Norwegian University of Life Sciences
Faculty of Environmental Science and Technology
Department of Ecology and Natural Resource Managment

Philosophiae Doctor (PhD)
Thesis 2014:09

On individual tree competition indices, airborne laser scanning, and plot edge bias

Om konkurranseindekser for enkelttrær, flybåren laserskanning og kanteffekter

Rune Østergaard Pedersen

On individual tree competition indices, airborne laser scanning, and plot edge bias

Om konkurranseindekser for enkelttrær, flybåren laserskanning og kanteffekter

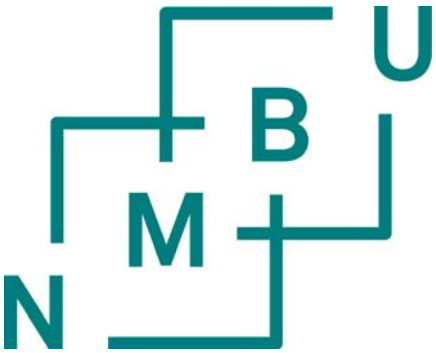
Philosophiae doctor (PhD) Thesis

Rune Østergaard Pedersen

Department of Ecology and Natural Resource Management

Norwegian University of Life Sciences

Ås 2014



Thesis number 2014:9
ISSN 1503-1667
ISBN 978-82-575-1189-0

PhD supervisors

Professor Erik Næsset (main supervisor)
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences
P.O. Box 5003, NO-1432 Ås Norway

Professor Terje Gobakken (co-supervisor)
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences
P.O. Box 5003, NO-1432 Ås Norway

Researcher Ole Martin Bollandsås (co-supervisor)
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences
P.O. Box 5003, NO-1432 Ås Norway

Evaluation committee

Professor Margarida Tomé
Instituto Superior Agronomia
Instituto Superior de Agronomia, Tapada da Ajuda, 1349-017 Lisboa, Portugal
E-mail: magatome@isa.utl.pt

Associate professor Phil Radtke
Department of Forest Resources and Environmental Conservation, Virginia Tech
Forest Res & Environ Cons (0324), 319E Cheatham Hall, Blacksburg, VA 24061, USA
E-mail: pradtke@vt.edu

UMBs committee coordinator

Associate professor Line Nybakken

Department of Ecology and Natural Resource Management

Norwegian University of Life Sciences

P.O. Box 5003, NO-1432 Ås Norway

E-mail: line.nybakken@nmbu.no

Preface

The present thesis is submitted in partial fulfillment of the PhD degree at the Norwegian University of Life Sciences Department of Ecology and Natural Resource Management, Norway. The project was initiated in 2010 under supervision of Professor Erik Næsset. Professor Terje Gobakken and Researcher Ole Martin Bollandsås served as co-supervisors.

I would like to thank the supervisor team for reading and commenting my manuscripts and synopsis, and in addition for giving me access to the data from Hedmark County, Østmarka Boreal Reserve and Aurskog-Høland municipality. This made it possible to write the thesis. Thanks also to Professor Ørjan Totland, Head of Department, for allowing me to change my topic and supervisor during my stay. A special thank to my very skilled, accurate field assistant and good friend Nenad Marjanovic. You are a very hard working person with a good heart. Thanks to Chief IT Adviser Peter Kellberg at Statistics Denmark for giving me a course in SAS®-macro programming many years ago, and for teaching me small tricks on how to do things. This was probably the solely most useful knowledge that I had before starting with my PhD studies. Thanks to Researcher Liviu Ene for encouragement during my stay and for pointing out that a paper can never be perfect, and to Dr. Lars Helge Frivold for still trying to perfect my synopsis. Thanks also to Dr. (with **Honors!**) Valeriya Tafintseva for your good mood and smile which makes everyone happy.

Ås January 1st, 2014

Contents

PREFACE ..... **III**

ABSTRACT ..... **VI**

DANSK SAMMENDRAG ..... **VIII**

LIST OF PAPERS ..... **X**

SYNOPSIS **1**

1. INTRODUCTION **3**

1.1. THE TERM COMPETITION 3

1.2. MEASURES OF STAND DENSITY 6

1.3. THE NEED FOR INDIVIDUAL TREE COMPETITION INDICES 7

1.4. TYPES OF INDIVIDUAL TREE CIS 8

1.5. OTHER MEASURES OF STAND STRUCTURE 13

1.6. AIRBORNE LASER SCANNING 13

1.7. SETTING AIRBORNE LASER SCANNING INTO THE CONTEXT OF COMPETITION 15

1.8. CONCEPTUAL FRAMEWORK 17

1.8.1. Step I – Field data 17

1.8.2. Step II – CI calculation 18

1.8.3. Step III – Plot edge bias correction 19

1.8.4. Step IV – Model evaluation and statistical inference 24

2. OBJECTIVES OF THE STUDIES **29**

3. STUDY AREAS AND MATERIALS **31**

3.1. HEDMARK COUNTY 31

3.2. AURSKOG-HØLAND MUNICIPALITY 32

3.3. ØSTMARKA BOREAL RESERVE 32

3.4. AIRBORNE LASER SCANNING DATA 34

4. PAPER I **35**

4.1. RESULTS AND DISCUSSION PAPER I 35

4.2. CONCLUSION PAPER I 39

4.3. Perspectives Paper I 41

5. PAPER II 43

5.1. Results and discussion Paper II 43

5.2. Conclusion Paper II 44

5.3. Perspectives Paper II 44

6. PAPER III 46

6.1. Results and discussion Paper III 46

6.2. Conclusion Paper III 54

6.3. Perspectives Paper III 55

7. PAPER IV 56

7.1. Results and discussion Paper IV 56

7.2. Conclusion Paper IV 57

7.3. Perspectives Paper IV 57

REFERENCES 58

ERRATA 69

PAPERS I-IV AND THEIR APPENDICES 70

Abstract

The thesis comprises an investigation of individual tree competition indices and their ability to predict individual tree growth at breast height in boreal forests located in Norway. The thesis consists of four papers referred to as Paper I-IV.

In Paper I a number of individual tree competition indices were derived from airborne laser scanning. A selection of existing individual tree competition indices were used as benchmarks, and tested against the derived competition indices in data from Østmarka Boreal Reserve. We tested the competition indices for their ability to predict diameter growth at breast height using various fixed search radii to identify competitors. The results show that competition indices based on airborne laser scanning perform as good as, and in some cases even better than existing spatially and non-spatially explicit competition indices, and that search radii beyond approximately 7 m do not increase index performance.

In **Paper II** we analyze the assumptions used in model evaluation of competition indices, more specifically statistical inference based on competition indices calculated from overlapping samples, using the permanent sample plots of the Norwegian National Forest Inventory located in Hedmark County. Our hypothesis was that sample overlap will cause spatial similarity which will lead to spatial autocorrelation. Competitors were isolated around each subject trees tree by means of a relascope or fixed sampling radius. Using statistical measures of dependence, we were able to show that spatial autocorrelation does not seem to increase the statistical type I error rate. Furthermore, the statistical type I error rate did not seem to correlate with measures of stand structure like the Gini-coefficient and Lorey´s mean height. A significant smoothing effect caused by sample overlap was observed by a decrease in the coefficient of variation of the samples for increasing search radii around the subject trees. However, the level of smoothing on the individual plot seems not to decrease the abilities of the competition indices to predict diameter growth at breast height of trees.

In **Paper III** I investigate how the components inverse distance and size-ratio in Hegyi´s distance weighted size-ratio behave in a spatially correlated field. I tested different kinds of standardization proposed in the literature to correct for increased spacing at different age-classes. A case study was made in Østmarka Boreal Reserve, which was supplemented by a spatial simulation study under different degrees of spatial autocorrelation and stand structure. A non-spatially explicit competition index was also included in the study. Calculations on the plot level in Østmarka Boreal Reserve of Moran´s *I* revealed that Hegyi´s competition index in most cases reduces the level of spatial autocorrelation, and statistical type I error in e.g. correlation tests, when compared to the level of spatial autocorrelation observed in diameter at breast height. By fractionizing Hegyi´s competition

index into the components inverse distance and size-ratio, I concluded that it is the size-ratio that decreases the positive spatial autocorrelation in the empirical data, especially for the highest levels of Moran´s *I* in diameter at breast height. For the simulation study this trend was not that clear and spatial autocorrelation also increased for the size-ratio for high mean values of the distribution of diameter at breast height. All tested competition indices seemed particular sensitive to the mean value of the distribution of diameter at breast height, and higher distribution mean values induce positive spatial autocorrelation. The simulated standard deviation of the distributions of diameter at breast height, and the spatial autocorrelation of trees seem to be of less importance. In the study I included local indicators of spatial association (LISA). The empirical data showed that LISA from Hegyi´s competition index was smaller for hotspots when compared to LISA of diameter at breast height (less positive spatial autocorrelation), which is a result of the size-ratio term in Hegyi´s competition index. A non-spatially explicit competition index seems to behave spatially more like diameter at breast height, thus preserving the spatial autocorrelation. An important idea derived from the study is that the best possible spatially explicit competition index to predict individual tree growth is a measure of local spatial autocorrelation of tree growth.

When trees outside the spatial range of the data area affect the trees inside this area, a border effect appears that leads to biased estimates of competition. This is known as plot edge bias. In **Paper IV** I present new methods for correcting plot edge bias using metrics derived from airborne laser scanning as auxiliary information in multivariate ratio estimators and regression models. Comparisons with existing methods based on simulation and linear expansion show, that the existing methods generally perform better than the ones based on airborne laser scanning. For all of the tested methods improvements in growth predictions measured by the adjusted coefficient of determination and AIC were small and only around one to two percent different from the original data. However, statistical tests showed that they were significant. In many cases plot edge bias correction did not improve predictions of individual tree growth, and the tested competition indices showed large variations in the effectiveness as predictors. It should be noted that some of the competition indices we derived in Paper I also eliminate plot edge bias, because a buffer of airborne laser data can be taken around the plot, and the physical positions of the competing trees need not to be known.

Keywords: Plot edge bias, individual tree competition indices, airborne laser scanning, statistical inference.

Dansk sammendrag

Denne afhandling indeholder en undersøgelse af konkurrenceindekser for enkeltræer og deres evne til at prædiktere individuel trævækst i brysthøjde i boreal norsk nåleskov. Afhandlingen består af fire videnskabelige artikler (refereres i dette danske sammendrag som Artikkel I-IV, ellers Paper I-IV).

I **Artikkel I** udledte og definerede vi en række individuelle konkurrenceindeks for enkeltræer fra flybåren laserskanning. Et udvalg af eksisterende individuelle konkurrenceindeks til enkelttræer blev anvendt som pejlemærker, som de udviklede konkurrenceindeks blev testet imod med materiale fra Østmarka Naturreservat. Vi evaluerede konkurrenceindeksene på deres evne til at prædiktere diameter vækst i brysthøjde, ved brug af faste søgeradier af variende afstand omkring subjekttræet til identifikation af konkurrenter. Resultaterne viser at konkurrenceindeks baseret på flybåren laserskanning prædikterer lige så godt og i nogle tilfælde bedre end eksisterende rumlige og ikke-rumlige konkurrenseindeks. Søgeradier mere end 7 m omkring subjekttræet forbedrer ikke indeksenes prædiktionsevner væsentligt.

I **Artikkel II** analyserede vi antagelserne, som bruges i model evaluering af konkurrenseindeks, mere specifikt statistisk inferens baseret på konkurrenseindeks, som er beregnet fra rumligt overlappende stikprøver. Analysen blev lavet med materiale fra den del af den norske Landsskogtakseringens prøveflader, der er lokaliseret i Hedmark Fylke. Vores hypotese var, at overlappende stikprøver vil forårsage rumlig lighed, hvilket vil lede til rumlig autokorrelation. Træernes konkurrenter blev isoleret med enten relaskop eller en fast søgeradius omkring træerne. Statistiske afhængighedsmål viste, at rumlig autokorrelation ikke øger den statistiske type I fejl . Ydermere, så korrelerer type I fejlen ikke med forskellige mål for bevoksningsstrukturen så som Gini-koefficienten og Lorey´s middelhøjde, hvilket betyder, at problemet heller ikke kan relateres til bestemte bevoksningstyper. Vi observerede en signifikant udglatningseffekt i form af en mindsket variationkoefficient i stikprøverne ved stigende søgeradius omkring træerne. Udglatningseffekten synes dog ikke at påvirke konkurrenceindeksenes evne til at prædiktere diameter vækst i brysthøjde hos træerne.

I **Artikkel III** undersøgte jeg, hvordan komponenterne invers distance og størrelsesratio i Hegyi´s afstandsvægtede indeks af størrelsesratier opfører sig i et rumligt korreleret felt. Forskellige måder foreslået i litteraturen til at korrigere for øget træafstand for forskellige aldersklasser blev også testet. Jeg lavede et empirisk studie i Østmarka Naturreservat, suppleret med et rumligt simuleringsstudie med forskellige niveauer af rumlig autokorrelation og bevoksningsstruktur. Et ikke-rumlig konkurrenceindeks blev også inkluderet i studiet. Beregninger af Moran´s *I* i Østmarka

Naturreservat afslørede at Hegyi´s konkurrenceindeks i mange tilfælde reducerer den rumlige autokorrelation, og dermed statistisk type I fejl i fx. korrelationstest, som blev observeret for brysthøjdediameter. Dette gælder specielt for de højeste niveauer of Moran´s *I*. Vha. en opdeling af Hegyi´s konkurrenceindeks i invers distance og størrelsesratio kunne det konkluderes, at det er størrelsesratioen som reducerer den rumlige autokorrelation i det empiriske data. Simuleringsstudiet viste ikke en nær så tydelig tendens, og for høje middelværdier af fordelingen af brysthøjdediameter, øges den rumlige autokorrelation også for størrelsesratioen. Alle testede konkurrenceindeks var meget følsomme overfor middelværdien af brysthøjdefordelingen, og højere simulerede fordelingsmiddelværdier øger den positive rumlige autokorrelation. Standardafvigelsen i fordelingen og den simulerede rumlige autokorrelation i brysthøjdediameteren synes at være af mindre betydning. Resultaterne synes ikke at ændre sig væsentlig ved korrektion for øget træafstand, dog giver en af korrektionsmetoderne (Pretzsch´s metode) en mindre positiv rumlig autokorrelation, og bedre evne til at korrelere med trævækst. Studier of lokale indikatorer på rumlig autockorrelation (forkortet som LISAer) i de empiriske data viste, at den positive rumlige autokorrelation (hotspot) vil være mindre i Hegyi´s konkurrenceindeks sammenlignet med brysthøjdediameter på grund af størrelsesratioen i Hegyi´s indeks. LISA af et ikke-rumligt konkurrenceindeks opførte sig mere som LISA af brysthøjdediameteren, og bevarede den lokale rumlige korrelation. En vigtig idé blev undfanget i studiet, nemlig at det bedst mulige rumlige konkurrenceindeks er et mål for rumlig autokorrelation af trævækst.

Når træer udenfor datasættets rumlige grænse påvirker træerne indenfor dette område, opstår en grænseeffekt. Dette kendes som kant-fejl (på engelsk plot edge bias). I **Artikkel IV** præsenterer jeg nye metoder til korrektion for kant-fejl ved brug af variable afledt fra flybåren laserskanning som hjælpeinformation i multivariate ratioestimatorer og regressionsmodeller. Hos alle de testede metoder var forbedringerne i vækstprediktion indenfor en til to procent af de ukorrigerede data målt med den justerede korrelationskoefficient og AIC af en vækstmodel. Dog var forskellen statistisk signifikant i mange tilfælde. Det er ikke altid at kant-fejlskorrektionen forbedrer prædiktionen af individuel trævækst. Dog synes de eksisterende metoder baseret på simulering af buffertræer og lineær ekspansion, at være generelt bedst. Det skal nævnes, at nogle af konkurrenceindeksene vi udledede i Artikkel I ikke har kant-fejl, fordi data kan udvides med en buffer omkring plottet, og fordi positionen af de konkurrerende træer ikke behøver at være kendt.

Nøgleord: Kant-fejl, konkurrenceindeks for enkelttræer, flybåren laserskanning, statistisk inferens.

List of papers

Paper I

Pedersen, R.Ø., Bollandsås, O.M., Gobakken, T., Næsset, E., 2012. Deriving individual tree competition indices from airborne laser scanning. For. Ecol. Manage. 280, 150-165.

Paper II

Pedersen, R.Ø., Næsset, E., Gobakken, T., Bollandsås, O.M., 2013. On the evaluation of competition indices - the problem of overlapping samples. For. Ecol. Manage. 310, 120-133.

Paper III

Pedersen, R.Ø., 2013. The behavior of Hegyi´s competition index in a spatially correlated field. Submitted.

Paper IV

Pedersen, R.Ø., 2013. Reducing the plot edge bias by means of airborne laser scanning? Manuscript.

Papers I and II are reprinted with kind permission from Elsevier. Papers are referred to by their Romans. Please notice that for the published papers, appendices are electrically available on the internet. I have reproduced these appendices in the thesis.

249 **Synopsis**

250

"When the Lord created the world and the people to live in it - an enterprise which, according to modern science, took a very long time - I could well imagine that He reasoned with Himself as follows: If I make everything predictable, these human beings, whom I have endowed with pretty good brains, will undoubtedly learn to predict everything, and they will thereupon have no motive to do anything at all, because they will recognise that the future is totally determined and cannot be influenced by any human action. On the other hand, if I make everything unpredictable, they will gradually discover that there is no rational basis for any decision whatsoever and, as in the first case, they will thereupon have no motive to do anything at all. Neither scheme would make sense. I must therefore create a mixture of the two. Let some things be predictable and let others be unpredictable. They will then, amongst many other things, have the very important task of finding out which is which."

E.F Schumacher

Small is beautiful – Economics as if people mattered

1. Introduction

1.1. The term competition

What is competition in a biological context? This question needs an answer in order to understand the topic on which this thesis elaborates. The term competition originates back to the fundamental work of Darwin (1859), and covers potentially all areas where living organisms are involved. Whereas Darwin focused on competition as a driving force in evolution for living organisms in general, and as something that works over generations, I focus on competition in plant communities, and more specific among trees, and the impact it has on the development of the tree in time and space. Kimmins (2004)(p 422) states about interspecific, i.e. between species competition: "*Interspecific competition occurs wherever two different species attempt to utilize the same resource when that resource is limited in supply. There is no competition when they share a common resource that exceeds their combined demands for it*". This definition is also valid for intraspecific competition, i.e. competition between trees of the same species. The stationarity of trees implies that they are forced to fight for resources with the neighboring trees where they grow, as they cannot move to a more suitable environment. What constitutes the limiting resource obviously depends on the environment where the tree grows, and the physiological needs of the plant. The limiting resource can also change over time, such that for instance water supply is only deficient in certain periods of the year, and variation also occurs between years (Wichmann, 2001). Skovsgaard and Vanclay (2013) review how spatial variation over smaller areas and temporal variation in climate may affect site productivity, and thereby also the limiting resources of the plant community.

One of the earliest attempts to put the ideas of Darwin into forest science was made by Kraft (1884), cited in (Assmann, 1970). Kraft (1884) introduced the concept of stand social status, to account for the size hierarchy of trees in a stand. By dividing the stand into social classes like suppressed – co-dominant and dominant individuals (Kraft has more subdivisions), Kraft (1884) made a link between the size of the tree and its growth relative to other individuals. This is illustrated in Figure 1, where the gray subject tree is surrounded by two white competitors.

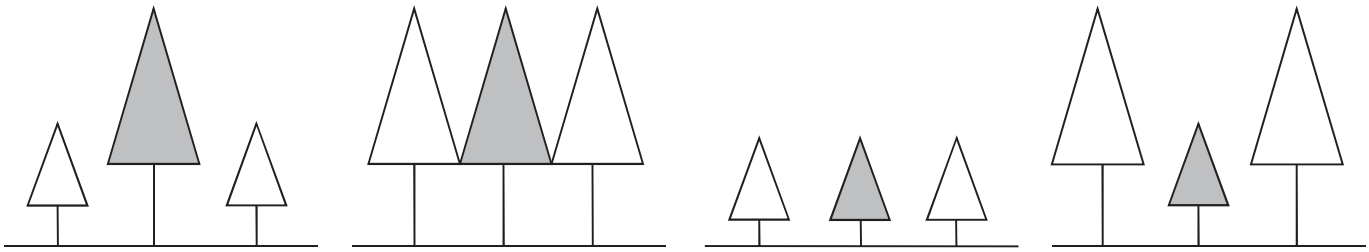


Figure 1. The social status of different subject trees (gray), each surrounded by two competitors (white).

In forest science the study of competition starts even before Darwin. Thus, the early works of Reventlow (1816, 1879) on thinning, initiated in the year 1793 and subsequently published, using stem analysis on oaks and beeches (Nord-Larsen, 2006), show the awareness of the response of trees to increased growing space and its potential for economic optimization. This has since developed into a whole branch of science "forest growth and yield", which continues to be studied for example through long-term experiments on thinning. Gizachew *et al.* (2012) give a recent example in Norway. The competition index (CI) or thinning index presented by Johann (1982) known as "Johann´s A-value" is a direct example on how a distance weighted size-ratio, an index type often used as a CI, may be used as an objective measure of stand density, constituting a link between thinning theory and competition.

According to Harper (1967) and Silvertown (1982) the response of a tree to competition can be divided into three classes. The first class is a reaction called "plastic response", where the plant changes its physical appearance for instance crown shape, to meet the changes of the environment caused by competition. The second is density related mortality, where the competition of resources causes depletion and finally death. The third is establishment of a size hierarchy, caused by for instance genetic differences, or gradients in soil structure. It is evident that the three consequences that Harper (1967) and Silvertown (1982) postulate competition may have on plants, are related. For instance, establishment of a size hierarchy may lead to suppression of individuals to such a degree that they die. The response to competition that we observe above ground is an adaptation of for instance crown plasticity in addition to the growth of the tree. A study of tree growth cannot in itself determine the level of competition that trees are exposed to, simply because trees can compensate for lack of a resource like light by changing the shape of the crown and stem, stretching for light (Schwinning and Weiner, 1998). Another example is that trees have the ability to compensate for

suppression when standing in shade, and some species may be more tolerant than others (Perry, 1985). Nilsson (1993) points out the connection between diameter and height growth when competition starts, and mentions how for example Norway spruce (*Picea abies* (L.) Karst.) responds to fertilization by increasing both diameter and height growth, whereas Scots pine (*Pinus sylvestris* L.) seems mostly to increase diameter and not height leading to different changes in stem taper. However, the plastic response is not limited to the stem taper, so Nilsson studied (Paper II of his dissertation) plastic response to competition by measuring stem volumes, branch basal areas, and number of current shots in young stands of Norway spruce and Scots pine. He concludes that both tree species respond to competition, but in different ways. Norway spruce tends to reduce the number of current shots, whereas in Scots pine both stem volumes, branch basal areas, and number of current shots are affected. Nilsson also argues that response to competition is time dependent, and that even-aged stands beyond the stage of crown closure may have a different response to competition than younger even-aged stands. One reason for this is the change of space available for each tree making for example the crown to height ratio different as time goes. This point of view is consistent with some stem taper studies of even-aged stands (Gray, 1956; Farrar, 1961; Assmann, 1970). The key point in stem taper development is canopy closure. When the stand is young, competition is low and the crown makes up a large percentage of the total tree height. See Husch et al. (2003) p 99 for a definition of total tree height. The young trees will have a shape similar to a solitary tree. The annual growth will therefore be distributed along the stem in a similar way as can be observed in a solitary tree, which means that the width of the annual tree-ring will decrease from the ground to the initiation of the crown. As the stand ages, and competition increases, the lowest part of the crown will die. The tree taper then changes, so that it becomes more evenly distributed in the lower parts of the stem, resulting in a cylindrical stem shape. The process may be “reversed” by heavy thinning, though changes in the crown/height ratio should also be considered.

