Data assimilation in forest inventories at stand level

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Cover: Data assimilation concept
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Abstract

Data assimilation (DA) is a potentially interesting method for forestry if new stand level data about forest attributes are made available at short time intervals. DA is a method where an estimate is forecasted by a model and updated when a new measurement is made. A weighted average of the forecast and the measurement is obtained as the new current state, which increases the accuracy of the estimate.
In areas like meteorology DA has been successfully applied for a long time. In this case the availability of very frequent satellite data makes it possible to update weather forecasts several times a day and obtain accurate forecasts.

Forest inventories in the traditional way, by field campaigns, are expensive and thus provide new data only every 10-20 years. During this long time a lot of changes due to growth, management and disturbances might occur in the forest stands of interest. Thus, old data are discarded when new data are obtained from a new campaign, and the forecasts of the current state are only based on the last measurement. Since many types of remotely sensed data, e.g. from laser scanners, optical satellite sensors, and radars, have become available during recent years, there are now good opportunities to apply DA also in the context of forest inventory. In this thesis I focus on stand level forest inventories.

A first theoretical study with simulated data showed that DA has a strong potential to be successfully applied in forestry and increase the accuracy of inventory estimates. However, the second study, the first with empirical data, pointed at problems to obtain equally good results in practice. In the third study, correlated prediction errors were identified as the plausible reason for this. The higher the correlations the less was found to be gained by applying DA. Despite several remaining challenges, the overall conclusion is that DA has a potential to make forest inventories more efficient in the future.

Keywords: Data assimilation, Kalman filter, remote sensing, forest inventory, correlated prediction errors

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Dataassimilering i skogliga beståndsinventeringar

Abstrakt

Dataassimilering (DA) är en intressant ny metod för skogsinventering, som kan användas när nya data erbjuds med korta intervall. DA innebär att en variabel skrivs fram med en framskrivningsmodell och när en ny mätning blir tillgänglig uppdateras det framskrivna värdet med mätningen genom att beräkna ett viktat genomsnitt. På så sätt kan noggrannheten i uppskattade värden förbättras.

Inom andra områden, t.ex. meteorologi, används DA framgångsrikt sedan lång tid tillbaka. Väderdata från satelliter finns tillgängliga med bara några timmars mellanrum. Väderprognoser kan därför uppdateras flera gånger om dagen för att öka deras noggrannhet.

Inventering av skogsbestånd har traditionellt sett gjorts genom fältinventeringar som av kostnadsskäl normalt endast genomförs vart tionde till tjugonde år. Under en så lång tid förändras skogstillståndet genom tillväxt och åtgärder, t.ex. föryngringsavverkning, gallring, eller genom stormskador. Därför uppdateras uppgifterna genom framskrivning baserad enbart på de senaste mätningarna. Som en följd av utvecklingen av nya effektiva fjärranalysmetoder erbjuds idag data från bl.a. laserskanning, och satelliter med optiska sensorer eller radar med allt kortare intervall. Noggrannheten vid skogsinventering bör därför kunna förbättras genom att tillämpa DA. Mitt fokus i denna avhandling är skogsuppskattning på beståndsnivå.

En första simuleringsstudie visade att det finns stor teoretisk potential för att effektivisera skogsinventering genom DA. Den andra studien baserades på empiriska data och visade på svårigheter att till fullo utnyttja DAs teoretiska potential i praktiken. I den tredje studien identifierades korrelerade prediktionsfel som en sannolikt bidragande orsak till detta och studien visade att felen i återkommande prediktioner baserade på flera typer av fjärranalysdata ofta är starkt korrelerade. Ju kraftigare korrelationerna är desto mindre effektiv blir DA. Trots kvarvarande utmaningar är slutsatsen från studierna att DA har en potential att i framtiden bidra till effektivare skogsinventeringar.

Keywords: dataassimilering, Kalmanfilter, fjärranalys, skogsinventering, korrelerade prediktionsfel

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Dedication

To my family

Contents

List of publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Sarah Ehlers, Anton Grafström, Kenneth Nyström, Håkan Olsson and Göran Ståhl (2013). Data assimilation in stand-level forest inventories. *Canadian Journal of Forest Research* 43: 1104-1113

II Mattias Nyström, Nils Lindgren, Jörgen Wallerman, Anton Grafström, Anders Muszta, Kenneth Nyström, Jonas Bohlin, Erik Willén, Johan E.S. Fransson, Sarah Ehlers, Håkan Olsson and Göran Ståhl (2015). Data assimilation in forest inventory: First empirical results. *Forests* 6: 4540-4557.

III Sarah Ehlers, Svetlana Saarela, Nils Lindgren, Eva Lindberg, Mattias Nyström, Anton Grafström, Håkan Olsson and Göran Ståhl (2017). Assessing correlations between remote sensing-based estimates of forest attributes for improved data assimilation. Submitted to *Canadian Journal of Forest Research*.

Paper I is reproduced with the permission of the publisher. Paper II is published as an open source article.

The contribution of Sarah Ehlers to the papers included in this thesis was as follows:

I Sarah Ehlers contributed to planning the study, ran the simulations, made the figures, participated in discussions, and wrote a major part of the paper.

II Sarah Ehlers participated in the planning of the article, provided the R code from the first study as a basis for the calculations, and participated in the discussions.

III Sarah Ehlers participated in the planning of the article, did the calculations (with provided R code), made the figures and tables, participated in the discussions and wrote a large part of the paper.

1 Introduction

Forest inventories are conducted for several reasons. At national level they are important for the development and follow-up of forest and environmental policy (e.g., Tomppo *et al.* 2010; Fridman *et al.* 2014). Such inventories are conducted in a large number of countries globally and the interest is growing due to emerging requirements related to biodiversity and climate change (e.g., Cienciala *et al.* 2008). Also, national forest inventories are often aggregated to regional and global estimates of relevance for global agreements such as the conventions on biodiversity and climate change. At sub-national level forest inventories are typically conducted by forest owners as a means to provide data for deciding upon appropriate short- and long term sustainable management (e.g., Wikström *et al.* 2011). Such inventories sometimes use methods similar to those in national forest inventories, i.e. sparse samples of field plots allocated across the area of interest in order to derive statistical estimates of state and change of forest characteristics (e.g., Fridman *et al.* 2014). However, more often they are conducted as stand level inventories, with the ambition to provide information about all forest stands in a forest holding (e.g., Ståhl 1992). Such inventories provide information needed for planning of forest operations, such as thinning, final felling, and regeneration (Thuresson *et al.* 1996).

