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1 Potential of using data assimilation to support forest planning

2

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23 **Abstract**

24 Uncertainty in forest information typically results in economic and ecological losses as a consequence of
25 suboptimal management decisions. Several techniques have been proposed to handle such
26 uncertainties. However, these techniques are often complex and costly. Data assimilation (DA) has
27 recently been advocated as a tool which may reduce the uncertainty and thereby improve the quality of
28 forest planning results. It offers an opportunity to make use of all new sources of information in a
29 systematic way, and thus provide more accurate and up-to-date information to forest planning. In this
30 study we refer to literature on handling uncertainties in forest planning as well as related literature from
31 other scientific fields in order to assess the potential benefits of using DA in forest planning. We identify
32 five major potential benefits: (i) The accuracy of the information will be improved; (ii) The information
33 will be kept up-to-date; (iii) The DA process will provide information with estimated accuracy; (iv)
34 Stochastic decision making can be applied, whereby the accuracy of the information can be utilized in
35 the decision making process; and (v) DA data allows for the analysis of optimal data acquisition
36 decisions.

37 Keywords: uncertainty; suboptimal loss; remote sensing; Bayesian statistics; stochastic optimization.

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44 1. Introduction

45 Wise management of forest resources requires accurate estimates of what is contained within the
46 forest. These estimates can be considered forest information, a collection of forest variables which can
47 be estimated through various inventorying techniques. This information is often organized in databases,
48 where relatively homogenous parcels of forested land area are aggregated as stands. Through thematic
49 maps, the various attributes can be shown spatially. Depending on the level of detail, the data will
50 contain specific information on the growing stock volume, height, tree species, age, area size and site
51 index of the stand. Traditionally, forest information has been acquired in the field through ocular
52 estimation or through objective samples, updated every 5-10 years. Recent developments in remote
53 sensing have allowed for the possibilities of acquiring forest information from distance at reduced cost
54 (Næsset 2002; Gobakken & Næsset 2004; Saad et al. 2015). Regardless of how forest information is
55 acquired, it is not free from errors and these errors are one of the many sources of uncertainty in forest
56 planning. Following the data acquisition, the old forest information would no longer be used in the
57 forest planning process, and the potential remaining value of the old information is thus ignored.

58

59 Uncertainty in forest information occurs due to random or systematic errors in the inventory estimates.
60 Systematic errors may occur as a result of subjective judgments or problems with measurement devices
61 that lead to consistent over- or underestimates of the true value (Ståhl 1992). Random errors are
62 unpredictable deviations, introduced by (random) measurement errors or through measuring only a
63 sample of the population of interest. The uncertainty of the initial state is propagated through the
64 growth models used to predict the future forest state (Mowrer 2000; Nyström & Ståhl 2001; Eid 2000).
65 Uncertainty in forest information typically leads to suboptimal decisions in forest planning (Duvemo &
66 Lämås 2006, Pukkala 1998). Therefore, considering and reducing uncertainty in forest information is of

67 major importance for forest planners; this is particularly relevant since forestry involves large economic,
68 ecological, and social values. Aside from inventory errors there are other sources of uncertainty which
69 can affect the optimal forest management plan, e.g., growth models (Nyström & Ståhl 2001), market
70 prices (Gong 1994), fire risk (Savage et al. 2010, González-Olabarria & Pukkala 2011), wind risk
71 (Heinonen et al. 2009) and climate change (Crowe & Parker 2008; Kangas & Kangas 2004; Pasalodos-
72 Tato et al. 2013; Yousefpour et al. 2012; Ferreira et al. 2016). As this study focuses on the link between
73 forest inventory data and forest planning, the only source of uncertainty that will be considered is the
74 uncertainty in the initial state of the forest resulting from errors in forest inventory data.