To complicate things further studies by Assmann (1970) confirmed, that the productivity when mixing shade tolerant and shade intolerant species is higher than when having just shade intolerant species in monoculture. Perry (1985) call this effect the “ecological combining ability”. However, the productivity of mixed species stands is more complex than this and a discussion of the term ecological niches (Pretzsch, 2009)(p 337) is required, in order to understand that this is not always the case. In summary the examples above show that competition is difficult to quantify by simple assumptions.

1.2. Measures of stand density

In the history of science it is often studies on larger scale of resolution that leads to studies on a microscopic scale. This was for instance the case in physics where atoms were studies after molecules. The study of competition in a forest stand does not follow this pattern, probably because the smaller unit - the tree - is easily detectable, and does not require sophisticated engineering devises in order to be studied. Nevertheless it can be useful to start looking at the studies of competition at a stand aggregated level, and then at a single-tree level.

The study of Yoda *et al.* (1963) is a fundamental reference for intraspecific competition in even-aged plant communities. Yoda *et al.* (1963) investigated the relationship between density of field crops and mortality. This and later contributions have become known under the name “the self-thinning law”, and postulates that the average level of living plant biomass per area unit is a function of the plant density multiplied by a species specific constant and raised to the power -3/2. The work of Yoda *et al.* (1963) focuses on monocultures, but of course competition can also appear interspecific, and the self-thinning law has been found to work for mixed species communities as well (Malmberg and Smith, 1982; Westoby, 1984). Other expressions for stand density exist, for instance Reineke (1933) presented a stand density index, which may be related to the self-thinning law under certain assumptions about the quadratic mean diameter (D_g) (Bredenkamp and Burkhart, 1990). Using logarithms, the mathematical expression of the self-thinning law can be linearized, and a line with a constant slope will appear when plotting average biomass per area unit against the measure of plant density. In their original works Yoda *et al.* (1963) and Reineke (1933) argued that the line slope was a constant for a variety of species. This has later been questioned by some authors, e.g. (Zeide, 1987; Skovsgaard, 1997), and recently improvements have been made to account for the fact that a simple straight line relationship on a logarithmic scale does not suffice (Cao *et al.*, 2000). However, despite the fact that the simple models of Yoda *et al.* (1963) and Reineke (1933) need adjustment for species and environment, they seem to make logical sense, because there seems to be some limit to the density of forest trees and their average size (Koch *et al.*, 2004). Further, these indices have the advantage of giving an absolute measure of competition pressure in the stand, which then can be compared to other stands. Zeide (2005) argues that Reineke´s index needs to account for the changes in the gap area (diminishing crown closure) over time in order to be a true measure of density. This is because trees do not have the ability to fill up gaps in the same way when they grow old due to changes in for instance crown proportion.

1.3. The need for individual tree competition indices

The self-thinning law serves as an indicator of competition over larger areas or management units. It cannot capture the micro-scale variation, and more specifically the interaction between individuals, of which some may benefit negatively and some, though it sounds contradictory, even positively from co-existence (Kelty *et al.*, 1992). Some authors have tried to link the competition level at a stand level to that of the individual tree. Krajicek (1961) developed the "crown competition factor" as a measure of potential stocking. The idea is to measure the area of the projected crown width in relation to the available area. This serves as a stand density measure, but it can also be used to quantify the position of the individual tree in the size hierarchy. Other attempts have been made using allometric relationships between surrogate variables. Pretzsch (2009)(p 405) describes how it is possible to link individual tree biomass to the average biomass per area unit predicted by the self-thinning law. In Norway Strand (1972) presented a CI based on the fact that growth of volume and basal area in a forest stand at a given age seems to be fairly independent of spacing, which is known as Langsæters rule (Skovsgaard and Vanclay, 2008). Assuming that this is true, the area available for the individual tree should be a good indicator of competition, because fewer trees per area unit means that growth is accumulated on fewer individuals, whereas many trees means little space and small growth for each tree. Using the ratio between potential and actual area available for the tree, Strand (1972) gives a measure of competition.

Ecologists have realized that competition and its impact on the virility of the individual tree are complicated, and that there is a need for a more detailed specification of the competition process. Weiner and Solbrig (1984) were among the first to use the term symmetry of competition to describe how trees respond to competition and exert competition on other trees. According to Weiner and Solbrig (1984), competition is completely symmetric if resources among individuals are divided equally (two-sided). Size-symmetric competition implies allocation of resources proportional to tree size and size asymmetric (one-sided) competition implies that a few larger individuals take all the resources. What kind of competition that is in play depends on the type of resource, and the tree species involved in the competitive process. Light is for instance considered a resource which leads to asymmetric competition, whereas competition for below ground resources like water and minerals are symmetric (Weiner *et al.*, 1997). The process of competition is a combined effect of several deficit resources. Therefore, competition and the growth and depletion of trees are often somewhere in-between the continuum completely symmetric and completely asymmetric. The introduction of the term symmetry of competition requires quantification of competition at the single-tree level, or at least a way to verify that trees respond to competition. The response to competition in the form of growth is the most commonly used method to investigate competition,

but as shown in the literature other aspects like crown plasticity can also be used (Purves *et al.*, 2007; Seidel *et al.*, 2011). It remains difficult to actually measure competition because what is measured depends upon the definition of competition. At stand level the Gini-coefficient (Gini, 1912; Weiner and Solbrig, 1984), skewness, and coefficient of variation of diameter at breast height (dbh) (Nilsson, 1994; Skovsgaard, 1997) have been used to describe development over time. But even for the whole stand such aggregate measures may not be a true indication of competition. For example, the increase in skewness of the empirical tree diameter distribution has been interpreted as a result of one-sided competition, because small size differences will give larger trees a relative higher growth rate causing skewness. However, the size-differentiation may simply be due to micro-scale variation in soil conditions, which may accelerate the growth of certain trees (Skovsgaard and Vanclay, 2013). A more general description of the structural development and size differentiation due to competition as reflected in the empirical diameter distribution over time was presented in the 1970s and 1980s. Hara (1984), Nilsson (1993) and (Skovsgaard, 1997) give introductions to the stand development over time as a function of growth, variance in growth, and mortality of trees using among other means the forward Kolmogoroff equation. Such an analysis may focus on the modality of the dbh distribution, like whether the distribution has one, two or more tops. Analytical tools such as the kurtosis of the distribution and graphical analysis often come short, because factors like the width of the diameter classes can affect the modality. Thus, it remains difficult to model the consequences of competition even at a stand level.

Because the complexity of competition at stand level evidently emerges from the competition between individual trees this naturally raises the question how individual tree competition may be quantified.

1.4. Types of individual tree CIs

One way to quantify competition is by an index, a single number given to each tree, which expresses the current competition load and social status of the tree. This approach is taken throughout the papers of the current thesis. Numerous indices exist in the literature and comprehensive descriptions are given by (Biging and Dobbertin, 1992; Biging and Dobbertin, 1995; Husch *et al.*, 2003; Pretzsch, 2009; Weiskittel *et al.*, 2011; Burkhart and Tomé, 2012).

An important distinction for CIs is if they are spatially explicit (i.e. distance dependent) or non-spatially explicit (i.e. distance independent)(Munro, 1974). Weiskittel *et al.* (2011) divide the spatially explicit CIs into the categories size-distance relationships, competitive influence zone, growing space indices, open-sky view, and light-interception CIs. Non-spatially explicit CIs are divided into absolute

and relative CIs. Weiskittel *et al.* (2011) claim that the non-spatially explicit CIs express two-sided competition while the spatially explicit CIs express one-sided competition.

An example of a size-distance relationship is the CI of Hegyi (1974), an index with a size-ratio between subject tree and competitor, multiplied by an inverse distance term, which assumes competition to be decreasing with distance. An example of the competitive influence zone CI is given by Bella (1971), where area overlaps from potential open grown tree crowns with the same dbh as the subject tree and competitors are accumulated. A growing space CI is for example area potentially available (APA) presented by Brown (1965). This CI uses polygons to express the available area for each tree and assumes equally distributed resources in the study area. A spatial tessellation may be applied to use this type of CI (Okabe, 2000). Open-sky view CIs models the competition of light and shadow effects by either hemispherical images (fish eye projection (Pretzsch, 2009)), ray tracing or by simulating the light conditions. An extensive review is given by Brunner (1998). The light-interception CI also tries to measure competition for light, by quantifying the absorption of light of the tree over time (Brunner and Nigh, 2000). A relative non-spatially explicit CI is an index where the size of the subject tree is set relative to a stand characteristic like D_g. See for example Glover and Hool (1979). An absolute non-spatially explicit CI does not have this characteristic. An example is the basal area of larger trees CI, where the competition pressure for the subject tree is calculated using the competitors larger than the subject tree (Wykoff, 1990).

Other attempts have been made which may not fit easily into the classical categorization of CIs by Weiskittel *et al.* (2011). For example, Shi and Zhang (2003) investigated how the local indicators of spatial autocorrelation (LISA) like Geary´s *C* (Geary, 1954) and Moran´s *I* coefficient (Moran, 1950) may be used as a CI. They find high correlations between these and a selection of existing CIs.

Stage and Ledermann (2008) combine the non-spatially explicit and spatially explicit CIs into semi-distance-independent CIs. These CIs have the structure of non-spatially explicit CIs, but the social status of the subject tree is calculated according to the near surroundings of the subject tree. Distance does not enter directly into semi-distance-independent CIs, which separates them from spatially explicit CIs. Another example of quantifying competition is to use coupled differential equations. Damgaard (1999) used a parameter in the coupled differential equations to express how trees in the size hierarchy respond to competition by means of a nonlinear growth model. The value of the parameter then determines the symmetry of the competition (Nord-Larsen *et al.*, 2006). Many CIs implicitly model competition as asymmetric. For instance, distance weighted size-ratios favor larger individuals over smaller.

A CI presented by Tomé and Burkhart (1989) deserves some extra attention, due to some results obtained in Paper I, presented in Subsection 4.1. The idea is that competition pressure is not merely the sum of the competing trees, but that small trees, and dead trees reduce competition while larger trees increase competition. Often, the presences of small or dead trees are an indication of a canopy opening (gap), where recruitment has taken place. Hence, if competition for light is important such an index might work well. This is seen from Equation 1 which is adapted from Burkhart and Tomé (2012)(p 217) where the competition pressure consists of the trees larger than the subject tree (CI_{larger}), reduced by the competition from the smaller ($CI_{smaller}$) and the dead trees (CI_{dead}).

Equation 1

$$CI = CI_{larger} - CI_{smaller} - CI_{dead}$$

The classical CIs used as benchmark references in the present thesis assume that the competition pressure is directionally independent, thus competitors standing aggregated may give the same competitive pressure as competitors which are scattered around the subject tree position. Lund (1999)(Paper 4 p 14 of his thesis) notes that this is not a reasonable assumption because it does not account for the fact that competing trees also affect each other because, they co-vary in space. Existing structural indices acknowledge the importance of directional dependency, for example the mean directional index (Illian *et al.*, 2008) used in Paper II (see appendix of Paper II). Newton and Jolliffe (1998) derive a number of CIs where direction is accounted for by calculating the "centre-of-mass" of the positions of competing trees, and use this centre-of-mass distance to the subject tree to account for the aggregation of competitors relative to the subject tree. In Paper I a similar concept is applied in a CI by means of the Gini-coefficient (Equations 21 and 22 of Paper I).

Many studies have compared different types of CIs, and so far, no single CI seems superior. One reason for this is mentioned by Strand (1972)(p 208) who states about using empirical data for evaluation of CIs: "*It will never be possible in this way to "prove" that the model is correct, but the method may be used to rule out many incorrect assumptions*". The statement of Strand is consistent with the viewpoint of the philosopher Popper on the falsification of a scientific hypothesis (Chalmers, 1999). According to Popper, we can never prove a scientific hypothesis; we can only try to falsify it. Generally, there seems to be consensus that spatially explicit CIs do not offer substantial improvement in growth predictions over non-spatially explicit CIs (Lorimer, 1983; Martin and Ek, 1984; Biging and Dobbertin, 1995; Rivas *et al.*, 2005), though some studies find a small improvement when applying spatially explicit CIs (Contreras *et al.*, 2011). Some authors hold that spatially explicit CIs often model above ground competition; while below ground competition for minerals and water

are not limited to the competitors identified using some mathematical search criteria (see 1.8.2 for elaboration on this topic). Dimov *et al.* (2008) mention that studies are often made in monospecific even-aged stands with little size differentiation, which may favor non-spatially explicit CIs; however, some studies have been conducted in mixed stands to test this and still find non-spatially explicit CIs being slightly better (Biging and Dobbertin, 1995), so this cannot be the whole explanation.

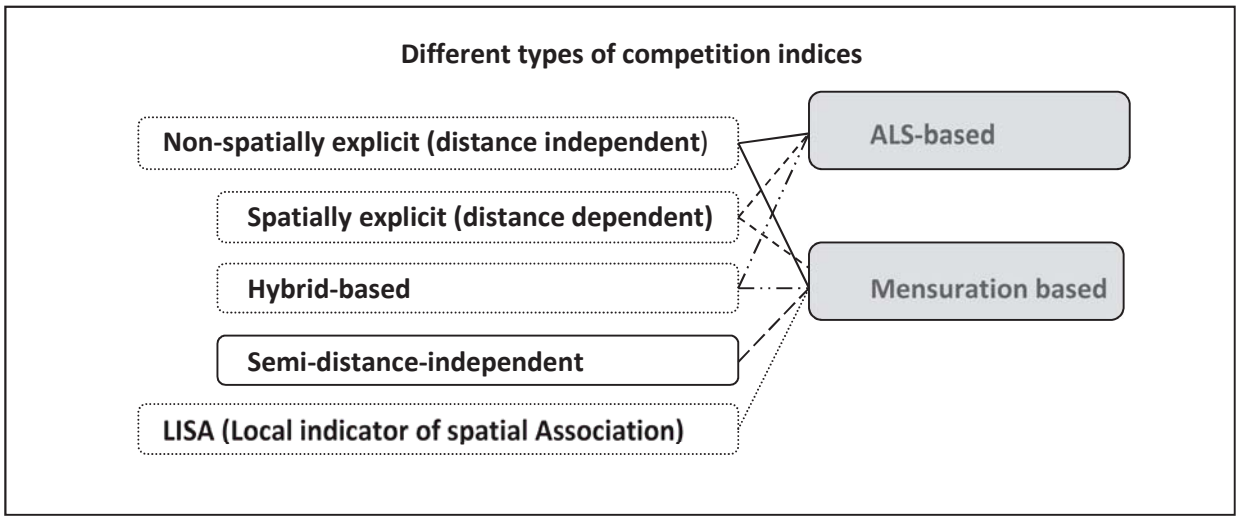
Weiskittel *et al.* (2011) state that many spatially explicit CIs fail to account for species differences, though this is also the case for most non-spatially explicit CIs, and some authors have accounted for this by incorporating species specific parameters into the CI (Richards *et al.*, 2008). Plot size may also matter, because too small plots may not allow identification of important competitors; this is related to plot edge bias. Besides, statistical reasons may also be important, which I will discuss more in Subsection 1.8.4 (Step IV of the evaluation process described in Subsection 1.8), and in particular in Paper II and Paper III.

An overview of some important types of CIs is given in Figure 2. I found it convenient to divide these CIs into two groups: ALS-based (airborne laser scanning) and mensuration based. This division will be used especially in the derivations of the CIs in Paper I. Mensuration based CIs presuppose that the size and maybe also the position of competitors and subject tree are known. ALS-based CIs (ALS-CI) use only the size and position of the subject tree. The hybrid-based CIs combine the ALS and mensuration based CIs. In the hybrid-based CIs, positions and proportions of all trees are needed, and are combined with ALS information. This shall be discussed more in detail in Paper I, and in Subsection 1.3. Figure 2 also shows which of the CIs that are used in the papers. With respect to the LISA-CIs these are not used directly, but LISAs are used to study the properties of the classic CIs in Paper III.

543

544

545



546

Figure 2. Different types of CIs or measures of spatial association especially important in the thesis. If the textbox around the CI/LISA is dotted it means that the CI is used in the thesis. The gray colored text boxes indicates the two overall classes of CI. The lines indicate which types belong to the ALS-based CIs and the mensuration based CIs.

1.5. Other measures of stand structure

Besides CIs, a number of other indices have been developed to describe stand structure as summarized by Pommerening (2002, 2008). Such indices may be used to get detailed information about species richness, diameter variation, and also density of the forest stand. They may be used to characterize the forest in terms of a quantitative number that can be applied in analysis to reveal patterns in the material, as done in Paper II. Such indices have also been used to simulate forest structures successfully. Pommerening and Stoyan (2008) used a simulated annealing procedure to construct a forest stand so that the distributions of a number of structural indices remained the same as could be observed in the data material. The Clark and Evans index (Clark and Evans, 1954) used in Paper II and IV is another example of how a structural index may be applied for simulation, and in Subsection 1.8.4 I will look into how this can be applied to studies of plot edge bias. I distinguish between two types of structural indices, micro and macro-scale. It is merely the resolution used which determines if the index belongs to one category or the other. For example the Gini-coefficient would be characterized as a macro-scale structural index because it assigns a single number to all trees over an area. The Mingling index used to describe how different tree species mingle in the stand (Füldner, 1995) gives a single number to each tree and is a micro-scale index. For formulas see the appendix of Paper II.

1.6. Airborne laser scanning

Since airborne laser scanning (ALS) is used in the present thesis, a short conceptual description is in order. ALS, or Light Detection and Ranging (LiDAR), is a remote sensing technique dating back to the 1960s and 1970s in which a transmitter mounted on an airplane sends laser pulses towards the ground. When the laser beam strikes an object with sufficiently large area, it will trigger a return or an echo. Using trigonometry and the speed of light, the three dimensional positions of the laser returns can be obtained (ALS-returns). From the ALS-returns, a model of the terrain can be made using an algorithm which separates those ALS-returns echoed from the ground from those that were echoed from the vegetation (Axelsson, 2000). According to Hyyppä *et al.* (2008), two main approaches exist when using ALS to predict forest attributes: the metric approach and the individual tree detection approach. The individual tree approach relies on identification of single-trees by means of a single-tree detection algorithm. Many such algorithms exist and a review is given by Vauhkonen *et al.* (2012). The single-tree detection algorithm will provide information about important individual tree variables like base crown height, total tree height, and crown width. These can then enter into CIs. The metric approaches look at trees at an aggregated level, and try to make predictions using statistical and mathematical transformations of the laser point cloud. This may for instance be maximum- or mean height of the ALS-returns height above ground. In this thesis a

combination of the two approaches is used, in the sense that some information about the subject tree, i.e. the target tree of interest is used. This could for instance be position of the subject tree, whereas other variables are derived from the metric approach.

The terrain model has been used to discriminate biomass and ground level for successful predictions of forestry attributes like Lorey´s mean height, volume per hectare (Næsset, 1997) or basal area distributions (Gobakken and Næsset, 2004). The first predictions of forestry attributes date to the mid- 1980s when Nelson *et al.* (1984) predicted canopy closure from ALS. Predictions are done using the metrics as regressors; they are mathematical transformations of the ALS-returns. Numerous ways have been applied to calculate metrics in the literature, e .g. (Bollandsås *et al.*, 2008; Ørka *et al.*, 2009). Næsset and Økland (2002) report estimates of individual total tree height, crown length, and crown height using materials from the study area of the current thesis Østmarka Boreal Reserve. The predictions deviate 17.6% for individual total tree height, 39.1% for crown base height and 10.5% for crown length from the true ground measurements. It is also possible to do species identification from ALS. Ørka *et al.* (2009) used linear discrimination analysis to differ conifers from broadleaves in Østmarka Boreal Reserve and report fairly correct classification, ranging from 88.6% for dominant to 63.6% for suppressed trees. Single-tree segmentation algorithms have been derived to identify the position and size of individual trees. In Norway, this has been done by Ene *et al.* (2012a) using the data from Aurskog-Høland Municipality and Solberg *et al.* (2009) using data from Østmarka Boreal Reserve. Næsset (2002) showed how forest inventories can be accurately made from ALS using a two-stage procedure based on field measurements. Different forest variables were successfully predicted by dividing the forest into strata, and calibrating stratum-wise models based on a number of field observations (plots). For example, he achieved an R^2 of stratum specific volume predictions between 0.80 and 0.93. Other variables were also predicted with high accuracy (R^2 between 0.39 and 0.95). Næsset (2004) showed how to apply the technique in an inventory in a cheap and accurate way. Ene *et al.* (2013) showed potential economic gain using ALS inventories instead of traditional ground inventories, by testing the precision and economics of different statistical sampling designs (Cochran, 1977; Särndal *et al.*, 2003) in data from Hedmark County in Norway.

1.7. Setting airborne laser scanning into the context of competition

Paper I is to my knowledge the first to set airborne laser scanning into a more systematic framework, where competition is the focus area. It should be mentioned that Maltamo *et al.* (2007) describe how airborne laser scanning may be used to quantify the input to a distance weighted size-ratio CI. Maltamo *et al.* (2007) applied a single-tree segmentation algorithm to calculate the position and the size of the tree. The results of Maltamo *et al.* (2007) reveal the large uncertainty the application of the single-tree segmentation algorithm introduces when using for instance crown width predicted by the algorithm. This happens because is difficult to determine the position and boundary of the tree, especially in a dense multilayered- canopy where the understory trees can be impossible to find. The coverage of the ALS-returns and the technical characteristics of the transmitter used may also matter, just as the climatic conditions, leaf on/off and tree species are important for the results (Ørka *et al.*, 2010). This was one of the motivations for trying to develop new CIs based on airborne laser scanning, in order to prevent the use of a single-tree detection algorithm to find competing trees (note that it may be needed to find positions of subject trees if used in areas, where trees are not positioned from ground measurements).

