

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

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

Om konkurranseindekser for enkeltrær, flybåren laserskanning og kanteffekter

Rune Østergaard Pedersen

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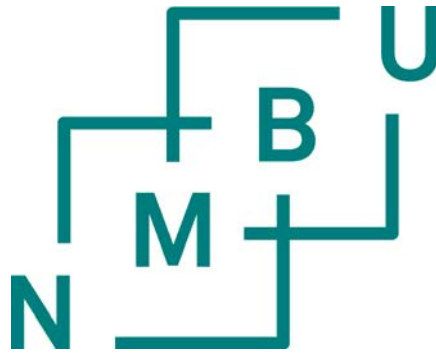
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36

37 **Preface**

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

42 I would like to thank the supervisor team for reading and commenting my manuscripts and
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55

56	Contents	
57	PREFACE	III
58	ABSTRACT	VI
59	DANSK SAMMENDRAG	VIII
60	LIST OF PAPERS	X
61	SYNOPSIS	1
62	1. INTRODUCTION	3
63	1.1. THE TERM COMPETITION	3
64	1.2. MEASURES OF STAND DENSITY	6
65	1.3. THE NEED FOR INDIVIDUAL TREE COMPETITION INDICES.....	7
66	1.4. TYPES OF INDIVIDUAL TREE CIs	8
67	1.5. OTHER MEASURES OF STAND STRUCTURE	13
68	1.6. AIRBORNE LASER SCANNING	13
69	1.7. SETTING AIRBORNE LASER SCANNING INTO THE CONTEXT OF COMPETITION	15
70	1.8. CONCEPTUAL FRAMEWORK	17
71	1.8.1. <i>Step I – Field data</i>	17
72	1.8.2. <i>Step II – CI calculation</i>	18
73	1.8.3. <i>Step III – Plot edge bias correction</i>	19
74	1.8.4. <i>Step IV – Model evaluation and statistical inference</i>	24
75	2. OBJECTIVES OF THE STUDIES	29
76	3. STUDY AREAS AND MATERIALS	31
77	3.1. HEDMARK COUNTY	31
78	3.2. AURSKOG-HØLAND MUNICIPALITY	32
79	3.3. ØSTMARKA BOREAL RESERVE	32
80	3.4. AIRBORNE LASER SCANNING DATA	34
81	4. PAPER I	35
82	4.1. RESULTS AND DISCUSSION PAPER I	35
83	4.2. CONCLUSION PAPER I	39

84	4.3.	PERSPECTIVES PAPER I	41
85	5.	PAPER II	43
86	5.1.	RESULTS AND DISCUSSION PAPER II	43
87	5.2.	CONCLUSION PAPER II	44
88	5.3.	PERSPECTIVES PAPER II	44
89	6.	PAPER III	46
90	6.1.	RESULTS AND DISCUSSION PAPER III	46
91	6.2.	CONCLUSION PAPER III	54
92	6.3.	PERSPECTIVES PAPER III	55
93	7.	PAPER IV	56
94	7.1.	RESULTS AND DISCUSSION PAPER IV	56
95	7.2.	CONCLUSION PAPER IV	57
96	7.3.	PERSPECTIVES PAPER IV	57
97		REFERENCES	58
98		ERRATA	69
99		PAPERS I-IV AND THEIR APPENDICES	70
100			

101 **Abstract**

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

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

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

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

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

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

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

165

166 **Dansk sammendrag**

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

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

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

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

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

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

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

231 **List of papers**

232

233 **Paper I**

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

236

237 **Paper II**

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

240 **Paper III**

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

243 **Paper IV**

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

245

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

249 **Synopsis**

250

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

261 **E.F Schumacher**

262 **Small is beautiful – Economics as if people mattered**

263

264 1. Introduction

265 1.1. The term competition

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

285 One of the earliest attempts to put the ideas of Darwin into forest science was made by Kraft
286 (1884), cited in (Assmann, 1970). Kraft (1884) introduced the concept of stand social status, to
287 account for the size hierarchy of trees in a stand. By dividing the stand into social classes like
288 suppressed – co-dominant and dominant individuals (Kraft has more subdivisions), Kraft (1884) made
289 a link between the size of the tree and its growth relative to other individuals. This is illustrated in
290 Figure 1, where the gray subject tree is surrounded by two white competitors.

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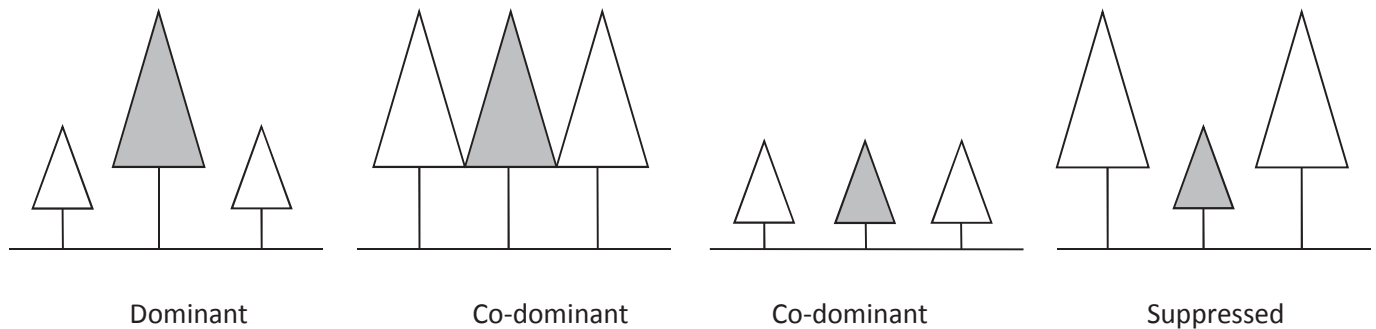
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301 **Figure 1. The social status of different subject trees (gray), each surrounded by two competitors (white).**

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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.

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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

325 suppression when standing in shade, and some species may be more tolerant than others (Perry,
326 1985). Nilsson (1993) points out the connection between diameter and height growth when
327 competition starts, and mentions how for example Norway spruce (*Picea abies* (L.) Karst.) responds
328 to fertilization by increasing both diameter and height growth, whereas Scots pine (*Pinus sylvestris* L.)
329 seems mostly to increase diameter and not height leading to different changes in stem taper.
330 However, the plastic response is not limited to the stem taper, so Nilsson studied (Paper II of his
331 dissertation) plastic response to competition by measuring stem volumes, branch basal areas, and
332 number of current shots in young stands of Norway spruce and Scots pine. He concludes that both
333 tree species respond to competition, but in different ways. Norway spruce tends to reduce the
334 number of current shots, whereas in Scots pine both stem volumes, branch basal areas, and number
335 of current shots are affected. Nilsson also argues that response to competition is time dependent,
336 and that even-aged stands beyond the stage of crown closure may have a different response to
337 competition than younger even-aged stands. One reason for this is the change of space available for
338 each tree making for example the crown to height ratio different as time goes. This point of view is
339 consistent with some stem taper studies of even-aged stands (Gray, 1956; Farrar, 1961; Assmann,
340 1970). The key point in stem taper development is canopy closure. When the stand is young,
341 competition is low and the crown makes up a large percentage of the total tree height. See Husch et
342 al. (2003) p 99 for a definition of total tree height. The young trees will have a shape similar to a
343 solitary tree. The annual growth will therefore be distributed along the stem in a similar way as can
344 be observed in a solitary tree, which means that the width of the annual tree-ring will decrease from
345 the ground to the initiation of the crown. As the stand ages, and competition increases, the lowest
346 part of the crown will die. The tree taper then changes, so that it becomes more evenly distributed in
347 the lower parts of the stem, resulting in a cylindrical stem shape. The process may be “reversed” by
348 heavy thinning, though changes in the crown/height ratio should also be considered.

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

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358 **1.2. Measures of stand density**

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

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

389

390 1.3. The need for individual tree competition indices

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

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

424 but as shown in the literature other aspects like crown plasticity can also be used (Purves *et al.*, 2007;
425 Seidel *et al.*, 2011). It remains difficult to actually measure competition because what is measured
426 depends upon the definition of competition. At stand level the Gini-coefficient (Gini, 1912; Weiner
427 and Solbrig, 1984), skewness, and coefficient of variation of diameter at breast height (dbh) (Nilsson,
428 1994; Skovsgaard, 1997) have been used to describe development over time. But even for the whole
429 stand such aggregate measures may not be a true indication of competition. For example, the
430 increase in skewness of the empirical tree diameter distribution has been interpreted as a result of
431 one-sided competition, because small size differences will give larger trees a relative higher growth
432 rate causing skewness. However, the size-differentiation may simply be due to micro-scale variation
433 in soil conditions, which may accelerate the growth of certain trees (Skovsgaard and Vanclay, 2013).
434 A more general description of the structural development and size differentiation due to competition
435 as reflected in the empirical diameter distribution over time was presented in the 1970s and 1980s.
436 Hara (1984), Nilsson (1993) and (Skovsgaard, 1997) give introductions to the stand development over
437 time as a function of growth, variance in growth, and mortality of trees using among other means the
438 forward Kolmogoroff equation. Such an analysis may focus on the modality of the dbh distribution,
439 like whether the distribution has one, two or more tops. Analytical tools such as the kurtosis of the
440 distribution and graphical analysis often come short, because factors like the width of the diameter
441 classes can affect the modality. Thus, it remains difficult to model the consequences of competition
442 even at a stand level.

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

446 **1.4. Types of individual tree CIs**

447 One way to quantify competition is by an index, a single number given to each tree, which expresses
448 the current competition load and social status of the tree. This approach is taken throughout the
449 papers of the current thesis. Numerous indices exist in the literature and comprehensive descriptions
450 are given by (Biging and Dobbertin, 1992; Biging and Dobbertin, 1995; Husch *et al.*, 2003; Pretzsch,
451 2009; Weiskittel *et al.*, 2011; Burkhart and Tomé, 2012).

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

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

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

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

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

488 A CI presented by Tomé and Burkhardt (1989) deserves some extra attention, due to some results
 489 obtained in Paper I, presented in Subsection 4.1. The idea is that competition pressure is not merely
 490 the sum of the competing trees, but that small trees, and dead trees reduce competition while larger
 491 trees increase competition. Often, the presences of small or dead trees are an indication of a canopy
 492 opening (gap), where recruitment has taken place. Hence, if competition for light is important such
 493 an index might work well. This is seen from Equation 1 which is adapted from Burkhardt and Tomé
 494 (2012)(p 217) where the competition pressure consists of the trees larger than the subject tree (CI_{larger}),
 495 reduced by the competition from the smaller ($CI_{smaller}$) and the dead trees (CI_{dead}).

496 **Equation 1**

$$497 \quad CI = CI_{larger} - CI_{smaller} - CI_{dead}$$

498 The classical CIs used as benchmark references in the present thesis assume that the competition
 499 pressure is directionally independent, thus competitors standing aggregated may give the same
 500 competitive pressure as competitors which are scattered around the subject tree position. Lund
 501 (1999)(Paper 4 p 14 of his thesis) notes that this is not a reasonable assumption because it does not
 502 account for the fact that competing trees also affect each other because, they co-vary in space.
 503 Existing structural indices acknowledge the importance of directional dependency, for example the
 504 mean directional index (Illian *et al.*, 2008) used in Paper II (see appendix of Paper II). Newton and
 505 Jolliffe (1998) derive a number of CIs where direction is accounted for by calculating the “centre-of-
 506 mass” of the positions of competing trees, and use this centre-of-mass distance to the subject tree
 507 to account for the aggregation of competitors relative to the subject tree. In Paper I a similar concept
 508 is applied in a CI by means of the Gini-coefficient (Equations 21 and 22 of Paper I).