75

76 Data assimilation (DA) is an approach to merge temporally separated data about some feature of
77 interest. The data may be acquired using different techniques. In the realm of forest inventory, DA has
78 the potential of improving the accuracy of the information and also to provide an estimate of the
79 uncertainty of the information (Czaplewski & Thompson 2008; Ehlers et al. 2013). The development and
80 use of DA has its history in, e.g., meteorology, where large amounts of spatiotemporal data are used to
81 forecast the weather (Ghil & Malanotte-Rizzoli 1991; Lahoz et al. 2010). In essence, DA is a process
82 which can merge data from different sources into a single usable source. One feature of this process is
83 the ability to combine the estimates of uncertainty from each data source to provide updated estimates
84 of the uncertainty for the information (Ehlers et al. 2013, Nyström et al. 2015). In a forestry context, a
85 typical setup could be to keep the information up to date by integrating growth models in the DA
86 process (Nyström et al. 2015) and to use remote sensing to obtain new estimates of the target forest
87 information at regular intervals at low cost (McRoberts et al. 2010).

88

89 The technical implementation of DA can be done through a variety of approaches. Two commonly
90 applied approaches are the Kalman filter (Welch & Bishop 2006) and Bayesian statistics (Dowd 2007).
91 Comparatively, the Kalman filter is simple to apply while the Bayesian approach is relatively demanding.
92 In both cases, existing (prior) information is forecasted to the time point when new data are acquired.
93 The forecasted and new information are then merged. An updated (posterior) estimate is obtained as a
94 weighted average (e.g., Ehlers et al. 2013; Figure 1). Through this process the quality of the information
95 will be improved by assigning less importance to the information with lower quality, updating both the
96 estimate and the estimates of uncertainty are also updated. This provides the forest planner with
97 information on both the point estimate of the study variable and its corresponding uncertainty. An
98 additional feature of the Bayesian approach is the estimation of probability distributions of the study
99 variables. Special features of the processes studied require special attention. For instance, large changes
100 (i.e. harvesting actions or storm fellings), require additional change detection procedures (e.g. using
101 multi-temporal remotely sensed data) to identify in what areas DA cannot be routinely applied.

102

103 <Figure 1 here>

104

105 While the current use of DA in forestry inventory applications is rather limited, research to the proper
106 application is ongoing. One concrete example of applying DA to improve forestry inventory estimations
107 is the work of Nyström et al. (2015). The DA process applied the extended Kalman filter (Welch & Bishop
108 2006) with univariate models and a few simplifying assumptions. The forest state information was
109 updated by the inclusion of both forecasting models and estimates of the forest state obtained through
110 laser scanning combined with field reference data from sample plots. The results suggest the
111 assimilation process improves the estimates of forest information over either only forecasted estimates

112 and the most recent estimates from the remotely sensed data. For more detailed description of the
113 applications readers are directed to Nyström et al. (2015).

114

115 Forest planning uses information about the current state of the forest to predict future results of
116 different forest management alternatives. Forest planning is motivated by the specific objectives of the
117 decision maker (Davis & Liu 1991; Edwards & Steins 1999; Kazana et al. 2003; Leskinen et al. 2009;
118 Pukkala 1998; Randhawa et al. 1996; Borges & Hoganson 2000). One simple economically orientated
119 objective is to maximizing profit or net present value (NPV). With more complicated objectives (i.e.
120 multiple goals) involving several spatiotemporal scales (Duvemo & Lämås 2006; Duvemo et al. 2014;
121 Kangas 2010), the need for accurate forest information increases. The information that relates to the
122 objectives of the decision maker have more importance; frequently these variables relate to the value of
123 timber and pulp wood in the forest stands (Bettinger et al. 2009; Davis et al. 2001; Eriksson 2008).

124

125 Forest planning occurs on a variety of temporal and spatial scales. The selection of scale may imply the
126 selection of specific management goals. For instance, in landscape level long term planning the goals
127 may involve nature conservation, carbon sequestration and balancing the volume, species composition,
128 and the distribution of harvest assortments. Alternatively, short term local scale harvest scheduling
129 may focus solely on facilitating timber procurement and logging procedures, with an aim to provide the
130 raw materials required for industrial demands (Bettinger et al. 2009; Davis et al. 2001; Eriksson 2008).
131 Considerations in the importance of uncertainty can differ between different spatial and temporal
132 scales.

