aged forests of Northern China

Material and methods: We simulated stands with different spatial structural characteristics and systematically compared their structure parameters when two to eight neighboring trees were selected.

Main results: Results showed that values of uniform angle index calculated in the same stand were different with different sizes of structure unit. When tree species and sizes were completely randomly interspersed, different numbers of neighbors had little influence on mingling and dominance indices. Changes of mingling or dominance indices caused by different numbers of neighbors occurred when the tree species or size classes were not randomly interspersed and their changing characteristics can be detected according to the spatial arrangement patterns of tree species and sizes.

Research highlights: The number of neighboring trees selected for analyzing stand spatial structure parameters should be fixed. We proposed that the four-tree structure unit is the best compromise between sampling accuracy and costs for practical forest management.

Keywords: Stand spatial structure; number of neighboring trees; uniform angle index; mingling; dominance.

Citation: Wang, H., Zhang, G., Hui, G., Li, Y., Hu, Y., Zhao, Z. (2016). The influence of sampling unit size and spatial arrangement patterns on neighborhood-based spatial structure analyses of forest stands. Forest Systems, Volume 25, Issue 1, e056. http://dx.doi.org/10.5424/fs/2016251-07968.

Received: 02 May 2015. **Accepted**: 09 Feb 2016

Funding: This paper was financially supported by the National Natural Science Foundation of China (31370638).

Competing interests: The authors have declared that no competing interests exist.

Correspondence should be addressed to Yanbo Hu: hyanbo@caf.ac.cn

Introduction

Forest management emphasizes the importance of structure and function, and focuses on achieving a natural state (Petritan *et al.*, 2012). Stand structure heterogeneity leads to increased species richness and contributes to forest stability and integrity (Latham *et al.*, 1998; Spies, 1998; Wang *et al.*, 2006). Stand spatial structure is focused on the description of relative tree positions (Kint *et al.*, 2003), and is generally considered to have three aspects: diversity of tree positions (spatial distribution), species diversity, and variation in the dimensions of trees (Gadow & Hui, 1999; Lei & Tang, 2002; Graz, 2006).

Recent studies have addressed various stand spatial structure parameters based on relationships between nearest-neighbor tree groups: uniform angle index, mingling, and dominance (Graz, 2008; Petritan *et al.*, 2012; Li *et al.*, 2012; Gao *et al.*, 2013, Zhang *et al.*, 2014; Szmyt, 2014; Bettinger & Tang, 2015). These have been implemented to assess tree spatial distribution patterns, quantify the degree of interspersion of tree species and reflect size dominance of trees, respectively. Among forest structure parameters, these are efficient in characterizing spatial structure and are cost efficient because researchers are not required to measure tree positions or distances between trees (Hui & Gadow, 2003). Researchers can evaluate these three structure parameters by comparing a reference tree with its *n* neighbors, simplifying sampling and making it possible to investigate forest structure and diversity along with traditional forest surveys. This set of structural parameters can be described by a mean structural index at the forest stand level or by a probability density distribution, and thus has a unique advantage in guiding forest structure management and simulating spatial structure.

Similar to the estimation of competition among individual trees, stand structure analysis requires the selection of neighboring trees around a reference tree before structure indices can be applied. Many methods exist to define neighboring trees (Pommerening, 2008), but they are typically used to analyze competition not structure. Hui & Gadow (2003) elaborated that four neighboring trees are easy to be detected in the vicinity of a reference tree and it had high accuracy in estimating the spatial distribution patterns of tree positions, species mingling and the dominance of tree sizes; therefore, they proposed that a reference tree and its four nearest neighbors formed the optimal structure unit and applied it in both spatial structure analysis and guiding forest structure adjustment in selective harvest events. However, it is unknown how the size of structure unit influences spatial structure analysis systematically. Furthermore, some other studies also have used Voronoi tessellations, fixed radii, or other methods, which were used in the estimation of tree competition effect, to apply structure parameters (Zhao *et al.*, 2010; Liu, 2011; Hao *et al.*, 2012; Li, 2012; Wu, 2012; Pastorella & Paletto, 2013). Unfortunately, conclusions have often been contradictory, especially for studies that have addressed the uniform angle index, possibly because of erroneous conclusions of stand spatial patterns (see below). Thus, it is unclear how one should identify neighboring trees to apply spatial structure indices and whether other potential selection methods are useful or not. Selecting a large number of neighboring trees, *n*, can allow us to collect more information but generally will also increase cost (Stamatellos & Panourgias, 2005); thus, it is necessary to find a balance between accuracy and sampling cost.

In this study, we selected two to eight neighboring trees to analyze how spatial structure indices are influenced by different sizes of tree structure unit in different spatial arrangement patterns. The aims of this study were to: (1) explore whether the selection of varying numbers of neighboring trees makes a difference on the analysis of structure indices and specify this influence at different situations; (2) propose the optimal structure unit size that compromises between accuracy and sampling cost.