509 Many studies have compared different types of CIs, and so far, no single CI seems superior. One
 510 reason for this is mentioned by Strand (1972)(p 208) who states about using empirical data for
 511 evaluation of CIs: “*It will never be possible in this way to “prove” that the model is correct, but the
 512 method may be used to rule out many incorrect assumptions*”. The statement of Strand is consistent
 513 with the viewpoint of the philosopher Popper on the falsification of a scientific hypothesis (Chalmers,
 514 1999). According to Popper, we can never prove a scientific hypothesis; we can only try to falsify it.
 515 Generally, there seems to be consensus that spatially explicit CIs do not offer substantial
 516 improvement in growth predictions over non-spatially explicit CIs (Lorimer, 1983; Martin and Ek,
 517 1984; Biging and Dobbertin, 1995; Rivas *et al.*, 2005), though some studies find a small improvement
 518 when applying spatially explicit CIs (Contreras *et al.*, 2011). Some authors hold that spatially explicit
 519 CIs often model above ground competition; while below ground competition for minerals and water

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

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

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

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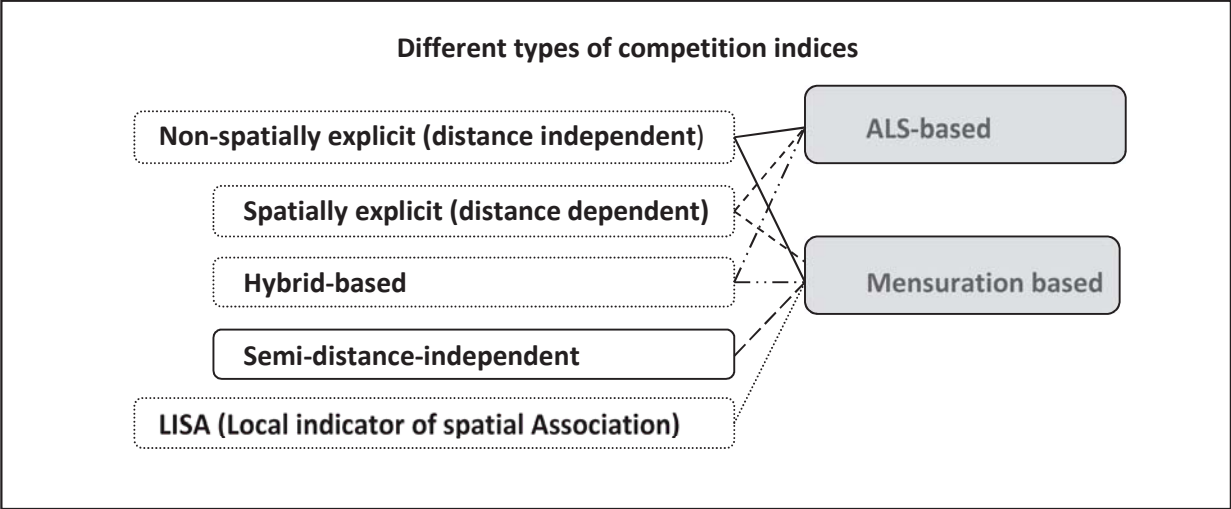


Figure 2. Different types of CIs or measures of spatial association especially important in the thesis. If the textbox around the CI/LISA is dotted it means that the CI is used in the thesis. The gray colored text boxes indicates the two overall classes of CI. The lines indicate which types belong to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

547 1.5. Other measures of stand structure

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

564 1.6. Airborne laser scanning

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

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

584 The terrain model has been used to discriminate biomass and ground level for successful
585 predictions of forestry attributes like Lorey's mean height, volume per hectare (Næsset, 1997) or
586 basal area distributions (Gobakken and Næsset, 2004). The first predictions of forestry attributes
587 date to the mid- 1980s when Nelson *et al.* (1984) predicted canopy closure from ALS. Predictions are
588 done using the metrics as regressors; they are mathematical transformations of the ALS-returns.
589 Numerous ways have been applied to calculate metrics in the literature, e .g. (Bollandsås *et al.*, 2008;
590 Ørka *et al.*, 2009). Næsset and Økland (2002) report estimates of individual total tree height, crown
591 length, and crown height using materials from the study area of the current thesis Østmarka Boreal
592 Reserve. The predictions deviate 17.6% for individual total tree height, 39.1% for crown base height
593 and 10.5% for crown length from the true ground measurements. It is also possible to do species
594 identification from ALS. Ørka *et al.* (2009) used linear discrimination analysis to differ conifers from
595 broadleaves in Østmarka Boreal Reserve and report fairly correct classification, ranging from 88.6%
596 for dominant to 63.6% for suppressed trees. Single-tree segmentation algorithms have been derived
597 to identify the position and size of individual trees. In Norway, this has been done by Ene *et al.*
598 (2012a) using the data from Aurskog-Høland Municipality and Solberg *et al.* (2009) using data from
599 Østmarka Boreal Reserve. Næsset (2002) showed how forest inventories can be accurately made
600 from ALS using a two-stage procedure based on field measurements. Different forest variables were
601 successfully predicted by dividing the forest into strata, and calibrating stratum-wise models based
602 on a number of field observations (plots). For example, he achieved an R^2 of stratum specific volume
603 predictions between 0.80 and 0.93. Other variables were also predicted with high accuracy (R^2
604 between 0.39 and 0.95). Næsset (2004) showed how to apply the technique in an inventory in a
605 cheap and accurate way. Ene *et al.* (2013) showed potential economic gain using ALS inventories
606 instead of traditional ground inventories, by testing the precision and economics of different
607 statistical sampling designs (Cochran, 1977; Särndal *et al.*, 2003) in data from Hedmark County in
608 Norway.

609

610 1.7. Setting airborne laser scanning into the context of competition

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

625 So far, most attempts of quantifying competition using ALS may be characterized as indirect, in
626 the sense that the variables studied are closely correlated with competition, but the calculations are
627 made at a stand level rather than at a single-tree level. One example of indirect specification is the
628 prediction of leaf area indices (LAI) from ALS (Jensen *et al.*, 2008; Solberg *et al.*, 2009; Jensen *et al.*,
629 2011), which are known to be important for modeling recruitment in stands (gap-models) (Botkin *et al.*,
630 1972), and may be viewed as a measure of competition at stand level.

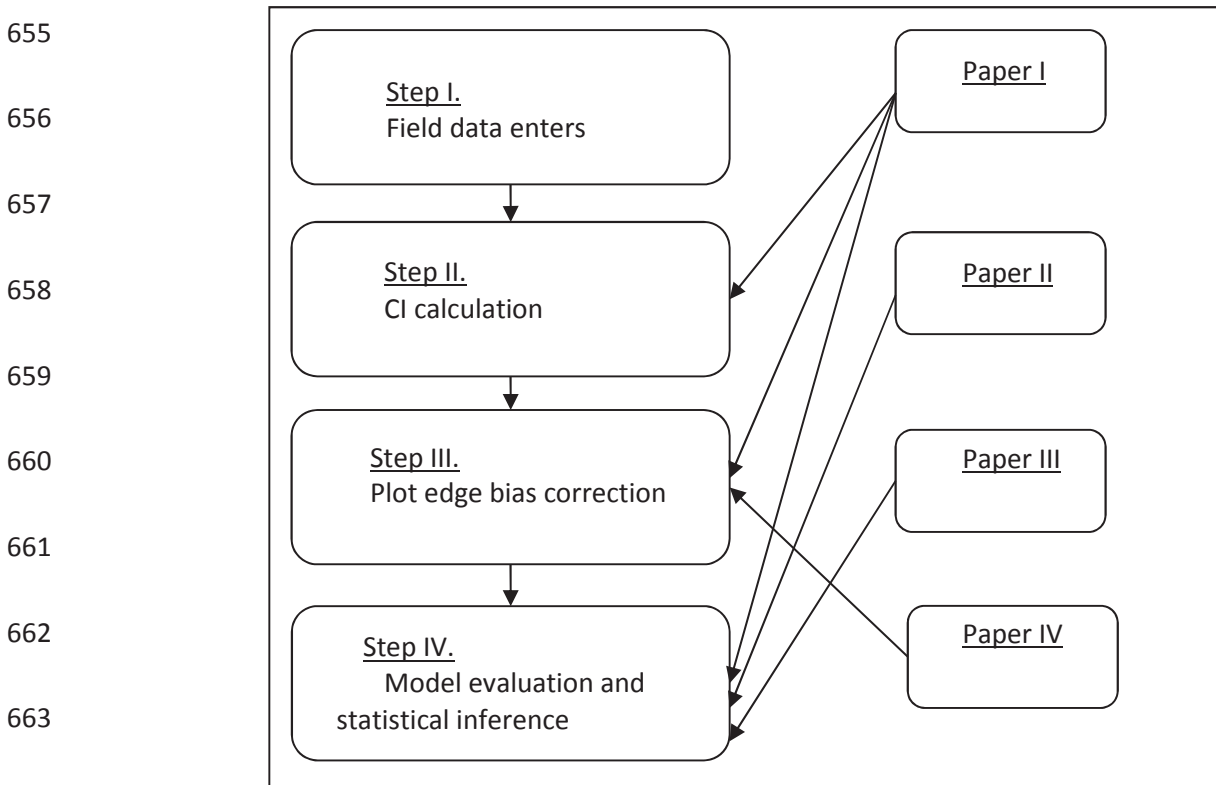
631 Varhola *et al.* (2012) investigated how laser derived forest metrics may be used in construction
632 of ALS synthetic hemispherical images, which is a popular way of estimating the LAI. Their method
633 involves a calibration of the ALS synthetic hemispherical images on the basis of in-situ optical
634 hemispherical camera images. They obtained satisfactory predictions of solar radiations by means of
635 a multiple regression model, demonstrating that it is possible to make cost-effective gap predictions
636 from ALS data. Bollandsås *et al.* (2008) showed how the so-called density metrics may be used as a
637 predictor of seedlings in Norway spruce. Since recruitment of Norway spruce often appears in gaps,
638 and gaps have less competition for light, it is reasonable to see this as indication of the ability of ALS
639 to quantify competition of trees. Seidel *et al.* (2011) used a terrestrial laser scanner to model the
640 crown shape and plastic response (see Subsection 1.1 regarding Harper (1967) and Silvertown
641 (1982)), and to test a hypothesis of crown plasticity in a mixed species forest. In Norway, Hauglin *et al.*
642 *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

649 1.8. Conceptual framework

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



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

666

667 1.8.1. Step I – Field data

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

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

693 1.8.2. Step II – CI calculation

694 Once the data is in hand, a number of different CIs need to be selected and tested.
695 Comprehensive reviews of different types of CIs can be found for example in Husch *et al.* (2003),
696 Burkhart and Tomé (2012) and Pretzsch (2009). The selection of a CI should not be made blindly, and
697 I use the rule that the tested CI should be possible to calculate using as few derived variables as
698 possible. In practice, this means that we were limited to use dbh and distance between trees.
699 However, it should be noticed that the ALS-CIs derived in Paper I use individual total tree height,
700 projected crown width, and crown base height predicted from a model. The goal was to test the CIs
701 derived from ALS against some well-known “classic” CIs, which have as little random measurement
702 error as possible. Most of the classic CIs are nonlinear transformations, and even the random
703 measurement error in dbh can result in biased estimates (Gertner and Dzialowy, 1984; Kangas,
704 1998). However, it is reasonable to assume that the variance of the measurement error in dbh is
705 small, and probably it is better using dbh than a derived variable like individual total tree height.
706 Further, the use of smoothed data predictions from a model reduces the variance artificially, and
707 tends to give optimistic results of model performance (Hasenauer and Monserud, 1997). Another
708 tenable argument favoring dbh over height is that many studies have found that the relative
709 variation in height due to competition is less than in dbh (Sjolte-Jørgensen, 1967; Lanner, 1985). The

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

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

731 **1.8.3. Step III – Plot edge bias correction**

732 Plot edge bias in a silvicultural context appears when trees outside the data range are affecting
733 the trees that constitute the dataset. This may for instance be neighboring trees outside a plot area,
734 which compete for resources with the trees in the plot. Ignoring these neighboring trees will lead to
735 biased estimates of competition. Various methods have been proposed to deal with the problem.
736 Two often applied techniques valid for non-circular plots are translation (also called shifting)
737 (Newnham, 1964; Lee, 1967), and mirror imposing (also called reflection) of the plots (Pretzsch,
738 2009). Mirror imposing may also be used for circular plots, only it is the search radius around each
739 subject tree that is used for edge correction in this situation, not the entire plot (Lilleleht *et al.*,
740 2013). For these methods the variation in the stand outside the plot is simply generated under the
741 assumption that the stand variation is similar to the plot variation. Despite their simplicity, these

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

744 Another alternative is the border method, which is also known as the guard method. This
745 method identifies a buffer zone and then only calculates competition for subject trees, which are at a
746 certain distance from the plot edge. While the method is unbiased, it has the weakness that it
747 reduces the number of trees remaining for analysis, and this may affect the results obtained. Hanisch
748 (1984) used a similar approach accepting a tree for analysis if the distance to a subjectively chosen
749 competitor was closer than the distance of the subject tree to the plot border; we used this method
750 in Paper II (See Figure 4 subplot d).