133

134 Even though uncertain information may lead to suboptimal decisions, the magnitude of the suboptimal
135 loss occurring as a consequence of imperfect forest information is never known (Kangas 2010); however,
136 it is often estimated (Holmström et al. 2003, Saad et al. 2014). Several studies (Holmström et al. 2003;
137 Kangas et al. 2014; Kangas 2010; Ståhl et al. 1994) suggest that cost-plus-loss analyses can be conducted
138 as a means to assess the appropriate level of information quality for certain cases. Incorporating
139 uncertainty into the planning process can be difficult due to intricate mathematical algorithms and the
140 limited ability of traditional mathematical programming methods, such as linear programming, to
141 account for uncertainty (Hoganson & Rose 1987; Pukkala 1998; Pasalodos-Tato et al. 2013, Ferreira et al.
142 2016). In complex forest planning and decision situations, to explicitly incorporating uncertainty into the
143 optimization model may be very difficult (Mowrer 2000). Therefore, forest planners in practice often
144 ignore uncertainty for simplicity.

145

146 Uncertainty in inventory information increases through time as growth models are used to update the
147 forest information (Nyström & Ståhl 2001; Fig 2). While the growth models may be of high quality,
148 predictions are simplifications, and there are no techniques available to remove the uncertainty of
149 predictions of the future forest state (Pietilä et al. 2010). The tool for controlling this uncertainty is to
150 collect new information.

151

152 <Figure 2 here>

153

154 The objective of this study is to explore, highlight and discuss the potential benefits in forest
155 management planning of using DA processes in forest inventories. The information provided by the DA

156 process contains novel features, but there are also challenges in applying DA. We highlight the potential
157 benefits of DA information for different forest planning contexts and discuss the challenges.

158

159

160

161 2. The potential for using DA in forest planning

162 DA has the potential to reduce uncertainties and provide estimates of uncertainties which can be used
163 to improve forest planning. With DA, new information is combined with the prior information producing
164 an improved estimate (called posterior information in Bayesian statistics) (Dane & Horowitz 1965;
165 Erdem & Keane 1996; Prueitt & Park 1997). Rather than discarding information following the acquisition
166 of new information, DA offers a framework for continuously building the new information on the old
167 information, which is updated and merged with new observations (Figure 1). This will allow the decision
168 maker to revise his choice of action and thus to overcome uncertainty.

169

170 The potential benefits of DA depend upon the use of the improved information in the forest planning
171 process. This depends upon the nature of optimization models or decision methods underlying the
172 applied forest planning tool. For forest planning tools based on deterministic optimization models, point
173 estimates of relevant forest variables are used to reflect the current state and future development of
174 the forest. The main benefit of using DA in planning originates from the improved accuracy in the initial
175 state of the forests. Through a sensitivity analysis, the robustness of the planning results can be
176 evaluated. The estimates of uncertainty obtained using DA are helpful in defining the relevant intervals
177 of uncertain forest variables to be tested in sensitivity analysis. However, the sensitivity analysis may

178 reveal that the planning results vary dramatically with changes in the values of the uncertain variables.
179 In that case, there is no obvious approach to evaluate which forest plan is optimal based on the results
180 of sensitivity analysis. In other words, if one applies a forest planning tool based on deterministic
181 optimization models, one cannot (fully) utilize the estimates of uncertainty. However, if one has access
182 to a planning tool with a stochastic optimization model, then both the point estimates and estimates of
183 uncertainty from DA can be used in the planning process, which can provide larger benefits than in the
184 case where only the point estimates are used (Birge & Louveaux 2011).

185

186 There are a variety of optimization methods available which can integrate estimates of uncertainty into
187 the planning process. The choice of which method to use depends upon on the requirements of the
188 optimization model and its tractability. For instance, robust optimization (Bertsimas & Sim 2004) can be
189 used to protect against the infeasibility of the constraints caused by the potential of uncertainty. In a
190 road building and harvest scheduling problem, Palma & Nelson (2014) introduced uncertainty into the
191 timber estimates, and found that the solution of the robust optimization model to solve road building
192 and harvest scheduling is less sensitive to uncertainty in timber volume information as compared to the
193 deterministic model commonly used in forestry. DA can potentially improve the quality of solution by
194 improving the quality of the timber estimates. One benefit of robust optimization is the limited increase
195 of problem size in comparison to the linear equivalent (Bertsimas & Sim 2004), thus if the linear
196 equivalent is tractable, the robust version should also be tractable.