Material and methods

Spatial structure parameters based on relationships between nearest-neighbor tree groups

Uniform angle index (W)

Hui & Gadow (2002) described the spatial distribution patterns of a population of trees based on the angles of the vectors joining a reference tree to its *n* nearest neighbors. One can count only the number of observed angles between two neighboring vectors, which are smaller than the standard angle (α_0), and then divide by the total number of angles, as follows:

$$W_i = \frac{1}{n}\sum_{j=1}^{n} z_{ij}, \text{ where } z_{ij} = \begin{cases} 1, & \alpha_{ij} < \alpha_0 \\ 0, & \text{otherwise} \end{cases} \text{ and } 0 \le W_i \le 1$$

When the value of W_i approaches zero, neighboring trees tend to be distributed more regularly around the reference tree. Conversely, when W_i approaches one, the distribution pattern tends to be clumped. In past studies, the standard angle, describing a situation where all *n* neighboring trees are distributed regularly around the reference tree, has been considered to be $\alpha_0 = \frac{360^0}{n}$. However, Hui & Gadow (2002) proposed that this situation is rare in nature and not all angles would larger than $\alpha_0 = \frac{360^0}{n}$ in an *n*-tree structure unit. Therefore, the standard angle should be smaller than this value. In this study, we propose that the standard angle should be $\alpha_0 = \frac{360^0}{n+1}$, consistent with Hui *et al.* (2007) and Pommerening & Stoyan (2006).

The range of *W* under a condition of complete spatial randomness (CSR) is the principle for the assessment of distribution patterns of trees in a forest. The value of *W* under CSR is larger than that seen with regular patterns, and smaller than that seen with aggregated patterns. Consequently, one can easily assess spatial patterns when the thresholds of *W* under CSR and *W* of investigated stands are known. Similar to the method that Hui & Gadow (2003) used to identify the range of W_{CSR}, we generated 1000 stands with random distribution patterns and calculated the average value ($\overline{W}_{CSR}$) and standard deviation (σ) of W_{CSR}; thus, the thresholds of W_{CSR} is $\overline{W}_{CSR} \pm 3\sigma$.

Species mingling

Mingling (M_i) is used to express the segregation of species in multi-species forests and is defined as the proportion of *n* nearest neighbors that are of different species than the reference tree (Gadow *et al.*, 2012). It is defined as follows:

$$M_i = \frac{1}{n}\sum_{j=1}^{n} v_{ij},$$

where $v_{ij} = \begin{cases} 0, & \textit{neighbor j belongs to the same species as reference tree i} \\ 1, & \textit{otherwise} \end{cases}$ and $0 \le M_i \le 1$

To determine the mingling variable for a whole stand, we summed all M_i values and divided by the number of trees. The bigger the M_i, the more tree species are intermingled.

Diameter dominance

Dominance (U) was defined as the proportion of the *n* nearest neighbors that were smaller than the reference tree:

$$U_i = \frac{1}{n}\sum_{j=1}^{n} k_{ij},$$

with $k_{ij} = \begin{cases} 0, & \textit{if neighbor j is smaller} \text{ than reference tree } i \\ 1, & \textit{otherwise} \end{cases}$ and $0 \le U_i \le 1$

Large values of U_i indicate that a given reference tree is suppressed by large trees; for trees in the largest diameter size class we obtained values of U_i approaching or equal to zero. Generally, U_{sp} is used to reflect the dominance of a particular species and U_{dbh} denotes the dominance of a specific diameter size class.

Edge effects

The treatment of edge trees, those close to plot boundaries, can affect the estimation of indices that include neighbor effects because it is possible that the true nearest neighbors are just outside the study area (Pommerening & Stoyan, 2006). Therefore, we used a buffer zone as an edge-correction method in this study. Trees located in the buffer area were considered neighboring, but not reference, trees. The width of the buffer zone (e.g., d = 5 m) should be neither too small nor too large to avoid wasting tree data, and a larger buffer zone width is required as the number of neighboring trees (two to eight) increases. We used (n + 1 m) to determine the buffer zone width.

Generating stands with different types of spatial structures

The simulated stands patterns and characteristics were based on the existing forest types in multi-species uneven-aged forests of Northern China. Most of the nature or semi-nature forests in this region were protected by the state with seldom commercial harvests. This region has a typical monsoon climate with dry, windy springs and warm, wet summers. Compared to temperate forests in other parts of the world, the tree vegetation in this region shows high species diversity and complex spatial structure. The average tree density in these nature forests is approximately 1,000 trees per hectare.

Different spatial patterns of tree locations

To test the ability of the uniform angle index to assess the distribution patterns caused by different structure-unit sizes, we simulated 20 stands whose spatial patterns approached random distributions with the Winkelmass software (Hui *et al.*, 2007; Petritan *et al.*, 2012); 10 stands were formed with regular patterns and 10 were formed with aggregated patterns. Regular patterns were generated by setting the uniform variation to 80%, which is slightly more regular than complete spatial randomness. The aggregated patterns were generated by setting 500 cluster numbers in 1-ha stands with 1000 trees. The aggregated patterns were slightly more clustered than complete spatial randomness. The pair correlation function, *g(r)*, is considered the most informative second-order summary characteristic (Illian et al., 2008). We used pair correlation function for the patterns of generated stands as a criterion of assessment of spatial distribution patterns at certain scales (Figure 1). There was some regularity (Figure 1a) or clustering (Figure 1b), compared to complete spatial randomness, at 2–6 m in the two different patterns.