So far, most attempts of quantifying competition using ALS may be characterized as indirect, in the sense that the variables studied are closely correlated with competition, but the calculations are made at a stand level rather than at a single-tree level. One example of indirect specification is the prediction of leaf area indices (LAI) from ALS (Jensen *et al.*, 2008; Solberg *et al.*, 2009; Jensen *et al.*, 2011), which are known to be important for modeling recruitment in stands (gap-models) (Botkin *et al.*, 1972), and may be viewed as a measure of competition at stand level.

Varhola *et al.* (2012) investigated how laser derived forest metrics may be used in construction of ALS synthetic hemispherical images, which is a popular way of estimating the LAI. Their method involves a calibration of the ALS synthetic hemispherical images on the basis of in-situ optical hemispherical camera images. They obtained satisfactory predictions of solar radiations by means of a multiple regression model, demonstrating that it is possible to make cost-effective gap predictions from ALS data. Bollandsås *et al.* (2008) showed how the so-called density metrics may be used as a predictor of seedlings in Norway spruce. Since recruitment of Norway spruce often appears in gaps, and gaps have less competition for light, it is reasonable to see this as indication of the ability of ALS to quantify competition of trees. Seidel *et al.* (2011) used a terrestrial laser scanner to model the crown shape and plastic response (see Subsection 1.1 regarding Harper (1967) and Silvertown (1982)), and to test a hypothesis of crown plasticity in a mixed species forest. In Norway, Hauglin *et al.* (2013) demonstrated how ALS and terrestrial scanners may be used to derive a model of the

643 crown surface. Though the aim of the study of Hauglin *et al.* (2013) was biomass estimation, it shows
644 the potential for deriving newer and more advanced crown models in boreal forest, which potentially
645 may also be applied in CIs (Bella, 1971). Metz *et al.* (2013) successfully used terrestrial laser scanning
646 to find the input variables to a crown shape CI presented by Pretzsch *et al.* (2002). This topic is briefly
647 mentioned in the present thesis by the hybrid-based CIs introduced in Paper I.

648

1.8. Conceptual framework

The thesis follows the four steps shown in Figure 3, and before I go into details about the results of the individual papers I will elaborate upon the different steps and how they lead to the objectives of the individual papers presented at the end of the subsection. Some parts of the steps I-IV also contain references to the papers, because a very sharp border between the methods in the papers and the background of the concepts is artificial.

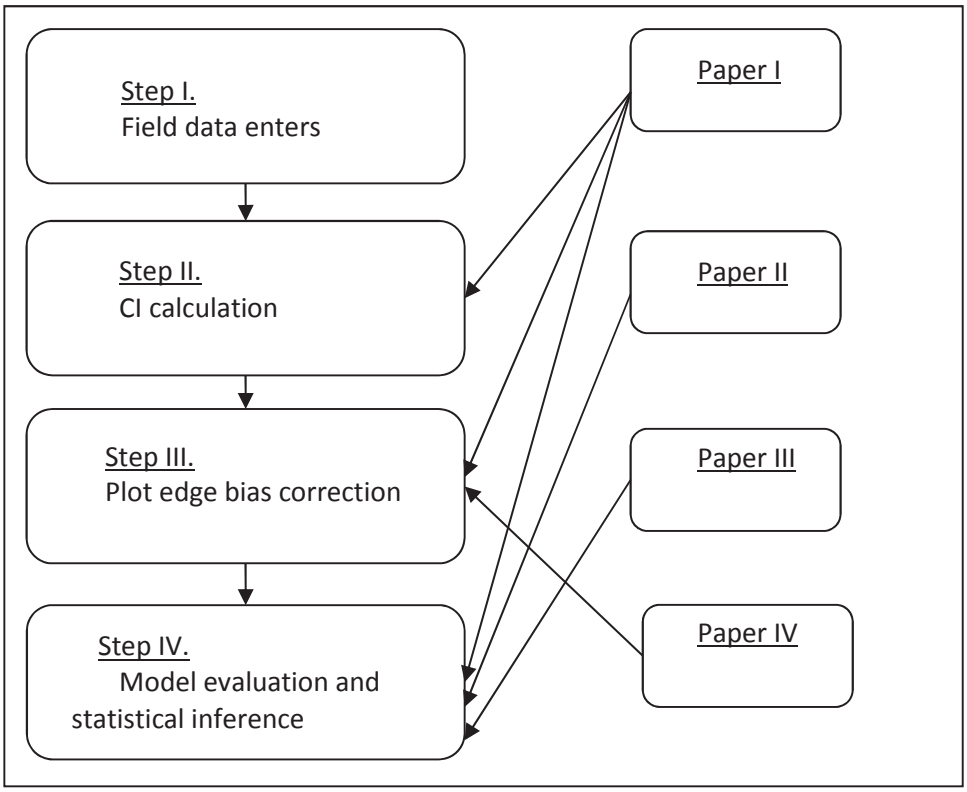


Figure 3. The different steps in the calculation and evaluation of the competition indices. The arrows show which step in the process that constitutes the main focus area of the papers. Some papers have more than one focus area.

1.8.1. Step I – Field data

While field data often is the most neglected part in scientific presentations, it is nevertheless the most important, because only accurate field data that can suit the purpose of the study will make it possible to explore the scientific hypothesis. When dealing with CIs, a number of relevant questions come to mind. The size of the data and the number of replications in each individual site are essential, but the variability between sites can also be of importance. When dealing with spatial data it may be relevant to consider the size of the individual plot. This is because all spatial statistical models require a number of observations in order to be valid (Cressie, 1991). In addition, small plots may potentially have large border effects, leading to a plot edge bias (See Step III).

As a rule both spatially explicit and non-spatially explicit CIs require large plots in order to give unbiased predictions (Alemdag 1978; Stage and Ledermann, 2008), however the exact size remains difficult to determine and should be optimized for each stand (Lappi, 2005). Cochran (1977) gives a comprehensive description of different spatial sampling strategies, such as simple random sampling, cluster sampling, and stratified random sampling. He mentions that (p 16): "Under the right conditions, any of these methods can give useful results". One important point that makes the sampling theme when dealing with competition different from many other situations is the need for repeated measurements over time. In practice, this means we are often limited to use the permanent sample plot of a national forest inventory (NFI), or a long-term experiment, and their sampling designs. Therefore, we are to some extent forced to use data that may have been collected for another purpose. In such situations, it may be interesting to use simulated data in order to test how different sampling strategies affect the values of the CIs, and to eliminate border effects. In Paper III I attack the problem by using simulation, which has the advantage that replications can be created, and different combinations of forest structure may be tested. Another problem using permanent sampling positions is that the influence zones of the different subject trees overlap. This can give problems with basic statistical assumptions of independence used for model evaluation, as I describe later in Paper II.

1.8.2. Step II – CI calculation

Once the data is in hand, a number of different CIs need to be selected and tested. Comprehensive reviews of different types of CIs can be found for example in Husch *et al.* (2003), Burkhart and Tomé (2012) and Pretzsch (2009). The selection of a CI should not be made blindly, and I use the rule that the tested CI should be possible to calculate using as few derived variables as possible. In practice, this means that we were limited to use dbh and distance between trees. However, it should be noticed that the ALS-CIs derived in Paper I use individual total tree height, projected crown width, and crown base height predicted from a model. The goal was to test the CIs derived from ALS against some well-known "classic" CIs, which have as little random measurement error as possible. Most of the classic CIs are nonlinear transformations, and even the random measurement error in dbh can result in biased estimates (Gertner and Dzialowy, 1984; Kangas, 1998). However, it is reasonable to assume that the variance of the measurement error in dbh is small, and probably it is better using dbh than a derived variable like individual total tree height. Further, the use of smoothed data predictions from a model reduces the variance artificially, and tends to give optimistic results of model performance (Hasenauer and Monserud, 1997). Another tenable argument favoring dbh over height is that many studies have found that the relative variation in height due to competition is less than in dbh (Sjolte-Jørgensen, 1967; Lanner, 1985). The

fact that some studies find an effect on height growth (Braathe, 1984) primarily on sites with low productivity does not justify to use height instead of dbh.

All CIs require a definition of a sampling procedure to point out the competing trees. Many different approaches exist. Commonly used methods are probabilistic sampling using relascope (Daniels, 1976), sampling of the n-nearest competitors (Soares and Tomé, 1999), or a circular search radius around the subject tree (Hegyi, 1974; Pedersen *et al.*, 2012). A particularly effective method is to use a search cone around the subject tree (Pukkala and Kolstroem, 1987; Pukkala, 1989). Bachmann (1998) found that no general recommendations can be given because the optimal search criteria vary with species, stand structure, and age, but the search cone method seems to give good results. Miina and Pukkala (2000) used a numerical algorithm and a log-likelihood estimate from a growth model to iteratively find the best search radius for different tree species. Others have found that relascope sampling seems to give good results, and Bachmann (1998) reported that fixed search radii were inferior to other methods. In all papers we apply a fixed search radius and in Paper II relascope sampling is also applied. We used a fixed search radius for classic CIs because the purpose in e.g. Paper I was to compare with ALS-returns, which are not uniquely allocated to each competing tree, contrary to what would be done using a single-tree segmentation algorithm. This means that for instance relascope sampling cannot be used for ALS-CIs. Many CIs decrease as the stand get older at the same stocking level. This is caused by an increased spacing between trees, and is neither in accordance with the self-thinning law of Yoda *et al.* (1963), nor consistent with Langsæters rule. Lorimer (1983) and Pretzsch *et al.* (2002) presented some solutions to this problem, which are discussed in Paper III.

1.8.3. Step III – Plot edge bias correction

Plot edge bias in a silvicultural context appears when trees outside the data range are affecting the trees that constitute the dataset. This may for instance be neighboring trees outside a plot area, which compete for resources with the trees in the plot. Ignoring these neighboring trees will lead to biased estimates of competition. Various methods have been proposed to deal with the problem. Two often applied techniques valid for non-circular plots are translation (also called shifting) (Newnham, 1964; Lee, 1967), and mirror imposing (also called reflection) of the plots (Pretzsch, 2009). Mirror imposing may also be used for circular plots, only it is the search radius around each subject tree that is used for edge correction in this situation, not the entire plot (Lilleleht *et al.*, 2013). For these methods the variation in the stand outside the plot is simply generated under the assumption that the stand variation is similar to the plot variation. Despite their simplicity, these

methods are often found well performing in practice. Pommerening and Stoyan (2006) attribute this to the fact that these methods often cancel out the error caused by the symmetry of the reflection.

Another alternative is the border method, which is also known as the guard method. This method identifies a buffer zone and then only calculates competition for subject trees, which are at a certain distance from the plot edge. While the method is unbiased, it has the weakness that it reduces the number of trees remaining for analysis, and this may affect the results obtained. Hanisch (1984) used a similar approach accepting a tree for analysis if the distance to a subjectively chosen competitor was closer than the distance of the subject tree to the plot border; we used this method in Paper II (See Figure 4 subplot d).

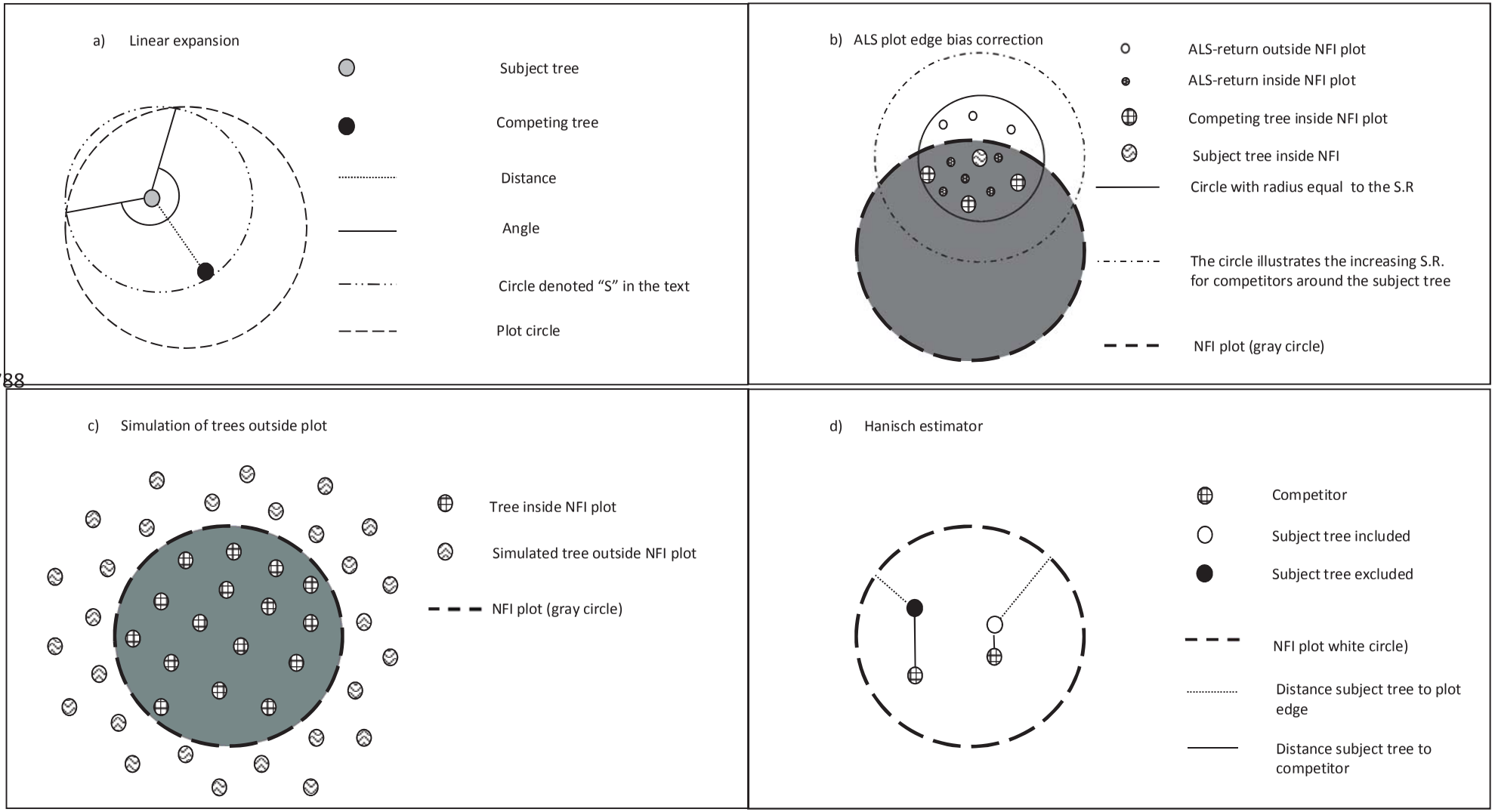
Methods of simulation have also been applied in the literature. Pommerening and Stoyan (2006) used point pattern analysis to generate the trees outside the plot (Cressie, 1991). They assumed that the trees follows a pattern like the Matérn hardcore process and by a simulated annealing procedure they constructed marked point patterns and positions for potential competitors. A mark is an attribute for example dbh or individual total tree height. The position and mark of the competitor are accepted according to some characteristic like the squared deviation of the diameter distribution observed on the plot. One weakness of this method is that it requires a subjective choice of a point pattern type, but often prior knowledge of point patterns in relation to forest type and species composition may be used, and Pommerening and Stoyan (2006) obtained satisfactory results using this method. In Paper IV I used a method much similar to the method of Pommerening and Stoyan (2006). I applied the R-script “Construction.R ” written by Dr. Pommerening (Pommerening, 2013), to simulate a point pattern with the same nearest neighbor distance (Clark and Evans, 1954) in a buffer around the plot, as is observed on the plot (Figure 4 subplot c). Diameters were calculated by a regression model using the nearest neighbor distance and plot level characteristics like D_g as regressors, by a gamma glm-regression with a log-link (Montgomery *et al.*, 2006)(p. 457-458). The gamma distribution is used because the dbh-distribution was skewed. The log-link ensured positive dbh predictions. The species marks are then put on the trees in the buffer using a multicategory logit model (glm-model)(Agresti, 2007)(p. 173). For each species class the multicategory logit model gives a probability of the tree belonging to that class, and the mark is put on the class with the highest probability.

In all papers the linear expansion method of Martin *et al.* (1977) was applied. This method is ratio based. If we make a circle *s*,centered at the subject tree, having radius equal to the distance between subject tree and competitor, then we can calculate the intersection between *s* and the plot edge (Figure 4 subplot a). The ratio between the circumference of this circle between the subject

tree and competitor, and the circumference of the same circle inside the plot constitutes what is known as the linear expansion factor (i.e. the ratio 360/Angle in Figure 4). The method is unbiased if we assume that the competing trees can be positioned randomly on the periphery of *s*. The method has the advantage of being simple to use and works for all geometric shapes.

In Figure 4 subplot b the method(s) based on ALS derived in paper IV are illustrated. By means of a search radius (S.R) around each subject tree, competitors are isolated and used to calculate CIs. In subplot b the white part of the S.R only contains ALS data, because it is not covered by the plot (e.g. NFI plot) (big gray circle). The idea is to adjust potential plot edge bias in the non-white area of the S.R by using ALS data in the whole of the S.R. Thus, ALS data serve as auxiliary information to adjust for plot edge bias. This is done using ratio-estimators (Gregoire and Valentine, 2008), and this will be described in Section 7 when discussing Paper IV. The dotted circle illustrates that different S.R were tested.

787



788

Figure 4. The different plot edge bias correction methods applied in the thesis. a) An illustration of the linear expansion method by Martin *et al.* (1977). b) The ratio-estimator approach presented in paper IV. c) A method based on simulated annealing presented in Paper IV (Pommerening and Stoyan, 2006). d) The Hanisch estimator used in Paper II (Hanisch, 1984).

Pommerening (2008) divided the edge correction methods into the categories plus sampling and minus sampling. Minus sampling means that the number of observations is reduced, an example is the use of an internal buffer or the Hanisch estimator. Plus sampling means that the number of observations is increased by additional measurements outside the plot area or conditional simulation of trees by for instance simulated annealing, translation or reflection. The use of airborne laser scanning as auxiliary information can be seen as a kind of plus sampling, though no additional ground measurements of the actual trees are made. Rather, information about the border trees is derived in an indirect way.

Some contradictive results regarding the effectiveness of plot edge bias correction can be found in the literature. Martin *et al.* (1977) find the linear expansion factor superior to the reflection and shifting methods when plots are rectangular in shape. Radtke and Burkhart (1998) use a stand generator approach, much similar to the one applied in Paper IV, to simulate the trees outside the plot area. It seems that the generator works better than the refection and shift method for mixed species forests, whereas the methods were equally good in even-aged forests. The bias of the plot edge bias correction methods increased with stand age, and was inversely related to plot size. In a study by Windhager (1997) in mixed forests of Norway spruce and Scots pine it turned out that the linear expansion factor and reflection methods were equally effective. Lilleleht *et al.* (2013) used the simulation method of Pommerening and Stoyan (2006; 2008) based on simulated annealing to reconstruct a buffer around each plot and conclude, that it is more efficient than reflection in reducing plot edge bias.

The use of plot edge bias correction methods based on simulation remains problematic when the purpose is to reveal the underlying principles of nature. Erroneous plot edge bias correction may disrupt conclusions, and therefore empirical methods are preferable. The derived CIs of Paper I are applicable using only the position of the subject tree, and suitable models to identify ALS-returns originating from the subject tree itself. Hence, plot edge bias may be eliminated by adding a buffer zone around the plot. For our derived CIs the results show that the bias of the individual tree growth model seems less affected by the distance of the subject tree to the edge, than is the case with a selection of classical CIs. This is important for future calibrations and testing of spatially explicit growth models, and currently a part of the Norwegian, Danish and the Finnish NFI´s already have ALS information at a plot level, enabling such tests.

1.8.4. Step IV – Model evaluation and statistical inference

Various methods have been proposed to evaluate CIs, and an extensive review is given by Burkhart and Tomé (2012) (p 234). Often a measure of statistical correlation like the Pearson or the Spearman rank correlation (Spearman, 1904) between plant growth and competition is investigated (Bachmann, 1998; Wichmann, 2001). Another much used method is to apply a growth model and measure the potential gain from including competition in R^2 or AIC (Daniels *et al.*, 1986; Tomé and Burkhart, 1989; Soares and Tomé, 1999). This may either be where competition enters directly as a regressor (often known as direct-estimation approach), or in a potential modifier function (Ek and Monserud, 1974; Leary, 1979), where the growth of a tree not affected by competition is reduced by a competition multiplier function (often known as potential modifier approach). When using multipliers the potential growth of a tree not affected by competition is reduced by competition usually assuming exponential decrease in growth for increasing competition pressure (Pretzsch, 2009)(p 454). The advantage of a multiplier function is that potential illogical values such as increasing growth with competition can be avoided. Thus, it is suitable in simulation studies where the CI is known to decrease growth. However, when evaluating newly derived CIs, it is not suitable because the index and its behavior should not be "forced" to behave in a certain way.

Alternatively, some statistical test may be conducted, founded upon sample based inferences, for investigating the significance of a CI as independent variable. All methods have pros and cons. Bachmann points out that a parametric growth model like e.g. the Richards model (Richards, 1959), can only be used to compare CIs if it is a correct model for the growth process. Further, the different CIs may perform better simply by choosing another growth model, and thus the ranking becomes arbitrary. Bachmann (1998) recommends the use of the Spearman rank correlation, because this can reveal potential nonlinear trends. When using regression models as well as measures of correlation, statistical inference in form of a test is needed in order to make judgments about the significance of the results. The ordinary statistical tests like t or F-tests require independence between residuals, otherwise variances will be overestimated, and p-values will be to small (overoptimistic) (Schabenberger and Pierce, 2002; Schabenberger and Gotway, 2005). The latter is known as statistical type I error, and may be minimized choosing a significance level which makes it harder to reject the null hypothesis. When calculating competition one often uses plots, where competition is calculated for all the trees on the plot. Each subject tree has a number of competitors, selected by some criteria. This leads to overlapping samples, because subject trees will share competitors in space, which will decrease the variation in data, relative to a situation where samples are independent from each other. Anselin (1988) calls splitting and subsequent uniting of spatial objects for non-hierarchical aggregation, and it is a source of spatial autocorrelation, i.e. correlation among

spatial objects (Tiefelsdorf, 1998). Thus, overlapping samples can lead to spatial autocorrelation and cause violation of the independence assumption made in statistical tests. A very intuitive definition of (positive) spatial autocorrelation is given by Tobler´s first law of geography (Tobler, 1970), stating "*everything is related to everything else, but near things are more related than distant things*". Negative spatial autocorrelation means that objects in space repulse each other.