197

198 While robust optimization protects against the infeasibility of specific constraints caused by uncertainty,
199 stochastic optimization integrates the uncertainty into the entire problem formulation (Birge &
200 Louveaux 2011). Stochastic programming problems can be formulated in many different ways, as

201 uncertainty can be considered in the objective function as well as in the constraints. In forest planning,
202 stochastic optimization is being researched to demonstrate the potential for the implementation into
203 practice (Garcia-Gonzalo et al. 2016, Eyvindson & Kangas 2016b). Stochastic programs have the
204 potential to answer different questions than their deterministic counterpart. For instance, issues of
205 individual risk preferences can be accounted for at the holding level. Related to the issue of DA, the
206 specific timing of when the data should be updated can be formulated as a multi-stage stochastic
207 optimization problem. Based on the preferences of the decision maker, and optimization model used,
208 the improvement of forest information could be timed specifically (Eyvindson et al. 2017).

209

210 One major hurdle to implement stochastic programming is the issue of problem size, which could easily
211 become too large to be tractable. If the entire stochastic problem needs to be formulated, issues of
212 tractability can be a major concern in forest planning problems (Eriksson 2006). One way to maintain
213 the tractability of stochastic optimization problems is to include a finite number of the possible values
214 of uncertain variables, e.g., through a set of scenarios (Birge & Louveaux 2011). The set of scenarios
215 should be large enough to appropriately reflect the uncertainties being considered and should be small
216 enough to keep the model tractable. The optimization problem should direct the discretization of the
217 set of scenarios, rather than simply trying to create a strong approximation to the original distribution
218 (King & Wallace 2012). For each optimization problem, the selected scenario set should be tested for
219 stability and solution quality, a variety of tools have been developed for this purpose (e.g. Kleywegt et
220 al. 2001; Bayraksan & Morton 2011). It is intuitively clear that the smaller the uncertainty is, the smaller
221 number of scenarios are needed to produce a good approximation of the uncertain variables.
222 Therefore, the use of DA can promote the tractability of the problems by reducing the uncertainty,
223 which will be reflected in the appropriate scenario set size used (Eyvindson & Kangas 2016a).

224

225 Whichever optimization method one uses to integrate estimates of uncertainty in forest planning, the
226 planning process typically becomes more complex and more costly. To highlight the benefit of using
227 methods which integrate estimates of uncertainty in forest planning, the value of the solution can be
228 evaluated. The value depends upon the specific problem and the preferences of the decision maker.
229 When dealing with individuals, risk preferences vary considerably, and the value of improved
230 information depends on the individual decision maker's acceptance of risk. At this level, the potential
231 benefits of integrating estimates of uncertainty can be evaluated through the value of the information.
232 This can be calculated directly by comparing the optimized results from different levels of data quality
233 (Kangas et al. 2014). In more complex decision situations involving several decision makers or
234 intangible benefits, the value of the improvement is more subjective and difficult to estimate. It
235 depends upon the subjective valuations of the decision maker(s) of the increased quality of the
236 management plan.

237

238 We would like to emphasize that the costs associated with implementing DA can be justified only if the
239 use of information from DA can result in adequately large improvements of the management plan. One
240 way to value the improvements in management plan is through the cost-plus-loss technique
241 (Holmström et al. 2003; Eid 2000). At stand levels, these studies identified the potential value from
242 obtaining perfect information by preventing losses. However, perfect information is not possible to
243 obtain, so the comparison could be made between with and without the use of DA. Similarly, Ståhl et al.
244 (1994) proposed a Bayesian approach to evaluate if an updated inventory should be conducted to
245 maximize the expected NPV. Both methods suggest that new information should be collected if the new
246 information has the potential to change the decision taken. For the case when the objective is to

247 maximize NPV, Holmström et al. (2003) suggests that new information should be collected only for
248 stands which are near the potential for management actions. However, in short term planning where
249 industry supply is addressed, the case may be different (Duvemo et al. 2014). With the advent of new
250 low cost information (i.e. from remote sensing) at scales larger than individual stands, the DA process
251 holds substantial advantages to forest planning.

