

# Gini coefficient predictions from airborne lidar remote sensing display the effect of management intensity on forest structure



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## ABSTRACT

In this study, two forest sites located in Finland were compared by means of predictions of Gini coefficient (GC) obtained from airborne laser scanning (ALS). We discuss the potential of the proposed method for identifying differences in structural complexity in relation with the management history of forests. The first study site (2200 ha), the Koli National Park (NP), includes areas where human intervention was restricted after 1907, in addition to forests which were protected only after the 1990s. The second study site in the municipality of Kiihtelysvaara (800 ha) has been under intensive management. These are commercial forests which include areas with different types of ownership: a large estate owned by an industrial company together with smaller private properties. We observed that GC predictions may be used to evaluate the effects of management practice on forest structure. Conservation and commercial forests showed significant differences, with the old-protected area of Koli having the highest, and the most intensively managed area in Kiihtelysvaara the lowest GC values. The effect of management history was revealed, as the 1990s' extensions of Koli NP were more similar to unprotected areas than to forests contained within the original borders of the 1907s' state property. Yet, their conservation status for almost two decades has been sufficient for developing significant differences against the outside of the NP. In Kiihtelysvaara, we found significant differences in GC according to the type of ownership. Moreover, the ALS predictions of GC also detected differences near lakeshores, which are driven by limitations on logging governed by Finnish law. Estimating this indicator with ALS remote sensing allowed to observe its spatial distribution and to detect peculiarities which would otherwise be unavailable from field plot sampling. Consequently, the method presented appears to be well suited for monitoring the effects of management practice, as well as verifying its compliance with legal restrictions.

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## 1. Introduction

### 1.1. The value of forest structure indicators

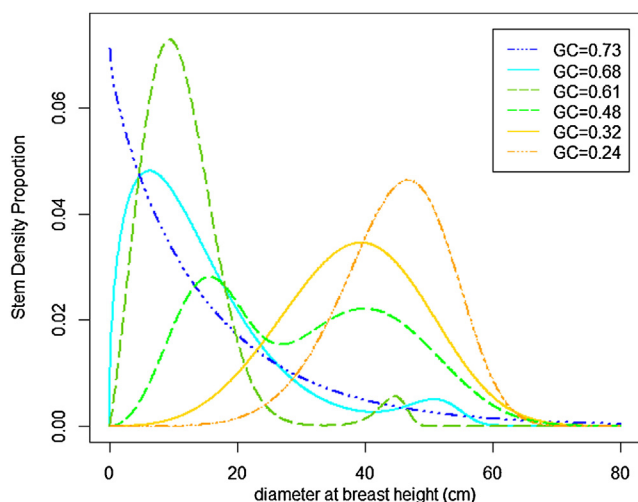
Structural properties of the canopy determine many ecological functions of forest habitats (Walz, 2008; Müller et al., 2014). Forest dynamics are characterized by changes in tree diameter distribution, either naturally (Knox et al., 1989; Oliver and Larson, 1996) or induced by silvicultural practice (Valbuena et al., 2013a). Forest management modifies natural successional stages (Utterer et al.,

1996), and thus the ecology of tree assemblages depends directly on management regimes (Cumming et al., 2000). Forest policy and land ownership may determine important changes in management history, and it can therefore be a crucial factor affecting structural properties of forests (Maltamo et al., 1997; Bergès et al., 2013). Concise indicators are needed for evaluating the effect of these factors on the structural properties of forests, and remote sensing can assist in the prediction of these indicators (Nagendra et al., 2013).

A basic summary of forest structural properties must include a measure of average or dominant tree size, plus another for relative density or canopy cover, and also a descriptor of variation in the distribution of tree sizes (Knox et al., 1989). The scope of this article is on the last one, and on practical applications of remote sensing-assisted predictions of a tree size inequality indicator: the Gini coefficient (GC). One of the components of forest structure is the distribution of tree diameters in a forest, whose properties

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**Fig. 1.** An illustration on the values of Gini coefficient (GC) for example diameter distributions of various shapes. Colours are coincident with those in Figs. 4 and 5. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

can be summarized by indicators of tree size variation (McElhinny et al., 2005). Information found in diameter distributions can be employed in assessing forest properties key to biodiversity, tree competition and succession (Brokaw and Lent, 1999). For this reason, concise indicators describing properties of diameter distributions can be useful for evaluating ecological assets, and for evaluating the effects of human activities on them (Rouvinen and Kuuluvainen, 2005). They can also be practical for promoting sustainable and efficient use of forest resources, since they can assist tree growth forecast computations or forest management optimization (Lixerød and Eid, 2006).