Paper II investigates how the spatial autocorrelation changes due to sampling design, and how type I and type II statistical errors are affected by sample overlap. Specifically it investigates how spatial autocorrelation affects the effective sample size through non-hierarchical aggregation of the competing trees. The effective sample size is the sample size when accounting for spatial autocorrelation, as if observations were independent. In Table 1 I have shown possible outcomes of a statistical test for the null hypothesis H_0: The CI and the variable growth are not correlated. If the statistical test falsely accepts the null hypothesis, i.e. the results states that with a chosen level of significance it is unlikely that competition and growth are correlated we have a statistical type I error. If, on the other hand the statistical test shows that we falsely reject a true null hypothesis, then we are talking about a statistical type II error. The statistical type I error may be minimized by the chosen level of significance. This implies that the distribution of the stochastic variable under the null hypothesis is known. The ability of the test to minimize the statistical type II error is termed the power of the test (Park, 2008). It can be assessed using assumptions about the true distribution of the statistical test size.

Table 1. Possible outcomes of a statistical hypothesis test, hereunder type I and type II statistical error. Adapted after Chihara and Hesterberg (2011).

Test result	Truth	
	Correlation exist	Correlation does not exist
No significant correlation between CI and growth	Type I error	Correct
Significant correlation between CI and growth	Correct	Type II error

Different measures of spatial autocorrelation exist. One such measure is the variogram used in geostatistics. The variogram was originally developed for spatial continuous data like oil fields. Thus, it is suitable when the spatial pattern is highly irregular, like in a natural forest. One form of the variogram is the semivariogram, and it takes the form shown in Equation 2 (Isaaks and Srivastava, 1989). The reason that Equation 2 is named "semi" is the multiplication by 0.5, which is done to give a measure of variance in the spatial field rather than two times the variance. Y is the measured quantity, for example dbh or CI. x is a vector with spatial coordinates. h is a vector with a lag

distance and if search directions are not assumed isotropic (directional independent) with a directional component.

Equation 2

$$\gamma(h) = \frac{1}{2}\mathrm{var}\{\mathrm{Y}(x+h) - \mathrm{Y}(x)\}$$

From the calculated semivariogram one can fit a parametric model to quantify the range, sill and nugget effect. The range is the distance, where spatial autocorrelation is present. The sill is the plateau that the semivariogram reaches at the range. The nugget effect is the variance observed at distances near zero, caused by for example measurement error (Isaaks and Srivastava, 1989)(p 143). Many parametric models can be fitted to the empirical semivariogram (Schabenberger and Gotway, 2005). A visual example of terms and models related to the semivariogram is given in Figure 10, which will be discussed more detailed in the Results and discussion section of Paper III.

Another common measure of spatial autocorrelation is Moran´s *I* (Moran, 1950). It is given by Equation 3. ω_{ij} is a spatial weight. Y is the value of interest of either the i´th subject tree and j´th neighbor. $\overline{\mathrm{Y}}$ is the mean. n is the number of trees. In the case of row standardization, which was used in the thesis, S_0 is given by $\sum_i \sum_j \omega_{ij}$.

Equation 3

$$Moran's\ I = \frac{n}{S_0}\frac{\sum_i \sum_j \omega_{ij}\left(\mathrm{Y}_i - \overline{\mathrm{Y}}\right)\left(\mathrm{Y}_j - \overline{\mathrm{Y}}\right)}{\sum_i \left(\mathrm{Y}_i - \overline{\mathrm{Y}}\right)^2}$$

Moran´s *I* has the range [-1,1], and contrary to most parametric covariance functions it can model negative spatial autocorrelation, and gives an overall measure of spatial autocorrelation. Moran´s *I* requires specification of a neighborhood, and though originally made for lattice data, it can be applied to irregular point patterns using a distance weighting criterion. Anselin (1995) presented the local indicator of spatial association LISA, which is a local edition of Moran´s *I* (an edition of Gerays´s C (Geary, 1954) was also given by Anselin (1995)), which can be used for identication of hot-spots, i.e. areas where objects are similar and coldspots, where dissimilar objects are positioned. The distributional properties of Moran´s *I* has been intensively discussed in the literature (Cliff and Ord,

1981), and Tiefelsdorf (1998) succeeded in deriving the exact distribution of Moran´s *I* under spatial autocorrelation. The effect of spatial autocorrelation on the effective sample size is discussed by (Dutilleul, 1993; Dale and Fortin, 2009; Dutilleul, 2011). We applied the correction of Clifford *et al.* (1989), which is suitable for bivariate relationships like the Spearman rank correlation and the Pearson correlation coefficient. In addition, we used a spatial bootstrap method proposed by Plant (2012), which uses a SAR-model (Whittle, 1954) to account for spatial autocorrelation and a linear mixed model (Schabenberger and Pierce, 2002).

In addition, to the traditional measures of spatial correlation we also applied the spatial rank correlation known as Tjøstheim´s *A* (Tjøstheim, 1978), which can calculate the correlation between two variables observed at the same spatial location. To my knowledge this has never been applied in the context of competition indices, so it deserves a brief explanation. A description is also given by Upton and Fingleton (1985) (p 259) and Glick (1982). It is calculated by ranking the CI and the growth at dbh (Δdbh) from smallest to largest observed values. From these ranked pairs the x-coordinate of the competition $x_{CI}(i)$, and similar for Δdbh ($x_{\Delta dbh}(i)$) enters Equation 4. A similar calculation is made for the y-coordinate. The observation is denoted i. The mean of the x and y coordinates are denoted $\bar{x}$ and $\bar{y}$.

Equation 4

$$A = \frac{\sum_i \left[\left(x_{CI}(i)-\bar{x}\right)\left(x_{\Delta dbh}(i)-\bar{x}\right)+\left(y_{CI}(i)-\bar{y}\right)\left(y_{\Delta dbh}(i)-\bar{y}\right)\right]}{\left(\sum_i\left[\left(x_{CI}(i)-\bar{x}\right)^2+\left(y_{CI}(i)-\bar{y}\right)^2\right]\sum_i\left[\left(x_{\Delta dbh}(i)-\bar{x}\right)\left(y_{\Delta dbh}(i)-\bar{y}\right)^2\right]\right)^{0.5}}$$

It can be shown that the variance (Var) of Tjøstheim´s *A*, under assumption of no spatial dependence between Δdbh and CI, is approximately equal to Equation 5. n is the number of observations. In Equation 5 x and y are the coordinate values of the i´th position.

Equation 5

$$Var(A) = \frac{\left(\sum x_i^2\right)^2 + 2\left(\sum x_i y_i\right)^2 + \left(\sum y_i^2\right)^2}{(n-1)\left(\sum x_i^2 + \sum y_i^2\right)}$$

The null hypothesis that the values of Δdbh and CI are not dependent on location, can be tested assuming asymptotic normality by a one-sided test (Kendall, 1962).

935 The advantage of Tjøstheim´s *A* when compared to the Spearman rank correlation is that it gives
936 a spatial measure of correlation. It is relevant to test this feature for spatially explicit CI because the
937 very idea is that including space as predictor should improve predictions of growth. Furthermore,
938 Tjøstheim´s *A* has the advantage that spatial autocorrelation is accounted for in a direct way, and
939 does not require adjustments of p-values of statistical tests like the adjustment proposed by Clifford
940 *et al.* (1989). As for the Spearman rank correlation the nonparametric nature of Tjøstheim´s *A*
941 eliminates the arbitrary choice of a growth model for evaluating the CIs.

942

2. Objectives of the studies

The objectives of the four papers of the dissertation are given below.

Paper I

- To derive a number of CIs, which utilize ALS information for calculating the competitive level of the individual tree.
- To select a number of existing CIs, in order to evaluate the performance of ALS-CIs against tested references.
- To investigate if it is possible to give accurate predictions of individual tree growth using ALS.
- To test the ability of the derived CIs to cope plot edge bias against the linear expansion method presented by Martin *et al.* (1977).

Paper II

- To investigate the validity of the comparison between different CIs which has routinely been conducted in the literature when not considering spatial autocorrelation. Especially reveal potential differences between non-spatially and spatially explicit CIs.
- To investigate if the sampling procedure of competitors may influence commonly used statistical measures so that the conclusions of an analysis of potential growth predictions from CIs may be invalid. In particular, to quantify the effect in type I and II statistical error, i.e., the effect of the non-hierarchical aggregation.
- To test the effect of plot edge bias correction on the performance of CIs, with special attention to the relation between plot edge bias correction and spatial autocorrelation.

Paper III

- To quantify how the spatial autocorrelation in the underlying variable dbh is changed in spatially and non-spatially explicit CIs.
- To compare the level of autocorrelation in the CIs, with the performance of the CIs in empirical data.
- To investigate how the components of Hegyi´s CI, the inverse distance and the size-ratio behave in a spatial field.
- To examine the effect of age correction of the CI on spatial autocorrelation and the performance of the CIs.

973

974 Paper IV

975 - To find suitable statistical methods for utilizing ALS as auxiliary information about the
976 competition pressure in the stand outside the plot in order to reduce the plot edge bias.
977 - To find ALS metrics correlated with competition, in order to find an efficient way of utilizing
978 the auxiliary information.
979 - To compare the derived methods with known alternatives of plot edge bias correction, and
980 situations with no plot edge bias correction.

981

3. Study areas and materials

Three different datasets are used. In Figure 5 the locations of the study sites are shown. In Table 2 I show some descriptive statistics of the materials, while more comprehensive descriptions can be found in the respective papers. Table 2 also shows which study site that is applied in which paper.

Table 2. Descriptive statistics on the plot level. h_L = Lorey´s mean height. Dg = quadratic mean diameter. N= stem number, BA = basal area. std = standard deviation.

Study site	Østmarka Boreal Reserve (no.of plots = 20) Papers (I, III)		
Variable	Mean	Range	std
h_L (m)	21.40	15.67-28.82	3.43
d_g (cm)	21.40	14.65-30.24	3.66
N (ha^{-1})	1047.50	630-1770	285.40
BA (m^2 ha^{-1})	34.7	21.6-45.3	0.54
Study site	Aurskog-Høland municipality (no of plots = 40) Papers (II, IV)		
Variable	Mean	Range	std
h_L (m)	16.19	10.73-23.18	3.09
d_g (cm)	17.11	10.31-25.88	3.26
N (ha^{-1})	1171.25	460 - 2440	517.31
BA (m^2 ha^{-1})	25.18	13.58 - 42.02	8.81
Study site	Hedmark County (no. of plots =557) Papers (II, IV)		
Variable	Mean	Range	std
h_L (m)	17.7	5.45-30.66	4.57
d_g (cm)	14.74	5.2-40.6	5.44
N (ha^{-1})	953.32	40-4640	718.67
BA (m^2 ha^{-1})	15.95	0.08-68.16	11.39

3.1. Hedmark County

The Hedmark County (HC) is located in south-east Norway and the total area is 27340 km^2. The data from HC consist of permanent circular sample plots of the Norwegian National Forest Inventory, located 140-925 m.a.s.l. The plot radius is 8.92 m (0.025 ha in size) and the plots are located in a 3*3 km grid, though in a 3*9 km grid in mountain locations (Anon., 2008). Of the 2309 permanent plots located in HC those that were characterized as unproductive forests according to the field workers (Anon., 2008), in addition to chose not covered by ALS, were discarded from further studies, leaving 557 plots for analysis. The plots used for competition studies in HC were measured twice in a five-year rotation inventory in the period 1999-2007. The data consists of almost all commonly forest tree species in Norway. However, the majority is Norway spruce (*Picea abies* (L.) Karst.), Scots pine (*Pinus*

sylvestris L.), and white or downy birch – (*Betula* ssp.*).* We stratified the data into the tree species classes conifer, pine, and others in order to make the investigations feasible.

3.2. Aurskog-Høland municipality

Aurskog-Høland municipality is located north-east of Oslo (59°50´N, 11°40´E, 172-388 m.a.s.l.) and covers 89 km^2. The 40 circular plots are scattered over Aurskog-Høland municipality . Thirty six of them have a size of 0.1 ha, and four plots that are located in young forest with high stem number are of 0.05 ha. Plots are with respect to stem number dominated by Norway spruce (around 48% on average) and Scots pine (around 38% on average). The remaining is mainly deciduous species dominated by *Betula* ssp. (around 14% on average).

3.3. Østmarka Boreal Reserve

Østmarka Boreal Reserve is located in the south-eastern part of Norway. The data consists of 20 circular plots, each with a size of 0.1 ha (59°50´ N, 11°02´E, 190-370 m.a.s.l.). The data is uneven-aged forest, which has not been exposed to logging since the 1940s (Økland, 1994). Plots are with respect to stem number dominated by Norway spruce (90 % on average), Scots pine (less than 1% on average) and the remaining are dominated by deciduous species (around 10% on average), mainly aspen (*Pópulus trémula* L.) and rowan (*Sorbus aucupária* L.).

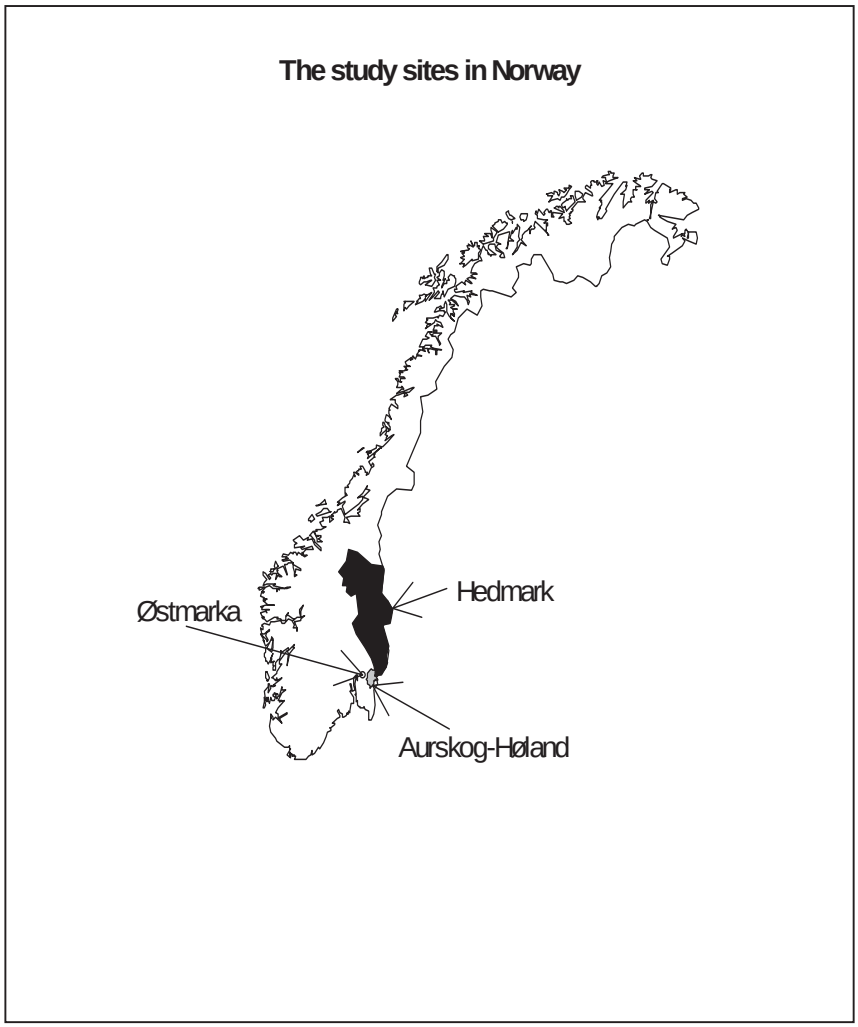


Figure 5. The location of the study sites in Norway. Hedmark County is shown in black, Aurskog-Høland municipality in gray, and Østmarka Boreal Reserve is shown as a dot.

3.4. Airborne laser scanning data

Small footprint airborne laser data were acquired in September 2006 for Hedmark County and in October 2003 for Østmarka Boreal Reserve. The data were used to calculate the density metrics used in Paper IV, and further as input to the CIs used in Papers I and II. The technical details regarding the acquisition and sensor setting are provided in Table 3. A model of the terrain was derived using the algorithm described by (Axelsson, 2000).

Table 3. Technical characteristics of the airborne laser acquisitions used in the thesis. In the table it is shown which paper each ALS-dataset is used in.

Study area		Østmarka Boreal reserve	Hedmark County
Acquisition settings	Paper	I	II,IV
	Date (year) of acquisition	10.09.2003	2006
	Platform	Hughes 500 helicopter	PA31 Piper Navajo fixed wing
	Canopy condition	Leaf-on	Leaf-on
	Flying altitude above ground (m)	600	800
	Flying speed (ms^{-1})	35	65
Sensor settings	Sensor	Optech ALTM 1233	Optech ALTM 3100
	Range capture (no. of echoes)	2	1-4
	Pulse repetition frequency (kHz)	33	100
	Scan frequency (Hz)	50	55
	Mean pulse density (m^{-2})	5.0	2.8
	Resolution[1] (m)	0.18	0.21
	Wavelength(s) (nm)	1064	1064

[1]**Resolution refers to the footprint size of ALS-data.**

4. Paper I

4.1. Results and discussion Paper I

A definition of how a ALS-return reflects the competitive level was made. Above ground ALS-returns are an indication of biomass and competition, and conversely ground ALS-returns are an indication of a canopy opening and less competition. Using this definition, a number of different ALS-CI were derived and tested against a list of existing CIs. Three new classes of CIs, non-spatially explicit, spatially explicit, and hybrid-based CI were defined. The non-spatially explicit CIs require definition of a neighborhood around the subject tree, and are also related to the semi-distance-independent dependent CIs (see Subparagraph 1.4 for an explanation of this CI). The borderline between non-spatially explicit ALS-CIs and spatially explicit ALS-CIs is that distance appears in the spatially explicit ALS-CIs. The hybrid-based CIs, are much similar in idea to the concept tested by Maltamo *et al.* (2007), namely to use the ALS-returns to derive the proportions of all trees. Since positions of competitors are needed, these indices are spatially explicit in the classical sense, and methods of plot edge bias correction need to be applied. The CIs contain different components, like angels of ALS-returns relative to the base of the position of the subject tree, the convex hull in 2-d, and the Gini-coefficient of the x,y and z coordinates of the ALS-returns around the subject tree.

For all ALS-CIs, except the hybrid-based ones, we removed the ALS-returns located inside the subject tree crown by means of an ellipsoidal crown model. For the hybrid-based CIs we used the crown model to isolate those ALS-returns that entered into the calculations of the CI. In addition, ALS-returns located under the projected crown width were removed (Figure 6). This was needed in order to eliminate problems with “self-competition”. The numerous indices and their characteristics are summarized in a table in the online electronic appendix of Paper I, which is reprinted in Table 4.

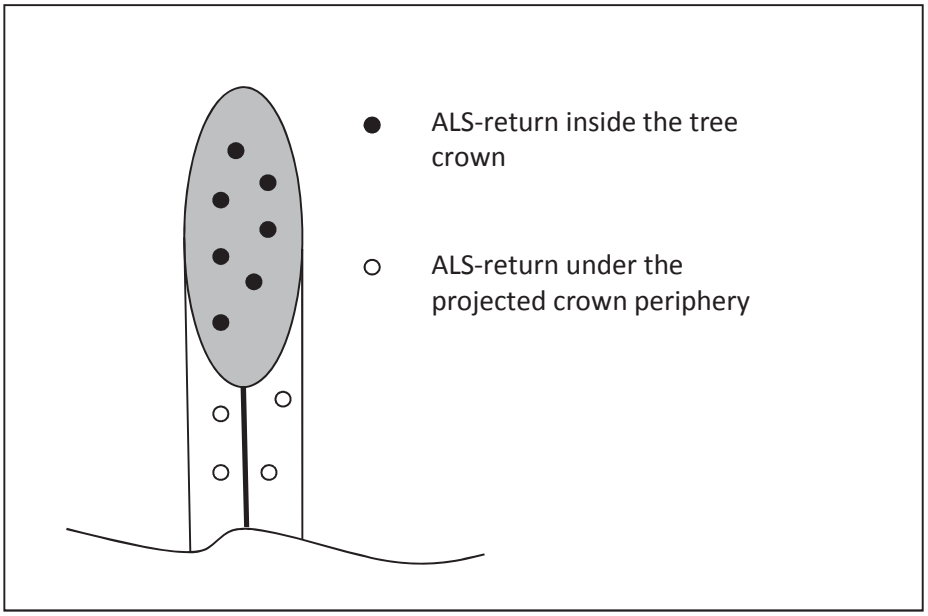


Figure 6. Isolation of ALS-returns inside the tree crown assuming the crown to be elliptical. Removal of ALS-returns under the vertically projected crown periphery.

Some of the ALS-CIs assume an even distribution of ALS-returns over the area. In reality, considerable variation may occur, and in order to make the values of the CIs comparable between trees, we used a ratio estimator to scale the search radii used to isolate the ALS-returns around the subject tree (Figure 7), which is rigorously described in Appendix A of Paper I. In cases where the number of ALS-returns is lower than the average, the search radius (S.R in Figure 7) is scaled downwards, and conversely, the radius will be increased if the number of ALS-returns is higher than the average.

The results showed that the ALS-CIs performed very well, and only Hegyi´s spatially explicit CI performed equally good as the best performing ALS-CI in the data from Østmarka Boreal Reserve. The Spearman rank correlation between CI and growth at dbh (Δdbh) varied for different search radii, and after around 7 m no improvement seemed detectable for the classic spatially explicit CIs. The highest Spearman rank correlation (Spearman, 1904) was around -0.56 for Hegyi´s CI and -0.55 for the ALS-CI. The ALS-CIs have a faster “convergence”, around four m competitor search radius and this may be due to the fact that ALS-returns mimic tree height, and relative variation is higher in tree height than in dbh. The classic non-spatially explicit CIs performed very well which is consistent with other studies. The non-spatially explicit ALS-CIs are simple to calculate, and despite the fact that one of the spatially explicit ALS-CIs performed slightly better they remain recommendable, also because this class of CIs is relative, and should be more robust to un-even number of ALS-returns per area unit. The hybrid-based CIs had the lowest explanatory power, due to exclusion of small and

suppressed trees which had not been hit by a laser beam, and thus did not allow calculations to be made.

A nonlinear growth model in the form presented by Zeide (1993) showed that the largest part of the variation (around 32%) could be explained by the dbh of the subject tree, though competition was also significant for pooled data. Plot specific regressions and correlation analysis revealed that competition does not always improve predictions of Δdbh, probably because competition is not the only factor important for tree growth. In addition, the ALS-CIs mimic above ground competition, not below ground competition. The distinction between above ground ALS-returns and ground ALS-returns was found to be correct. The CIs based on ground ALS-returns showed a weak positive correlation with Δdbh, which is a justification of the ideas of Tomé and Burkhart (1989), who use CIs where smaller and dead trees reduce the competitive pressure that the subject tree is exposed to (see Equation 1).