751 Methods of simulation have also been applied in the literature. Pommerening and Stoyan (2006)
752 used point pattern analysis to generate the trees outside the plot (Cressie, 1991). They assumed that
753 the trees follows a pattern like the Matérn hardcore process and by a simulated annealing procedure
754 they constructed marked point patterns and positions for potential competitors. A mark is an
755 attribute for example dbh or individual total tree height. The position and mark of the competitor are
756 accepted according to some characteristic like the squared deviation of the diameter distribution
757 observed on the plot. One weakness of this method is that it requires a subjective choice of a point
758 pattern type, but often prior knowledge of point patterns in relation to forest type and species
759 composition may be used, and Pommerening and Stoyan (2006) obtained satisfactory results using
760 this method. In Paper IV I used a method much similar to the method of Pommerening and Stoyan
761 (2006). I applied the R-script "Construction.R" written by Dr. Pommerening (Pommerening, 2013), to
762 simulate a point pattern with the same nearest neighbor distance (Clark and Evans, 1954) in a buffer
763 around the plot, as is observed on the plot (Figure 4 subplot c). Diameters were calculated by a
764 regression model using the nearest neighbor distance and plot level characteristics like D_g as
765 regressors, by a gamma glm-regression with a log-link (Montgomery *et al.*, 2006)(p. 457-458). The
766 gamma distribution is used because the dbh-distribution was skewed. The log-link ensured positive
767 dbh predictions. The species marks are then put on the trees in the buffer using a multcategory logit
768 model (glm-model)(Agresti, 2007)(p. 173). For each species class the multcategory logit model gives
769 a probability of the tree belonging to that class, and the mark is put on the class with the highest
770 probability.

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

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

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

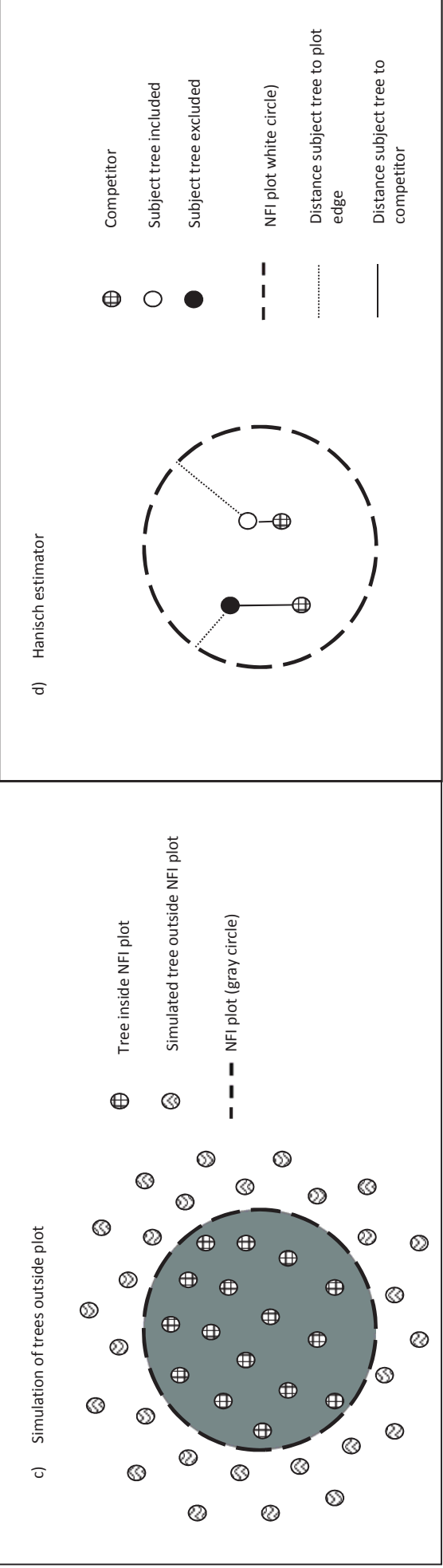
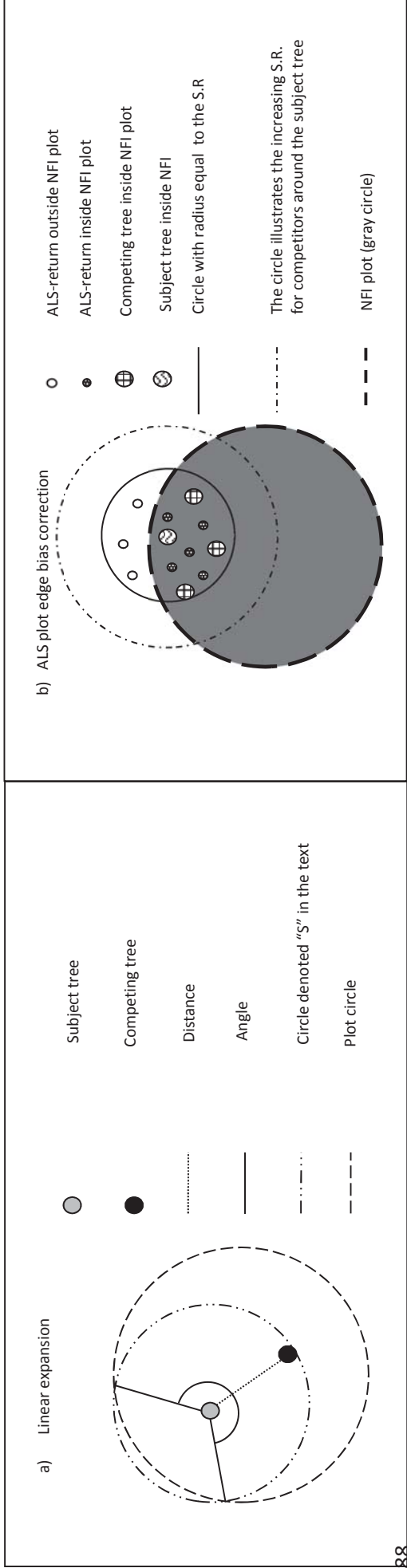


Figure 4. The different plot edge bias correction methods applied in the thesis. a) An illustration of the linear expansion method by Martin *et al.* (1977). b) The ratio-estimator approach presented in paper IV. c) A method based on simulated annealing presented in Paper IV (Pommerening and Stoyan,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

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

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

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

819

820

821 1.8.4. Step IV – Model evaluation and statistical inference

822 Various methods have been proposed to evaluate CIs, and an extensive review is given by
823 Burkhart and Tomé (2012) (p 234). Often a measure of statistical correlation like the Pearson or the
824 Spearman rank correlation (Spearman, 1904) between plant growth and competition is investigated
825 (Bachmann, 1998; Wichmann, 2001). Another much used method is to apply a growth model and
826 measure the potential gain from including competition in R^2 or AIC (Daniels *et al.*, 1986; Tomé and
827 Burkhart, 1989; Soares and Tomé, 1999). This may either be where competition enters directly as a
828 regressor (often known as direct-estimation approach), or in a potential modifier function (Ek and
829 Monserud, 1974; Leary, 1979), where the growth of a tree not affected by competition is reduced by
830 a competition multiplier function (often known as potential modifier approach). When using
831 multipliers the potential growth of a tree not affected by competition is reduced by competition
832 usually assuming exponential decrease in growth for increasing competition pressure (Pretzsch,
833 2009)(p 454). The advantage of a multiplier function is that potential illogical values such as
834 increasing growth with competition can be avoided. Thus, it is suitable in simulation studies where
835 the CI is known to decrease growth. However, when evaluating newly derived CIs, it is not suitable
836 because the index and its behavior should not be “forced” to behave in a certain way.

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

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

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

874 **Table 1. Possible outcomes of a statistical hypothesis test, hereunder type I and type II statistical error. Adapted**
 875 **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

876

877 Different measures of spatial autocorrelation exist. One such measure is the variogram used in
 878 geostatistics. The variogram was originally developed for spatial continuous data like oil fields. Thus,
 879 it is suitable when the spatial pattern is highly irregular, like in a natural forest. One form of the
 880 variogram is the semivariogram, and it takes the form shown in Equation 2 (Isaaks and Srivastava,
 881 1989). The reason that Equation 2 is named "semi" is the multiplication by 0.5, which is done to give
 882 a measure of variance in the spatial field rather than two times the variance. Y is the measured
 883 quantity, for example dbh or CI. x is a vector with spatial coordinates. h is a vector with a lag

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

886

887 **Equation 2**

$$888 \quad \gamma(h) = \frac{1}{2} \text{var}\{Y(x+h) - Y(x)\}$$

889 From the calculated semivariogram one can fit a parametric model to quantify the range, sill and
 890 nugget effect. The range is the distance, where spatial autocorrelation is present. The sill is the
 891 plateau that the semivariogram reaches at the range. The nugget effect is the variance observed at
 892 distances near zero, caused by for example measurement error (Isaaks and Srivastava, 1989)(p 143).
 893 Many parametric models can be fitted to the empirical semivariogram (Schabenberger and Gotway,
 894 2005). A visual example of terms and models related to the semivariogram is given in Figure 10,
 895 which will be discussed more detailed in the Results and discussion section of Paper III.

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

900 **Equation 3**

$$901 \quad \text{Moran's } I = \frac{n}{S_0} \frac{\sum_i \sum_j \omega_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2}$$

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

910 1981), and Tiefelsdorf (1998) succeeded in deriving the exact distribution of Moran's I under spatial
 911 autocorrelation. The effect of spatial autocorrelation on the effective sample size is discussed by
 912 (Dutilleul, 1993; Dale and Fortin, 2009; Dutilleul, 2011). We applied the correction of Clifford *et al.*
 913 (1989), which is suitable for bivariate relationships like the Spearman rank correlation and the
 914 Pearson correlation coefficient. In addition, we used a spatial bootstrap method proposed by Plant
 915 (2012), which uses a SAR-model (Whittle, 1954) to account for spatial autocorrelation and a linear
 916 mixed model (Schabenberger and Pierce, 2002).

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

926 **Equation 4**

$$927 \quad A = \frac{\sum_i [(x_{CI}(i) - \bar{x})(x_{\Delta dbh}(i) - \bar{x}) + (y_{CI}(i) - \bar{y})(y_{\Delta dbh}(i) - \bar{y})]}{\left(\sum_i [(x_{CI}(i) - \bar{x})^2 + (y_{CI}(i) - \bar{y})^2] \sum_i [(x_{\Delta dbh}(i) - \bar{x})(y_{\Delta dbh}(i) - \bar{y})]^2 \right)^{0.5}}$$

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

931 **Equation 5**

$$932 \quad Var(A) = \frac{(\sum x_i^2)^2 + 2(\sum x_i y_i)^2 + (\sum y_i^2)^2}{(n-1)(\sum x_i^2 + \sum y_i^2)}$$

933 The null hypothesis that the values of Δdbh and CI are not dependent on location, can be tested
 934 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

943 **2. Objectives of the studies**

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

945 Paper I

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

953 Paper II

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

963 Paper III

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

972

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

982 **3. Study areas and materials**

983 Three different datasets are used. In Figure 5 the locations of the study sites are shown. In Table
 984 2 I show some descriptive statistics of the materials, while more comprehensive descriptions can be
 985 found in the respective papers. Table 2 also shows which study site that is applied in which paper.

986

987 **Table 2. Descriptive statistics on the plot level. h_L = Lorey's mean height. D_g = quadratic mean diameter. N= stem**
 988 **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

989

990 **3.1. Hedmark County**

991 The Hedmark County (HC) is located in south-east Norway and the total area is 27340 km². The
 992 data from HC consist of permanent circular sample plots of the Norwegian National Forest Inventory,
 993 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
 994 km grid, though in a 3*9 km grid in mountain locations (Anon., 2008). Of the 2309 permanent plots
 995 located in HC those that were characterized as unproductive forests according to the field workers
 996 (Anon., 2008), in addition to those not covered by ALS, were discarded from further studies, leaving
 997 557 plots for analysis. The plots used for competition studies in HC were measured twice in a five-
 998 year rotation inventory in the period 1999-2007. The data consists of almost all commonly forest tree
 999 species in Norway. However, the majority is Norway spruce (*Picea abies* (L.) Karst.), Scots pine (*Pinus*

1000 *sylvestris* L.), and white or downy birch – (*Betula* ssp.). We stratified the data into the tree species
1001 classes conifer, pine, and others in order to make the investigations feasible.