252

253 Implementing techniques which incorporate all of the information provided by DA will require
254 significant changes to the current decision support system (DSS) tools and additional education for
255 forest planners. The current DSS tools are designed to simulate forest growth and development through
256 deterministic models, with forest information expressed as point estimates. Depending on the
257 optimization tool being used, adjustments can be made to current DSSs to generate the required
258 information for the optimization models. For instance, simulators can integrate inventory and growth
259 model errors and produce a large number of scenarios for use in stochastic programming. Once
260 integrated into the DSS, forest planners will need to understand the changes, and be able to inform
261 decision makers of the potential impact on the planning process. Thus, to integrate DA into current DSSs
262 will require additional development of the tools, on both the data processing side and the optimization
263 side.

264

265 Below we list and discuss five reasons why DA processes have potential to improve forest planning.
266 These possibilities are important to consider in forest planning, as DA processes are likely to be
267 implemented in forest inventories in the future.

- 268 1- *The accuracy of the information will be improved* since new data are continuously merged with
269 old forecasted information. DA processes can incorporate series of remote sensing data that
270 may otherwise be difficult to use. This will improve accuracy and increase the probability of
271 making correct decisions and thus improve the forest planning and decision making processes.
272 DA also offers a cost-efficient means to utilize all new sources of information (i.e., at the given
273 cost of the inventories) and will ensure that the posterior information always has the highest
274 possible accuracy.
- 275 2- *The information will be kept up-to-date even though no new measurement is made.* A backbone
276 of the DA process is the forecasting mechanism, which can be applied even if no new
277 measurement is made in a certain time period. Thus the existing information will always be up-
278 to-date, which improves the planning possibilities. Also, whenever new data arrive these will be
279 assimilated with the existing information whereby up-to-date posterior information is obtained.
280 Changes in the forest due to forest management, such as thinnings, will be continuously
281 monitored (Kangas 1991).
- 282 3- *The DA process will provide information with estimated accuracy.* Contrary to the current
283 situation where databases typically contain only point estimates DA databases will comprise
284 uncertainty estimates as well. Estimated accuracy of the estimates is important since the
285 decision maker may, at least intuitively, utilize this knowledge in the decisions. With this kind of
286 knowledge the scenario analysis technique could be applied as an add-on to existing DSSs. For
287 example, different starting values could be simulated and the effects on the decisions evaluated.
288 If this is repeated many times utilizing the estimated accuracy of the information, the
289 consequences of using data with the given level of uncertainty can be evaluated.
- 290 4- *Stochastic decision making methods can be applied, which can integrate the estimated*
291 *uncertainty of the information into the decision making process.* Several DA processes provide

292 entire (joint) probability distributions of true values, which can be used in stochastic
293 optimization methods. In addition, Bayesian decision theory (Hirshleifer & Riley 1979) might be
294 applied as decisions are selected based on evaluations over the entire range of potential true
295 values of the state variables. To utilize this possibility, DSSs would need to be further developed
296 to account for probabilistic state descriptions and forecasts rather than basing the calculations
297 on point estimates. This would imply a paradigm shift in planning and it must be carefully
298 evaluated to what extent it would be possible to apply this in short and long term planning, due
299 to the substantially larger problem spaces that will be encountered. With stochastic decision
300 making, many important features of decision making under uncertainty can be incorporated,
301 such as the risk preferences of the decision maker.

302 5- *DA data allows for the analysis of optimal data acquisition decisions.* As an extension to the
303 fourth point, use of DA data has potential to not only consider the uncertainty in the
304 information for traditional forest management decisions (such as thinning and clear-felling) but
305 also to analyze whether or not it would be cost-efficient to acquire new information. This was
306 demonstrated by Ståhl et al. (1994) in a research study where Bayesian decision making was
307 incorporated in a dynamic programming setting. It was shown by Kangas et al. (2014) that
308 acquiring new information while optimizing the harvest decision is profitable. In this case, the
309 challenges linked to developing DSSs for practical uses would be even larger than in the fourth
310 point. On top of the general Bayesian decision making algorithms there would also be a need
311 for algorithms that evaluate data acquisition alternatives. This would increase the dimension of
312 the problem even further.