Different spatial interspersion of tree species

We simulated three types of species spatial interspersion patterns 1000 times in an area with density of 1,000 trees per hectare, and calculated the average mingling index: (1) complete spatial randomness pattern for tree locations and 10 randomly assigned species; (2) random distribution of tree locations in a stand and the trees located in the

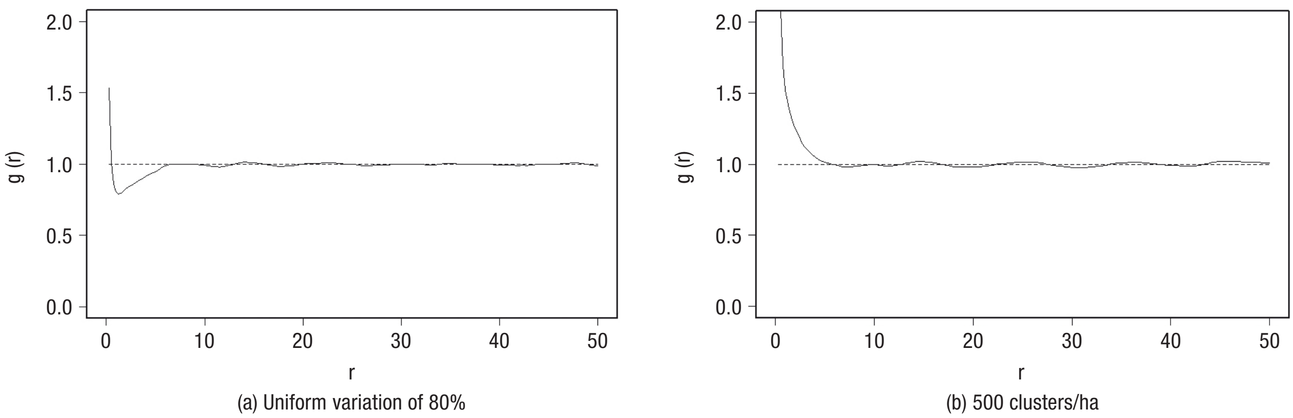

Figure 1. Schematic shapes of pair correlation functions for patterns of two kinds of generated stands (solid line) and a Possion process (dashed line). Values of *g(r)* lager than 1 indicate clustering, and conversely, values of *g(r)* smaller than 1 indicate regular patterns.

buffer zone were assigned to species 10. Then we divided the core area (60 × 60 m) into nine evenly sized cells (20 × 20 m), and assigned each cell one of the remaining species numbered one to nine; thus, trees of the same species located in the core area were aggregated in a cell; (3) random distribution of tree locations, and trees of the same species were mutually exclusive (the distance between two trees of the same species was at least 3 m).

Different spatial interspersion of tree size

Tree locations were distributed randomly within the stand as a whole. We generated trees with diameters of 0–45 cm and evenly divided these into nine size classes that contained approximately the same numbers of trees. Then we simulated four types of spatial-interspersion patterns for the diameter classes. A summary of this process follows.

(1) All generated diameters were randomly assigned to tree locations.

(2) Trees with diameters of 0–5 cm (smallest class) and 40–45 cm (largest class) were respectively placed in the central cell of the plot, and trees in all other size classes were randomly distributed in other cells; thus, each of the nine size classes occupied a 20 × 20-m cell.

(3) Trees with diameters of 0–5 cm were mutually exclusive and all other trees were randomly distributed in the plot. The distance between an arbitrary two trees of the smallest size class was at least 3 m.

(4) Trees in the middle size class (20–25 cm) in the central cell of the plot, and the remaining classes were distributed according to the following three spatial interspersion types: (a) smaller classes (0-20 cm) were distributed in the four cells nearest to the central cell, and larger classes (25-45 cm) were distributed in the four cells farthest from the central cell (Figure 2 left), (b) larger classes were distributed in the four cells nearest to the central cell, and smaller classes were distributed in the four cells farthest from the central cell (Figure 2 middle), and (c) each of the smaller and larger classes were distributed in the four cells nearest to the central cell, so smaller and larger trees were equally distributed around the central cell (Figure 2 right). This was performed 1000 times for each of the simulated spatial interspersion patterns of tree size.

Results

The influence of different structure-unit sizes on the uniform angle index

We calculated the uniform angle indices of the 1000 generated stands under CSR, and found that $\overline{W}_{CSR}$ varied with an increasing number of neighbors and that

Large	**Small**	Large
Small	20-25 cm	**Small**
Large	**Small**	Large

Small	**Large**	Small
Large	20-25 cm	**Large**
Small	**Large**	Small

Small	**Small**	Large
Large	20-25 cm	**Large**
Large	**Small**	Small

Figure 2. Three spatial interspersion patterns of smaller (0-20 cm) and larger trees (25-45 cm).

the overall trend had a decreasing-increasing shape (Figure 3). $\bar{W}_{CSR}$ reached its maximum, 0.667, in the two-tree structure unit and it approached 0.5 when three or four neighbors were selected. When the number of neighbors was five to eight, $\bar{W}_{CSR}$ increased with an increasing number of neighboring trees. $_{CSR}$ reached 0.562 in the case of $n = 8$. The standard deviation (σ) of $\bar{W}_{CSR}$ also varied with n. When fewer neighboring trees were selected, i.e., two or three, σ was very large, being 0.018 and 0.011 for $n = 2$ and $n = 3$, respectively. However, it remained stable at ~0.007, when four or more neighboring trees were selected. The threshold of $\bar{W}_{CSR}$ in different structure units is shown in Table 1, determined using $\bar{W}_{CSR} \pm 3\sigma$.