1002 **3.2. Aurskog-Høland municipality**

1003 Aurskog-Høland municipality is located north-east of Oslo (59°50'N, 11°40'E, 172-388 m.a.s.l.)
1004 and covers 89 km². The 40 circular plots are scattered over Aurskog-Høland municipality . Thirty six of
1005 them have a size of 0.1 ha, and four plots that are located in young forest with high stem number are
1006 of 0.05 ha. Plots are with respect to stem number dominated by Norway spruce (around 48% on
1007 average) and Scots pine (around 38% on average). The remaining is mainly deciduous species
1008 dominated by *Betula* ssp. (around 14% on average).

1009 **3.3. Østmarka Boreal Reserve**

1010 Østmarka Boreal Reserve is located in the south-eastern part of Norway. The data consists of 20
1011 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-
1012 aged forest, which has not been exposed to logging since the 1940s (Økland, 1994). Plots are with
1013 respect to stem number dominated by Norway spruce (90 % on average), Scots pine (less than 1% on
1014 average) and the remaining are dominated by deciduous species (around 10% on average), mainly
1015 aspen (*Pópulus trémula* L.) and rowan (*Sorbus aucupária* L.).

1016

1017

1018



1019

1020 **Figure 5. The location of the study sites in Norway. Hedmark County is shown in black, Aurskog-Høland municipality**
1021 **in gray, and Østmarka Boreal Reserve is shown as a dot.**

1022

1023

1024 **3.4. Airborne laser scanning data**

1025 Small footprint airborne laser data were acquired in September 2006 for Hedmark County and in
 1026 October 2003 for Østmarka Boreal Reserve. The data were used to calculate the density metrics used
 1027 in Paper IV, and further as input to the CIs used in Papers I and II. The technical details regarding the
 1028 acquisition and sensor setting are provided in Table 3. A model of the terrain was derived using the
 1029 algorithm described by (Axelsson, 2000).

1030

1031 **Table 3. Technical characteristics of the airborne laser acquisitions used in the thesis. In the table it is shown which**
 1032 **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

1033

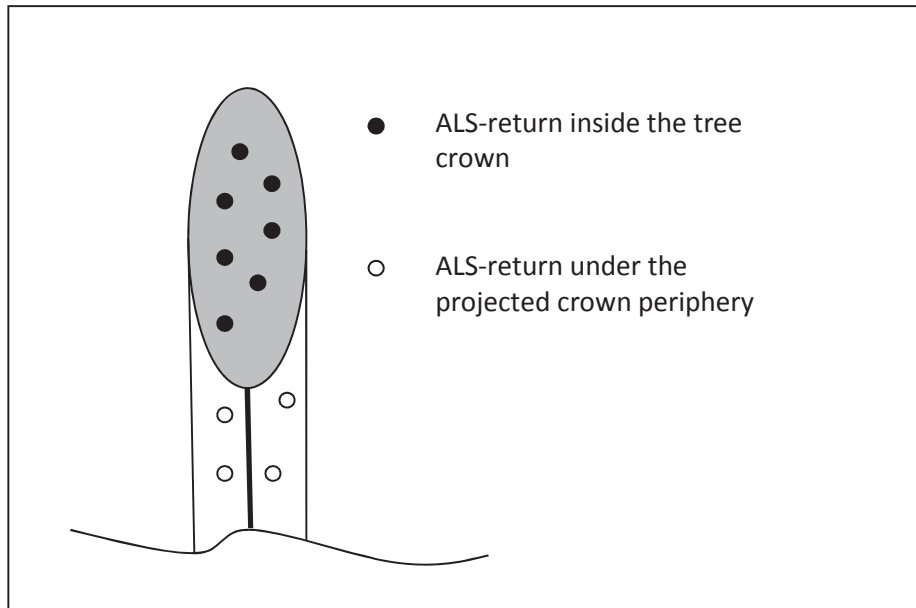
1034 ¹Resolution refers to the footprint size of ALS-data.

1035 **4. Paper I**1036 **4.1. Results and discussion Paper I**

1037 A definition of how a ALS-return reflects the competitive level was made. Above ground ALS-
1038 returns are an indication of biomass and competition, and conversely ground ALS-returns are an
1039 indication of a canopy opening and less competition. Using this definition, a number of different ALS-
1040 CI were derived and tested against a list of existing CIs. Three new classes of CIs, non-spatially
1041 explicit, spatially explicit, and hybrid-based CI were defined. The non-spatially explicit CIs require
1042 definition of a neighborhood around the subject tree, and are also related to the semi-distance-
1043 independent dependent CIs (see Subparagraph 1.4 for an explanation of this CI). The borderline
1044 between non-spatially explicit ALS-CIs and spatially explicit ALS-CIs is that distance appears in the
1045 spatially explicit ALS-CIs. The hybrid-based CIs, are much similar in idea to the concept tested by
1046 Maltamo *et al.* (2007), namely to use the ALS-returns to derive the proportions of all trees. Since
1047 positions of competitors are needed, these indices are spatially explicit in the classical sense, and
1048 methods of plot edge bias correction need to be applied. The CIs contain different components, like
1049 angles of ALS-returns relative to the base of the position of the subject tree, the convex hull in 2-d,
1050 and the Gini-coefficient of the x,y and z coordinates of the ALS-returns around the subject tree.

1051 For all ALS-CIs, except the hybrid-based ones, we removed the ALS-returns located inside the
1052 subject tree crown by means of an ellipsoidal crown model. For the hybrid-based CIs we used the
1053 crown model to isolate those ALS-returns that entered into the calculations of the CI. In addition,
1054 ALS-returns located under the projected crown width were removed (Figure 6). This was needed in
1055 order to eliminate problems with “self-competition”. The numerous indices and their characteristics
1056 are summarized in a table in the online electronic appendix of Paper I, which is reprinted in Table 4.

1057



1058

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.

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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.

1067

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

1078

1079 suppressed trees which had not been hit by a laser beam, and thus did not allow calculations to be
1080 made.

1081 A nonlinear growth model in the form presented by Zeide (1993) showed that the largest part of
1082 the variation (around 32%) could be explained by the dbh of the subject tree, though competition
1083 was also significant for pooled data. Plot specific regressions and correlation analysis revealed that
1084 competition does not always improve predictions of Δdbh , probably because competition is not the
1085 only factor important for tree growth. In addition, the ALS-CIs mimic above ground competition, not
1086 below ground competition. The distinction between above ground ALS-returns and ground ALS-
1087 returns was found to be correct. The CIs based on ground ALS-returns showed a weak positive
1088 correlation with Δdbh , which is a justification of the ideas of Tomé and Burkhart (1989), who use CIs
1089 where smaller and dead trees reduce the competitive pressure that the subject tree is exposed to
1090 (see Equation 1).

1091 In Paper I we make a distinction between the social status of each tree when compared to the
1092 near surroundings (near social status), and when compared to the stand (stand social status). The
1093 rationale is that biological factors like evapotranspiration and nutrient demands cannot merely be
1094 seen as a proxy of the nearest competing trees, but rather of the stand. Possible age differences
1095 between trees in addition to the time development of the stand should be considered. Studies of
1096 cutting cycles of ponderosa pine plantations have also shown that trees grown in gaps, do not grow
1097 as well as expected if only looking at the near surroundings (Hensold, 1988), and plant physiological
1098 arguments have also been given (Koch *et al.*, 2004).

1099

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1102

1103 Some of the derived ALS-CIs have the ability of eliminating plot edge bias, because a buffer of
 1104 ALS-returns can be taken outside the plot area. An analysis revealed that some of the ALS-CIs seemed
 1105 to give less biased predictions of growth near the plot edge, thus indicating a reduction in plot edge
 1106 bias. However, a lot of noise is present in the data, and the 20 plots in Østmarka Boreal Reserve are
 1107 not sufficient to see the effect. Some of the results of Paper I indicate that classic non-spatially
 1108 explicit indices may have plot edge bias, which has also been noted by others (Stage and Wykoff,
 1109 1998; Lappi, 2005). Reasons for this can be that the social status of trees is not reflected by the plot if
 1110 the stand is very heterogeneous. This problem is expected to increase as plot size decreases. In fact,
 1111 it has been shown that the coefficient of variation of a measure of density (e.g. biomass) increases
 1112 with plot size, indicating that the stand variation is not captured sufficiently in small plots (Jaakkola,
 1113 1967).

1114

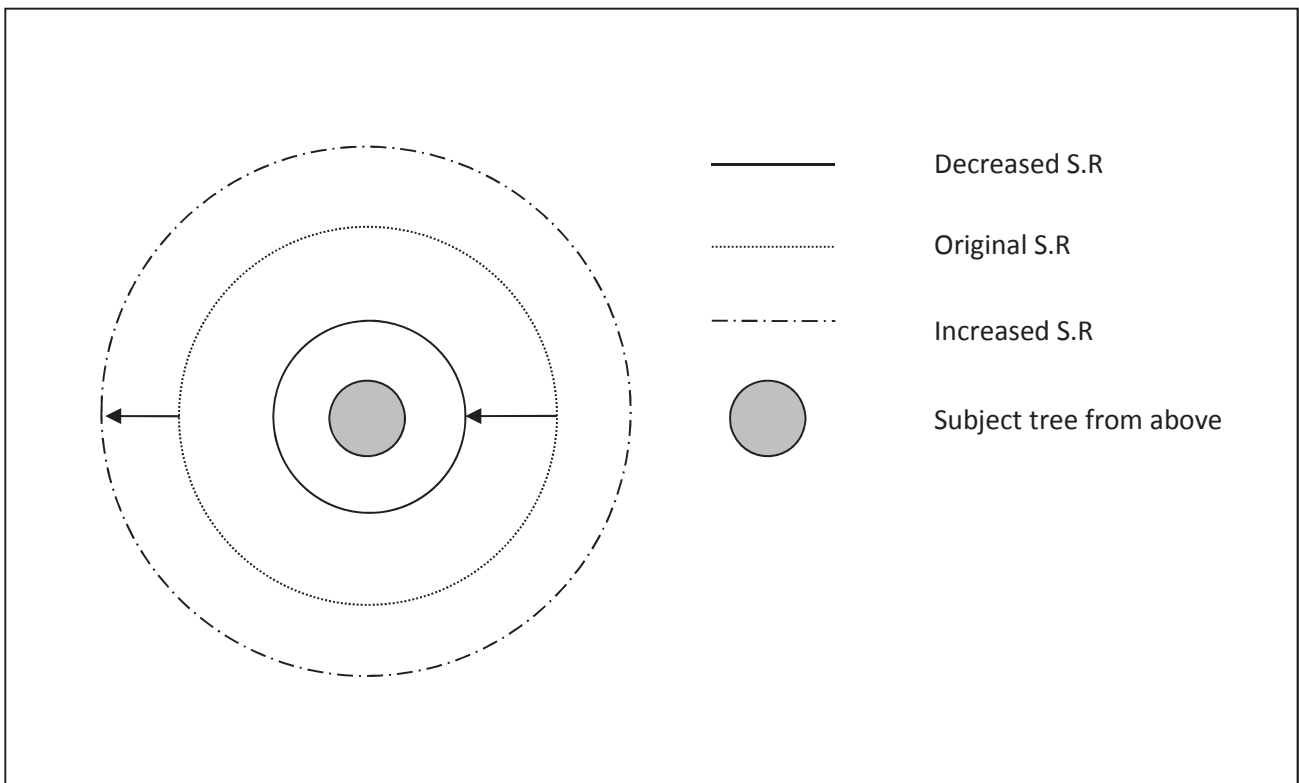


Figure 7. Illustration of how the ratio-estimator scales the search radius (S.R) so that the density of ALS-returns per area unit fits the average. The subject tree is seen from above.