Stand level inventories can be conducted using many different methods (e.g., Ståhl 1992). Since they need to cover large areas and be regularly updated to provide accurate information an important issue for practical forestry is to keep the costs of stand level inventories at moderate levels without sacrificing accuracy. Ideally, but seldom used in practice, cost-plus-loss analysis (e.g. Holmström *et al.* 2003) can be applied as a means to assess which inventory method leads to the lowest cost-plus-loss, i.e. the lowest sum of inventory costs plus expected losses due to non-optimal decisions made when using the data in planning forest management.

A very accurate but also very expensive method for stand level inventory involves measuring all the trees in a forest stand. This type of method is seldom practiced due to the large labour costs required. Sample plot inventories (Lindgren 1984) are sometimes carried out, especially in case the requirements for appropriate and known accuracy are high. Normally a certain number of sample plots are allocated systematically across the stand of interest and all the trees are measured on the sample plots together with registrations of stand and site features, such as site quality. Instead of sample plots, relascope measurements may be carried out (Bitterlich 1984). In both cases, statistical principles are applied to estimate forest characteristics at stand level as well as the corresponding uncertainty, normally expressed as a standard error. However, to obtain precise estimates normally several plots are required and thus those types of methods also tend to be expensive for stand level inventories.

A traditional method for stand level inventory is based on ocular assessments (Ståhl 1992). With such assessmenst the experience of surveyors is utilized and stand level characteristics are registered following visual inspection or following measurements at a few “typical” locations within a stand. A drawback with this type of inventory is that it is difficult to control the quality of the data, and ocular assessments are known to contain substantial systematic errors that vary between surveyors (ibid.).

Following the introduction of aerial photographs in the 1920s, the field based methods have been complemented by methods utilizing remotely sensed (RS) data. For a long time, the main use of aerial photographs in connection with forest inventories was the delineation of stands. During the 20th century a normal procedure for stand level inventory was to delineate stands from aerial photographs and assess forest characteristics within stands through ocular methods during field visits (Ståhl 1992). In the 1980s methods were developed whereby measurements of some core stand attributes were made in the aerial photographs, through manual interpretation (Åge 1987). Further, a major development of methods for forest inventory based on RS started in the 1970s when multispectral satellite data from the Landsat satellites became available (e.g., Hill *et al.* 1999; Hansen *et al.* 2008; Tomppo *et al.* 2008). Similar optical satellites, such as the SPOT satellites, have been utilised extensively for forest inventories (e.g., Davi *et al.* 2006; Wolter *et al.* 2009). Thus, during the past four decades the development of new RS methods has been rapid, and the testing and implementation of new techniques in forest inventories has been intensive. Important examples of such RS methods are radar satellites (Fransson, 1999), Light Detection And Ranging (LiDAR) from airborne profilers and scanners (e.g., Nelson *et al.* 1988, 1997; Næsset 1997; Hyyppä and Inkinen 1999), and digital air photos which are becoming increasingly important due to novel uses of 3D point-cloud techniques (Leberl *et al.* 2010; Bohlin *et al.* 2012; Breidenbach and Astrup 2012). Data from most of these RS sources can be made available at short intervals and the accuracy of core forest attributes such as growing stock volume and height is steadily improving, not least due to the introduction of the LiDAR technique (e.g., Nelson *et al.* 1988, Næsset 1997; Hyyppä and Inkinen 1999; Hyyppä *et al.* 2008; Maltamo 2009; Næsset 2009, Lindgren 2017; Gobakken *et al.* 2012; Næsset *et al.* 2013). In the following some more details are provided for some important RS methods.

The development of forestry applications based on LiDAR acquisition began in the late 1970s. Solodukhin *et al.* (1976, 1977) used a profiling laser for the study of felled trees. Later, the technique was applied from aircrafts (Solodukhin *et al.* 1979, Kuliasov *et al.* 1979), but following these early applications the technique appears not to have been used so often for forest inventories, but Nelson (1984) and Maclean *et al*. (1986) made forest inventory tests with profiling LiDAR in the 1980s in the USA and Canada. Towards the end of the century the general development of the laser technique made it interesting for larger-scale forest survey studies (e.g. Nelson 1997), especially since it was found that LiDAR data were strongly correlated with forest biomass. While the first studies used profiling LiDAR, laser scanning (e.g. Hyppä and Inkinen 1999, Næsset 1997) made the LiDAR technique even more useful for forest surveys. The method by Næsset (2002) has become known as the area-based approach, which was a starting point for a rapid development of applied LiDAR-based forest inventories. Currently, there are several studies conducted on developing forestry applications based on a fusion of LiDAR data with other types of RS data, such as data from multispectral satellite sensors, space-borne radars, etc. (e.g., Nelson *et al.* 2009; Næsset *et al*. 2013; Saarela *et al*. 2016).

The Landsat missions for civilian use were initiated in the early 1970s. Landsat 1 was launched 1972. Since then, 8 missions have been launched, with one failure (Landsat 6). Data collected by Landsat 5 and 7 have been widely used in forestry applications, and some significant studies are those by Tomppo (1993, 2006), and Tomppo *et al.* (1999). Landsat 5 was launched in 1984 and decommissioned in January 2013. It carried the Multispectral Scanner System (MSS) and the Thematic Mapper (TM) instruments. The TM is an advanced, multispectral scanning sensor collecting data in seven spectral bands simultaneously, with approximately 30 m resolution. Another multispectral sensor which has provided data for forestry applications is SPOT (Satellite Pour l'Observation de la Terre, lit. "Satellite for observation of Earth"), a commercial high-resolution optical imaging Earth observation satellite system. The SPOT constellation has been supplying high-resolution, wide-area optical imagery since 1986. The SPOT-5 HRG instrument provided data with a spatial resolution of 2.5 to 5 meters in the panchromatic mode and 10 meters in the multispectral mode.