Because σ was very large for $n = 2$ and $n = 3$, we may have misjudged non-random distribution patterns that were very close to random. Therefore, we tested whether it was possible to assess these distribution patterns. Pair correlation functions for the generated stands in Section 2.3.1 showed that these were non-random patterns at small scales. We recorded the number of stands that were misjudged with respect to distribution patterns in 10 regular and 10 aggregated spatial patterns. For the 10 stands with regular patterns, 8 and 3 stands were misjudged for $n = 2$ and $n = 3$, respectively, and no errors were found for other values of n. For stands with aggregated patterns, all stands were assessed incorrectly for the two-tree structure unit, but we detected no errors for structure units with more than two neighboring trees.

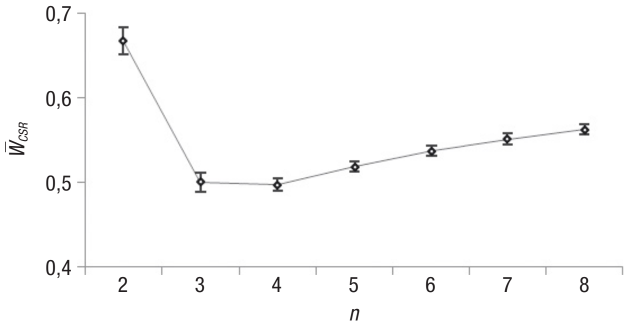

Figure 3. Schematic shape of means of uniform angle indices under CSR ($\bar{W}_{CSR}$) and standard deviation (σ) with different sizes of structure unit.

Figure 4 illustrates the probability distribution of uniform angle indices under CSR for three and eight neighboring trees (spatial patterns were generated 1000 times). The probability distribution of eight neighboring trees is more detailed than that of three because there are more probabilities of uniform angle indices for the former. The probabilities of $W = 0$ or $W = 1$ are very close to zero for $n = 8$, as there are few situations in which all angles are smaller or larger than the standard angle when many angles exist in a structure unit.

Influence of different structure unit sizes on mingling and dominance

When species were distributed randomly within the stand, we found no relationship between the mingling index and the size of the structure unit (Figure 5a). The mingling value remained stable at 0.9 regardless of the number of neighboring trees. When individuals of the same species were aggregated, values of mingling were less than those of random patterns and increased with an increasing number of neighboring trees (Figure 5b). We found a high linear correlation between n and mingling, where the coefficient of determination was 0.992. The lowest value of mingling for $n = 2$ was 0.11 and the largest for $n = 8$ was 0.19, the difference between them being 0.08. When the same species were mutually exclusive, namely, when trees of the same species were distributed regularly within the stand, mingling values were larger than those of random patterns and decreased with an increasing number of neighboring trees (Figure 5c), contrary to the trend for aggregated patterns. The difference between the largest and smallest values was 0.05.

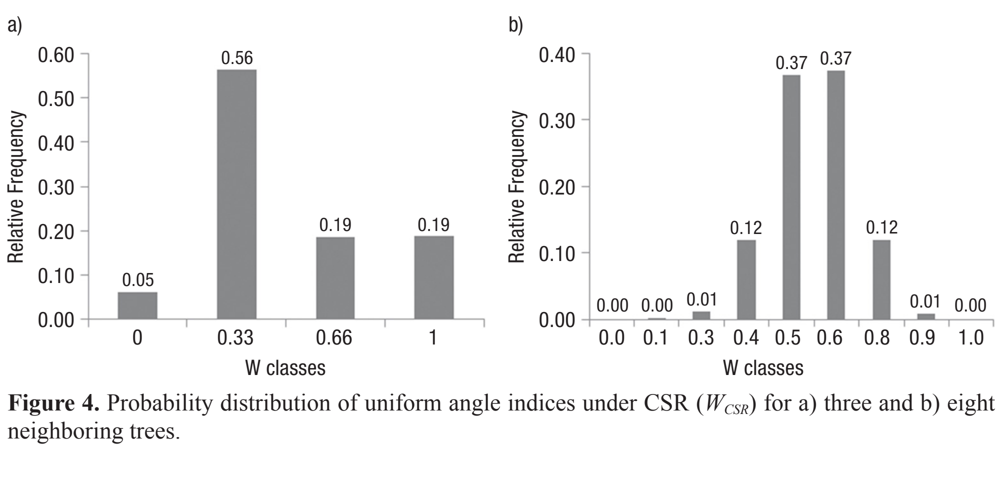

Figure 4. Probability distribution of uniform angle indices under CSR (W_{CSR}) for a) three and b) eight neighboring trees.