1115 4.2. Conclusion Paper I

1116 The objectives of creating and testing CIs based on ALS were met, and predictions from ALS-
1117 based CIs were in many cases as good as the best performing existing CIs. The many ALS-CIs we
1118 derived are summarized in Table 4 and identified by their equation number in Paper I. Important
1119 characteristics listed in the table include whether the search radius (S.R) to find competitors is fixed
1120 or variable from tree to tree. Furthermore, Table 4 shows if the CI considers the near social status of
1121 subject tree (N.S.S), as well as its position in the stand hierarchy (S.S.S). In addition, it can be seen
1122 from Table 4 if the density of biomass in different levels of canopy is quantified in the ALS-CI
1123 (D.O.B.C.), and also if the overall density of the canopy (O.D.C.) is quantified. Some of the CIs use
1124 angles (Angle) and distances (Dist) when calculated. The table also indicates which of the CIs that
1125 need scaling for uneven number of ALS-returns per area unit (Scaling). Some of the CIs eliminate plot
1126 edge bias as shown in the column Eliminate, and in most of them the positions of competitors need
1127 not to be known, which is indicated in the column denoted C.P.

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1131 **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**
 1132 **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 =**
 1133 **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**
 1134 **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	(Hegy, 1974)
Equation 24	F	Yes	No	Yes	No	Yes	No	No	No	Yes	(Hegy, 1974)
Equation 25	F	Yes	No	No	No	Yes	No	No	No	Yes	Current study

1135

1136

1137 **4.3. Perspectives Paper I**

1138 All the CIs we tested were constructed under the simplified assumption that the pressure of
 1139 competition is not species specific. Interspecific CIs have been presented in the literature. The
 1140 principle is shown in Equation 6. The term λ_k is a species-specific parameter, $Dist$ is distance
 1141 between the i 'th subject tree and the j 'th of n competitors. Another possibility of extending the
 1142 flexibility is to put parameters on dbh and $Dist$. For instance, Canham *et al.* (2004) found the
 1143 parameters of such a model using nonlinear optimization, and Richards *et al.* (2008) used a neural
 1144 network approach.

1145 **Equation 6**

$$1146 \quad CI = \sum_{j \neq i}^n \lambda_k \frac{dbh_j}{Dist_{ij}}$$

1147 A reason for not including species-specific parameters into the ALS-CIs is that for some of the CIs
 1148 it is difficult to isolate which ALS-returns that belongs to which tree. The hybrid-based CIs allow
 1149 including terms that may be species specific. Ørka *et al.* (2009) demonstrated how laser derived
 1150 metrics within the crown may be used as explanatory variables in a linear discrimination analysis, to
 1151 discriminate between conifers and broadleaves. The tradeoff is the inaccuracy in the classification
 1152 (93.3 and 81.7 percent correctly classified for large conifers and broadleaves respectively, dropping
 1153 to 57.7 and 68.4 percent for small trees), which may also be attributed to problems of correctly
 1154 fragmenting the crown proportions in the existing single-tree segmentation algorithms. Usually,
 1155 simple assumptions are made about the crown shape, such as a cylinder, and even when more
 1156 realistic models are made, problems of overlapping crowns may appear. This problem of crown
 1157 isolation is less apparent when using some of the ALS-CIs, because the uncertainty of crown
 1158 proportions only involves the subject tree. In further research it would be interesting to investigate
 1159 the tradeoff between the uncertainty of crown proportions following species classification, and the
 1160 possible gain by distinction between species in the hybrid-based ALS-CIs.

1161 For example, one of the hybrid-based ALS-CIs presented in Paper I (equation 23 of Paper I) may
 1162 take the form given in Equation 7 when differentiating species by a species specific parameter λ_k .
 1163 The species specific parameters may be estimated using nonlinear optimization (Pommerening *et al.*,
 1164 2011). X is a metric of the ALS-returns inside the tree crown. H_{95} is 95 pct. of the individual total
 1165 tree height. H_{95Max} is the 95'th percentile of the empirical distribution of individual total tree height

1166 in the study area. Calculations are made for the i 'th subject tree and j 'th competitor. $Dist$ is distance
 1167 between the i 'th subject tree and the j 'th of n competitors.

1168 **Equation 7**

1169
$$CI = \sum_{i \neq j}^n l_i \frac{X_j^{\lambda_k}}{X_i^{\lambda_k} (Dist_{ij} + 1)} \frac{H_{95j}}{H_{95i} H_{95Max}}$$

1170 The concept of stand social status coincides with the point of view of Adlard (1977) who believes
 1171 that the complexity of competition can only be accurately captured by combining several explanatory
 1172 variables, each of which quantifying specific areas of competition. Thus, Adlard (1977) suggests
 1173 combining CIs of hydrology and light to explain a larger proportion of variation. This needs to be
 1174 tested when using ALS, and because both hydrology (Varhola *et al.*, 2012) and LAI (Solberg *et al.*,
 1175 2009) have been successfully modeled from ALS, an extension seems feasible. Further, terrestrial
 1176 scanners also give possibilities of modeling the plastic response of the tree crown. This was shown by
 1177 Seidel *et al.* (2011), who presented a method for modelling the direction of competition and the
 1178 crown asymmetry caused by competition pressure in a mixed species forest.

1179 The CIs of Paper I may be used in forestry production models, used as a planning tool for forest
 1180 practitioners. We have only tested the CIs on materials from Hedmark County and Østmarka Boreal
 1181 Reserve, and future investigations should preferably include data from the whole of the Norwegian
 1182 NFI. ALS has been successfully applied to predict growth of individual trees (Yu *et al.*, 2005), and most
 1183 studies so far are made as change detection, where the change in for instance individual total tree
 1184 height is calculated using laser. The ALS-CIs allows for prediction of growth. Further inclusion of ALS-
 1185 CIs in mortality and regeneration models is also possible, just as the variables terrain slope and
 1186 aspect may be calculated (Stumberg *et al.*, 2013). In addition, the use over broader areas requires
 1187 the use of a single-tree detection algorithm. This may give problems with finding the small and
 1188 suppressed trees (Solberg *et al.*, 2006; Ene *et al.*, 2012a), which are mostly affected by competition.
 1189 New investigations are needed to see how well competition can be quantified for areas with no
 1190 ground truth positions. As mentioned in the discussion of Paper I, the hybrid- based ALS-CIs may
 1191 show a higher potential when individual tree properties are derived from a terrestrial laser scanner.
 1192 Lindberg *et al.* (2011) showed how stem attributes may be predicted with no or just a small bias by
 1193 combining ALS and terrestrial laser data, and it is reasonable to assume that these indices may have a
 1194 wider applicability in the future.

1195 In Paper I we also consider methods for handling angles of the laser beam and terrain elevation
1196 (this is seen in Appendix C of Paper I). Because these methods are only theoretically derived, they
1197 need to be verified in practice. However, it is reasonable to assume that both the terrain and the
1198 angle of the laser beam, will affect the competitive level. This is also true for classical CIs, but due to
1199 economic and practical difficulties with estimation of the slope and aspect these are often ignored,
1200 or at least only calculated under the assumption of an even ground surface. From the terrain model,
1201 slope and aspect may be calculated with high accuracy from ALS, and these calculations may also be
1202 applied for classic CIs. As mentioned by Miina and Pukkala (2002) CIs may be further improved by
1203 including directional terms because the geographical position influences the solar radiation through
1204 shadow effects of competing trees. Miina and Pukkala applied ecological field theory to do this, but
1205 other options like the mean directional index (Illian *et al.*, 2008) used in Paper II can be applied.

1206 Several studies have focused on change detection using ALS, i.e. the change in for instance
1207 individual total tree height between two acquisitions. While this may be of interest when calculating
1208 CO₂ quotas, and also to monitor potential climate effects, forest managers will probably limit their
1209 interest to a single overflying with a prognosis of individual tree growth as outcome. The derived ALS-
1210 CIs allow single-tree growth models to be constructed. However, the problem of detecting
1211 suppressed trees makes it more realistic to make a size class model from airborne laser scanning. For
1212 such a model, research is needed to show how the competition should be incorporated. In principle,
1213 a stand-level expression of competition like the self-thinning rule may be sufficient, adapted
1214 somehow to each size class.

1215 5. Paper II

1216 5.1. Results and discussion Paper II

1217 In paper II we exploit the spatial autocorrelation in CIs and Δdbh . We quantified the effect of
1218 spatial autocorrelation on the effective sample size by means of the correction by Clifford *et al.*
1219 (1989) and a spatial bootstrap method (Plant, 2012), using a SAR- model (Whittle, 1954) for the
1220 Spearman rank correlation. Besides, we used a spatial regression model to model the spatial
1221 autocorrelation. It can easily be seen that the spatial autocorrelation induced will also be dependent
1222 on the selection of competitors, because the amount of overlapping competitors in the samples will
1223 affect the spatial autocorrelation. Therefore, we used a relascope and a circle around the subject
1224 tree in order to test the effect on the effective sample size and the resulting type I and type II
1225 statistical error. The statistical type II error was assessed by a power analysis.

1226 The results show that spatial autocorrelation in CI is present when competitors are selected
1227 within 3-4 m search radius around the subject tree. However, when simultaneously accounting for
1228 the effect of spatial autocorrelation in Δdbh and CI the effect on the effective sample size appears
1229 negligible. The same conclusion applies when using the spatial regression approach. In order to test if
1230 spatial autocorrelation was more noticeable in certain stand structures, we correlated the relative
1231 change in the effective sample size when correcting for spatial autocorrelation to the original sample
1232 size, with different measures of stand structures (Pommerening, 2002). These were measures of
1233 macro- and micro-scale variation like Lorey's mean height and volume per hectare. The results show
1234 that no measure of forest structure seems to give high levels of spatial autocorrelation for any of the
1235 CIs investigated. A statistical power analysis revealed that the power of the non-spatially explicit CI is
1236 higher than for the spatially explicit CI. The implications are that the statistical type II error will be
1237 lower for the non-spatially explicit CI.

1238 **5.2. Conclusion Paper II**

1239 The analysis showed that statistical type I error induced by spatial autocorrelation remains a
1240 smaller problem for spatially explicit CIs. Only within very short search radii of 3-4 m spatial
1241 autocorrelation arises. When looking at spatial autocorrelation for bivariate relations all methods
1242 agree that statistical type I error is a minor problem. The plot edge bias correction method presented
1243 by Martin *et al.* (1977) seems not to affect the conclusions, whereas the Hanisch method removes
1244 too many observations in the 250 m² plots to make it useful. Sampling using a relascope gave better
1245 predictions, and did not change the level of spatial autocorrelation when compared to sampling using
1246 a fixed search radius. The study revealed a significant smoothing effect caused by sample overlap,
1247 but it was not possible to document that the smoothing (similarity) affects the predictions in any
1248 negative way. The small plot size may matter here, and more research is needed on larger plots.
1249 Potential differences in the power of the statistical tests using the different CIs were observed, which
1250 may affect the statistical type II error.

1251 **5.3. Perspectives Paper II**

1252 During the peer review of Paper II one of the reviewers raised critique that the plots were too
1253 small to give accurate models of spatial autocorrelation, arguing that other studies have used plots
1254 between 1200 and 2500 m² (Pommerening and Särkkä, 2013) and approximately 2 ha (Fox *et al.*,
1255 2007). The critique is just with respect to the uncertainty in the estimates of spatial dependency on
1256 each plot, and again, this means that further studies on larger plots are desirable.

1257 The results showing smoothing of CIs have a number of perspectives. The use of sample overlap
1258 is not limited to CI, but a number of structural indices and diversity indices for example given by
1259 (Pommerening, 2002; Pommerening and Stoyan, 2006) will suffer from the same problem. New
1260 investigations are needed in order to see the magnitude of the problem in different stand structures.
1261 In fact, sample overlap has a long history in forest inventory, where it is known as sampling with
1262 partial replacement (Gregoire and Valentine, 2008). In the context of sampling, it is often successive
1263 surveys of the same sampling area which leads to correlation among the sampling units. Ware and
1264 Cunia (1962) presented a composite estimator to weight units which were subject of repeated
1265 measurements and those which were not. The aim is to come with an overall estimate of a target
1266 variable minimizing the standard error of the estimate. This way of thinking, to estimate a total based
1267 on some subunits, is very appealing for CIs, because the individual measurements should be set
1268 relative to a maximum. More research is needed to connect spatially explicit CIs to the self-thinning
1269 law of Yoda *et al.* (1963) and Reineke (1933). Several authors have already seen the need for
1270 standardization of spatially explicit CIs, which could serve as a proxy for maximum competition
1271 pressure. Lorimer (1983) was among the first to notice that the value of Hegyi's CI decreases with
1272 increased spacing, despite the fact that Langsæter's hypothesis claims that the growth in the stand
1273 remains fairly constant over a wide range of spacing. The correction of Lorimer (1983) solves this
1274 problem, but the problem of correlated units from sample overlap and smoothing remains. Radtke *et*
1275 *al.* (2003) used a probabilistic method to make sure that CIs were comparable between stands of
1276 same age but of different spacing. This method is limited to large plots to give a sufficient sample
1277 size. Pretzsch *et al.* (2002) standardized distances using the expected nearest neighbor distance
1278 under complete spatial randomness (Clark and Evans, 1954). To make CIs comparable between sites
1279 new methods are needed, that standardize the value of the CI, and at the same time handles
1280 problems of spatial autocorrelation and smoothing caused by sample overlap. One such method may
1281 be geographically weighted regression (GWR), which is featured in Paper III. Also methods of
1282 geostatistics may prove useful, in particular the methods to estimate the global moments of a
1283 distribution using indicator variables (Isaaks and Srivastava, 1989)(chapter 11). Furthermore, the use
1284 of geostatistical methods have the advantage that the loss of variation caused by sample overlap can
1285 be eliminated, and allow to use data from the most applied design namely long term experiments on
1286 smaller plots.