The development of space-based radars, also referred to as space-borne Synthetic Aperture Radar (SAR), began in the late 1960s primary for military purposes. SAR is relatively insensitive to atmospheric disturbances and can acquire image data regardless of weather conditions. Nowadays, there is a number of commercial SAR satellites, the most popular is the Earth observation satellite TerraSAR-X, which was launched in 2007 and has been operational since January 2008. With its twin satellite TanDEM-X, launched in 2010, TerraSAR-X acquires data for the World Digital Elevation Model (DEM). When the ground level is known it can be subtracted from the satellite data derived DEM to calculate an interferometric SAR height (ISH), correlated with vegetation height and density, and thus biomass. Additionally, the coherence (COH) obtained from the radar processing has been shown to be correlated with several forest variables. (e.g., Treuhaft and Siqueira, 2004;

Karjalainen *et al.* 2012; Persson and Fransson, 2016). Both ISH and COH become available after interferometric processing of two radar images.

With the many RS methods that are nowadays available at low cost, practitioners question how to make best use of all the new information. Using only the last estimate may not be a good idea since it may stem from an RS method that is not very accurate. However, data assimilation (Asch *et al.* 2016) offers a framework for how new estimates can be continuously merged with existing, forecasted, estimates in an efficient manner. Note that, in this thesis, the terms *estimation* and *prediction* are used almost as synonyms. The conceptual difference is, however, that estimation refers to the assessment of a fixed parameter, the value of which is unknown, while prediction refers to the assessment of a random variable, as is typically the case in regression analysis where the dependent variable is treated as random (Chatterjee and Hadi 2015).

Data assimilation has been used for a long time in areas like meteorology, climate and ocean modelling, and even in the search for oil and minerals (e.g. Gihl 1991, Dorigo *et al.* 2007). For example, it has been shown that good improvements of previously established methods for forecasting weather can be obtained by using DA (Rabier 2006). Weather forecasts can be improved by combining the measured data with mathematical forecast models, which contain a number of uncertainties just like the measurements. Nowadays, satellites provide data at short time intervals and getting new data every few hours allows for precise weather forecasts (ibid.).

A new area where DA might be used is forestry, where the rapid development of new types of remote sensing methods provides a wealth of data about forest stands and landscapes. One of the keys for successful forest management planning is to have accurate information about the forest stands (Saad *et al.* 2017) and if DA can provide such data at low cost the method would be very useful in forestry. However, DA has only recently been suggested for application in this context (e.g., Paper I, Paper II), and it is not used in practice yet. The aim of applying DA would be to obtain better estimates of the current state and forecasts, of core forest attributes, preferably at stand level.

Using DA the old information is updated through forecasts and when new data is made available the old data is merged with the new to obtain a new, better, estimate of the current state. Thus, old data are not just discarded, as in traditional forest inventories. The availability of new data at short intervals is especially important in forestry since a lot may happen during longer intervals, like 10-20 years. Stands may be thinned, clear-cut, or damaged by storm.

DA is not one method that fits to all problems but there are several approaches. To apply data assimilation, one has to decide which method is best applicable for the given problem. One way of classifying methods is to distinguish between sequential and non-sequential DA (e.g., Bouttier and Courtier. 1999), see Figure 1. Sequential assimilation makes use of the past observations until current time while non-sequential assimilation, also called retrospective assimilation, takes also observations into account that are made in the future seen from the time point of interest. This can be used in cases where reanalyses are done. Further, both the sequential DA and the non-sequential DA can be divided into intermittent and continuous (in time) methods (ibid.). This means that using an intermittent method the observations are available in small batches resulting in “steps” in the correction (as seen in Fig. 1) while using continuous methods observations are made continuously and the assimilated output will be smooth across time. In most problems where DA is used, sequential DA is applied, since observations from the future are not available.

Another approach is to fit a new model to the observations. This can be done in cases where the observations are highly trusted and the existing forecast model needs to be improved. This is a case where non-sequential assimilation can be used.

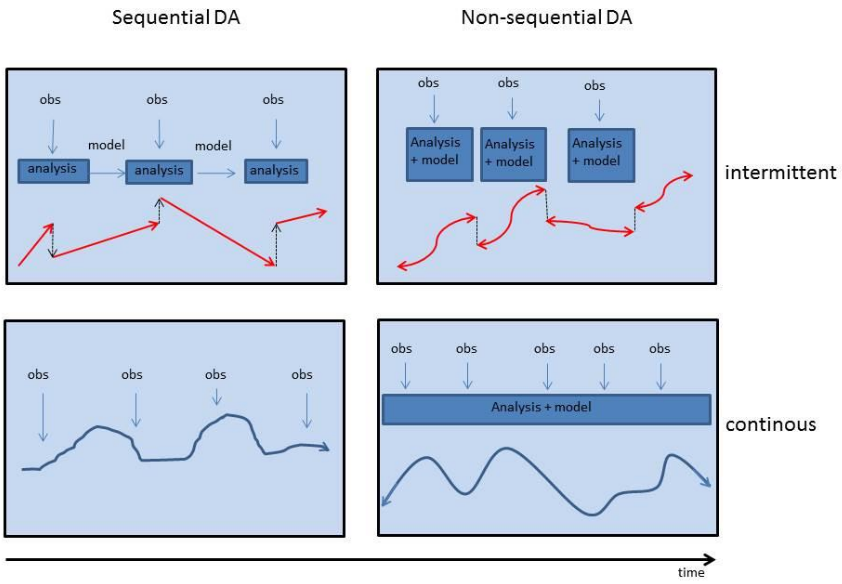

Figure 1 Overview of DA concepts. The left panels show the sequential methods, on the right the non-sequential DA methods are shown. The method used in this thesis is intermittent sequential DA, see text for details.

In case of forest management where one is interested in forecasting the estimates, intermittent sequential DA should be applied.

Further, many different technical approaches can be applied in DA. A first division of methods in this context is to separate between methods adopting frequentist vs. Bayesian views. The first case is the traditional view of treating unknown quantities as fixed parameters which can be estimated. The famous Kalman filter (e.g. Kalman 1960, Welsh and Bishop 2006) is an important example of this kind. Among other things it assumes observations to be independent and normally distributed and forecasting models to be linear. With the extended Kalman filter (Welsh and Bishop 2006), forecasts with non-linear models can be handled. The Bayesian view (Wikle and Berliner 2007) lets the true parameter value follow a probability distribution, and in the assimilation step Bayes theorem is applied. Bayesian approaches may be very demanding, especially when the joint distribution of several variables of interest must be taken into account. To solve this and similar problems so called particle filters can be used as a straightforward way to approximate the needed distributions by simulating and aggregating the development across time of individual “particles” (Arulampalan *et al.* 2002).