In Paper I we make a distinction between the social status of each tree when compared to the near surroundings (near social status), and when compared to the stand (stand social status). The rationale is that biological factors like evapotranspiration and nutrient demands cannot merely be seen as a proxy of the nearest competing trees, but rather of the stand. Possible age differences between trees in addition to the time development of the stand should be considered. Studies of cutting cycles of ponderosa pine plantations have also shown that trees grown in gaps, do not grow as well as expected if only looking at the near surroundings (Hensold, 1988), and plant physiological arguments have also been given (Koch *et al.*, 2004).

Some of the derived ALS-CIs have the ability of eliminating plot edge bias, because a buffer of ALS-returns can be taken outside the plot area. An analysis revealed that some of the ALS-CIs seemed to give less biased predictions of growth near the plot edge, thus indicating a reduction in plot edge bias. However, a lot of noise is present in the data, and the 20 plots in Østmarka Boreal Reserve are not sufficient to see the effect. Some of the results of Paper I indicate that classic non-spatially explicit indices may have plot edge bias, which has also been noted by others (Stage and Wykoff, 1998; Lappi, 2005). Reasons for this can be that the social status of trees is not reflected by the plot if the stand is very heterogeneous. This problem is expected to increase as plot size decreases. In fact, it has been shown that the coefficient of variation of a measure of density (e.g. biomass) increases with plot size, indicating that the stand variation is not captured sufficiently in small plots (Jaakkola, 1967).

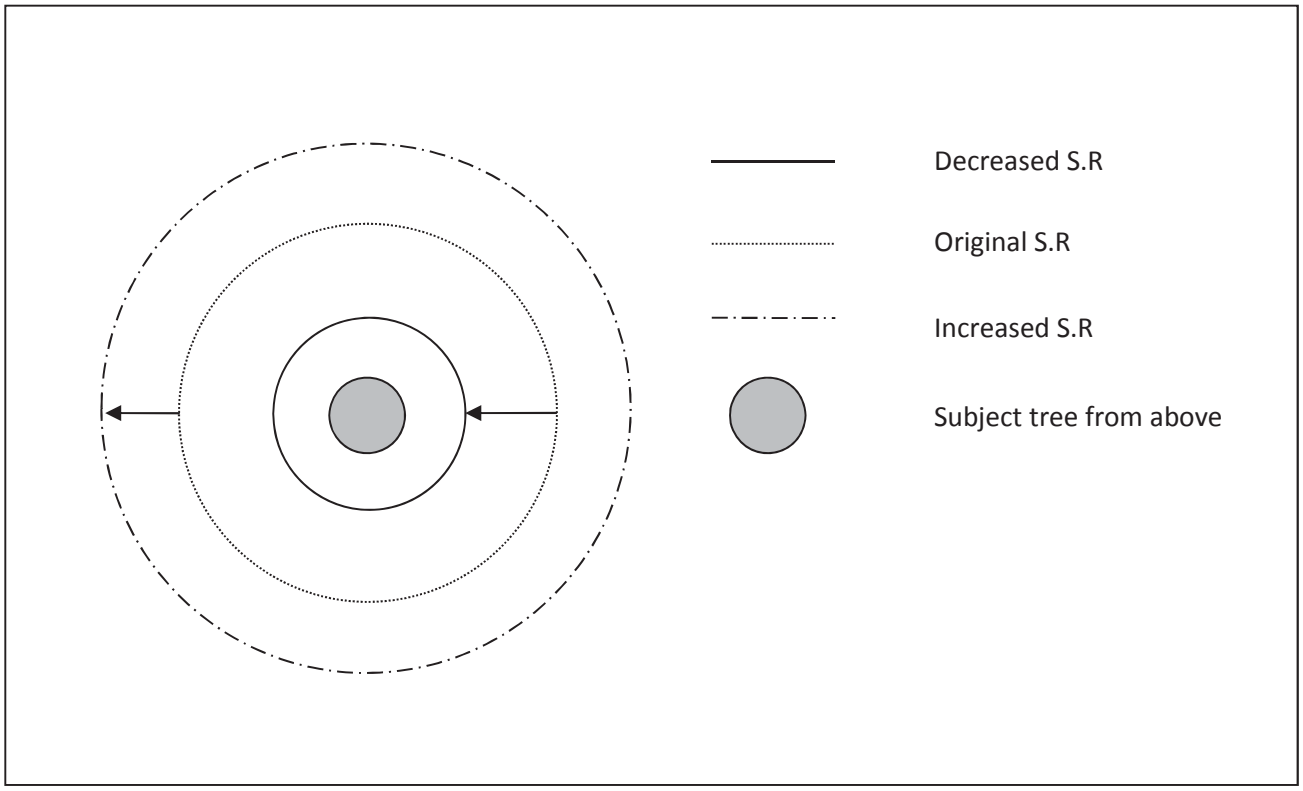


Figure 7. Illustration of how the ratio-estimator scales the search radius (S.R) so that the density of ALS-returns per area unit fits the average. The subject tree is seen from above.

4.2. Conclusion Paper I

The objectives of creating and testing CIs based on ALS were met, and predictions from ALS-based CIs were in many cases as good as the best performing exciting CIs. The many ALS-CIs we derived are summarized in Table 4 and identified by their equation number in Paper I. Important characteristics listed in the table include whether the search radius (S.R) to find competitors is fixed or variable from tree to tree. Furthermore, Table 4 shows if the CI considers the near social status of subject tree (N.S.S), as well as its position in the stand hierarchy (S.S.S). In addition, it can be seen from Table 4 if the density of biomass in different levels of canopy is quantified in the ALS-CI (D.O.B.C.), and also if the overall density of the canopy (O.D.C.) is quantified. Some of the CIs use angels (Angle) and distances (Dist) when calculated. The table also indicates which of the CIs that need scaling for uneven number of ALS-returns per area unit (Scaling). Some of the CIs eliminate plot edge bias as shown in the column Eliminate, and in most of them the positions of competitors need not to be known, which is indicated in the column denoted C.P.

Table 4. Summary of the properties of the ALS-CIs and how they are calculated. The equation number refers to the equation number in Paper I, *not* the equation numbers in the synopsis. S.R = Search radius. N.S.S = Near social status. S.S.S. = Stand social status. D.O.B.C. = Density of biomass in different levels of canopy. O.D.C = Overall density of canopy. Dist = Distance to subject-tree. Angle = Angle between ground level for subject tree and ALS-return. Scaling = Is scaling of the CSZ needed according to Appendix A of Paper I. Eliminate = Index eliminate plot edge bias. C.P. = Does the competitors (trees) positions need to be known. F = Fixed search radius. V = Variable search radius. Ind = indirectly.

Equation number	S.R	N.S.S	S.S.S	D.O.B.C.	O.D.C.	Dist	Angle	Scaling	Eliminate	C.P.	References
Non-spatially explicit											
Equation 5	F	Yes	No	No	Yes	No	No	No	Yes	No	Current study
Equation 6	F	Yes	No	Yes	No	No	No	No	Yes	No	Current study
Equation 7	F	Yes	No	Yes	No	No	No	No	Yes	No	Current study
Equation 8	F	Yes	No	Yes	Yes	No	No	No	Yes	No	Current study
Equation 9	F	Yes	No	Yes	Yes	No	No	No	Yes	No	Current study
Equation 10	V	Yes	No	Yes(Ind)	Yes(Ind)	No	No	Yes	Yes	No	Current Study
Equation 11	V	Yes	No	Yes(Ind)	Yes(Ind)	No	No	Yes	Yes	No	Current study
Equation 12	V	Yes	No	Yes(Ind)	Yes(Ind)	No	No	Yes	Yes	No	Current study
Equation 17	None	No	Yes	No	No	No	No	No	Yes	No	Current study
Spatially explicit											
Equation 13	V	Yes	No	No	No	Yes	No	Yes	Yes	No	Current study
Equation 14	V	Yes	No	No	No	No	No	Yes	Yes	No	Current study
Equation 16	V	Yes	No	No	No	Yes	Yes	Yes	Yes	No	Current Study
Equation 19	V	Yes	No	No	No	Yes	No	Yes	Yes	No	Current study
Equation 20	V	Yes	Yes	No	No	No	Yes	Yes	Yes	No	Current study
Equation 21	F	Yes	Yes	No	No	Yes	No	Yes	Yes	No	Current study
Equation 22	F	Yes	Yes	No	No	Yes(ind)	No	Yes	Yes	No	Current study
Hybrid-based CI											
Equation 23	F	Yes	No	Yes	Yes	Yes	No	No	No	Yes	**(Hegyi, 1974)**
Equation 24	F	Yes	No	Yes	No	Yes	No	No	No	Yes	**(Hegyi, 1974)**
Equation 25	F	Yes	No	No	No	Yes	No	No	No	Yes	Current study

4.3. Perspectives Paper I

All the CIs we tested were constructed under the simplified assumption that the pressure of competition is not species specific. Interspecific CIs have been presented in the literature. The principle is shown in Equation 6. The term λ_k is a species-specific parameter, $Dist$ is distance between the i´th subject tree and the j´th of *n* competitors. Another possibility of extending the flexibility is to put parameters on dbh and $Dist$. For instance, Canham *et al.* (2004) found the parameters of such a model using nonlinear optimization, and Richards et al (2008) used a neural network approach.

Equation 6

$$CI = \sum_{j \neq i}^{n} \lambda_k \frac{dbh_j}{Dist_{ij}}$$

A reason for not including species-specific parameters into the ALS-CIs is that for some of the CIs it is difficult to isolate which ALS-returns that belongs to which tree. The hybrid-based CIs allow including terms that may be species specific. Ørka et al. (2009) demonstrated how laser derived metrics within the crown may be used as explanatory variables in a linear discrimination analysis, to discriminate between conifers and broadleaves. The tradeoff is the inaccuracy in the classification (93.3 and 81.7 percent correctly classified for large conifers and broadleaves respectively, dropping to 57.7 and 68.4 percent for small trees), which may also be attributed to problems of correctly fragmenting the crown proportions in the existing single-tree segmentation algorithms. Usually, simple assumptions are made about the crown shape, such as a cylinder, and even when more realistic models are made, problems of overlapping crowns may appear. This problem of crown isolation is less apparent when using some of the ALS-CIs, because the uncertainty of crown proportions only involves the subject tree. In further research it would be interesting to investigate the tradeoff between the uncertainly of crown proportions following species classification, and the possible gain by distinction between species in the hybrid-based ALS-CIs.

For example, one of the hybrid-based ALS-CIs presented in Paper I (equation 23 of Paper I) may take the form given in Equation 7 when differentiating species by a species specific parameter λ_k. The species specific parameters may be estimated using nonlinear optimization (Pommerening *et al.*, 2011). X is a metric of the ALS-returns inside the tree crown. H_{95} is 95 pct. of the individual total tree height. H_{95Max} is the 95´th percentile of the empirical distribution of individual total tree height

in the study area. Calculations are made for the i´th subject tree and j´th competitor. $Dist$ is distance between the i´th subject tree and the j´th of *n* competitors.

Equation 7

$$CI = \sum_{i \neq j}^{n} l_i \frac{X_j^{\lambda_k}}{X_i^{\lambda_k}(Dist_{ij}+1)} \frac{H_{95\,j}}{H_{95i} H_{95Max}}$$

The concept of stand social status coincides with the point of view of Adlard (1977) who believes that the complexity of competition can only be accurately captured by combining several explanatory variables, each of which quantifying specific areas of competition. Thus, Adlard (1977) suggests combining CIs of hydrology and light to explain a larger proportion of variation. This needs to be tested when using ALS, and because both hydrology (Varhola *et al.*, 2012) and LAI (Solberg *et al.*, 2009) have been successfully modeled from ALS, an extension seems feasible. Further, terrestrial scanners also give possibilities of modeling the plastic response of the tree crown. This was shown by Seidel *et al.* (2011), who presented a method for modelling the direction of competition and the crown asymmetry caused by competition pressure in a mixed species forest.

The CIs of Paper I may be used in forestry production models, used as a planning tool for forest practitioners. We have only tested the CIs on materials from Hedmark County and Østmarka Boreal Reserve, and future investigations should preferably include data from the whole of the Norwegian NFI. ALS has been successfully applied to predict growth of individual trees (Yu *et al.*, 2005), and most studies so far are made as change detection, where the change in for instance individual total tree height is calculated using laser. The ALS-CIs allows for prediction of growth. Further inclusion of ALS-CIs in mortality and regeneration models is also possible, just as the variables terrain slope and aspect may be calculated (Stumberg *et al.*, 2013). In addition, the use over broader areas requires the use of a single-tree detection algorithm. This may give problems with finding the small and suppressed trees (Solberg *et al.*, 2006; Ene *et al.*, 2012a), which are mostly affected by competition. New investigations are needed to see how well competition can be quantified for areas with no ground truth positions. As mentioned in the discussion of Paper I, the hybrid- based ALS-CIs may show a higher potential when individual tree properties are derived from a terrestrial laser scanner. Lindberg *et al.* (2011) showed how stem attributes may be predicted with no or just a small bias by combining ALS and terrestrial laser data, and it is reasonable to assume that these indices may have a wider applicability in the future.

In Paper I we also consider methods for handling angles of the laser beam and terrain elevation (this is seen in Appendix C of Paper I). Because these methods are only theoretically derived, they need to be verified in practice. However, it is reasonable to assume that both the terrain and the angle of the laser beam, will affect the competitive level. This is also true for classical CIs, but due to economic and practical difficulties with estimation of the slope and aspect these are often ignored, or at least only calculated under the assumption of an even ground surface. From the terrain model, slope and aspect may be calculated with high accuracy from ALS, and these calculations may also be applied for classic CIs. As mentioned by Miina and Pukkala (2002) CIs may be further improved by including directional terms because the geographical position influences the solar radiation through shadow effects of competing trees. Miina and Pukkala applied ecological field theory to do this, but other options like the mean directional index (Illian *et al.*, 2008) used in Paper II can be applied.

Several studies have focused on change detection using ALS, i.e. the change in for instance individual total tree height between two acquisitions. While this may be of interest when calculating CO_2 quotas, and also to monitor potential climate effects, forest managers will probably limit their interest to a single overflying with a prognosis of individual tree growth as outcome. The derived ALS-CIs allow single-tree growth models to be constructed. However, the problem of detecting suppressed trees makes it more realistic to make a size class model from airborne laser scanning. For such a model, research is needed to show how the competition should be incorporated. In principle, a stand-level expression of competition like the self-thinning rule may be sufficient, adapted somehow to each size class.

5. Paper II

5.1. Results and discussion Paper II

In paper II we exploit the spatial autocorrelation in CIs and Δdbh. We quantified the effect of spatial autocorrelation on the effective sample size by means of the correction by Clifford et al. (1989) and a spatial bootstrap method (Plant, 2012), using a SAR- model (Whittle, 1954) for the Spearman rank correlation. Besides, we used a spatial regression model to model the spatial autocorrelation. It can easily be seen that the spatial autocorrelation induced will also be dependent on the selection of competitors, because the amount of overlapping competitors in the samples will affect the spatial autocorrelation. Therefore, we used a relascope and a circle around the subject tree in order to test the effect on the effective sample size and the resulting type I and type II statistical error. The statistical type II error was assessed by a power analysis.

The results show that spatial autocorrelation in CI is present when competitors are selected within 3-4 m search radius around the subject tree. However, when simultaneously accounting for the effect of spatial autocorrelation in Δdbh and CI the effect on the effective sample size appears negligible. The same conclusion applies when using the spatial regression approach. In order to test if spatial autocorrelation was more noticeable in certain stand structures, we correlated the relative change in the effective sample size when correcting for spatial autocorrelation to the original sample size, with different measures of stand structures (Pommerening, 2002). These were measures of macro- and micro-scale variation like Lorey´s mean height and volume per hectare. The results show that no measure of forest structure seems to give high levels of spatial autocorrelation for any of the CIs investigated. A statistical power analysis revealed that the power of the non-spatially explicit CI is higher than for the spatially explicit CI. The implications are that the statistical type II error will be lower for the non-spatially explicit CI.

5.2. Conclusion Paper II

The analysis showed that statistical type I error induced by spatial autocorrelation remains a smaller problem for spatially explicit CIs. Only within very short search radii of 3-4 m spatial autocorrelation arises. When looking at spatial autocorrelation for bivariate relations all methods agree that statistical type I error is a minor problem. The plot edge bias correction method presented by Martin *et al.* (1977) seems not to affect the conclusions, whereas the Hanisch method removes too many observations in the 250 m^2 plots to make it useful. Sampling using a relascope gave better predictions, and did not change the level of spatial autocorrelation when compared to sampling using a fixed search radius. The study revealed a significant smoothing effect caused by sample overlap, but it was not possible to document that the smoothing (similarity) affects the predictions in any negative way. The small plot size may matter here, and more research is needed on larger plots. Potential differences in the power of the statistical tests using the different CIs were observed, which may affect the statistical type II error.

5.3. Perspectives Paper II

During the peer review of Paper II one of the reviewers raised critique that the plots were too small to give accurate models of spatial autocorrelation, arguing that other studies have used plots between 1200 and 2500 m^2 (Pommerening and Särkkä, 2013) and approximately 2 ha (Fox *et al.*, 2007). The critique is just with respect to the uncertainty in the estimates of spatial dependency on each plot, and again, this means that further studies on larger plots are desirable.

The results showing smoothing of CIs have a number of perspectives. The use of sample overlap is not limited to CI, but a number of structural indices and diversity indices for example given by (Pommerening, 2002; Pommerening and Stoyan, 2006) will suffer from the same problem. New investigations are needed in order to see the magnitude of the problem in different stand structures. In fact, sample overlap has a long history in forest inventory, where it is known as sampling with partial replacement (Gregoire and Valentine, 2008). In the context of sampling, it is often successive surveys of the same sampling area which leads to correlation among the sampling units. Ware and Cunia (1962) presented a composite estimator to weight units which were subject of repeated measurements and those which were not. The aim is to come with an overall estimate of a target variable minimizing the standard error of the estimate. This way of thinking, to estimate a total based on some subunits, is very appealing for CIs, because the individual measurements should be set relative to a maximum. More research is needed to connect spatially explicit CIs to the self-thinning law of Yoda *et al.* (1963) and Reineke (1933). Several authors have already seen the need for standardization of spatially explicit CIs, which could serve as a proxy for maximum competition pressure. Lorimer (1983) was among the first to notice that the value of Hegyi´s CI decreases with increased spacing, despite the fact that Langsæter´s hypothesis claims that the growth in the stand remains fairly constant over a wide range of spacing. The correction of Lorimer (1983) solves this problem, but the problem of correlated units from sample overlap and smoothing remains. Radtke *et al.* (2003) used a probabilistic method to make sure that CIs were comparable between stands of same age but of different spacing. This method is limited to large plots to give a sufficient sample size. Pretzsch *et al.* (2002) standardized distances using the expected nearest neighbor distance under complete spatial randomness (Clark and Evans, 1954). To make CIs comparable between sites new methods are needed, that standardize the value of the CI, and at the same time handles problems of spatial autocorrelation and smoothing caused by sample overlap. One such method may be geographically weighted regression (GWR), which is featured in Paper III. Also methods of geostatistics may prove useful, in particular the methods to estimate the global moments of a distribution using indicator variables (Isaaks and Srivastava, 1989)(chapter 11). Furthermore, the use of geostatistical methods have the advantage that the loss of variation caused by sample overlap can be eliminated, and allow to use data from the most applied design namely long term experiments on smaller plots.

6. Paper III

6.1. Results and discussion Paper III

In paper III I use Moran´s *I* and LISAs to quantify the degree of spatial autocorrelation in Hegyi´s distance weighted size-ratio CI.

I studied the change in spatial autocorrelation between CI and dbh by separating the distance weighted-size-ratio into an invers distance part and a size-ratio part. Different methods of standardization presented by Lorimer (1983) and a modified form of the approach by Pretzsch *et al.* (2002) were tested. These standardization techniques are used to make index values from different age classes comparable, and are incorporated into for example the SILVA stand simulator (Pretzsch *et al.*, 2002).

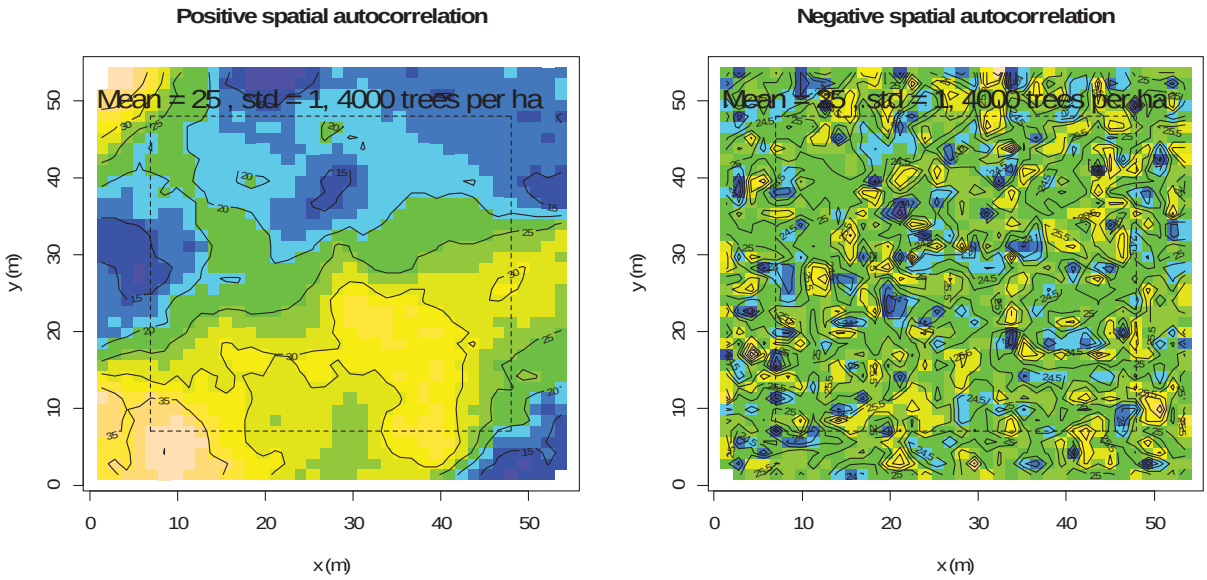
The second order stationarity of the spatial field. i.e. the constant of variance of the spatial field was tested using geographic weighted regression (GWR) by means of a permutation approach. GWR is a spatial regression technique which allows regression coefficients to vary for each location over the area (Fotheringham *et al.*, 2002). A study of the distribution of these regression coefficient reveals if the values of the variable can be considered spatially isotropic, i.e. directional independent. The permutation approach used was suggested by Fotheringham (Brunsdon *et al.*, 1998; Fotheringham, 2000), and I randomly rearranged the original data during 100 permutations. For each rearrangement, a GWR-fit was obtained, and the standard deviations of the regression coefficient on each plot were calculated. If the data is stationary, the standard deviation of the local regression estimates from the random rearrangement should not deviate much from the standard deviation of the local regression estimates of the original data.