Table 1. Means of uniform angle indices under complete spatial randomness ($\bar{W}_{CSR}$), standard deviation (σ), and the thresholds of W_{CSR} for different sizes of structure unit.

n	2	3	4	5	6	7	8
$\bar{W}_{CSR}$	0.667	0.500	0.497	0.518	0.537	0.551	0.562
σ	0.016	0.011	0.007	0.006	0.006	0.007	0.006
$\bar{W}_{CSR} - 3\sigma$	0.613	0.466	0.475	0.500	0.518	0.531	0.542
$\bar{W}_{CSR} + 3\sigma$	0.721	0.534	0.517	0.536	0.556	0.571	0.581

Similar to random patterns of species, values of dominance remained stable for the three diameter classes when tree diameters were randomly interspersed within the stand. Dominance values were 0.95, 0.5, and 0.05 for the smallest, middle, and largest classes, respectively (Figure 6a, d, f). The three diameter classes occurred as suppressed, intermediate, and dominant trees.

When trees with diameters of 0–5 cm were aggregated, dominance values were smaller than those of random patterns and increased with an increasing number of neighboring trees (Figure 6b); thus, the pressure from neighboring trees increased accordingly. The difference between the largest value for n = 8 and the smallest value for n = 2 was 0.04. Conversely, when trees of the smallest diameter class were mutually exclusive or were distributed regularly within the stand, dominance values decreased slowly with an increasing number of neighboring trees (Figure 6c).

When trees of the largest diameter class (40–45 cm) were aggregated, dominance values were smaller than those of random patterns and decreased from 0.447 to 0.404 with an increasing number of neighboring trees (Figure 6e); thus, the pressure from neighboring trees decreased accordingly. The difference between the largest value for n = 2 and the smallest value for n = 8 was 0.05.

We observed three spatial interspersion types when trees with diameters in the middle class were aggregated in the core area of the stand (Figure 2). The manner in which dominance varied differed. When trees in the middle diameter class had more small trees around them, their dominance values decreased with increasing n; however, their dominance values increased with n when they were surrounded by more large trees. Dominance values remained stable at ~0.5 when there were equal numbers of small and large trees distributed around trees in the middle diameter class (Figure 6g).

We concluded that changes in mingling values or dominance indices caused by variation in the number of neighboring trees depended on the spatial interspersion patterns of tree species or size.

Discussion

Many approaches have been used to characterize forest structure and structure parameters (Gadow *et al.*, 2012), but those based on relationships between nearest-neighbor tree groups are the effective and less expensive, since these set of parameters can be acquired simply by point sampling method without knowing the mapped data of forest and they are easy to calculate and interpret (Aguirre *et al.*, 2003). The selection of appropriate number of neighbors determines reasonable estimation of spatial arrangement patterns and the amount of inventory work. Although the fixed number structure unit (e.g. four-tree structure unit) has been successfully applied in the structure attributes analysis, our results showed the neighborhood-based structure analyses can be influenced by the structure unit size. For the estimation of the patterns of tree locations, we found that selecting different numbers of neighboring trees strongly influenced the uniform angle index. Its

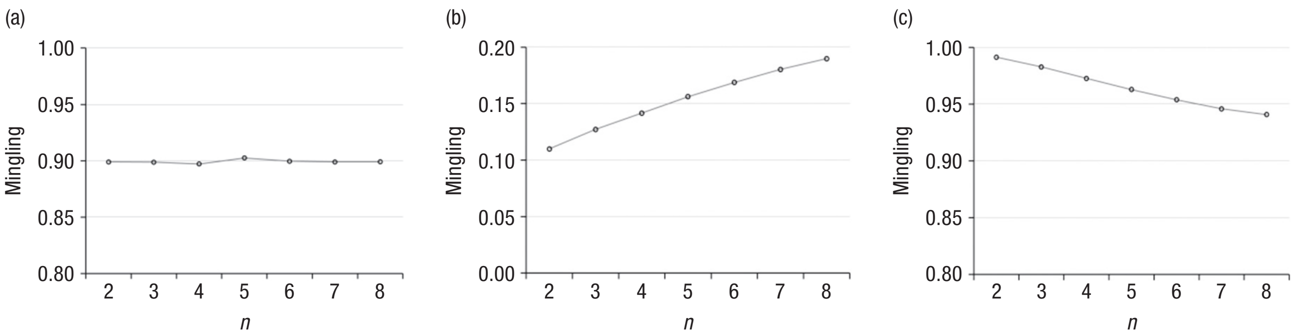

Figure 5. Variation in mingling values with an increasing number of neighboring trees when (*a*) random distribution of species, (b) clumped distribution of similar species and (c) regular distribution of similar species.