1.1 Objectives

The overall objective of this thesis was to make a first assessment of whether or not data assimilation has a potential to be successfully applied in stand-level forest inventories and to outline methods that may be applied in adapting DA to forest inventory applications. The specific objectives of the three papers were to:

(i) Evaluate the potential usefulness of DA in forest inventories through a simulation study, and to compare a Bayesian assimilation method with the extended Kalman filter.

(ii) Assess to what extent the theoretical results could be reproduced in a study using empirical data, using the extended Kalman filter.

(iii) Evaluate to what extent prediction errors using different types of remotely sensed data are correlated and assess the effects of such correlations in DA compared to using independent predictions.

2 Materials and methods

2.1 A study with simulated data (Paper I)

The first study was a theoretical comparison of two different DA approaches, the extended Kalman filter and a Bayesian approach. Both approaches are intermittent sequential assimilation approaches. The proposed stand level DA application was based on the following steps:

(1) An initial estimate of the current state of the attribute of interest, in this case growing stock volume, as well as the corresponding uncertainty of the estimate is assumed.

(2) A forecasting model gives a prediction of the estimate until current time as well as a prediction of the uncertainty of the forecast.

(3) A new measurement is available in current time, together with the prediction from the forecasting model.

(4) The actual DA step where the estimate (from step 2) is weighted with the new measurement (step 3) to obtain a new best estimate as well as the corresponding uncertainty.

(5) This cycle (1)-(4) will then be repeated a certain number of times depending on the number of new measurements.

In addition to these five steps it might be necessary to check if any major disturbances occur during the period of interest in the stand. If so, the assimilation procedure might need to be restarted. However, in the simulation study no such disturbances were assumed.

For the measurements a linear model was assumed where Z_t is the estimator of true state, x_t, at time *t*. The estimator is assumed to be unbiased so that

$$Z_t = x_t + V_t, \tag{1}$$

where $E(V_t) = 0$ and the variance is $V(Z_t) = V(V_t) = r_t^2$.

2.1.1 First approach: The Extended Kalman filter

The forecasting (growth) model applied was based on regression analysis using data from permanent sample plots of the Swedish National Forest Inventory (NFI). The model was non-linear, which required the use of the extended Kalman filter (EKF) since the ordinary Kalman filter requires linear functions. The EKF is similar to the Kalman filter but uses Taylor linearization in the estimation of variances due to the forecast (Welch and Bishop, 2006)

Using the EKF involves two main steps (Figure 2), the forecast step and the measurement and assimilation step, which are repeated the desired number of time steps. In the first step, the forecast is updated to obtain an estimate in current time.

Let $\hat{x}_0$ be the initial estimate with a variance denoted by p_0^2; then the forecast (Eq. 2) and its variance (Eq. 3) can be written as

$$\tilde{x}_t = f(\hat{x}_{t-1}, 0, t-1) = \hat{x}_{t-1} + g(\hat{x}_{t-1}, t-1) + W_t \tag{2}$$

and

$$\tilde{p}_t^2 = a_t^2 p_{t-1}^2 + q_t^2, \tag{3}$$

where

$$a_t = \frac{d}{dx} f(\hat{x}_{t-1}, 0, t-1). \tag{4}$$

The random term W_t is assumed to be normally distributed with zero mean and variance q_t^2. The forecasted estimate is then weighted with the new estimate in the measurement and assimilation step. This results in a new estimate (Eq. 5) and its corresponding variance (Eq. 6) given by

$$\hat{x}_t = (1 - K_t)\tilde{x}_t + K_t \tilde{z}_t \tag{5}$$

and

$$p_t^2 = (1 - K_t)\tilde{p}_t^2, \tag{6}$$

where $\tilde{z}_t$is the measurement and K is the so called Kalman gain, i.e. the weight assigned to the new measurement, given by $K_t = \frac{\tilde{p}_t^2}{\tilde{p}_t^2 + r_t^2}$. Note that this weighting corresponds to assigning weights inversely proportional to the variance of the estimators involved. Most weight is thus assigned to the more reliable estimate. A Kalman gain near one lays almost all weight on the new measurement while a gain near zero implies that the measurement (almost) does not contribute to the assimilation.

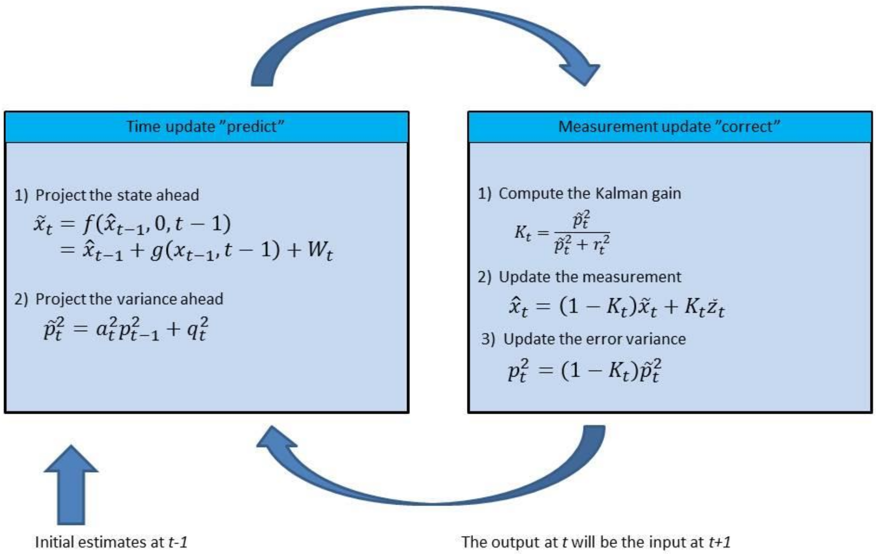

Figure 2 The cycle of forecast and measurement updates in DA using a Kalman filter.

