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Applying fractal analysis to stem distribution maps

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ABSTRACT

The position and size of trees is basic information available for most forest-research sites. Based on such information, various stand structural indices and measures can be calculated that describe the two-dimensional or three-dimensional forest structure.

We used fractal analysis to calculate the box-dimension (D_b) as a measure of structural complexity that can be derived from stem positions and stem diameters. D_b is supposed to combine information on tree size, tree distribution and stem density in a single meaningful measure. We wanted to know how powerful the method is if applied to two-dimensional stem distribution maps. Based on 125 research plots (coniferous, deciduous and mixed stands) we found that across typical forest systems in Germany there is no benefit from using the box-dimension. Stem number and mean tree diameter determined D_b values and there was almost no sensitivity observed for existing differences in stem distribution pattern. We conclude that D_b is a measure of stand density but, for the investigated forests, it does not provide information on tree distribution pattern if applied to the stem base maps.

1. Introduction

Many ecosystem functions and services, such as ecosystem health status, economic value, carbon storage or biodiversity are related to the spatial structure of the forest (e.g. Roberge et al., 2017; Li et al., 2017; Zhang et al., 2017; Puettmann et al., 2012; Gossner et al., 2014). Measuring forest structure in a direct and holistic manner is an extremely difficult, laborious and expensive task with conventional methods (e.g. Seidel et al., 2011). For this reason, past research often focused on identifying indices or measures that are based on easy to measure single tree attributes like size and position, which can be used as surrogates for 'forest structure'. For example, it was shown that the point distribution pattern of stem locations along with the height information of each tree could be used as a measure of structural heterogeneity of a stand (cf. SCI-Index by Zenner and Hibbs, 2000). Other indices addressed size pattern of trees, like Füldner's tree size differentiation index (Füldner, 1995), or distribution pattern, like Clark-Evans' Index of aggregation (Clark and Evans, 1954). However, such indices have limitations. For example, the SCI, as well as its improved pendant ESCI (enhanced structural complexity index; Beckschäfer et al., 2013), cannot be calculated for a defined area (like an inventory plot), but only for an area enclosed by the trees' positions. The Clark-Evans' index, requires an edge correction (Donnelly, 1978; Pommerening and Stoyan, 2006) to create solid results and it does not consider tree sizes. Furthermore, it compares the observed distribution of tree stem positions with that of randomly positioned trees. In this simulated "random" forest, trees can be placed unrealistically close next to one another. Additionally, different random simulations naturally result in different outcomes. This hampers a straightforward comparison of results from different studies.

Most indices use the number of trees and their positions (x-y-coordinate) and/or a proxy for the individuals' dimensions (usually diameter at breast height or tree height). These three characteristics are in the focus as they provide information on (i) *how many* objects are present, giving a density estimation, and (ii) *how are they distributed* in space, providing a proxy for forest structure.

If both, density and distribution of objects are to be addressed, fractal analysis (Mandelbrot, 1977), so far rarely used in forest research, may be a useful tool. Fractal analysis is a means for the combined analysis of object structures and spatial configurations of elements (Mandelbrot, 1977; Zeide and Pfeifer, 1991; Kaye, 1994; Jonckheere et al., 2006).

In this study, we used the box-dimension (D_b) from fractal analysis to investigate its potential to address tree size, tree number, and two-dimensional tree distribution pattern at once. We compared the information gained from D_b with modelling approaches using conventional measures of tree size and tree distribution.

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2. Materials and methods

2.1. Study sites and data

We used data from 125 forest research plots of the Biodiversity Exploratories (Fischer et al., 2010, www.biodiversity-exploratories.de) that are located in three major geographic regions across Germany: the Hainich, the Swabian Alb and the Schorfheide-Chorin. Each plot was 100 by 100 m in extent (1 ha). Within the Biodiversity Exploratories, a full inventory of all trees greater than 7 cm in diameter at breast height (DBH) was conducted on all plots between 2014 and 2016. In total, we used the position (xy-coordinate) and DBH-information of more than 61.000 trees, with 493 trees per plot on average (standard deviation: ± 383 trees). The investigated plots represent forests from varying developmental phases, management regimes, ages, main tree species and tree species richness. Details on the plots can be found in Ehbrecht et al. (2017).

We calculated the number of stems per plot N (stems ha^{-1}), the arithmetic mean of the DBH d (cm), the basal area G ($m^2 ha^{-1}$) and the Clark-Evans' index of aggregation CE (Clark and Evans, 1954) for each plot based on the inventory data.

2.2. Drawing stem-base maps

Using Mathematica® (Wolfram Research, Champaign, USA), we drew a stem-base map for each study plot based on the xy-coordinates of each tree located in the plot and its corresponding DBH (see Fig. 1). Tree stem cross-sections were drawn as filled black circles according to scale. Each map was saved as tif-file with a fixed extent of 1000 by 1000 pixels (2 m buffer on all sites) with white background color and a resolution of 100 dpi.