The data from Østmarka Boreal Reserve constitute a limited sample size, and in order to get more understanding of the behavior of Hegyi´s CI in a spatially correlated field I conducted a simulation study. In the simulations I varied the degree of spatial autocorrelation between positive spatial autocorrelation, where trees of the same size are positioned closer to each other, and negative spatial autocorrelation where trees of different size are located closer in space. Both scenarios are observed in nature. For example, Pommerening and Särkkä (2013) used the mark variogram (Illian *et al.*, 2008) to analyze a number of simulated stands and time series of tree growth in order to show that negative spatial autocorrelation occurs, and what it says about the stand structure. Among the reasons for negative spatial autocorrelation, Pommerening and Särkkä (2013)

mention self-thinning, human made thinning, and size differentiation caused by competition as important factors.

I applied three different simulation methods to test the effect of spatial autocorrelation in Paper III. The first simulation method is the one presented by Haining (1990) which allows simulation of both positively and negatively correlated variables. This is done by varying a spatial parameter λ between -1 and 1. Minus 1 is extreme negative spatial dependency, and plus 1 is extreme positive spatial dependency. Haining´s method is based on the frequently used spatial error model. The method of Haining has the advantage that the range of spatial autocorrelation can be set to biologically realistic values, by specification of a spatial weight matrix. A spatial weight matrix is an indicator matrix giving the value 1 to a neighbor tree, otherwise 0 (Cliff and Ord, 1981); it can also be a weighting function instead of an indicator variable.

In Figure 8 I show an example of two realizations of a spatially correlated field of dbh. Notice that for illustration purposes I applied another plot size in Figure 8 than applied in the simulations of Paper III. The subplots are made by a smoothing function to visualize the size differences. Both simulations are made using a normal distribution with standard deviation 1 and mean 25 for 4000 trees per ha, assuming trees within 3 m to be spatially correlated. We see on the left side how positive spatial autocorrelation makes the trees look more similar in space. The plot to the right has a patchier pattern caused by the repulsing of identically sized trees. In order to remove edge effects, I made a buffer around each plot, removing all trees between the dotted square and the plot border in Figure 8 as subject trees. The simulations in Paper III were made for different standard deviations and means of the normal and the univariate distributions.

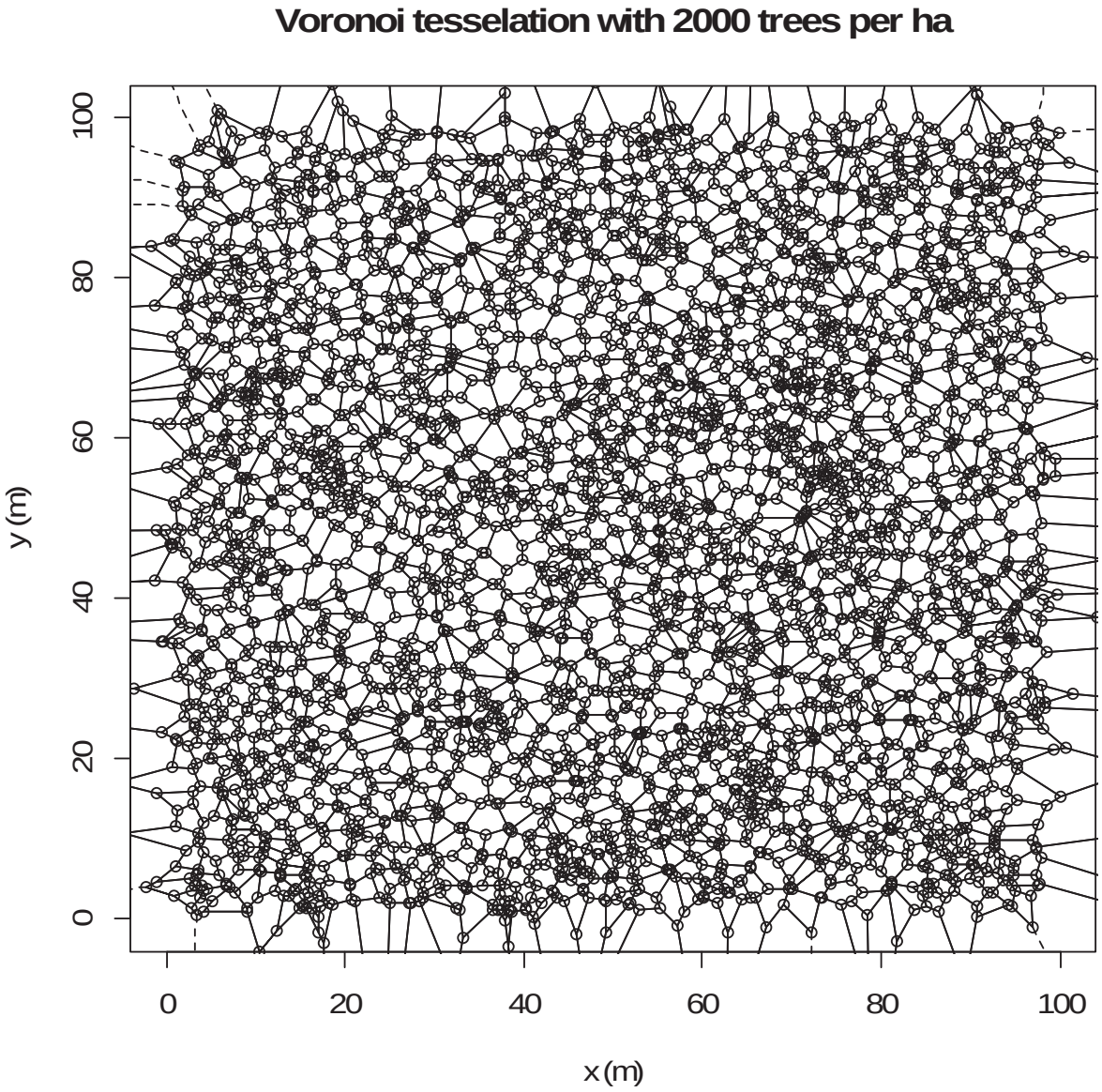


1341

1342 **Figure 8. Simulations from a spatial error model using the method of (Haining, 2003) of spatially correlated tree**
1343 **diameters at breast height. The diameters at breast height are distributed $N(25,1)$. The density is 4000 tree*ha^{-1}. On**
1344 **the left subplot I show extreme positive spatial autocorrelation with autocorrelation parameter $\lambda = 0.99$. On the right**
1345 **subplot I show extreme negative spatial autocorrelation $\lambda = -0.99$. Trees within 3 m are assumed to be correlated.**
1346 **The plot is obtained by a contour algorithm (Crawley, 2013). std = standard deviation.**

1347 The second simulation method is inspired by the work of Kershaw Jr *et al.* (2010). Kershaw Jr *et*
1348 *al.* (2010) use a copula based simulation method to create spatially correlated variables. Copulas are
1349 tools much used in economics, but more recently also used in forest science (Ene *et al.*, 2012b). A
1350 copula is a mathematical transformation from one distribution to another, preserving the marginals.
1351 Thus, a copula allows to generate e.g. normally distributed spatially correlated variables and to
1352 transform them to any distribution desirable. This is justified using Sklar´s theorem (Nelsen, 2009),
1353 which is a mathematical proof that such a transformation can be made. For example if one uses a
1354 Gaussian copula, then for *n* variables one would simulate a vector *t* with length *l* from a standard
1355 normal distribution. These would then be made uniform (U) by stripping the marginals using the
1356 inverse of the cumulative normal distribution, i.e. applying the so-called inverse transformation
1357 method (Owen *et al.*, 2009)(p 338).Thus, $U = F(N(o,1))^{-1}$. From the correlated uniform distributed
1358 variables any distribution can be obtained by using the inverse transformation method again, only
1359 this time by applying the inverse of for instance the cumulative exponential distribution. The method
1360 of Kershaw *et al.* (2010) uses the area of a Voronoi polygon to calculate the area potentially
1361 available. An example is given in Figure 9. Here a square plot with 2000 trees per hectare from a
1362 Poisson distributed forest is tessellated. The methods of Haining (1990) and Kershaw Jr *et al.* (2010)
1363 have the advantage of being applicable to point patterns which are discrete spatial observations,
1364 thus they are suitable for forests.

1365



1366

1367 **Figure 9. A Voronoi tessellation applied to a random point pattern of 10,000 square meters, using 2000 trees per**
1368 **hectare (ha). Notice that tree positions in the polygons are not shown!**

1369

The third method is made for a spatial continuum, and is known as a Gaussian random field (Dutilleul, 2011)(p 275). It is developed within geostatistics, where variables are continuously distributed in space. It has the advantage that it allows for precise specification of spatial autocorrelation through a parametric model of the empirical semivariogram shown in Equation 2. In Paper III an exponential variogram model was applied, and fitted to the estimates of the empirical omnidirectional estimates of semivariance.

Figure 10 shows the estimate of the spherical semivariogram from Østmarka Boreal Reserve for Hegyi´s CI and dbh for plot number 1. The pattern is similar for other plots in Østmarka Boreal Reserve and shows that the spatial autocorrelation in dbh is reduced in Hegyi´s CI. This result is an extension of the conclusion from Paper II, because the potential statistical type I error rate in e.g. correlation tests is reduced when comparing the level of spatial autocorrelation for Hegyi´s CI with what is originally seen in dbh. This does however not imply that positive spatial autocorrelation is not a problem when using Hegyi´s and other CIs, just that it is reduced compared to dbh. The pioneering work of Reed and Burkhart (1985) shows that the level of spatial autocorrelation in basal area varies with stand age and competition level. Since the results of Paper III indicate that Moran´s *I* for dbh (which of course are expected to behave similar to individual tree basal area) has strong correlations with Hegyi´s CI, the level of spatial autocorrelation in CIs, can be expected to follow the pattern that Reed and Burkhart (1985) observed for individual tree basal area. This shows the difficulties in making conclusions from a single survey.

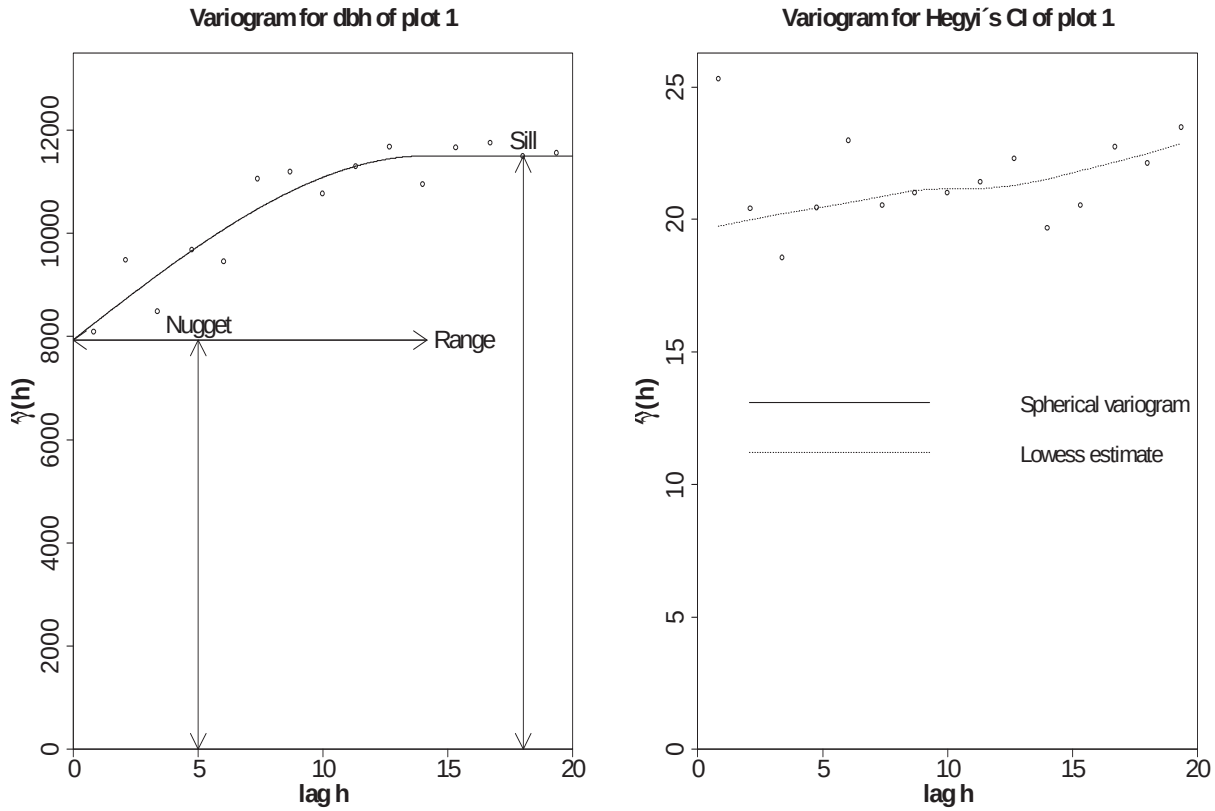


Figure 10. The semivariance of lag class h $\hat{\gamma}(h)$ calculated for dbh (left side) and Hegyi´s CI (right side) using the measurements of plot 1. For dbh a parametric fit of the spherical variogram is given by the solid line. On the graph the range nugget and sill estimated by the spherical variogram are shown. The lowess estimate of $\hat{\gamma}(h)$ for Hegyi´s CI is given by the dotted line.

Moran´s *I* was used in Paper III to get a relative value of spatial autocorrelation for comparisons between dbh and Hegyi´s CI for all plots. The results confirm the trend shown in the spherical variogram in Figure 10, i.e. almost all plots show a decreasing level of spatial autocorrelation. In Figure 11 Moran´s *I* of Hegyi´s CI is plotted against Moran´s *I* of dbh for each plot. A few positive values of Moran´s *I* of Hegyi´s CI can be observed when the level of spatial autocorrelation in dbh is low. The lowess estimate shown as the smooth line in Figure 10, reveals that spatial autocorrelation in Hegyi´s CI decreases with increasing spatial autocorrelation for dbh.

In Paper III, extensions of such an analysis, not shown in this synopsis, reveal that it is the size-ratio term of Hegyi´s CI, which is responsible for the reduction in spatial autocorrelation. The inverse distance term increases positive autocorrelation and statistical type I error in e.g. the test of the Spearman rank correlation. Thus, when the inverse distance is used as a CI, a correction method like the one proposed by Clifford *et al.* (1989) for spatial autocorrelation is needed in order to get valid statistical inference. It should be noted that in addition to confirming that the inverse distance

component increases the positive spatial autocorrelation, simulation studies also revealed that the original Hegyi´s CI and the size-ratio may cause positive spatial autocorrelation. The mean of the simulated dbh-distributions seems to be determining if positive spatial autocorrelation appears. A higher mean leads to a higher positive spatial autocorrelation. Stem number and spatial autocorrelation in dbh seem to be less important. This means that older stands with a large mean dbh should be corrected for statistical type I error before conclusions based on statistical inference can be made.

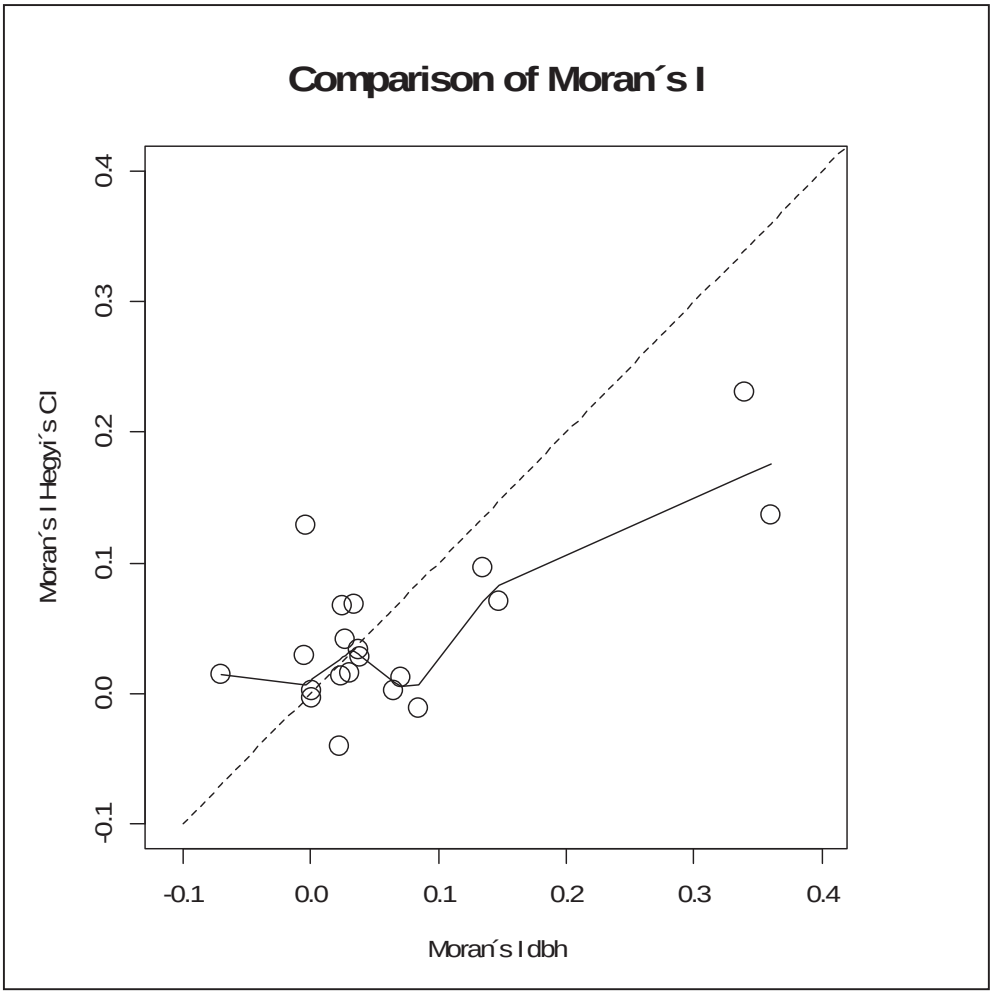


Figure 11. Moran´s *I* for Hegyi´s CI plotted against the same for dbh for each of the 20 plots in Østmarka Boreal Reserve. The dotted line indicates that the two variables are similar. The smoothed line is the lowess estimate. The search radius is 7 m around the subject tree using a binary weight in the calculations of Moran´s *I*.

Lorimer (1983) pointed out that Hegyi´s CI decreases with spacing, when the size-ratio term is the same, and made a correction for it. Pretzsch *et al.* (2002) have suggested another correction by dividing all distances with the average distance of the trees in the search radius given complete spatial randomness, by means of the Clark and Evens index (Clark and Evans, 1954)(see also Burkhart

and Tomé (2012) p 220). In Paper III I used a modified method, dividing the distance between each subject tree and competitor with the correction factor and not the "center-of-mass" originally proposed by Pretzsch *et al.* (2002). It can be seen from Paper III that the correction methods of Lorimer (1983) and the modified method of Pretzsch *et al.* (2002) reduce Moran´s *I* even more than the original Hegyi´s CI. Furthermore, these correction methods seem to improve the correlation between Δdbh and CI. Thus, these correction methods are recommendable both from at predictive and a statistical perspective.

To study the effect of increased flexibility in Hegyi´s CI, I used a version of Hegyi´s CI slightly modified after Richards *et al.* (2008) (Richards CI) which puts a parameter to each of the three stochastic variables distance, subject tree size, and competitor tree size. This version is simpler than the original one of Richards *et al.* (2008) to avoid the use of non-linear optimization. The results show that Richards CI correlates much less than any other CI tested in Paper III with Δdbh, probably because dbh is used as regressor in its calibration, and therefore explains most of the variation in the data. The correlations between the LISA of Moran´s *I* derived from dbh vs. LISA of Moran´s *I* for the various CI reveal something interesting. All CIs show a positive trend. This means, that similar sized trees in space tend to have the same competition level in space. One explanation for this is the fact that e.g. Hegyi´s CI utilizes dbh, and therefore naturally will have a spatial correlation with dbh. However, for Hegyi´s CI there seems to be a small downward trend, which means that "very hot" hotpots and "very cold" coldspots of the LISA are not as "hot" and "cold" for Hegyi´s CI (see subparagraph 1.8.4 for more explanation of these terms). This result is connected with the building of a size hierarchy, because even very similar sized trees will become dissimilar in space after assigning them a value using Hegyi´s CI. The results also show something else that is interesting. The non-spatially explicit CI used, which applies D_g and dbh has a strong correlation with LISA of dbh. This means that the non-spatially explicit CI mimics the spatial autocorrelation of the tree´s dbh, though opposite proportional as seen by the sigh of the correlation, and in cases where dbh is a good predictor of Δdbh, this index will be superior to Hegyi´s CI. In Paper I we showed, using the same material from Østmarka Boreal Reserve that 32 percent of the explained variation in Δdbh was due to dbh, and only around 2 percent was due to CI.

Paper III reveals that the correlation between LISA Δdbh and LISA CI is very weak. This is surprising because one should expect a spatial index that aims to predict Δdbh to be spatially correlated with Δdbh. This result has lead to the following hypothesis, which should be tested further in future studies :

"*The best expression of CI in a spatial context is local indicators of spatial association (LISA) of the growth (or relative growth) variable. Any CI which has the same spatial autocorrelation as growth will be the one which has the highest explanatory power*".

If the hypothesis is true it means that spatially explicit CI indices often fail to predict spatial growth because they do not equal the spatial autocorrelation of Δdbh. If we look at expressions of LISA for Morans *I*, it is highly unlikely that any CI can ever have the exactly same value of LISA Morans *I* as Δdbh, especially because in many cases dbh enters as variable in the CI. Therefore, in most cases the CI merely changes the spatial correlation of dbh, though it will to a small degree correlate with LISA Δdbh. A considerable improvement in the performance of spatially explicit CIs should therefore be expected if LISA Δdbh is used as dependent variable, and the CI as independent variable. Notice that one may need to apply the previous growth period to calculate LISA, in order to make predictions of the successive growth period. One can then apply the optimization routines of e.g. (Richards *et al.*, 2008), to find the parameters of the classical CIs. However, such an optimization may be unnecessary, because it would be more effective simply to use LISA of Δdbh directly as a CI. Spatial autocorrelation of course depends on the definition of neighborhood, and the mathematical measure used. Finding the most proper definition of spatial neighborhood for LISA of Δdbh in such a case, is also an idea for further research. One important point is that even if the hypothesis is true it does not mean that any other CI cannot give the best predictions of growth, only that if this is the case then it is not spatial, and/or it does not capture competition. It may for instance be possible to create an index that models the spatial correlation in dbh, which gives better predictions of Δdbh, simply because size is a more important parameter than competition for growth in space. Such a scenario may appear if soil conditions favor strong micro-scale gradients in site conditions.