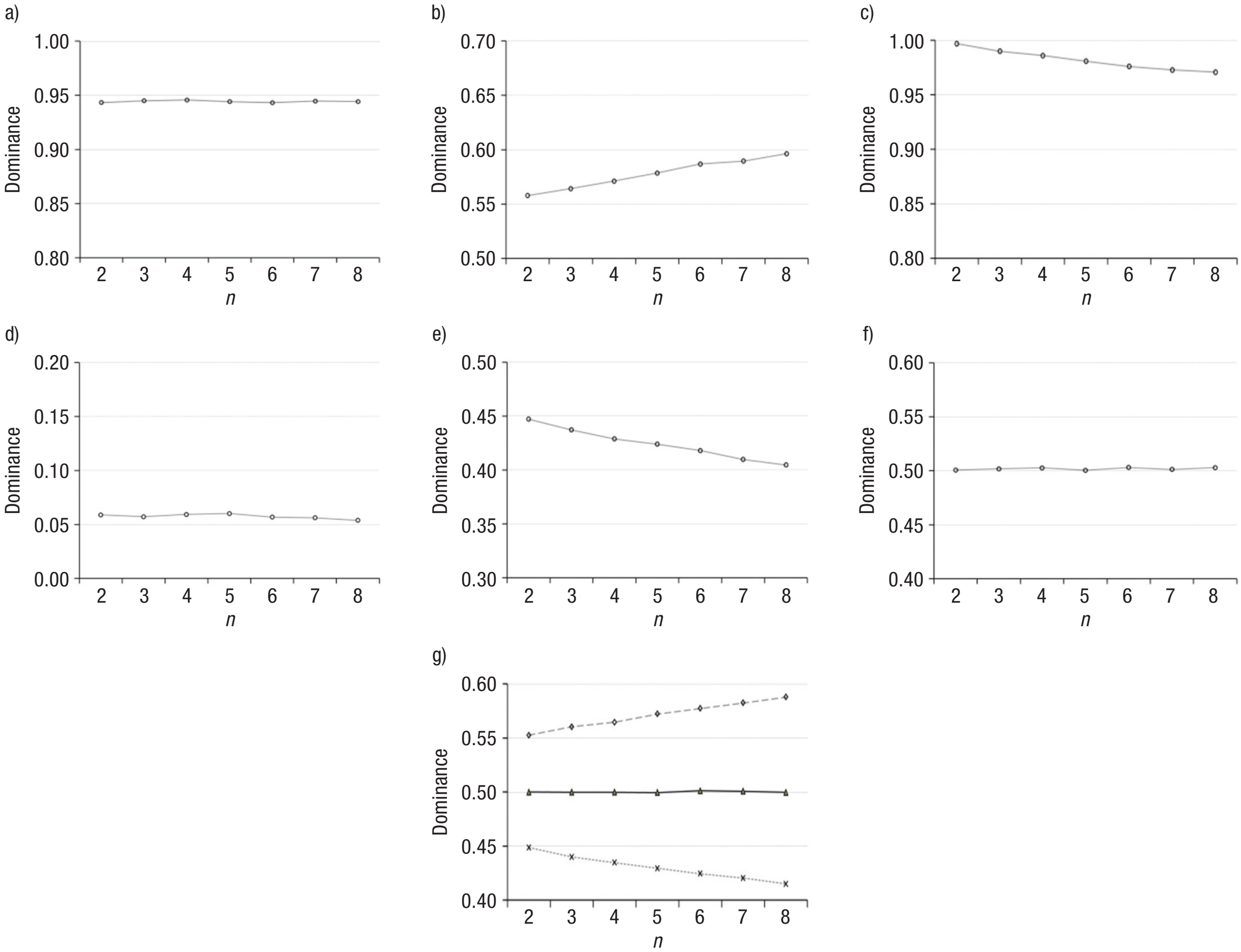

Figure 6. Variation in dominance values with an increasing number of neighboring trees. (*a*), (d) and (f) shows random dispersal of dbh 0-5cm, 40-45cm and 20-25cm, respectively. (b) and (e) shows clumped dispersal of dbh 0-5cm and 40-45cm. (c) regular dispersal of dbh 0-5cm. (g) clumped dispersal of dbh 20-25cm when more large trees (dashed line), more small trees (dotted line) and equal numbers of small and large trees(solid line) distribute around them.

values obtained from different sizes of structure units under complete spatial randomness differed and were not always ~0.5. The uniform angle index can be calculated only with a fixed number of neighboring trees in the same stand. For example, the average value of the uniform angle index under CSR would be ~0.5 when three neighboring trees are selected, but would increase to 0.56 when eight neighboring trees are selected, indicating similar conclusions even with different values. However, some studies (Zhao *et al.*, 2010; Liu, 2011; Hao *et al.*, 2012; Li, 2012; Wu, 2012; Pastorella & Paletto, 2013) used other methods which were different from fixed four-tree unit, e.g., Voronoi tessellations or fixed radii, to calculate the arithmetic mean of uniform angle index of a stand and their results were unreliable due to erroneous application of assessment criterion. Our results indicated that one should carefully define the number of neighbors and standard angle when using uniform angle index to assess trees spatial distribution patterns. Our results concerning the thresholds of uniform angel index under complete spatial randomness in different structure units also provided evidence to apply it with other numbers of neighbors instead of four neighbors.