2.1.2 Second approach: The Bayesian method

As noted in the introduction the Bayesian approach assumes that the true value of the parameter of interest has a probability distribution. Thus, the probability distribution in this case is forecasted across time and the assimilation step involves applying Bayes theorem (Hoff 2009). With this method there is no need to approximate the growth model through linearization and the method works without specific distributional assumptions, since in our case we estimated an empirical distribution at each time point. The same growth function as in the case of EKF was applied. Also in this approach, a forecasting and updating step was performed in each time step. As an initial distribution we assumed a normal distribution. The mean of the posterior (forecasted and updated) distribution is the new point estimate of the current state. The posterior is projected in time and becomes the new prior distribution which is then updated by a new measurement and the new posterior is obtained, as according to the principles of Bayes theorem (Figure 3).

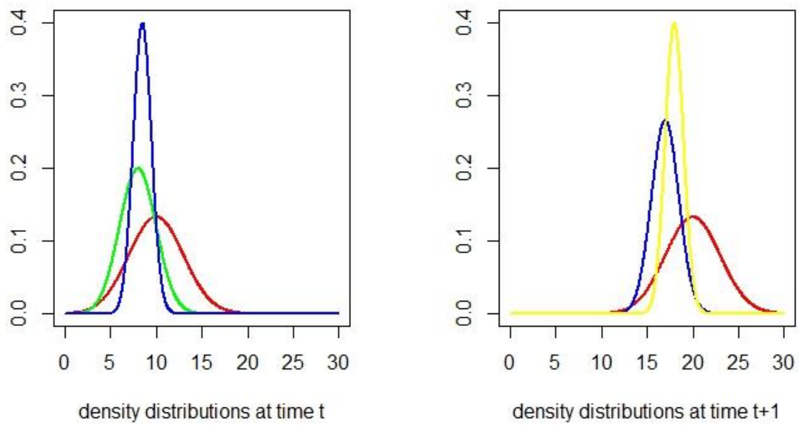

Figure 3 The figure shows the principle of the updating and measurement steps of the whole distribution using the Bayesian approach. The green line is the prior distribution at time *t* which is updated with the measurement distribution, the red line on the left, and weighted to obtain the posterior distribution, the blue line on the left. At time *t+1* the prior distribution is represented by the blue line, the measurement by the red line and the resulting posterior distribution by the yellow line.

Figure 3 shows the principle of updating the whole distribution. The green distribution represents the prior distribution at time *t* (which is the forecasted posterior from time *t-1*) and the measurement distribution at time *t* is shown in red colour (left panel). A posterior distribution (blue colour) is obtained using Bayes' theorem. It can be seen that the variance of the posterior distribution is less than both the variance of the measurement and the variance of the prior, which means a gain in precision. In the next cycle, the forecast of the posterior distribution at time *t* is the new prior distribution at *t+1*, represented by the blue distribution, the red distribution represents the new measurement at *t+1* and the yellow distribution is the resulting posterior distribution.

To investigate the potential usefulness of DA in forestry applications, case studies based on simulated data were conducted. Growing stock volume was the variable handled through DA, while other stand characteristics of interest were assumed to be known. The starting age was set to 20 years, the site index was assumed to be 20, the tree species composition was assumed to be 60% spruce, 10% pine, and 30% broad-leaved trees. The starting volume was assumed to be normally distributed with an expectation of $40m^3/ha$ and a standard deviation of 30% of the expected value. A time interval of five years was assumed in most cases, but for a few cases a two years interval was evaluated. The measurement (prediction) errors were set to 30% (standard deviation of the mean), as would be realistic for predictions based on spectral satellite data (Magnusson and Fransson 2004) or 10%, which would be realistic for predictions based on laser data (Naesset *et al.* 2004). The forecasting errors were set to 60% (standard deviation of the mean) as a realistic case and 30%, to study the effect of having better growth models. For simplicity we assumed that the observed measurement coincided with the forecasted estimate.

For this study, our hypothesis was that we would obtain different results from the EKF compared to the Bayesian approach, since the EKF is based on an approximation of variances through Taylor linearization. Further, it was of interest to assess the consequences of the different assumptions of error magnitudes on the DA results.

2.2 A study with empirical data (Paper II)

The empirical data used in Paper II were obtained from the study site Remningstorp in Southern Sweden (Lat. 58°30’ N, Long. 13°40’) (Figure 4). The forests in the study area are dominated by Norway spruce and Scots pine. It is a quite flat area with only limited elevations.

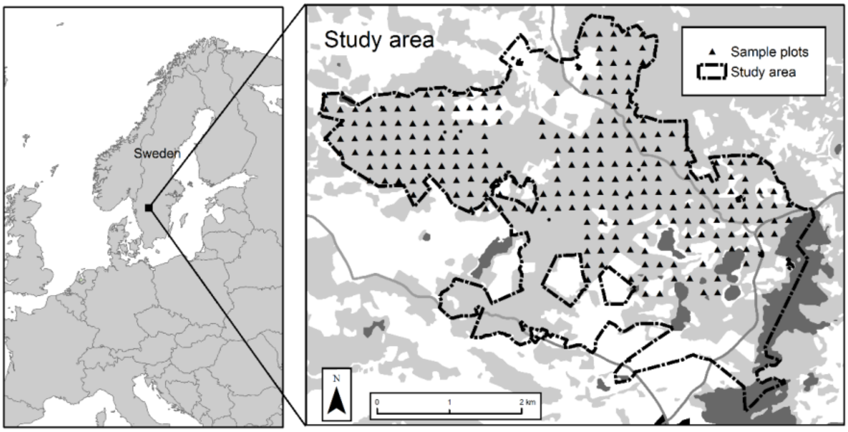

Figure 4 Overview of the study area in southern Sweden (Lat. 58°30’ N, Long. 13°40’). The location of the 10m radius sample plots which were used in the study are marked with black triangles. ©Swedish National Land Survey I2014/00764.From Paper III.

To develop models for estimating the state of the desired characteristics (volume (V), basal area (BA) and Lorey’s mean height (H_L)), field data from the Swedish National Forest Inventory (NFI) from sample plots from two different field campaigns were used. To obtain the estimates for V, H_L and BA as well as the corresponding variances RS data from aerial image matching were applied. For validating the results of the DA and the two commonly used methods applied in practice, i.e. either using the last estimate only or making a forecast from the first estimate, field plot validation data were applied. These plots were 314 m^2 large, located within homogenous stands without any major influences from cuttings or other disturbances during the study period.