6.2. Conclusion Paper III

The simulation study and the empirical study have both agreements and disagreements. The two studies coincide when showing that using inverse distance as a measure of competition generates positive spatial autocorrelation. In the empirical study Moran´s *I* showed a decreasing trend for CIs compared to dbh especially for high levels of positive spatial autocorrelation in dbh. The replications made in the simulations do not confirm a decrease in Moran´s *I* for Hegyi´s CI, inverse distance, or the size-ratio. Among the distributional properties of dbh such as standard deviation and mean, the simulations show that the mean of the simulated dbh distribution is the most important factor in changing the level of spatial autocorrelation in CIs. The higher the mean, the more positive spatial autocorrelation, and therefore old stands with a high mean diameter need correction for spatial autocorrelation in statistical tests. The standard deviation and the degree of spatial autocorrelation

in dbh are less important for the spatial autocorrelation in CI. Thus, it is not possible to conclude that because dbh has a negative spatial autocorrelation, the derived spatially explicit CI will have the same. Of the correction methods for increased spacing with age by Lorimer (1983) and Pretzsch *et al.* (2002), especially the method of Pretzsch *et al.* (2002) seems to reduce the level of positive spatial autocorrelation, and at the same time improves predictions when compared to results with no spacing with age correction. Thus, this method is recommendable from a statistical and predictive perspective.

The study also focuses on the spatial autocorrelation on a local scale quantified by LISAs. The results from the empirical data show that the spatially explicit CIs seem to build up a size hierarchy at the local scale when compared to dbh. The use of GWR shows that the spatial field has an increased level of nonstationarity in the spatially explicit CIs when compared to the non-spatially explicit CI. This suggests that non-spatially explicit CIs give good predictions because they mimic the explanatory power of dbh in space. The LISA-analysis also confirmed that LISA of the non-spatially explicit CI mimic the spatial autocorrelation of dbh. The most pure expression of competition is growth, and in space it is spatial autocorrelation of growth (Subsection 6.1). The analysis of correlation between LISA of Δdbh and CI only revealed weak correlations. This suggests that CIs work by mimicking dbh in space - a strong predictor of growth. But if the purpose is modeling of spatial competition, a measure of spatial autocorrelation of Δdbh should work better, or a CI which mimics this. This does of course not mean that such an index will be a stronger predictor of growth, only a stronger predictor of spatial competition.

6.3. Perspectives Paper III

The results in Paper II and Paper III throw a light on the understanding of how spatially explicit CIs behave in a spatial statistical context, and the validity of statistical inference derived from the CIs. One important problem connected with the investigations, which is not tested in any of the papers, is the problem of spatial misalignment, and how different techniques may be applied to improve the efficiency of the estimated level of competition. Spatially explicit CIs are spatially aligned by summation of the competition pressure of the competing trees into a value for each subject tree. However, from a statistical perspective such a summation may not be the best way of aligning the spatial data. One way of improving the CIs is to use the theory of random variables. It can be shown that linear weighting of stationary random variables should sum to 1 in order to be unbiased. This assumption of unbiasedness is underlying interpolation techniques such as inverse linear interpolation and kriging. When using Hegyi´s CI each competitor is interpolated to the position of the subject tree by 1/distance, and thus the condition for unbiasedness is not fulfilled. Instead of

using this simple weighting, improvements using geostatistical techniques should be tested. In the case of inverse distance the interpolation using the weight given by Equation 8 could be a simple alternative (Isaaks and Srivastava, 1989) (p 257). $\overline{CI}$ is the inverse distance weighted value of the competition index (CI) for the i´th tree. $Dist_{ij}$ is the distance between the j´th competitor and the i´th subject tree. The unbiasedness of interpolation is done by dividing with the sum of inverse distances, in a much similar way as proposed by Lorimer (1983) and Pretzsch et al. (2002). Summation is done for *n* competitors.

Equation 8

$$\overline{CI}_i = \frac{\sum_{i \neq 1}^{n} \frac{1}{Dist_{ij}} CI_i}{\sum_{i \neq 1}^{n} \frac{1}{Dist_{ij}}}$$

The use of such a standardization is also underlying ordinary kriging, and interpolation by means of polygons and triangulation (Isaaks and Srivastava, 1989) (chapter 11 and 12). The modeling would then be a two step procedure, firstly interpolating the values of the competitors to yield a CI, which would enter to the growth model. Recent methods of Bayesian hierarchical modeling allows for modeling directly without such a two step procedure, and this is an interesting field to be explored (Banerjee *et al.*, 2004)(chapter 7).

Paper III was limited to randomly distributed tree positions. However, trees form many other point patterns than random patterns. Thus, an obvious extension of the study is to test the effect of regularity and clustering. Today soft-ware packages like spatstat of R® (Baddeley and Turner, 2005) and the software developed by Kershaw Jr *et al.* (2010) allow for simulation of various point patterns, under different correlation structures of the individual tree parameters.

7. Paper IV

7.1. Results and discussion Paper IV

The methods used for plot edge bias correction derived in Paper IV rest on the simple method of ratio-estimators. Ratio estimators have a long history in forest science (Johnson, 2000). Often, a simple ratio between a variable that is known for the entire population, and another target variable is used to adjust the estimate of the target variable. This simple ratio may be extended to the case of several ratios, yielding a multivariate ratio estimator (Olkin, 1958). In Paper IV I explore the use of the

multivariate ratio- estimator. Such an estimator requires weights to be given to each of the ratios. I made use of a method initially described by Olkin (1958) for finding the weights firmly described by Cochran (1977) (p 184-186). In addition, I also identified weights by use of restricted linear regression (Waterman, 1974) and multiple linear regression. In the latter case, the ratios just enter as parameters in a regression model. The simulated annealing method is a modification of a method proposed by Pommerening and Stoyan (2008). The results show that the existing methods (simulated annealing and linear expansion) seem slightly better than the ALS based methods in improving plot specific correlations between CIs and Δdbh. The evaluation method applied in the study has the weakness that the true values of the CIs are not known. Therefore, the evaluation assumes that any improvement in the prediction of Δdbh is due to the fact that the CIs have come closer to their true values using plot edge bias correction. However, it is possible to improve correlations if the plot edge bias corrected CI mimics another strong predictor of stand structure, e.g. canopy height.

7.2. Conclusion Paper IV

While the proposed method using multivariate ratios to adjust plot edge bias is simple to use, the low correlations between laser metrics and CIs make the classical methods of plot edge bias correction work better. If ALS is to be used for plot edge bias correction, other types of indices should be tested and/or better correlations with ALS metrics should be found.

7.3. Perspectives Paper IV

Another obvious way to reduce plot edge bias is to use a single-tree detection algorithm to identify the trees outside the plot border. The method should be fairly simple to apply, and contrary to the method presented in Paper IV, has the advantage that it does not rely on a correlation between the CI and laser metrics. The weak correlations observed between density metrics and CIs, in addition to potential multicollinearity problems (Montgomery *et al.*, 2006) due to near linear dependency between metric variables, show that this is a concern. The performance of such a method depends on the power of the single-tree detection algorithm. Solberg *et al.* (2006) applied the same material, that is used in the current thesis from Østmarka Boreal Reserve, and showed that dominant trees which are expected to exert most competition to the trees on the plot, can be correctly identified and positioned in 93% of the cases. For the suppressed trees, the detection rate dropped down to 19%. Because the majority of plot edge effects may be attributed to dominant trees outside the plot, the lack of detection of suppressed trees may not matter that much, though in some forest types the understory may have considerable biomass. Applying a single-tree detection algorithm to a forest type where it is not calibrated may give very inaccurate results as demonstrated

by Vauhkonen *et al.* (2012). Vauhkonen *et al.* (2012) showed how higher density of biomass in the stands can give an increased error rate in the number of correctly identified trees. In cases with only very few plots one could consider using photo images if they exist. It should however be noticed that the canopy may be too dense for a single-tree detection algorithm to work, and in such cases the method presented in Paper IV remains an easy and simple alternative.

References

Adlard, P.G., 1977. Estimation of tree competition and coorperation in forest stands. In: Brunig, E.F. (Ed.), Trans. of the Int. Man and Biosphere IUFRO workshop on Trop. Rainforest Ecosys. Res. , Hamburg-Reinbek, pp. 149-161.

Agresti, A., 2007. An introduction to categorical data analysis. John Wiley & Sons, Inc. , Hoboken, New Jersey.

Alemdag , I.S., 1978. Evaluation of some competition indices for the prediction of diameter increment in planted white spruce. Canadian Forestry Service, Department of the Environment, Canada.

Anon., 2008. Landskogsskogstakseringens feltinstruks 2008. Skog og Landskab, Norway (http://www.skogoglandskap.no/publikasjon/landsskogtakseringens_feltinstruks_2008) (last date accessed: March 2013).

Anselin, L., 1988. Spatial econometrics: methods and models. Kluwer Academic Publishers, Dordrecht.

Anselin, L., 1995. Local Indicators of Spatial Association—LISA. Geogr. Anal. 27, 93-115.

Assmann, E., 1970. The principles of forest yield study: studies in the organic production, structure, increment and yield of forest stands. Pergamon Press, Oxford.

Axelsson, P., 2000. DEM generation from laser scanner data using adaptive TIN models. Int. Arch. Photogramm. Remote Sens., Amsterdam, pp. 110-117.

Bachmann, M., 1998. Indizes zur Erfassung der Konkurrenz von Einzelbäumen. Methodische Untersuchung in Bergmischwäldern. Forstwissenschaftliche Fakultät der Universität München und Bayerische Landesanstalt für Wald und Forstwirtschaft, München. PhD thesis, pp. 1-261.

Baddeley, A., Turner, R., 2005. spatstat: An R Package for Analyzing Spatial Point Patterns. J. Stat. Softw. 12, 1–42.

Banerjee, S., Carlin, B.P., Gelfand, A.E., 2004. Hierarchical Modeling and Analysis for Spatial Data. Chapman & Hall/CRC, Boca Raton, Florida.

Bella, I.E., 1971. A New Competition Model for Individual Trees. For. Sci. 17, 364-372.

1616 Biging, G.S., Dobbertin, M., 1992. A Comparison of Distance-Dependent Competition Measures for
1617 Height and Basal Area Growth of Individual Conifer Trees. For. Sci. 38, 695-720.

1618 Biging, G.S., Dobbertin, M., 1995. Evaluation of Competition Indices in Individual Tree Growth
1619 Models. For. Sci. 41, 360-377.

1620 Bollandsås, O.M., Hanssen, K.H., Marthiniussen, S., Næsset, E., 2008. Measures of spatial forest
1621 structure derived from airborne laser data are associated with natural regeneration patterns in an
1622 uneven-aged spruce forest. For. Ecol. Manage. 255, 953-961.

1623 Botkin, D.B., Janak, J.F., Wallis, J.R., 1972. Some Ecological Consequences of a Computer Model of
1624 Forest Growth. J. Ecol. 60, 849-872.

1625 Braathe, P., 1984. Development of regeneration with different mixtures of conifers and broadleaves.
1626 Res. pap. Nor. For. Res. Inst. 11, 1-20.

1627 Bredenkamp, B.V., Burkhart, H.E., 1990. An examination of spacing indices for *Eucalyptus grandis*.
1628 Can. J. For. Res. 20, 1909-1916.

1629 Brown, S., 1965. Point density in stems per acre. New Zealand Forestry Research Wellington, New
1630 Zealand, p. 12.

1631 Brunner, A., 1998. A light model for spatially explicit forest stand models. For Ecol. Manage. 107, 19-
1632 46.

1633 Brunner, A., Nigh, G., 2000. Light absorption and bole volume growth of individual Douglas-fir trees.
1634 Tree Physiol. 20, 323–332.

1635 Brunsdon, C., Fotheringham, S., Charlton, M., 1998. Geographically Weighted Regression-Modelling
1636 Spatial Non-Stationarity. J. R. Stat. Soc. Series D 47, 431-443

1637 Burkhart, H.E., Tomé, M., 2012. Modeling Forest Trees and Stands. Springer, New York.

1638 Canham, C.D., LePage, P.T., Coates, K.D., 2004. A neighborhood analysis of canopy tree competition:
1639 effects of shading versus crowding. Can. J. For. Res. 34, 778-787.

1640 Cao, Q.V., Dean, T.J., Baldwin Jr, V.C., 2000. Modeling the Size-Density Relationship in Direct-Seeded
1641 Slash Pine Stands. For. Sci. 46, 317-321.

1642 Chalmers, A.F., 1999. What is this thing called science? Open University Press, Buckingham.

1643 Chihara, L., Hesterberg, T., 2011. Mathematical statistics with resampling and R. John Wiley & Sons,
1644 Inc. , Hoboken, New Jersey.

1645 Clark, P.J., Evans, F.C., 1954. Distance to nearest neighbor as a measure of spatial relationships in
1646 populations. Ecology 35, 445-453.

1647 Cliff, A.D., Ord, J.K., 1981. Spatial processes : models & applications. Pion, London.

1648 Clifford, P., Richardson, S., Hemon, D., 1989. Assessing the Significance of the Correlation between
1649 Two Spatial Processes. Biometrics 45, 123-134.

1650 Cochran, W.G., 1977. Sampling techniques. Wiley, New York.

1651 Contreras, M.A., Affleck, D., Chung, W., 2011. Evaluating tree competition indices as predictors of
1652 basal area increment in western Montana forests. For. Ecol. Manage. 262, 1939-1949.

1653 Crawley, M.J., 2013. The R Book. John Wiley & Sons, Ltd, London.

1654 Cressie, N.A.C., 1991. Statistics for spatial data. Wiley, New York.

1655 Dale, M.R.T., Fortin, M., 2009. Spatial Autocorrelation and Statistical Tests: Some Solutions J. Agri.,
1656 Biol. Environ. Stat 14, 188-206.

1657 Damgaard, C., 1999. A test of asymmetric competition in plant monocultures using the maximum
1658 likelihood function of a simple growth model. Ecol. Model. 116, 285-292.

1659 Daniels, R.F., 1976. Notes: Simple Competition Indices and Their Correlation with Annual Loblolly
1660 Pine Tree Growth. For. Sci. 22, 454-456.

1661 Daniels, R.F., Burkhart, H.E., Clason, T.R., 1986. A comparison of competition measures for predicting
1662 growth of loblolly pine trees. Can. J. For. Res. 16, 1230-1237.

1663 Darwin, C., 1859. On the origin of species by means of natural selection or the preservation of
1664 favoured races in the struggle for life. John Murray, London.

1665 Dimov, L.D., Chambers, J.L., Lockhart, B.R., 2008. Five-year radial growth of red oaks in mixed
1666 bottomland hardwood stands. For. Ecol. Manage. 255, 2790-2800.

1667 Dutilleul, P., 1993. Modifying the t test for Assessing the Correlation Between Two Spatial Processes.
1668 Biometrics 49, 305-314.

1669 Dutilleul, P., 2011. Spatio-temporal heterogeneity: concepts and analyses. Cambridge University
1670 Press, Cambridge.

1671 Ek, A.R., Monserud, R.A., 1974. Trials with program FOREST: growth and reproduction simulation for
1672 mixed species even- or uneven-aged forest stands In: Fries, J. (Ed.), Growth Models for Tree and
1673 Stand Simulation. International Union of Forestry Research Organizations working party S4.01-4:
1674 proceedings of meetings in 1973. Royal College of Forestry, Stockholm, Sweden pp. 56-69.

1675 Ene, L., Næsset, E., Gobakken, T., 2012a. Single tree detection in heterogeneous boreal forests using
1676 airborne laser scanning and area-based stem number estimates. Int. J. Remote Sens. 33, 5171-5193.

1677 Ene, L.T., Næsset, E., Gobakken, T., Gregoire, T.G., Ståhl, G., Holm, S., 2013. A simulation approach
1678 for accuracy assessment of two-phase post-stratified estimation in large-area LiDAR biomass surveys.
1679 Remote Sens. Environ. 133, 210-224.

1680 Ene, L.T., Næsset, E., Gobakken, T., Gregoire, T.G., Ståhl, G., Nelson, R., 2012b. Assessing the accuracy
1681 of regional LiDAR-based biomass estimation using a simulation approach. Remote Sens. Environ. 123,
1682 579-592.

1683 Farrar, J.L., 1961. Longitudinal variation in the thickness of the annual ring. For. Chron. 37, 323-349.

1684 Fotheringham, A.S., 2000. Quantitative Geography. Sage, London, United Kingdom.

1685 Fotheringham, A.S., Brunsdon, C., Charlton, M., 2002. Geographically weighted regression : the
1686 analysis of spatially varying relationships. Wiley, Chichester.

1687 Fox, J.C., Bi, H., Ades, P.K., 2007. Spatial dependence and individual-tree growth models: I.
1688 Characterising spatial dependence. For. Ecol. Manage. 245, 10-19.

1689 Füldner, K., 1995. Strukturbeschreibung von Buchen-Edellaubholz-Mischwäldern [Describing forest
1690 structures in mixed beech-ash-maple-sycamore stands] Forst. Fak. Göttingen. University of
1691 Göttingen, Göttingen, Germany. PhD thesis.

1692 Geary, R.C., 1954. The Contiguity Ratio and Statistical Mapping. Inc. Stat. 5, 115-146.

1693 Gertner, G.Z., Dzialowy, P.J., 1984. Effects of measurement errors on an individual tree-based growth
1694 projection system. Can. J. For. Res. 14, 311-316.

1695 Gini, C., 1912. Variabilita e mutabilita: Contributo allo studio delle distribuzioni e relazioni
1696 stastistiche. Studi Economico-Giuridici dell´ Universita di Cagliari 3, 1-158.

1697 Gizachew, B., Brunner, A., Øyen, B.-H., 2012. Stand responses to initial spacing in Norway spruce
1698 plantations in Norway. Scand. J. For. Res. 27, 637-648.

1699 Glick, B.J., 1982. A Spatial Rank-Order Correlation Measure. Geogr. Anal. 14, 177-181.

1700 Glover, G.R., Hool, J.N., 1979. A Basal Area Ratio Predictor of Loblolly Pine Plantation Mortality. For.
1701 Sci. 25, 275-282.

1702 Gobakken, T., Næsset, E., 2004. Estimation of diameter and basal area distributions in coniferous
1703 forest by means of airborne laser scanner data. Scand. J. For. Res. 19, 529 - 542.

1704 Gray, H.R., 1956. The form and taper of forest-tree stems In: Imperial Forestry Institute (Ed.), Paper
1705 32. Imperial Forestry Institute, University of Oxford, Oxford, pp. 1-79.

1706 Gregoire, T.G., Valentine, H.T., 2008. Sampling strategies for natural resources and the environment.
1707 Chapman & Hall/CRC, Boca Raton, Fla.

1708 Haining, R., 2003. Spatial data analysis : theory and practice. Cambridge University Press, Cambridge.

1709 Haining, R.P., 1990. Spatial Data Analysis in the Social and Environmental Sciences. Cambridge
1710 University Press, Cambridge.

1711 Hanisch, K.-H., 1984. Some remarks on estimators of the distribution function of nearest neighbour
1712 distance in stationary spatial point processes. Mat. Oper. Stat. 15, 409-412.

1713 Hara, T., 1984. A stochastic model and the moment dynamics of the growth and size distribution in
1714 plant populations. J. Theor. Biol. 109, 173-190.

1715 Harper, J.L., 1967. A Darwinian approach to plant ecology. J. Ecol. 55, 247-270.

1716 Hasenauer, H., Monserud, R.A., 1997. Biased predictions for tree height increment models developed
1717 from smoothed 'data'. Ecol. Model. 98, 13-22.

1718 Hauglin, M., Dibdiakova, J., Gobakken, T., Næsset, E., 2013. Estimating single-tree branch biomass of
1719 Norway spruce by airborne laser scanning. ISPRS J. Photogramm. Remote Sens. 79, 147-156.

1720 Hegyi, F., 1974. A simulation model for managing jack-pine stands. In: Fries, J. (Ed.), Growth Models
1721 for Tree and Stand Simulation. International Union of Forestry Research Organizations working party
1722 S4.01-4: proceedings of meetings in 1973. Royal College of Forestry, Stockholm, Sweden, pp. 74-90.

1723 Hensold, T., 1988. Evaluating alternative target structures for an uneven-aged ponderosa pine stand
1724 using the Stand Prognosis Model. Extension Forestry. University of Idaho Moscow, Idaho, MSc thesis.

1725 Husch, B., Kershaw, J.A., Beers, T.W., 2003. Forest mensuration. John Wiley & Sons, Hoboken, New
1726 Jersey.

1727 Hyyppä, J., Hyyppä, H., Leckie, D., Gougeon, F., Yu, X., Maltamo, M., 2008. Review of methods of
1728 small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. Int. J.
1729 Remote Sens. 29, 1339-1366.

1730 Illian, J., Penttinen, A., Stoyan, H., Stoyan, D., 2008. Statistical analysis and modelling of spatial point
1731 patterns. John Wiley & Sons, Chichester.

1732 Isaaks, E.H., Srivastava, R.M., 1989. Applied geostatistics. Oxford University Press, New York.

1733 Jaakkola, S., 1967. On the use of variable size plots for increment research In: DVFFA (Ed.),
1734 Proceedings of IUFRO XIV Congress, Section 25. German Union of Forest Research Organisations
1735 (DVFFA) München pp. 371-378.

1736 Jensen, J.L.R., Humes, K.S., Hudak, A.T., Vierling, L.A., Delmelle, E., 2011. Evaluation of the MODIS LAI
1737 product using independent lidar-derived LAI: A case study in mixed conifer forest. Remote Sens.
1738 Environ. 115, 3625-3639.

1739 Jensen, J.L.R., Humes, K.S., Vierling, L.A., Hudak, A.T., 2008. Discrete return lidar-based prediction of
1740 leaf area index in two conifer forests. Remote Sens. Environ. 112, 3947-3957.

1741 Johann, K., 1982. Der "A-Wert"-ein objektiver Parameter zur Bestimmung der Freistellungsstärke von
1742 Zentralbäumen. Berichte der Jahrestagung des Deutschen Verbandes Forstlicher. Sektion
1743 Ertragskunde, in Weibersbrunn pp. 146-158.