Several studies showed that appropriate selection of potential neighboring competitors of a subject tree depended on the radius of influence zone (Pukkala & Kolström, 1987) and different selection approaches (Aakala *et al.*, 2013; Maleki *et al.*, 2015) have been used among competition indices. However, our results showed that the influence of structure unit size on mingling and dominance structural indices depended on tree species and size spatial arrangement patterns to a great extent. Thus, these methods which are suitable for competition analysis may not have advantages in neighborhood-based structure analysis. The mingling and dominance values remain stable regardless of varying number of neighboring trees under complete randomly distribution of tree species and size. Generally, however, this situation seldom occurs under nature conditions. The dispersion of a tree species always is relation to others (Graz, 2004) and the spatial correlation between tree sizes was detected with negative autocorrelation between neighboring individuals (Suzuki *et al.*, 2008; Pommerening & Särkkä, 2013). The changes in mingling or dominance values caused by the variation in structure unit size indicated that an arbitrarily defined number of neighbors, selected for neighborhood-based spatial structure analyses, only focuses on a certain scale, and it can not recognize the range of spatial correlation at non-random distribution patterns. If one is interested in the spatial scales and correlations or interactions ranges between trees (e.g., the range of aggregation of species) the second-order characteristics are preferred (Barbeito *et al.*, 2009; Suzuki *et al.*, 2008; Pommerening *et al.*, 2011)

Second-order characteristics provides more detailed information of forest structure characteristics when mapped data from large observation windows are available, however, exhaustive measurement of trees positions is time consuming and costly, especially in steep and dense natural forests, and its calculation process is complicated (Illian *et al.*, 2008). Thus, nearest neighbor statistics analysis still is preferred in practical forest inventory. The ideal structure unit size should be a compromise between accuracy and cost. We found that we may have biased assessment of distribution patterns of trees locations with respect to non-random patterns that were very close to random distribution patterns when two or three neighboring trees were used. While these random or close to random distribution patterns are common to see in nature forests (Szwagrzyk & Czerwczak, 1993; Petritan *et al.*, 2012; Dong *et al.*, 2014), the estimation with small structure unit sizes should be used carefully. Finally, we proposed that when one is interested in both performance and cost, a four-tree structure unit performs best for assessing tree distribution patterns, depicting species segregation, and reflecting dominance, while still being cost effective.

References

Aakala T, Fraver S, D'Amato AW, Palik BJ, 2013. Influence of competition and age on tree growth in structurally complex old-growth forests in northern Minnesota, USA. For Ecol Manag 308: 128-135.

Aguirre O, Hui G, Gadow Kv, Jiménez J, 2003. An analysis of spatial forest structure using neighbourhood-based variables. For Ecol Manag 183: 137-145.

Barbeito I, Fortin MJ, Montes F, Canellas I, 2009. Response of pine natural regeneration to small-scale spatial variation in a managed Mediterranean mountain forest. Appl Veg Sci 12: 488-503. http://dx.doi.org/10.1111/j.1654-109X.2009.01043.x

Bettinger P, Tang M, 2015. Tree-Level harvest optimization for structure-based forest management based on the species mingling index. Forests 6: 1121-1144. http://dx.doi.org/10.3390/f6041121

Dong L, Liu Z, Li F, Jiang L, 2014. Quantitative analysis of forest spatial structure and optimal species composition for the main forest types in Daxing'anling, Northeast China. Forest Research 27: 734-740.

Gadow Kv, Hui G, 1999. Modeling forest development. Kluwer academic publishers, Netherlands. http://dx.doi.org/10.1007/978-94-011-4816-0

Gadow Kv, Zhang CY, Wehenkel C, Pommerening A, Corral-Rivas J, Korol M, Myklush S, Hui GY, Kiviste A, Zhao XH, 2012. Forest structure and diversity. In: Pukkala T, Gadow Kv. (Eds.), Continuous Cover Forestry, Book Series Managing Forest Ecosystems. Springer Science+Business Media B.V., 29–84 pp. http://dx.doi.org/10.1007/978-94-007-2202-6_2

Gao G, Ding G, Wang H, Zang Y, Liang W, An Y, He Y, 2013. Short Communication. Restoring monoculture plantation using stand spatial structure analysis. Forest Syst 22: 147-151. http://dx.doi.org/10.5424/fs/2013221-03294

Graz FP, 2004. The behavior of the species mingling index Msp in relation to species dominance and dispersion. Eur J Forest Res 123: 87–92. http://dx.doi.org/10.1007/s10342-004-0016-8

Graz FP, 2006. Spatial diversity of dry savanna woodlands: assessing the spatial diversity of a dry savanna woodland stand in northern Namibia using neighborhood-based measures. Biodivers Conserv 15:1143–1157. http://dx.doi.org/10.1007/s10531-004-3105-6

Graz FP, 2008. The behaviour of the measure of surround in relation to the diameter and spatial structure of a forest stand. Eur J Forest Res 127:165–171. http://dx.doi.org/10.1007/s10342-007-0193-3

Hao YL, Zhang HR, Tang SZ, 2012. Determination method of cutting tree based on forest stand spatial structure optimization. Journal of Northwest Forestry University 27:163-168.