Making use of aerial image matching data the following models (Eqs. 7-9) for the mean height, volume, and basal area were estimated through regression analysis to

$$H_L = \beta_0 + \beta_1 P95 + \beta_2 D + \varepsilon, \tag{7}$$

$$V = \exp(\beta_3 + \beta_4 P95 + \beta_5 \ln(p95)) + \varepsilon, \tag{8}$$

and

$$BA = \exp(\beta_6 + \beta_7 P30 + \beta_8 \ln(p95)) + \varepsilon, \tag{9}$$

respectively, where P30 and P95 are the 30th and 95th percentiles of the height distribution of image matching points at each plot, respectively, D is the ratio of matched points with heights larger than 2m above ground to all matched points at each plot, and the ε:s are residual terms with zero expectation.

Like in Paper I the EKF was applied for the data assimilation. Also like Paper I, the variables site index (SI), tree species composition, and age were assumed to be measured without error. The forecasting and assimilation steps were the same as in Paper I, described above, but with the important difference that in Paper II empirical data were applied.

To assess the performance of the three methods: DA, most recent estimate, and forecast from the first measurement, deviations between predicted values and field measurements for the validation plots at the last time point were calculated. The root mean square error (RMSE; Eq. 10) and the mean deviation (MD; Eq. 11) were calculated as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{10}$$

and

$$MD = \frac{1}{n}\sum_{i=1}^{n} e_i. \tag{11}$$

In these formulas, e_i is the observed deviation for the i:th validation plot.

2.3 A study of correlated prediction errors (Paper III)

The data used for Paper III were obtained from the study site Remningstorp, i.e. the same study site as in Paper II, see Figure 4. Three different remote sensing data sources were used for the investigation of correlated errors in predictions of forest attributes through regression analysis. These were laser scanning data, TanDEM-X InSAR radar data, and multispectral data from the SPOT 5 satellite.

To assess the correlation between the prediction errors it was assumed that the residual deviations from the regression models consist of two components: one random plot effect that remains the same over at least a short period of time and one component of white noise, i.e. a random term that is independent of the plot random effect and across predictions.

Thus, the assumed model was

$$X_{sit} = S_{it} + b_{si} + \delta_{sit}, \tag{12}$$

where X_{sit} is the regression analysis-based prediction of a forest characteristic using RS sensor type s on plot i at time point t, S_{it} is the corresponding true value, b_{si} is the plot random effect, specific to sensor type s, and δ_{sit} is white noise. The expectation values of b and δ are zero and their variances depend on the type of RS data used and the general plot conditions. The prediction error, r_{sit} is

$$r_{sit} = b_{si} + \delta_{sit}. \tag{13}$$

With this model assumption, the b-term will make the prediction errors correlated across time on a given plot (assuming the time period is fairly short, so that the general plot conditions do not change). The correlation between the prediction errors from two subsequent predictions with the same sensor type will be (assuming $var(\delta)$ remaining the same at both time points)

$$corr(r_{si1}, r_{si2}) = \frac{cov(r_{si1}, r_{si2})}{\sqrt{var(r_{si1})\, var(r_{si2})}} = \frac{var(b_{si})}{var(b_{si}) + var(\delta_{si})}. \tag{14}$$

This model should be reasonable when plot level predictions are based on regression analysis, using RS data as predictor variables, with characteristics of interest from plot level field measurements as dependent variables (cf. Ståhl 1992).

To estimate the correlations, pairs of plot level prediction errors across the 117 plots in Remningstorp were selected. Assuming the variance of the plot level random effect as well as the variance of the white noise being the same for all plots, the correlation was estimated according to the standard formula

$$\widehat{corr}(\hat{r}_{s1}, \hat{r}_{s2}) = \frac{\widehat{cov}(\hat{r}_{s1}, \hat{r}_{s2})}{\sqrt{\widehat{var}(\hat{r}_{s1})\, \widehat{var}(\hat{r}_{s2})}}. \tag{15}$$

The caps indicate that the quantities are estimated following the regression analysis, e.g. $\hat{r}_{s1}$ is the notation for residuals obtained from the regression analysis based on data at time point 1 from the sensor *s*. Since three pairs of data were available for a given sensor and nine pairs for a given combination of two sensors, the average correlation across all pairs was computed using average covariances and variances across all three or nine pairs.

2.3.1 Demonstrating the effect of correlations in DA

To demonstrate the importance of assessing and accounting for correlations between subsequent RS-based estimates, it was shown how the precision of DA-based predictions develop when correlations were assumed to be zero, and when correlations were appropriately accounted for.

Denoting two predictions X_1 and X_2, we form the weighted average X_{DA} as

$$X_{DA} = aX_1 + (1-a)X_2. \tag{16}$$

The weight, a, is chosen so that the variance of X_{DA} is minimized. This variance is

$$\begin{aligned} var(X_{DA}) = {} & a^2 var(X_1) + (1-a)^2 var(X_2) \\ & +2a(1-a)cov(X_1, X_2). \end{aligned} \tag{17}$$

The minimization is easily achieved using standard optimization and the result is

$$a = \frac{var\,(X_2) - cov\,(X_1, X_2)}{var\,(X_1) + var\,(X_2) - 2cov\,(X_1, X_2)}. \tag{18}$$

where a corresponds to the Kalman gain, i.e. the weight allocated to the new prediction (X_1 in this case). From this formula it is clear that not only the variances matter but also the covariances (or the correlations) between the predictions in the computation of weights. Thus, assuming independent predictions in case they are not will lead to non-optimal weighting.

The consequences of correlated prediction errors for different cases were investigated using simulated data. In this thesis summary we present results from three different simulated series corresponding to 10-RS based predictions using the same sensor within a short period of time. The correlations between prediction errors were assumed to be 0, 0.4 and 0.8. The standard deviations of the DA predictions as well as the weights were calculated.

3 Results

3.1 A study with simulated data (Paper I)

The results of the simulations in Paper I clearly indicated that DA has a potential to be successfully implemented in forestry.