2.3. Calculating the box-dimension of stem distribution maps

The box-dimension (D_b) is considered a holistic measure of structural complexity and can be used to estimate the fractal dimension of objects (Mandelbrot, 1977). Several studies presented its application to images (e.g. Sarkar and Chaudhuri, 1994; Carlin, 2000) but, to our knowledge, it has not been applied to stem-base maps until today.

Based on a new routine written in Mathematica® D_b was calculated for the stem-base map of each plot. It was defined as the slope of the fitted straight line (least-square fit) through a plot of log(*N*) over log(1/*r*), with log() being the natural logarithm, and *N* being the number of squares of size *r* needed to enclose all black pixels in the image (Mandelbrot, 1977). Black pixels represent tree stem cross-sections and the size of the squares (*r*) was measured based on the edge-length of the squares. A visualization of the calculation of the box-dimension of an exemplary plot is presented in Fig. 1.

The regression line was fitted between the upper box-size cutoff (greatest edge-length), defined by the size of the study plots including the buffer zone (r = 104 m) and the lower box-size cutoff, defined as 1/128th of the upper cutoff (r = 0.8125 m edge length). Consequently, the used r-values for the calculation of the regression line were 104 m (1/1), 52 m (1/2), 26 m (1/4), 13 m (1/8), 6.5 m (1/16), 3.25 m (1/32), 1.625 m (1/64) and 0.8125 m (1/128). Smaller square sizes were computationally too costly. Furthermore, we argue that squares of the next subsequent step size would be hardly the size (0.40625 m) of the diameter of many of the trees in the plots.

2.4. Statistics

To analyze the relationship between D_b and tree number N, tree size d, tree stocking G, and two-dimensional tree distribution pattern CE we used linear additive modelling. Predictor variables were log-transformed – log(N), log(d), log(G), and log(CE + 1) – and also kept untransformed when appropriate (d, G, and CE). We used the "dredge" function of the R package "MuMIn" (Bartón, 2016) which generates a set of models with all possible combinations of predictor variables and weighted the models based on their Akaike information criteria for small samples sizes (AICc). In order to avoid overfitting, the number of predictor terms was restricted to three which resulted in 64 models. For all models with a $\Delta AICc < 4$ we assessed the relative importance of predictor variables using proportional marginal variance decomposition PMVD (see Grömping, 2006), which is the weighted average explained variance over orderings among predictors, and (squared) CAR scores (Zuber and Strimmer, 2011), which measure the correlations between the response and the Mahalanobis-decorrelated predictors (PMVD and CAR function of R package "relaimpo"). All analyses were performed using R (Vers. 3.4.0, R Core Team 2017).

3. Results

A significant positive relationship was found between the box-dimension (D_b) of the stem-base map and the number of stems log(N) (adj. $R^2 = 0.903$, Fig. 2A) while a strong negative-linear relationship was found between D_b and the mean diameter d (adj. $R^2 = 0.508$, Fig. 2B). For basal area G (Fig. 2C) and Clark-Evans' index of aggregation CE (Fig. 2D) no univariate effect on box-dimension was observed, even though the slope was significant for the basal area ($p = 0.002$).

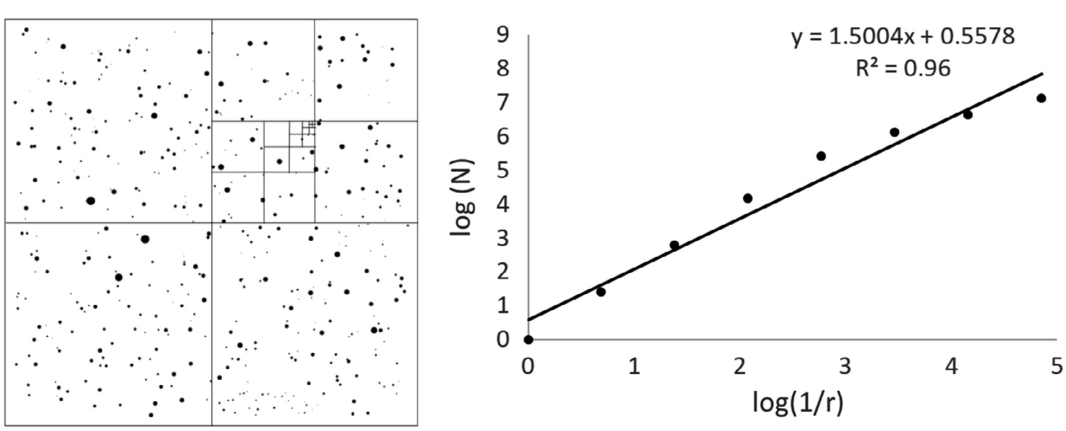

Fig. 1. (left): Stem-base map of an exemplary plot (HEW40; Hainich). Each tif-file covers an area of 104 by 104 m (100 plus two meter buffer on each side). The image was successively divided into subunits with half the edge-length of the previous image. For visibility reasons only the subdivisions of a selected area are shown. For each square size the number of squares one needs to cover all black pixels (tree stem cross-sections) was determined. Right: Exemplary scatter plot of log(N) over log(1/r) for the same plot (HEW40) as shown in the left. The slope of the regression line is 1.5004 and equals D_b of the image.