1287

1288

1289 **6. Paper III**1290 **6.1. Results and discussion Paper III**

1291 In paper III I use Moran's I and LISAs to quantify the degree of spatial autocorrelation in Hegyi's
1292 distance weighted size-ratio CI.

1293 I studied the change in spatial autocorrelation between CI and dbh by separating the distance
1294 weighted-size-ratio into an inverse distance part and a size-ratio part. Different methods of
1295 standardization presented by Lorimer (1983) and a modified form of the approach by Pretzsch *et al.*
1296 (2002) were tested. These standardization techniques are used to make index values from different
1297 age classes comparable, and are incorporated into for example the SILVA stand simulator (Pretzsch *et al.*,
1298 2002).

1299 The second order stationarity of the spatial field. i.e. the constant of variance of the spatial field
1300 was tested using geographic weighted regression (GWR) by means of a permutation approach. GWR
1301 is a spatial regression technique which allows regression coefficients to vary for each location over
1302 the area (Fotheringham *et al.*, 2002). A study of the distribution of these regression coefficient
1303 reveals if the values of the variable can be considered spatially isotropic, i.e. directional independent.
1304 The permutation approach used was suggested by Fotheringham (Brunsdon *et al.*, 1998;
1305 Fotheringham, 2000), and I randomly rearranged the original data during 100 permutations. For each
1306 rearrangement, a GWR-fit was obtained, and the standard deviations of the regression coefficient on
1307 each plot were calculated. If the data is stationary, the standard deviation of the local regression
1308 estimates from the random rearrangement should not deviate much from the standard deviation of
1309 the local regression estimates of the original data.

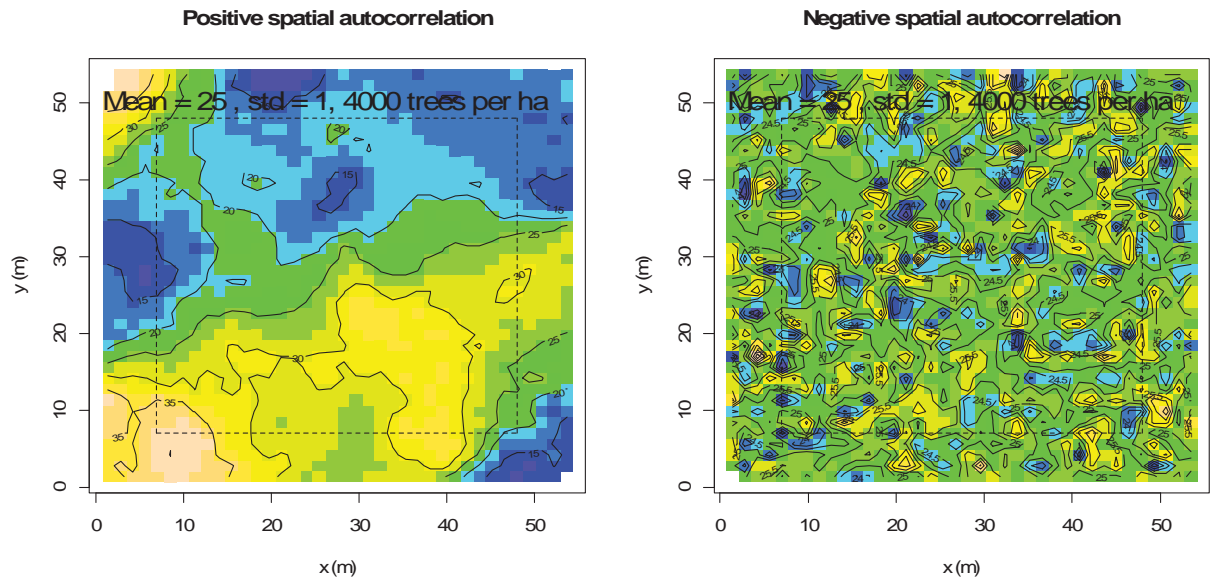
1310 The data from Østmarka Boreal Reserve constitute a limited sample size, and in order to get
1311 more understanding of the behavior of Hegyi's CI in a spatially correlated field I conducted a
1312 simulation study. In the simulations I varied the degree of spatial autocorrelation between positive
1313 spatial autocorrelation, where trees of the same size are positioned closer to each other, and
1314 negative spatial autocorrelation where trees of different size are located closer in space. Both
1315 scenarios are observed in nature. For example, Pommerening and Särkkä (2013) used the mark
1316 variogram (Illian *et al.*, 2008) to analyze a number of simulated stands and time series of tree growth
1317 in order to show that negative spatial autocorrelation occurs, and what it says about the stand
1318 structure. Among the reasons for negative spatial autocorrelation, Pommerening and Särkkä (2013)

1319 mention self-thinning, human made thinning, and size differentiation caused by competition as
1320 important factors.

1321 I applied three different simulation methods to test the effect of spatial autocorrelation in Paper
1322 III. The first simulation method is the one presented by Haining (1990) which allows simulation of
1323 both positively and negatively correlated variables. This is done by varying a spatial parameter λ
1324 between -1 and 1. Minus 1 is extreme negative spatial dependency, and plus 1 is extreme positive
1325 spatial dependency. Haining's method is based on the frequently used spatial error model. The
1326 method of Haining has the advantage that the range of spatial autocorrelation can be set to
1327 biologically realistic values, by specification of a spatial weight matrix. A spatial weight matrix is an
1328 indicator matrix giving the value 1 to a neighbor tree, otherwise 0 (Cliff and Ord, 1981); it can also be
1329 a weighting function instead of an indicator variable.

1330 In Figure 8 I show an example of two realizations of a spatially correlated field of dbh. Notice that
1331 for illustration purposes I applied another plot size in Figure 8 than applied in the simulations of
1332 Paper III. The subplots are made by a smoothing function to visualize the size differences. Both
1333 simulations are made using a normal distribution with standard deviation 1 and mean 25 for 4000
1334 trees per ha, assuming trees within 3 m to be spatially correlated. We see on the left side how
1335 positive spatial autocorrelation makes the trees look more similar in space. The plot to the right has a
1336 patchier pattern caused by the repulsing of identically sized trees. In order to remove edge effects, I
1337 made a buffer around each plot, removing all trees between the dotted square and the plot border in
1338 Figure 8 as subject trees. The simulations in Paper III were made for different standard deviations
1339 and means of the normal and the univariate distributions.

1340



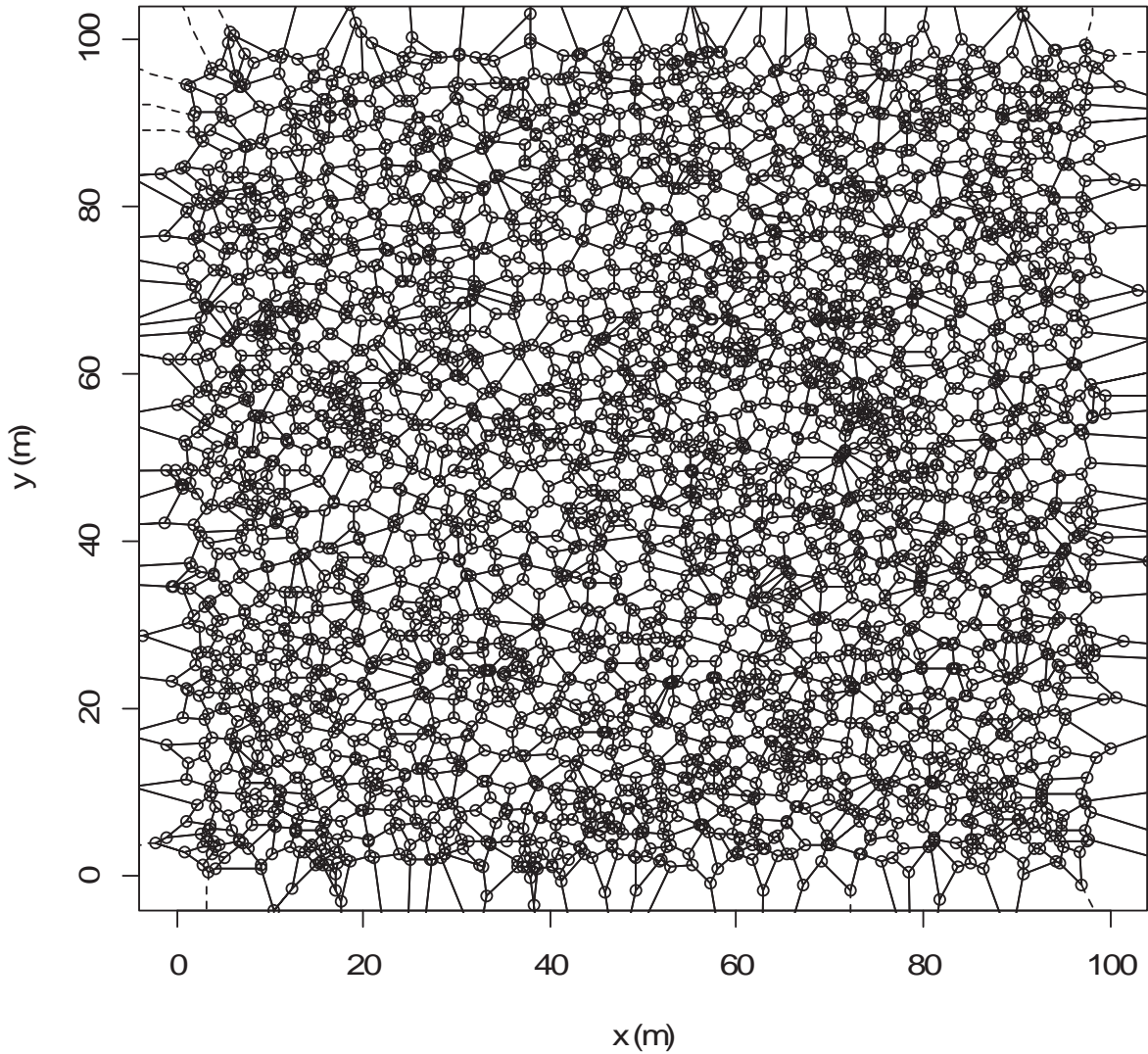
1341

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 $4000 \text{ tree} \cdot \text{ha}^{-1}$. 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