Looking at the gain of applying DA in forest inventory we could see that the variances could be decreased by 9 to 64% after an assimilation period of ten years, i.e. a substantially higher precision was obtained. The best improvements of the precision of individual predictions were obtained for the case when a precise growth model was applied in combination with imprecise inventories. Least improvements were obtained when an imprecise growth model was applied in combination with precise inventories.

In Figure 5 four different cases are shown, based on simulated stand developments from 20 to 70 years with inventories every five years. The cases are separated by different assumptions regarding the precision of inventories and growth forecasts. The reason for increasing magnitudes of errors over time despite using DA is that both inventory and growth errors are relative, i.e. their standard deviations are larger when the volume is large.

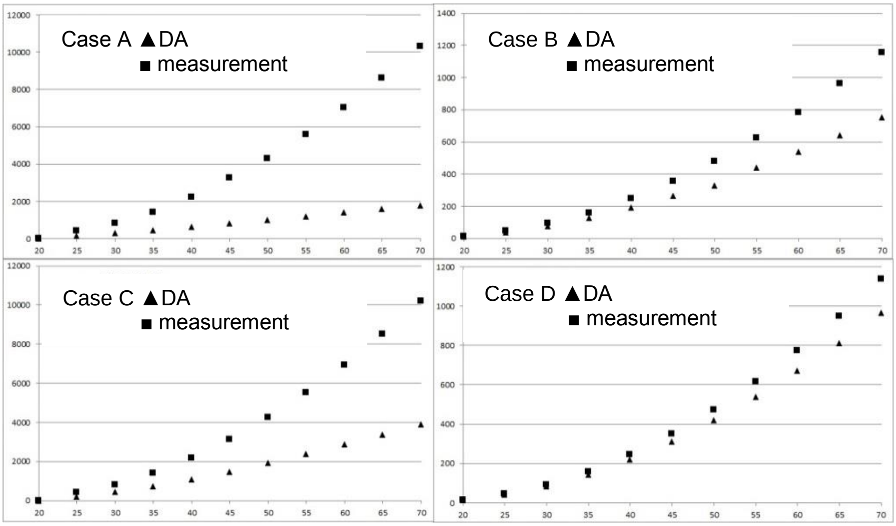

Figure 5 Variance versus age. In case A and B a forecast error (relative standard deviation) of 30% is assumed, while the inventory errors are 30% in case A and 10% in case B. In cases C and D the forecast error is 60% and the inventory error 30% in case C and 10% in case D. The triangles represent the DA based variances and the quadrats the measurement based variances. From Paper I.

By assuming shorter time intervals, i.e. getting new data every second year compared to every fifth year, the variances could be decreased even more, i.e. the gain of applying DA was higher, because more data were available.

Looking at the distributions (in the Bayesian approach) after several measurements and updating steps (see Figure 4 in paper I), it was seen that the variances get larger (according to our assumption of relative errors) but the distributions remain almost normally distributed. The higher the measurement error the less weight the measurement gets in the final distribution, i.e. poor inventories combined with good forecasts results in domination of the forecast part in the final distribution.

Comparing the Bayesian approach with the EKF approach, is must be noticed that the results of the EKF do not give distributions but the mean predicted value as well as the corresponding estimated variance. The comparison showed that the mean values of the predictions were almost the same using both methods but the estimated variances were always lower using EKF compared to the Bayesian method (Figure 6).

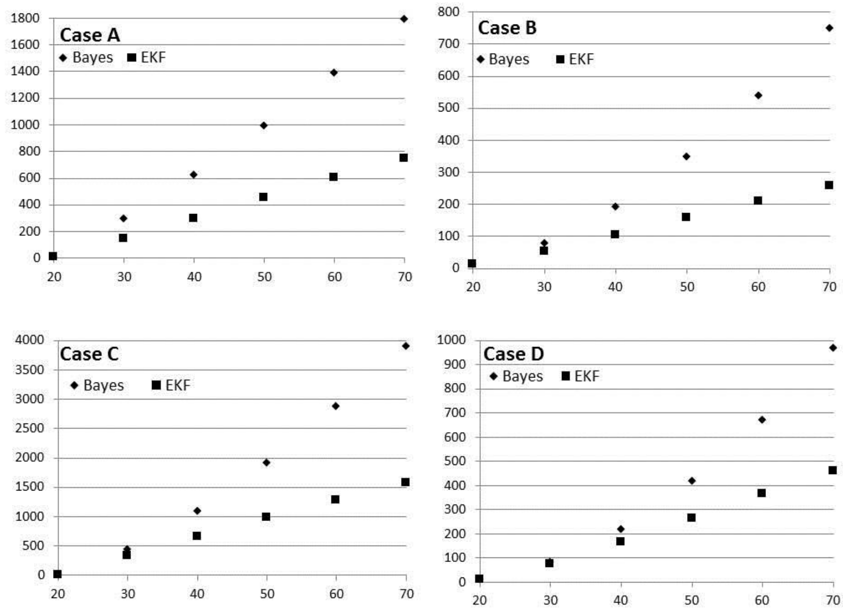

Figure 6 Comparison of estimated variances with the Bayesian method and the EKF for cases A-D. From Paper I.

3.2 A study with empirical data (Paper II)

Receiving promising results using simulated data made it interesting to investigate the performance of DA using empirical data. In Paper II, empirical data from the Remningstorp test site and the EKF were applied. The results were expressed in terms of RMSE and mean deviation from comparing the DA results with measurements on large plots.

We obtained the result (Table 1) that the RMSEs were mostly smaller using DA than applying the two established methods, i.e. taking the most recent estimate or forecasting the estimates from the first estimate in the time series, which shows that DA increased the accuracy of the estimates. However, the improvements due to DA in comparison with the two other methods were rather modest.

Table 1 Comparison of the RMSEs of the three different methods: DA, the most recent estimate, forecasting from the first estimate.

Target variable	DA	Most recent estimate	Forecasted
Volume	1.7 (8.5%)	1.6 (8.0%)	2.0 (9.9%)
Basal area	3.1 (9.5%)	3.5 (10.8%)	4.7 (14.5%)
Height	41.0 (13.3%)	44.1 (14.3%)	63.5 (20.6%)

Table 2 shows that the DA-based predictions had very small mean deviations while the two other methods in some cases had larger mean deviations.