1744 Johnson, E.W., 2000. Forest sampling desk reference. CRC Press, Boca Raton, Florida.

1745 Kangas, A.S., 1998. Effect of errors-in-variables on coefficients of a growth model and on prediction
1746 of growth. For. Ecol. Manage. 102, 203-212.

1747 Kelty, M.J., Larson, B.C., Oliver, C.D. (Eds.), 1992. The Ecology and Silviculture of Mixed-species
1748 Forests: A Festschrift for David M. Smith. Kluwer Academic Publishers, Netherlands.

1749 Kendall, M.G., 1962. Rank correlation methods. Griffin, London.

1750 Kershaw Jr, J.A., Richards, E.W., McCarter, J.B., Oborn, S., 2010. Spatially correlated forest stand
1751 structures: A simulation approach using copulas. Comput. Electron. Agric. 74, 120-128.

1752 Kimmins, J.P., 2004. Forest ecology: a foundation for sustainable forest management and
1753 environmental ethics in forestry. Prentice Hall, Upper Saddle River, New Jersey.

1754 Koch, G.W., Sillett, S.C., Jennings, G.M., Davis, S.D., 2004. The limits to tree height. Nature 428, 851-
1755 854.

1756 Kraft, G., 1884. Beiträge zur Lehre von den Durchforstungen. Schlagstellungen und Lichtungshieben.
1757 Klindworth Verlag, Hannover.

1758 Krajicek, J.E., Brinkman, K.A., Gringrich, S.F., 1961. Crown Competition - A Measure of Density. For.
1759 Sci. 7, 35-42.

1760 Lanner, R.M., 1985. On the sensitivity of height growth to spacing. For Ecol. Manage. 13, 143-148.

1761 Lappi, J., 2005. Plot size related measurement error bias in tree growth models. Can. J. For. Res. 35,
1762 1031-1040.

1763 Leary, R.A., 1979. Design. A generalized forest growth projection system applied to the lake states
1764 region, USDA For. Serv. Gen. Tech. Rep. NC-49. North Central Forest Experimental Station St. Paul,
1765 USA, pp. 5-15.

1766 Lee, Y., 1967. Stand models for lodgepole pine and limits to their application. Department of
1767 Forestry. Univ. of B.C. , Vancouver, Canada. PhD thesis, pp. 1-332.

1768 Lilleleht, A., Sims, A., Pommerening, A., 2013. Spatial forest structure reconstruction as a strategy for
1769 mitigating edge-bias in circular monitoring plots. For. Ecol. Manage. In Press.

1770 Lindberg, E., Holmgren, J., Olofsson, K., Olsson, H., 2011. Estimation of stem attributes using a
1771 combination of terrestrial and airborne laser scanning. Eur. J. For. Res. , 1-15.

1772 Lorimer, C.G., 1983. Tests of age-independent competition indices for individual trees in natural
1773 hardwood stands. For. Ecol. Manage. 6, 343-360.

1774 Lund, J., 1999. Statistical inference and perfect simulation for point processes observed with noise.
1775 Department of Mathematics and Physics. The Royal Veterinary and Agricultural University,
1776 Frederiksberg, Denmark. PhD thesis, pp. 1-14 + appendices.

1777 Malmberg, C., Smith, H., 1982. Relationship between plant weight and density in mixed populations
1778 of *Medicago sativa* and *Trifolium pratens*. Oikos 38, 365-368.

1779 Maltamo, M., Packalén, P., Peuhkurinen, J., Suvanto, A., Pesonen, A., Hyyppä, J., 2007. Quality
1780 assessment of a Forest Inventory Baced on Airborne Laser Scanning. ISPRS Workshop on Laser
1781 Scanning 2007 and SilviLaser 2007, Espoo, Finland, pp. 270-279.

1782 Martin, G.L., Ek, A.R., 1984. A Comparison of Competition Measures and Growth Models for
1783 Predicting Plantation Red Pine Diameter and Height Growth. For. Sci. 30, 731-743.

1784 Martin, G.L., Ek, A.R., Monserud, R.A., 1977. Control of plot edge bias in forest stand growth
1785 simulation models. Can. J. For. Res. 7, 100-105.

1786 Metz, J., Seidel, D., Schall, P., Scheffer, D., Schulze, E.-D., Ammer, C., 2013. Crown modeling by
1787 terrestrial laser scanning as an approach to assess the effect of aboveground intra- and interspecific
1788 competition on tree growth. For. Ecol. Manage. 310, 275-288.

1789 Miina, J., Pukkala, T., 2000. Using numerical optimization for specifying individual-tree competition
1790 models. For. Sci. 46, 277-283.

1791 Miina, J., Pukkala, T., 2002. Application of ecological field theory in distance-dependent growth
1792 modelling. For. Ecol. Manage. 161, 101-107.

1793 Montgomery, D.C., Peck, E.A., Vining, G.G., 2006. Introduction to linear regression analysis. Wiley,
1794 Hoboken, New Jersey.

1795 Moran, P.A.P., 1950. Notes on Continuous Stochastic Phenomena. Biometrika 37, 17-23.

1796 Munro, D.D., 1974. Forest growth model - a prognosis. In: Fries, J. (Ed.), Growth models for tree and
1797 stand simulation. Royal College of Forestry, Stockholm, pp. 7-21.

1798 Nelsen, R.B., 2009. An introduction to copulas. Springer, New York.

1799 Nelson, R., Krabill, W., MacLean, G., 1984. Determining forest canopy characteristics using airborne
1800 laser data. Remote Sens. Environ. 15, 201-212.

1801 Newnham, R.M., 1964. The development of a stand model for Douglas fir. Department of Forestry.
1802 The University of British Columbia, Vancouver, Canada. PhD thesis, pp. 1-201.

1803 Newton, P.F., Jolliffe, P.A., 1998. Assessing processes of intraspecific competition within spatially
1804 heterogeneous black spruce stands. Can. J. For. Res. 28, 259-275.

1805 Nilsson, U., 1993. Competition in young stands of Norway Spruce and Scots pine. Southern Swedish
1806 Forest Research Centre. Swedish University of Agricultural Sciences., Alnarp, Sweden. PhD thesis.

1807 Nilsson, U., 1994. Development of growth and stand structure in Picea abies stands planted at
1808 different initial densities. Scand. J. For. Res. 9, 135-142.

1809 Nord-Larsen, T., 2006. Modelling the growth of European beech (Fagus sylvatica L.) in Denmark.
1810 Danish Center for Forest, Landscape and Planning. The Royal Veterinary and Agricultural University,
1811 Copenhagen. PhD thesis, pp. 1-190.

1812 Nord-Larsen, T., Damaard, C., Weiner, J., 2006. Quantifying size-asymmetric growth among individual
1813 beech trees. Can. J. For. Res. 36, 418-425.

1814 Næsset, E., 1997. Estimating timber volume of forest stands using airborne laser scanner data.
1815 Remote Sens. Environ. 61, 246-253.

1816 Næsset, E., 2002. Predicting forest stand characteristics with airborne scanning laser using a practical
1817 two-stage procedure and field data. Remote Sens. Environ. 80, 88-99.

1818 Næsset, E., 2004. Practical large-scale forest stand inventory using a small-footprint airborne
1819 scanning laser. Scand. J. For. Res. 19, 164-179.

1820 Næsset, E., Økland, T., 2002. Estimating tree height and tree crown properties using airborne
1821 scanning laser in a boreal nature reserve. Remote Sens. Environ. 79, 105-115.

1822 Okabe, A., 2000. Spatial tessellations: concepts and applications of Voronoi diagrams. Wiley,
1823 Chichester.

1824 Olkin, I., 1958. Multivariate ratio estimation for finite populations. Biometrika 45, 154-165

1825 Owen, J., Maillardet, R., Robinson, A., 2009. Scientific Programming and Simulation Using R. CRC
1826 Press, Taylor & Francis Group, New York.

1827 Park, H.M., 2008. Hypothesis Testing and Statistical Power of a Test, working paper. The University
1828 Information Technology Services, Center for Statistical and Mathematical Computing, Indiana
1829 University, http://www.indiana.edu/~statmath/stat/all/power/index.html (last date accessed:
1830 January 2013).

1831 Pedersen, R.Ø., Bollandsås, O.M., Gobakken, T., Næsset, E., 2012. Deriving individual tree
1832 competition indices from airborne laser scanning. For. Ecol. Manage. 280, 150-165.

1833 Perry, D.A., 1985. The competition process in forest stands. In: Cannell, M.G.R., Jackson, J.E. (Eds.),
1834 Attributes of trees as crop plants. Institute of Terrestrial Ecology, Huntingdon, United Kingdom, pp.
1835 481-506.

1836 Plant, R.E., 2012. Spatial data analysis in ecology and agriculture using R. CRC Press, Boca Raton,
1837 Florida.

1838 Pommerening, A., 2002. Approaches to quantifying forest structures. Forestry 75, 305-324.

1839 Pommerening, A., 2008. Analysing and modelling Spatial Woodland Structure University of Natural
1840 Resources and Applied Life Sciences, Vienna, Austria. D.Sc. dissertation p. 37 + appendices.

1841 Pommerening, A., 2013. CRANCOD - A Program for the Analysis and Reconstruction of Spatial Forest
1842 Structure. Prof. Dr. Arne Pommerening, Bern University of Applied Sciences, School of Agricultural,
1843 Forest and Food Sciences., http://www.crancod.org/wiki/index.php?title=Main_Page (last date
1844 accessed: January 2013).

1845 Pommerening, A., LeMay, V., Stoyan, D., 2011. Model-based analysis of the influence of ecological
1846 processes on forest point pattern formation—A case study. Ecol. Model. 222, 666-678.

1847 Pommerening, A., Stoyan, D., 2006. Edge-correction needs in estimating indices of spatial forest
1848 structure. Can. J. For. Res. 36, 1723-1739.

1849 Pommerening, A., Stoyan, D., 2008. Reconstructing spatial tree point patterns from nearest
1850 neighbour summary statistics measured in small subwindows. Can. J. For. Res. 38, 1110-1122.

1851 Pommerening, A., Särkkä, A., 2013. What mark variograms tell about spatial plant interactions. Ecol.
1852 Model. 251, 64-72.

1853 Pretzsch, H., 2009. Forest Dynamics, Growth and Yield: From Measurement to Model. Springer-
1854 Verlag Berlin Heidelberg, Berlin, Heidelberg.

1855 Pretzsch, H., Biber, P., Ďurský, J., 2002. The single tree-based stand simulator SILVA: construction,
1856 application and evaluation. For. Ecol. Manage. 162, 3-21.

1857 Pukkala, T., 1989. Methods to describe the competition process in a tree stand. Scand. J. For. Res. 4,
1858 187-202.

1859 Pukkala, T., Kolstroem, T., 1987. Competition indices and the prediction of radial growth in Scots
1860 pine. Silva Fennica 21, 55-67.

1861 Purves, D.W., Lichstein, J.W., Pacala, S.W., 2007. Crown Plasticity and Competition for Canopy Space:
1862 A New Spatially Implicit Model Parameterized for 250 North American Tree Species. PLoS ONE. 2

1863 Radtke, P.J., Burkhart, H.E., 1998. A comparison of methods for edge-bias compensation. Can. J. For.
1864 Res. 28, 942-945.

1865 Radtke, P.J., Westfall, J.A., Burkhart, H.E., 2003. Conditioning a distance-dependent competition
1866 index to indicate the onset of inter-tree competition. For. Ecol. Manage. 175, 17-30.

1867 Reed, D.D., Burkhart, H.E., 1985. Spatial Autocorrelation of Individual Tree Characteristics in Loblolly
1868 Pine Stands. For. Sci. 31, 575-587.

1869 Reineke, L.H., 1933. Perfecting a stand density index for even-aged forests. J. Agric. Res. 46, 627-638.

1870 Reventlow, C.D.F., 1816. Formeentlige Resultater af endeel fortsatte Undersögelser angaaende
1871 Indflydelsen af Træernes giensidige Afstand paa deres mere eller mindre fordeelagtige Vegetation.
1872 Det kongelige Danske Videnskabernes Selskabs Skrivter for Aar 1809, 1810, 1811 og 1812 Række, 6.
1873 Bind, II. Hæfte.

1874 Reventlow, C.D.F., 1879. Forslag til en forbedret Skovdrift, grundet paa Undersøgelser over Træernes
1875 Vegetation i Danmarks of Slesvigs Skove. P. Hauberg & Co., Kjøbenhavn.

1876 Richards, F.J., 1959. A Flexible Growth Function for Empirical Use. J. Exp. Bot. 10, 290-330.

1877 Richards, M., McDonald, A.J.S., Aitkenhead, M.J., 2008. Optimisation of competition indices using
1878 simulated annealing and artificial neural networks. Ecol. Model. 214, 375-384.

1879 Rivas, J.J.C., González, J.G.Á., Aguirre, O., Hernández, F.J., 2005. The effect of competition on
1880 individual tree basal area growth in mature stands of Pinus cooperi Blanco in Durango (Mexico). Eur.
1881 J. For. Res. 124, 133-142.

1882 Schabenberger, O., Gotway, C.A., 2005. Statistical Methods for Spatial Data Analysis. Chapman &
1883 Hall/CRC, Boca Raton, Florida.

1884 Schabenberger, O., Pierce, F.J., 2002. Contemporary statistical models for the plant and soil sciences.
1885 CRC Press, Boca Raton, Florida.

1886 Schwinning, S., Weiner, J., 1998. Mechanisms Determining the Degree of Size Asymmetry in
1887 Competition among Plants. Oecologia 113, 447-455.

1888 Seidel, D., Leuschner, C., Müller, A., Krause, B., 2011. Crown plasticity in mixed forests—Quantifying
1889 asymmetry as a measure of competition using terrestrial laser scanning. For. Ecol. Manage. 261,
1890 2123-2132.

1891 Shi, H., Zhang, L., 2003. Local Analysis of Tree Competition and Growth. For. Sci. 49, 938-955.

1892 Silvertown, J.W., 1982. Introduction to plant population ecology. Longman, London.

1893 Sjolte-Jørgensen, J., 1967. The influence of spacing on the growth and development of coniferous
1894 plantations. Int. Rev. For. Res. 2, 43-95.

1895 Skovsgaard, J.P., 1997. Management of Sitka spruce without thinnings. An analysis of stand structure
1896 and volume production of unthinned stands of Sitka struce (*Picea Sitchensis* (Bong.) Carr.) in
1897 Denmark Forskningsserien no. 19. Forskningscentret for Skov & Landskab, Hørsholm, Denmark. Dr.
1898 agro. thesis, p. 525.

1899 Skovsgaard, J.P., Vanclay, J.K., 2008. Forest site productivity: a review of the evolution of
1900 dendrometric concepts for even-aged stands. Forestry 81, 13-31.

1901 Skovsgaard, J.P., Vanclay, J.K., 2013. Forest site productivity: a review of spatial and temporal
1902 variability in natural site conditions. Forestry 86, 305 –315.

1903 Soares, P., Tomé, M., 1999. Distance-dependent competition measures for eucalyptus plantations in
1904 Portugal. Ann. For. Sci. 56, 307–319.

1905 Solberg, S., Brunner, A., Hanssen, K.H., Lange, H., Næsset, E., Rautiainen, M., Stenberg, P., 2009.
1906 Mapping LAI in a Norway spruce forest using airborne laser scanning. Remote Sens. Environ. 113,
1907 2317-2327.

1908 Solberg, S., Næsset, E., Bollandsås, O.M., 2006. Single Tree Segmentation Using Airborne Laser
1909 Scanner Data in a Structurally Heterogeneous Spruce Forest. Photogramm. Eng. Remote Sens. 72,
1910 1369-1378

1911 Spearman, C., 1904. The Proof and Measurement of Association between Two Things. Am. J. Psychol.
1912 15, 72-101.

1913 Stage, A.R., Ledermann, T., 2008. Effects of competitor spacing in a new class of individual-tree
1914 indices of competition: semi-distance-independent indices computed for Bitterlich versus fixed-area
1915 plots. Can. J. For. Res. 38, 890-898.

1916 Stage, A.R., Wykoff, W.R., 1998. Adapting Distance-Independent Forest Growth Models to Represent
1917 Spatial Variability: Effects of Sampling Design on Model Coefficients. For. Sci. 44, 224-238.

1918 Strand, L., 1972. A model for stand growth. In: Unknown (Ed.), 3rd Conf. IUFRO Advisory Group of
1919 Forest Statisticians, Jouy-en-Josas, 7-11 sept. 1970. Institutt National de la Recherche Agronomique,
1920 Paris, pp. 207-216.

1921 Stumberg, N., Ørka, H.O., Bollandsås, O.M., Gobakken, T., Næsset, E., 2013. Classifying tree and
1922 nontree echoes from airborne laser scanning in the forest–tundra ecotone. Can. J. Remote Sens. , 1-
1923 12.

1924 Särndal, C.-E., Swensson, B., Wretman, J., 2003. Model Assisted Survey Sampling. Springer, New York.

1925 Tiefelsdorf, M., 1998. Modelling spatial processes: The identification and analysis of spatial
1926 relationships in regression residuals by means of Moran´s I (Germany). Wilfrid Laurier University,
1927 Canada. PhD thesis, pp. 1-201.

1928 Tjøstheim, D., 1978. A Measure of Association for Spatial Variables. Biometrika 65, 109-114.

1929 Tobler, W., 1970. A computer movie simulating urban growth in the Detroit region Econ. Geogr. 46,
1930 234-240.

1931 Tomé, M., Burkhart, H.E., 1989. Distance-Dependent Competition Measures for Predicting Growth of
1932 Individual Trees. For. Sci. 35, 816-831.

1933 Upton, G.J.G., Fingleton, B., 1985. Spatial Data Analysis by Example, Vol.1: Point Pattern and
1934 Quantitative Data. John Wiley & Sons, New York.

1935 Varhola, A., Frazer, G.W., Teti, P., Coops, N.C., 2012. Estimation of forest structure metrics relevant
1936 to hydrologic modeling using coordinate transformation of airborne laser scanning data. Hydrol.
1937 Earth Syst. Sci. Discuss. 9, 5531-5573.

1938 Vauhkonen, J., Ene, L., Gupta, S., Heinzel, J., Holmgren, J., Pitkänen, J., Solberg, S., Wang, Y.,
1939 Weinacker, H., Hauglin, K.M., Lien, V., Packalén, P., Gobakken, T., Koch, B., Næsset, E., Tokola, T.,

Maltamo, M., 2012. Comparative testing of single-tree detection algorithms under different types of forest. Forestry 85, 27-40.

Ware, K.D., Cunia, T., 1962. Continuous Forest Inventory With Partial Replacement of Samples. For. Sci. monograph 3, 1-40.

Waterman, M.S., 1974. A restricted least squares problem. Technometrics 16, 135-136.

Weiner, J., Solbrig, O.T., 1984. The meaning and measurement of size hierarchies in plant-populations. Oecologia 61, 334-336.

Weiner, J., Wright, D.B., Castro, S., 1997. Symmetry of Below-Ground Competition between Kochia scoparia Individuals Oikos 79, 85-91.

Weiskittel, A.R., Hann, D.W., Kershaw Jr, J.A., Vanclay, J.K., 2011. Forest Growth and Yield Modeling Wiley-Blackwell, United Kingdom.

Westoby, M., 1984. The self-thinning rule. Advan. Ecol. Res. 14, 167-225.

Whittle, P., 1954. On stationary processes in the plane. Biometrika 41, 434-449.

Wichmann, L., 2001. Annual Variations in Competition Symmetry in Even-aged Sitka Spruce. Ann. Bot. 88, 145-151.

Windhager, M. (Ed), 1997. Die Berechnung des Ek und Monserud (1974) Konkurrenzindex für Randbäume nach unterschiedlichen Berechnungsmethoden. [Calculation of the Ek and Monserud (1974) competition index for edge trees using alternative computing methods.]. Freiburg, Germany.

Wykoff, W.R., 1990. A Basal Area Increment Model for Individual Conifers in the Northern Rocky Mountains. For. Sci. 36, 1077-1104.

Yoda, K., Kira, T., Ogawa, H., Hozumi, K., 1963. Self thinning in overcrowded pure stands under cultivated and natural conditions. J Biol., Osaka City University 14, 106-129.

Yu, X., Hyyppä, J., Kaartinen, H., Hyyppä, H., Maltamo, M., Rönnholm, P., 2005. Measuring the growth of individual trees using multi-temporal airborne laser scanning point clouds Workshop "Laser scanning 2005". ISPRS Enschede, the Netherlands, pp. 204-208.

Zeide, B., 1987. Analysis of the 3/2 Power Law of Self-Thinning. For. Sci. 33, 517-537.

Zeide, B., 1993. Analysis of growth equations. For. Sci. 39, 594-616.

Zeide, B., 2005. How to measure stand density. Trees 19, 1-14.

Økland, B., 1994. Mycetophilidae (Diptera), an insect group vulnerable to forestry practices? A comparison of clearcut, managed and semi-natural spruce forests in southern Norway. Biodivers. Conserv. 3, 68-85.

Ørka, H.O., Næsset, E., Bollandsås, O.M., 2009. Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data. Remote Sens. Environ. 113, 1163-1174.

Ørka, H.O., Næsset, E., Bollandsås, O.M., 2010. Effects of different sensors and leaf-on and leaf-off canopy conditions on echo distributions and individual tree properties derived from airborne laser scanning. Remote Sens. Environ. 114, 1445-1461.

Errata

Equation 3 in Paper I should read:

$$h_i^2 = c^2 x_i^2 + y_i^2$$

The caption of Table B.3 in the appendix of Paper I should add “Numbers in () indicate plot edge bias correction has been made.”. This has been corrected in the thesis print, but not in the online version.

Table 1 in Paper I should read “Recruitment (fraction of broadleaves alive in 2003)”

1986 **Papers I-IV and their appendices**

Paper I
Pedersen, R.Ø., Bollandsås, O.M., Gobakken, T. & Næsset, E. 2012. Deriving individual tree competition indices from airborne laser scanning. - For. Ecol. Manage. 280: 150-165.
DOI: 10.1016/j.foreco.2012.05.043

Paper II
Pedersen, R.Ø., Næsset, E., Gobakken, T. & Bollandsås, O.M. 2013. On the evaluation of competition indices - the problem of overlapping samples. - For. Ecol. Manage. 310: 120-133.
DOI: 10.1016/j.foreco.2013.07.040

Paper III
Pedersen, R.Ø. 2013. The behavior of Hegyi´s competition index in a spatially correlated field.
(Submitted)

Paper IV
Pedersen, R.Ø. 2013. Reducing the plot edge bias by means of airborne laser scanning?
(Manuscript)

ISBN: 978-82-575-1189-0
ISSN: 1503-1667

Norwegian University
of Life Sciences

Postboks 5003
NO-1432 Ås, Norway
+47 67 23 00 00
www.nmbu.no