Voronoi tessellation with 2000 trees per ha



1366

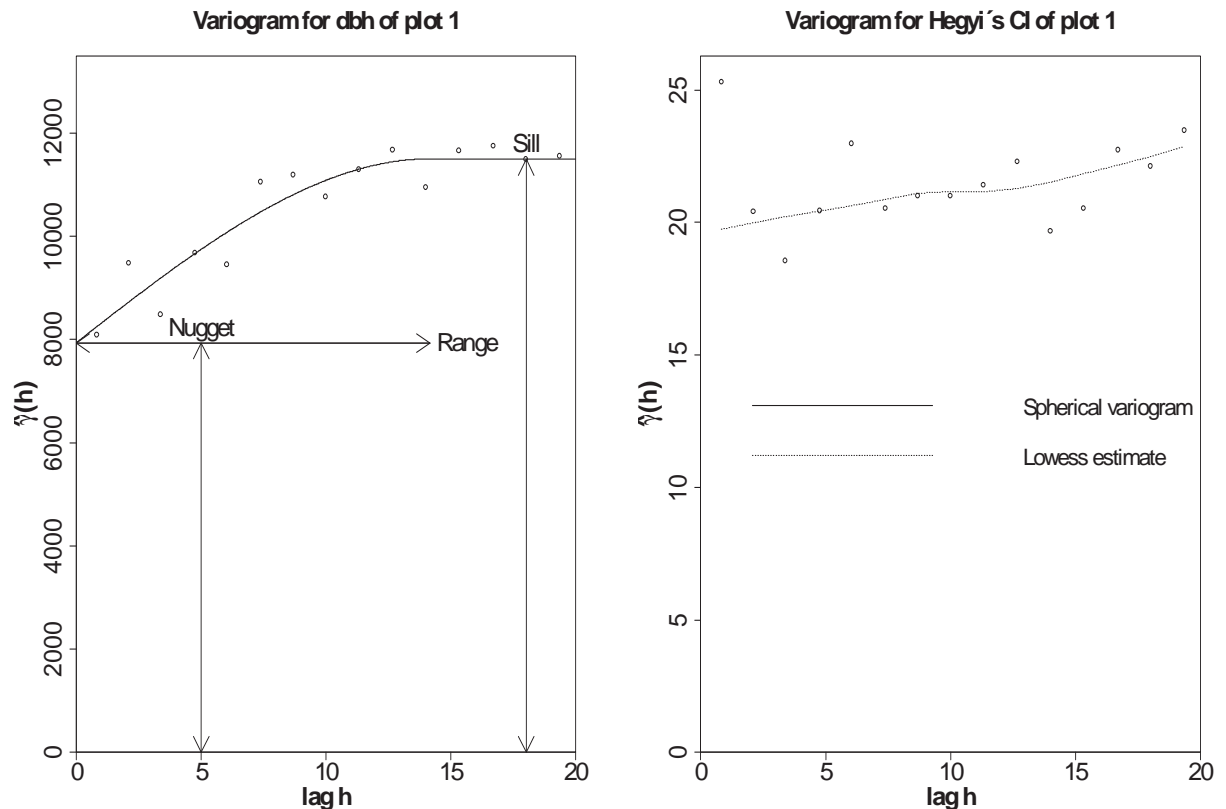
1367 **Figure 9. A Voronoi tessellation applied to a random point pattern of 10,000 square meters, using 2000 trees per**
1368 **hectare (ha). Notice that tree positions in the polygons are not shown!**

1369

1370 The third method is made for a spatial continuum, and is known as a Gaussian random field
1371 (Dutilleul, 2011)(p 275). It is developed within geostatistics, where variables are continuously
1372 distributed in space. It has the advantage that it allows for precise specification of spatial
1373 autocorrelation through a parametric model of the empirical semivariogram shown in Equation 2. In
1374 Paper III an exponential variogram model was applied, and fitted to the estimates of the empirical
1375 omnidirectional estimates of semivariance.

1376 Figure 10 shows the estimate of the spherical semivariogram from Østmarka Boreal Reserve for
1377 Hegyi's CI and dbh for plot number 1. The pattern is similar for other plots in Østmarka Boreal
1378 Reserve and shows that the spatial autocorrelation in dbh is reduced in Hegyi's CI. This result is an
1379 extension of the conclusion from Paper II, because the potential statistical type I error rate in e.g.
1380 correlation tests is reduced when comparing the level of spatial autocorrelation for Hegyi's CI with
1381 what is originally seen in dbh. This does however not imply that positive spatial autocorrelation is not
1382 a problem when using Hegyi's and other CIs, just that it is reduced compared to dbh. The pioneering
1383 work of Reed and Burkhart (1985) shows that the level of spatial autocorrelation in basal area varies
1384 with stand age and competition level. Since the results of Paper III indicate that Moran's I for dbh
1385 (which of course are expected to behave similar to individual tree basal area) has strong correlations
1386 with Hegyi's CI, the level of spatial autocorrelation in CIs, can be expected to follow the pattern that
1387 Reed and Burkhart (1985) observed for individual tree basal area. This shows the difficulties in
1388 making conclusions from a single survey.

1389



1390

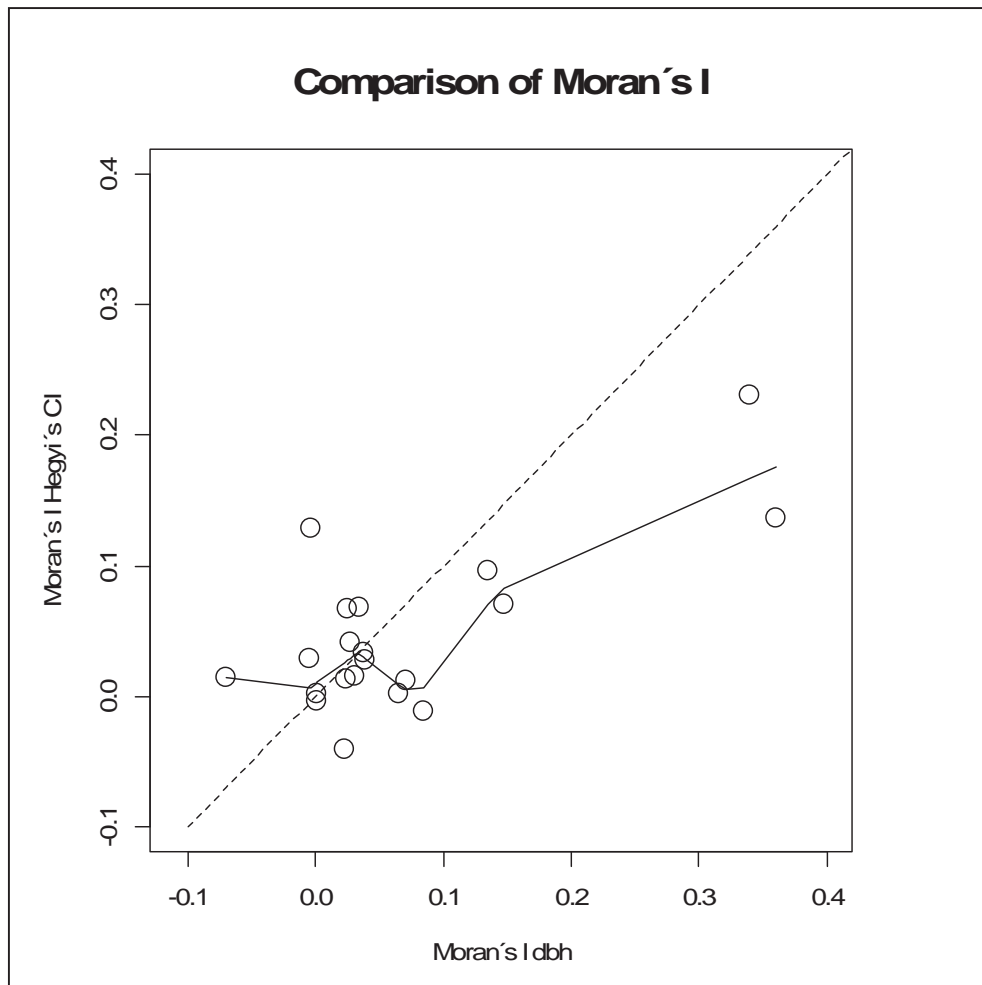
1391 **Figure 10.** The semivariance of lag class h $\hat{\gamma}(h)$ calculated for dbh (left side) and Hegyi's CI (right side) using the
 1392 measurements of plot 1. For dbh a parametric fit of the spherical variogram is given by the solid line. On the graph the
 1393 range nugget and sill estimated by the spherical variogram are shown. The lowess estimate of $\hat{\gamma}(h)$ for Hegyi's CI is
 1394 given by the dotted line.

1395

1396 Moran's I was used in Paper III to get a relative value of spatial autocorrelation for comparisons
 1397 between dbh and Hegyi's CI for all plots. The results confirm the trend shown in the spherical
 1398 variogram in Figure 10, i.e. almost all plots show a decreasing level of spatial autocorrelation. In
 1399 Figure 11 Moran's I of Hegyi's CI is plotted against Moran's I of dbh for each plot. A few positive
 1400 values of Moran's I of Hegyi's CI can be observed when the level of spatial autocorrelation in dbh is
 1401 low. The lowess estimate shown as the smooth line in Figure 10, reveals that spatial autocorrelation
 1402 in Hegyi's CI decreases with increasing spatial autocorrelation for dbh.

1403 In Paper III, extensions of such an analysis, not shown in this synopsis, reveal that it is the size-
 1404 ratio term of Hegyi's CI, which is responsible for the reduction in spatial autocorrelation. The inverse
 1405 distance term increases positive autocorrelation and statistical type I error in e.g. the test of the
 1406 Spearman rank correlation. Thus, when the inverse distance is used as a CI, a correction method like
 1407 the one proposed by Clifford *et al.* (1989) for spatial autocorrelation is needed in order to get valid
 1408 statistical inference. It should be noted that in addition to confirming that the inverse distance

1409 component increases the positive spatial autocorrelation, simulation studies also revealed that the
 1410 original Hegyi's CI and the size-ratio may cause positive spatial autocorrelation. The mean of the
 1411 simulated dbh-distributions seems to be determining if positive spatial autocorrelation appears. A
 1412 higher mean leads to a higher positive spatial autocorrelation. Stem number and spatial
 1413 autocorrelation in dbh seem to be less important. This means that older stands with a large mean
 1414 dbh should be corrected for statistical type I error before conclusions based on statistical inference
 1415 can be made.



1416

1417 **Figure 11. Moran's I for Hegyi's CI plotted against the same for dbh for each of the 20 plots in Østmarka Boreal**
 1418 **Reserve. The dotted line indicates that the two variables are similar. The smoothed line is the lowest estimate. The**
 1419 **search radius is 7 m around the subject tree using a binary weight in the calculations of Moran's I.**

1420

1421 Lorimer (1983) pointed out that Hegyi's CI decreases with spacing, when the size-ratio term is
 1422 the same, and made a correction for it. Pretzsch *et al.* (2002) have suggested another correction by
 1423 dividing all distances with the average distance of the trees in the search radius given complete
 1424 spatial randomness, by means of the Clark and Evans index (Clark and Evans, 1954)(see also Burkhart

1425 and Tomé (2012) p 220). In Paper III I used a modified method, dividing the distance between each
 1426 subject tree and competitor with the correction factor and not the “center-of-mass” originally
 1427 proposed by Pretzsch *et al.* (2002). It can be seen from Paper III that the correction methods of
 1428 Lorimer (1983) and the modified method of Pretzsch *et al.* (2002) reduce Moran’s *I* even more than
 1429 the original Hegyi’s CI. Furthermore, these correction methods seem to improve the correlation
 1430 between Δdbh and CI. Thus, these correction methods are recommendable both from a predictive
 1431 and a statistical perspective.

1432 To study the effect of increased flexibility in Hegyi’s CI, I used a version of Hegyi’s CI slightly
 1433 modified after Richards *et al.* (2008) (Richards CI) which puts a parameter to each of the three
 1434 stochastic variables distance, subject tree size, and competitor tree size. This version is simpler than
 1435 the original one of Richards *et al.* (2008) to avoid the use of non-linear optimization. The results show
 1436 that Richards CI correlates much less than any other CI tested in Paper III with Δdbh , probably
 1437 because dbh is used as regressor in its calibration, and therefore explains most of the variation in the
 1438 data. The correlations between the LISA of Moran’s *I* derived from dbh vs. LISA of Moran’s *I* for the
 1439 various CI reveal something interesting. All CIs show a positive trend. This means, that similar sized
 1440 trees in space tend to have the same competition level in space. One explanation for this is the fact
 1441 that e.g. Hegyi’s CI utilizes dbh, and therefore naturally will have a spatial correlation with dbh.
 1442 However, for Hegyi’s CI there seems to be a small downward trend, which means that “very hot”
 1443 hotspots and “very cold” coldspots of the LISA are not as “hot” and “cold” for Hegyi’s CI (see
 1444 subparagraph 1.8.4 for more explanation of these terms). This result is connected with the building
 1445 of a size hierarchy, because even very similar sized trees will become dissimilar in space after
 1446 assigning them a value using Hegyi’s CI. The results also show something else that is interesting. The
 1447 non-spatially explicit CI used, which applies D_g and dbh has a strong correlation with LISA of dbh. This
 1448 means that the non-spatially explicit CI mimics the spatial autocorrelation of the tree’s dbh, though
 1449 opposite proportional as seen by the sign of the correlation, and in cases where dbh is a good
 1450 predictor of Δdbh , this index will be superior to Hegyi’s CI. In Paper I we showed, using the same
 1451 material from Østmarka Boreal Reserve that 32 percent of the explained variation in Δdbh was due
 1452 to dbh, and only around 2 percent was due to CI.