313

314 3. Concluding remarks

315 Improving forest information through DA processes offers several benefits to forest planners. The
316 primary benefits are the improved accuracy of the current forest information and the uncertainty
317 estimates surrounding this information. To utilize the benefits of DA, current DSS tools require the
318 ability to explicitly incorporate information about the uncertainty of forest information and make
319 modifications so that stochastic optimization tools can be used. There are several techniques applied in
320 research which can handle uncertainty, but that implementation in DSSs in practice seems to be missing
321 except in SIMO (e.g., Rasinmäki et al. 2009); however, the application that consider uncertainty in SIMO
322 is not yet widely used. Thus there is a need to develop DSSs that can incorporate uncertainty in the
323 decision making process, e.g., through Bayesian approaches where the probability distribution of true
324 values can be utilized. Furthermore, DA systems in forestry need to be further investigated and
325 developed in order to be implemented properly in forestry. Only a few empirical studies of using DA for
326 forest information (e.g., Nyström et al. 2015) have been conducted so far and it is recommended to
327 further assess the benefits of DA in forest inventories.

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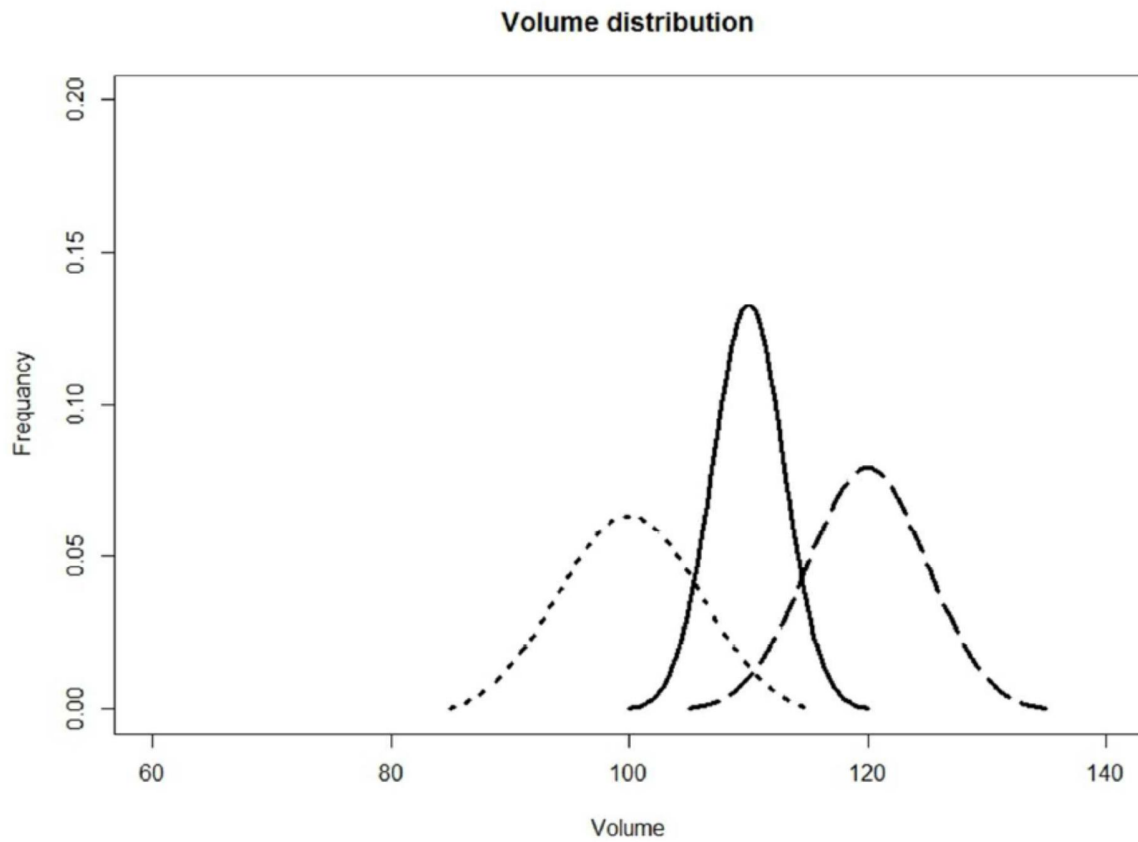