Hui GY, Gadow KV, 2002. Das Winkelmass-Theoretische Überlegungen zum optimalen Standardwinkel. Allg F U J Ztg 41: 173–177.

Hui GY, Gadow KV, 2003. Quantitative Analysis of Forest Spatial Structure. Science and Technology Press, Beijing, 16–18 pp.

Hui GY, Li L, Zhao ZH, Dang PX, 2007. The comparison of methods in analysis of the tree spatial distribution pattern. Acta Ecologica Sinica 27: 4717-4728. http://dx.doi.org/10.1016/S1872-2032(08)60008-6

Illian J, Penttinen A, Stoyan H, Stoyan D, 2008. Statistical Analysis and Modelling of Spatial Point Patterns. John Wiley, England. 218 pp.

Kint V, Meirvenne MV, Nachtergale L, Geudens G, Lust N, 2003. Spatial methods for quantifying forest stand structure development: a comparison between nearest neighbor indices and variogram analysis. For Sci 49:36–49.

Latham PA, Zuuring HR, Coble DW, 1998. A method for quantifying vertical forest structure. For Ecol Manag 104: 157–170.

Lei XD, Tang SZ, 2002. Indicators on Structural diversity within stand: a review. Scientia Silvae Sin 38:140—146.

Li J, 2012. Study on structural characteristics and growth model of typical stand types in Southern collective forest. Dissertation. Central South University of Forestry and Technology, Changsha.

Li Y, Hui G, Zhao Z, Hu Y, 2012. The bivariate distribution characteristics of spatial structure in natural Korean pine broad-leaved forest. J Veg Sci 23: 1180-1190. http://dx.doi.org/10.1111/j.1654-1103.2012.01431.x

Liu YJ, 2011. Study of forest stand spatial structure and competition based on three-dimensional simulation technique. Dissertation. Beijing Forestry University, Beijing.

Maleki K, Kiviste A, Korjus H, 2015. Analysis of individual tree competition effect on diameter growth of silver birch in Estonia. Forest Syst 24: e023. http://dx.doi.org/10.5424/fs/2015242-05742

Pastorella F, Paletto A, 2013. Stand structure indices as tools to support forest management: an application in Trentino forests (Italy). J For Sci 59:159-168.

Petritan AM, Biris IA, Merce O, Turcu D, Petritan IC, 2012. Structure and diversity of a natural temperate sessile oak (Quercus petraeaL.)-European Beech (Fagus sylvaticaL.). For Ecol Manag 280:140–149.

Pommerening A, 2008. Analysing and modelling spatial woodland structure. Doctoral thesis. University of Natural Resources and Applied Life Sciences, Vienna.

Pommerening A, Stoyan D, 2006. Edge correction needs in estimating indices of spatial forest structure. Can J For Res 36: 1723-1739. http://dx.doi.org/10.1139/x06-060

Pommerening A, Gonçalves AC, Rodríguez-Soalleiro R, 2011. Species mingling and diameter differentiation as second-order characteristics. Allg F U J Ztg 182: 115-129.

Pommerening A, Särkkä A, 2013. What mark variograms tell about spatial plant interactions. Ecol Model 251: 64-72. http://dx.doi.org/10.1016/j.ecolmodel.2012.12.009

Pukkala T, Kolström T, 1987. Competition indices and the prediction of radial growth in Scots pine. Silva Fenn 21: 55-76. http://dx.doi.org/10.14214/sf.a15463

Spies TA, 1998. Forest structure: a key to the ecosystem. Northwest Sci 72: 34–36.

Stamatellos G, Panourgias G, 2005. Simulating spatial distributions of forest trees by using data from fixed area plots. Forestry 78:305-312. http://dx.doi.org/10.1093/forestry/cpi028

Suzuki SN, Kachi N, Suzuki JI, 2008. Development of a local size-hierarchy causes regular spacing of trees in an even-aged Abies forest: analyses using spatial autocorrelation and the mark correlation function. Ann Bot 102: 435–441. http://dx.doi.org/10.1093/aob/mcn113

Szmyt J, 2014. Spatial statistics in ecological analysis: from indices to functions. Silva Fenn 48: 1008. http://dx.doi.org/10.14214/sf.1008

Szwagrzyk J, Czerwczak M, 1993. Spatial patterns of trees in natural forests of East-Central Europe. J Veg Sci 4: 469-476. http://dx.doi.org/10.2307/3236074

Wang D, Tang S, Chiu C, 2006. Impact four years after thinning on the growth and stand structure of Taiwania plantation in the Liukuei experimental forest. Taiwan J For Sci 21: 339–351.

Wu A, 2012. Analyzing and optimizing forest stand spatial structure based on high-resolution remote sensing image. Dissertation. Beijing Forestry University, Beijing.

Zhang C, Zhao X, Gadow Kv, 2014. Analyzing selective harvest events in three large forest observational studies in North Eastern China. For Ecol Manag 316: 100-109.

Zhao C, Li J, Li J, 2010. Quantitative analysis of forest stand spatial structure based on Voronoi Diagram & Delaunay Triangulated Network. Scientia Silvae Sin 46: 78-84.