1453 Paper III reveals that the correlation between LISA Δdbh and LISA CI is very weak. This is
 1454 surprising because one should expect a spatial index that aims to predict Δdbh to be spatially
 1455 correlated with Δdbh . This result has led to the following hypothesis, which should be tested further
 1456 in future studies :

1457 *“The best expression of CI in a spatial context is local indicators of spatial association (LISA) of the*
 1458 *growth (or relative growth) variable. Any CI which has the same spatial autocorrelation as growth will*
 1459 *be the one which has the highest explanatory power”.*

1460 If the hypothesis is true it means that spatially explicit CI indices often fail to predict spatial
 1461 growth because they do not equal the spatial autocorrelation of Δdbh . If we look at expressions of
 1462 LISA for Moran's I , it is highly unlikely that any CI can ever have the exactly same value of LISA Moran's
 1463 I as Δdbh , especially because in many cases dbh enters as variable in the CI. Therefore, in most cases
 1464 the CI merely changes the spatial correlation of dbh , though it will to a small degree correlate with
 1465 LISA Δdbh . A considerable improvement in the performance of spatially explicit CIs should therefore
 1466 be expected if LISA Δdbh is used as dependent variable, and the CI as independent variable. Notice
 1467 that one may need to apply the previous growth period to calculate LISA, in order to make
 1468 predictions of the successive growth period. One can then apply the optimization routines of e.g.
 1469 (Richards *et al.*, 2008), to find the parameters of the classical CIs. However, such an optimization may
 1470 be unnecessary, because it would be more effective simply to use LISA of Δdbh directly as a CI.
 1471 Spatial autocorrelation of course depends on the definition of neighborhood, and the mathematical
 1472 measure used. Finding the most proper definition of spatial neighborhood for LISA of Δdbh in such a
 1473 case, is also an idea for further research. One important point is that even if the hypothesis is true it
 1474 does not mean that any other CI cannot give the best predictions of growth, only that if this is the
 1475 case then it is not spatial, and/or it does not capture competition. It may for instance be possible to
 1476 create an index that models the spatial correlation in dbh , which gives better predictions of Δdbh ,
 1477 simply because size is a more important parameter than competition for growth in space. Such a
 1478 scenario may appear if soil conditions favor strong micro-scale gradients in site conditions.

1479 **6.2. Conclusion Paper III**

1480 The simulation study and the empirical study have both agreements and disagreements. The two
 1481 studies coincide when showing that using inverse distance as a measure of competition generates
 1482 positive spatial autocorrelation. In the empirical study Moran's I showed a decreasing trend for CIs
 1483 compared to dbh especially for high levels of positive spatial autocorrelation in dbh . The replications
 1484 made in the simulations do not confirm a decrease in Moran's I for Hegyi's CI, inverse distance, or
 1485 the size-ratio. Among the distributional properties of dbh such as standard deviation and mean, the
 1486 simulations show that the mean of the simulated dbh distribution is the most important factor in
 1487 changing the level of spatial autocorrelation in CIs. The higher the mean, the more positive spatial
 1488 autocorrelation, and therefore old stands with a high mean diameter need correction for spatial
 1489 autocorrelation in statistical tests. The standard deviation and the degree of spatial autocorrelation

1490 in dbh are less important for the spatial autocorrelation in CI. Thus, it is not possible to conclude that
 1491 because dbh has a negative spatial autocorrelation, the derived spatially explicit CI will have the
 1492 same. Of the correction methods for increased spacing with age by Lorimer (1983) and Pretzsch *et al.*
 1493 *al.* (2002), especially the method of Pretzsch *et al.* (2002) seems to reduce the level of positive spatial
 1494 autocorrelation, and at the same time improves predictions when compared to results with no
 1495 spacing with age correction. Thus, this method is recommendable from a statistical and predictive
 1496 perspective.

1497 The study also focuses on the spatial autocorrelation on a local scale quantified by LISAs. The
 1498 results from the empirical data show that the spatially explicit CIs seem to build up a size hierarchy at
 1499 the local scale when compared to dbh. The use of GWR shows that the spatial field has an increased
 1500 level of nonstationarity in the spatially explicit CIs when compared to the non-spatially explicit CI.
 1501 This suggests that non-spatially explicit CIs give good predictions because they mimic the explanatory
 1502 power of dbh in space. The LISA-analysis also confirmed that LISA of the non-spatially explicit CI
 1503 mimic the spatial autocorrelation of dbh. The most pure expression of competition is growth, and in
 1504 space it is spatial autocorrelation of growth (Subsection 6.1). The analysis of correlation between
 1505 LISA of Δdbh and CI only revealed weak correlations. This suggests that CIs work by mimicking dbh in
 1506 space - a strong predictor of growth. But if the purpose is modeling of spatial competition, a measure
 1507 of spatial autocorrelation of Δdbh should work better, or a CI which mimics this. This does of course
 1508 not mean that such an index will be a stronger predictor of growth, only a stronger predictor of
 1509 spatial competition.

1510 **6.3. Perspectives Paper III**

1511 The results in Paper II and Paper III throw a light on the understanding of how spatially explicit
 1512 CIs behave in a spatial statistical context, and the validity of statistical inference derived from the CIs.
 1513 One important problem connected with the investigations, which is not tested in any of the papers, is
 1514 the problem of spatial misalignment, and how different techniques may be applied to improve the
 1515 efficiency of the estimated level of competition. Spatially explicit CIs are spatially aligned by
 1516 summation of the competition pressure of the competing trees into a value for each subject tree.
 1517 However, from a statistical perspective such a summation may not be the best way of aligning the
 1518 spatial data. One way of improving the CIs is to use the theory of random variables. It can be shown
 1519 that linear weighting of stationary random variables should sum to 1 in order to be unbiased. This
 1520 assumption of unbiasedness is underlying interpolation techniques such as inverse linear
 1521 interpolation and kriging. When using Hegyi's CI each competitor is interpolated to the position of
 1522 the subject tree by $1/\text{distance}$, and thus the condition for unbiasedness is not fulfilled. Instead of

1523 using this simple weighting, improvements using geostatistical techniques should be tested. In the
 1524 case of inverse distance the interpolation using the weight given by Equation 8 could be a simple
 1525 alternative (Isaaks and Srivastava, 1989) (p 257). \overline{CI} is the inverse distance weighted value of the
 1526 competition index (CI) for the i 'th tree. $Dist_{ij}$ is the distance between the j 'th competitor and the
 1527 i 'th subject tree. The unbiasedness of interpolation is done by dividing with the sum of inverse
 1528 distances, in a much similar way as proposed by Lorimer (1983) and Pretzsch et al. (2002).
 1529 Summation is done for n competitors.

1530 **Equation 8**

$$1531 \quad \overline{CI}_i = \frac{\sum_{i \neq j}^n \frac{1}{Dist_{ij}} CI_j}{\sum_{i \neq j}^n \frac{1}{Dist_{ij}}}$$

1532 The use of such a standardization is also underlying ordinary kriging, and interpolation by means
 1533 of polygons and triangulation (Isaaks and Srivastava, 1989) (chapter 11 and 12). The modeling would
 1534 then be a two step procedure, firstly interpolating the values of the competitors to yield a CI, which
 1535 would enter to the growth model. Recent methods of Bayesian hierarchical modeling allows for
 1536 modeling directly without such a two step procedure, and this is an interesting field to be explored
 1537 (Banerjee *et al.*, 2004)(chapter 7).

1538 Paper III was limited to randomly distributed tree positions. However, trees form many other
 1539 point patterns than random patterns. Thus, an obvious extension of the study is to test the effect of
 1540 regularity and clustering. Today soft-ware packages like spatstat of R® (Baddeley and Turner, 2005)
 1541 and the software developed by Kershaw Jr *et al.* (2010) allow for simulation of various point patterns,
 1542 under different correlation structures of the individual tree parameters.

1543 **7. Paper IV**

1544 **7.1. Results and discussion Paper IV**

1545 The methods used for plot edge bias correction derived in Paper IV rest on the simple method of
 1546 ratio-estimators. Ratio estimators have a long history in forest science (Johnson, 2000). Often, a
 1547 simple ratio between a variable that is known for the entire population, and another target variable
 1548 is used to adjust the estimate of the target variable. This simple ratio may be extended to the case of
 1549 several ratios, yielding a multivariate ratio estimator (Olkin, 1958). In Paper IV I explore the use of the

1550 multivariate ratio- estimator. Such an estimator requires weights to be given to each of the ratios. I
1551 made use of a method initially described by Olkin (1958) for finding the weights firmly described by
1552 Cochran (1977) (p 184-186). In addition, I also identified weights by use of restricted linear regression
1553 (Waterman, 1974) and multiple linear regression. In the latter case, the ratios just enter as
1554 parameters in a regression model. The simulated annealing method is a modification of a method
1555 proposed by Pommerening and Stoyan (2008). The results show that the existing methods
1556 (simulated annealing and linear expansion) seem slightly better than the ALS based methods in
1557 improving plot specific correlations between CIs and Δdbh . The evaluation method applied in the
1558 study has the weakness that the true values of the CIs are not known. Therefore, the evaluation
1559 assumes that any improvement in the prediction of Δdbh is due to the fact that the CIs have come
1560 closer to their true values using plot edge bias correction. However, it is possible to improve
1561 correlations if the plot edge bias corrected CI mimics another strong predictor of stand structure, e.g.
1562 canopy height.

1563 **7.2. Conclusion Paper IV**

1564 While the proposed method using multivariate ratios to adjust plot edge bias is simple to use, the
1565 low correlations between laser metrics and CIs make the classical methods of plot edge bias
1566 correction work better. If ALS is to be used for plot edge bias correction, other types of indices should
1567 be tested and/or better correlations with ALS metrics should be found.

1568 **7.3. Perspectives Paper IV**

1569 Another obvious way to reduce plot edge bias is to use a single-tree detection algorithm to
1570 identify the trees outside the plot border. The method should be fairly simple to apply, and contrary
1571 to the method presented in Paper IV, has the advantage that it does not rely on a correlation
1572 between the CI and laser metrics. The weak correlations observed between density metrics and CIs,
1573 in addition to potential multicollinearity problems (Montgomery *et al.*, 2006) due to near linear
1574 dependency between metric variables, show that this is a concern. The performance of such a
1575 method depends on the power of the single-tree detection algorithm. Solberg *et al.* (2006) applied
1576 the same material, that is used in the current thesis from Østmarka Boreal Reserve, and showed that
1577 dominant trees which are expected to exert most competition to the trees on the plot, can be
1578 correctly identified and positioned in 93% of the cases. For the suppressed trees, the detection rate
1579 dropped down to 19%. Because the majority of plot edge effects may be attributed to dominant
1580 trees outside the plot, the lack of detection of suppressed trees may not matter that much, though in
1581 some forest types the understory may have considerable biomass. Applying a single-tree detection
1582 algorithm to a forest type where it is not calibrated may give very inaccurate results as demonstrated

1583 by Vauhkonen *et al.* (2012). Vauhkonen *et al.* (2012) showed how higher density of biomass in the
 1584 stands can give an increased error rate in the number of correctly identified trees. In cases with only
 1585 very few plots one could consider using photo images if they exist. It should however be noticed that
 1586 the canopy may be too dense for a single-tree detection algorithm to work, and in such cases the
 1587 method presented in Paper IV remains an easy and simple alternative.

1588

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1976

1977

1978 **Errata**

1979 Equation 3 in Paper I should read:

1980
$$h_i^2 = c^2 x_i^2 + y_i^2$$

1981 The caption of Table B.3 in the appendix of Paper I should add “Numbers in () indicate plot edge
1982 bias correction has been made.”. This has been corrected in the thesis print, but not in the online
1983 version.

1984 Table 1 in Paper I should read “Recruitment (fraction of broadleaves alive in 2003)”

1985

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.

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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](https://doi.org/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.

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Paper IV

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

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