### 1.2. The Gini coefficient as a concise indicator for tree diameter distributions

Many types of approaches can be used for describing diameter distributions of forests (Maltamo and Gobakken, 2014): (1) probability distribution functions, such as Weibull (Bailey and Dell, 1973); (2) distribution-free methods, such as percentile descriptions (Borders et al., 1987); (3) imputation methods, such as nearest neighbour (Maltamo and Kangas, 1998); or (4) using indices of diameter differentiation (von Gadow et al., 2012: 52). The last of the approaches – i.e., (4) – has the advantage of providing a simple and concise indicator that can be used to rank forest types according to their structural complexity. Lixerød and Eid (2006) and Valbuena et al. (2012) compared the reliability of a variety of indicators describing forest structure, finding the GC as the most suitable option. The GC evaluates relations of relative dominance in forest assemblages (Weiner and Solbrig, 1984). It can thus be used for stratifying the forest area into homogeneous forest structural types (Fig. 1), according to the shape of their diameter distributions (Bollandsås and Næsset, 2007). These characteristics make it very valuable for the study of forest dynamics and successional stages (Knox et al., 1989; Valbuena et al., 2013a). For this reason, the GC can also be a good proxy for ecological properties related to biodiversity and habitat quality (Rouvinen and Kuuluvainen, 2005; Vihervaara et al., 2015).

The GC is a mathematical measure of inequality which is employed in a plethora of fields, though it was originally conceived in economics to assess the degree of equitability in the share of wealth among individuals in a society (Gini, 1921). Values of GC can be mapped for a wide range of variables, such as land use,

and the resulting cartography can be employed to evaluate heterogeneity at various spatial scales (Zheng et al., 2013). When applied to tree assemblages, GC quantifies the relative inequality in size among trees growing in proximity, i.e., competing for resources (Weiner, 1990). It can also be used to compare between-stand heterogeneity at landscape level, or changes over time (Lundqvist, 1994). Valbuena et al. (2012) found that GC outperforms other indicators of forest structure relating to tree size heterogeneity, due to the consistency of its underlying mathematical assumptions. Lixerød and Eid (2006) showed that the GC has the ability to reliably discriminate forest structural types and rank them in a logical order (Fig. 1). It has therefore been regarded as the most appropriate statistic summarizing tree diameter distributions, as Weiner and Solbrig (1984) argued on its independence of scale and sample size. Independence of scale in practice means that it allows to compare tree populations differing on their mean or dominant tree size (Valbuena et al., 2012), and changes in a same population over time (Weiner, 1990). Independence of sample size, in this case, signifies that forest with different stand density or canopy cover are comparable as well (Lixerød and Eid, 2006). The GC can be employed to interpret the composition of vertical strata in a forest through their basal area-weighted distributions (Valbuena et al., 2013a), as well as the relations of relative dominance among them (Weiner and Solbrig, 1984). Valbuena et al. (2012) proved that the value of GC=0.5 can be used to discriminate even-sized forests from uneven-sized ones. GC values below this threshold are obtained in forest areas with only one (or a very dominant) cohort – typically of close-to-normal distributions (Fig. 1). Values approaching GC=0.5 show more irregular structures, whereas values above it denote the majority of the basal area being located in the lower strata – typically of negative exponential or bimodal distributions (Fig. 1).

When GC is used to measure tree size inequality, the basal area occupied by individual trees is considered for its calculation (Bollandsås and Næsset, 2007; Valbuena et al., 2013b). Relative differences are expressed by dividing by the sample mean, so that GC ranges [0,1] and hence it is a statistic of concentration (relative dispersion), like the coefficient of variation (CV) (Weiner, 1990). However, while CV is calculated from conventional moments, the GC is equivalent to the L-coefficient of variation (L-CV; Valbuena et al., 2015) which is computed from L-moments instead (Hosking, 1990). L-moments have also been praised for being more robust (viz. insensitive to outliers) and efficient estimators (i.e., accurate and unbiased for small sample sizes) than conventional moments (Hosking, 1990). Also, while the CV is obtained from the standard deviation, which calculates the dispersion of tree basal areas around their average, L-CV and GC consider differences among individual tree pairs. Therefore, L-CV is more independent from their mean, and hence better suited for describing skewed distributions (Sankarasubramanian and Srinivasan, 1999), typical of uneven-sized forests (Fig. 1).

### 1.3. Remote sensing applied to mapping forest structure indicators

Airborne laser scanning (ALS) can be used to assess and monitor the structural complexity of forests on a large scale (Zellweger et al., 2013, 2014). Properties related to habitat heterogeneity may be studied with ALS, and employed for testing ecological hypotheses (Müller et al., 2014). The complexity of three-dimensional structure of ALS datasets must be simplified into concise indicators that can be used as a proxy for attributes related to habitat ecology and condition (Nagendra et al., 2013). Valbuena et al. (2013b) showed that different predictors derived from ALS are related to the GC and other indicators employed to describe tree diameter distributions. These indicators have been used to predict the spatial

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