Figure 1. The forecasted information of the timber volume (dotted line), i.e., prior distribution, is combined with the new information (dashed line) in order to obtain the posterior distribution (solid line), which results in an updated estimate of the timber volume. As shown the posterior distribution is narrower compared to the prior distribution.

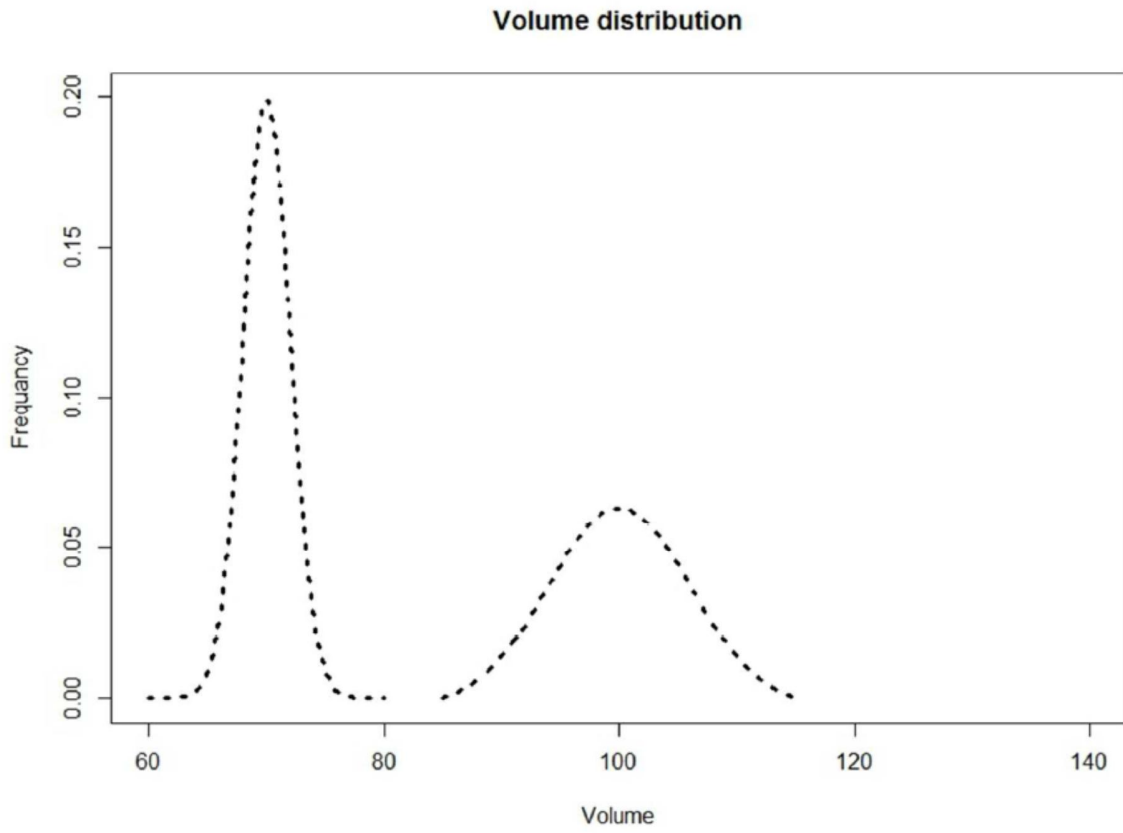


Figure 2. An illustration of the timber volume development's distribution when the growth function evolves over time. As shown the variation in the timber volume increased.