Table 2 Mean deviation (MD) from the field measurement in 2011. A positive MD means that the value is on average overestimated compared to the field measurements. In parentheses is the relative MD.

Target variable	DA	Most recent estimate	Forecasted
Volume	0.73 (0.3%)	-10.0 (-3.4%)	35.7 (12.0%)
Basal area	-0.89 (-2.8%)	-2.12 (-6.7%)	1.47 (4.7%)
Height	0.19 (1.0%)	0.12 (0.6%)	0.27 (1.4%)

Comparing the results of Paper I and Paper II indicated problems to reach the full theoretical potential of applying DA in practice.

3.3 A study of correlated prediction errors (Paper III)

In Paper III we investigated to what extent the residual errors of RS-based predictions based on different sensors were correlated, and the influence of correlated errors on the gain of using DA.

The correlation between estimates obtained from pairs of datasets from the same sensor and across sensors is shown in Tables 3 and 4, for the attributes growing stock volume and mean height.

Table 3 Average correlation for the prediction error of Lorey’s mean height.

Sensor	ALS	SPOT 5	TanDEM-X
ALS	0.57	-	-
SPOT 5	0.21	0.84	-
TanDEM-X	0.36	0.37	0.60

Table 4 Average correlations for the prediction error of the volume per hectare.

Sensor	ALS	SPOT 5	TanDEM-X
ALS	0.75	-	-
SPOT 5	0.49	0.91	-
TanDEM-X	0.63	0.65	0.84

Summarizing the results, we can say that we obtained strong correlations using the same sensor for all predictions and sensors except for the height measured by ALS and TanDEM-X. The average correlations between different types of sensors in general were weaker, especially in case of height measurements.

In Figure 7 it can be seen that the effect of DA decreases a lot when errors are correlated, even if a moderate correlation of 0.4 is assumed. The decrease is higher the higher the error correlations are. After ten assimilation steps the standard deviation of the prediction could be decreased to 32% of the original standard deviation when prediction errors are not correlated. With a correlation of 0.4 the standard deviation can be decreased to 68% of the original standard deviation and a strong correlation of 0.8 leads to a decrease to only 91% of the original standard deviation.

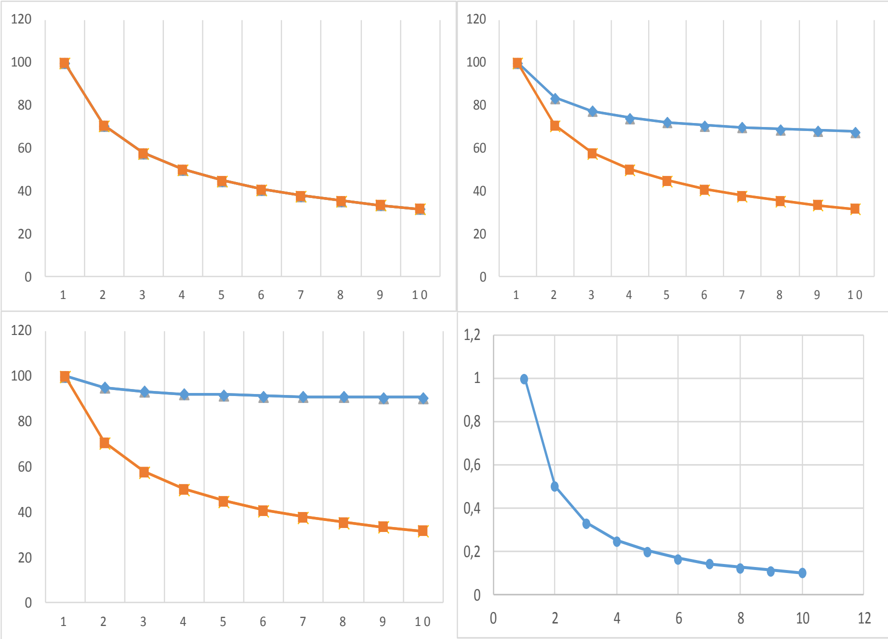

Figure 7 The relative standard deviations of the DA based prediction after ten assimilated predictions from the same type of RS sensor, if the error correlations are ignored. In the upper left case zero correlation is assumed, in the upper right case a correlation of 0.4 is assumed, in the lower left a correlation of 0.8 is assumed.The lower right shows the weight allocated to the new prediction in all cases.(From paper III.)

The weight that is allocated to the new prediction decreases during the ten assimilation steps from 1, i.e. all weight on the new RS-based prediction, to 0.1. When the same sensor was used in all assimilation steps, the same optimal weighting scheme is obtained when errors are correlated and when they are uncorrelated. But as shown in Paper III this is not the case when data from different sensor types are mixed in the DA.

4 Discussion

Overall, the studies point at both possibilities and problems for implementing DA to improve stand-level forest inventories. On the positive side there is a wealth of remotely sensed data which are strongly correlated with forest attributes like height, biomass, and volume, and which are possible to acquire at short intervals at relatively low cost (Nyström 2015). However, predictions based on such data were found to have correlated errors, which to some extent limit the usefulness of DA (cf. Stewart *et al.* 2008). Further, abrupt changes in forest state due to management and other disturbances need to be taken into account through appropriate change detection methods (e.g. Olsson 1994). This issue was not addressed in the thesis.

Considering the individual studies the simulation study with independent measurements (Paper I) led to substantial improvements of the DA-based predictions compared to using only the last measurement.

In some of the simulated cases, the variances decreased a lot, the most in cases with a relatively high measurement error combined with very good forecasts, the least for cases with low measurement errors and less precise forecasts. One of the more realistic cases is probably case D (see Paper I), where we assumed a forecast error of 60% (relative standard deviation) and a measurement error of 10 %, which resembles the case of using accurate sensors like ALS (Naesset *et al.* 2004) together with a crude growth model. However, in this case the decrease of variance was the least from applying DA. On the other hand, less precise RS-based predictions typically are cheaper and can be obtained at shorter intervals, e.g. from spectral satellites. Thus, more observations might be included in the assimilation, and in such cases (Paper I) the improvement of DA compared to using the last measurement was found to be substantial.

The longer the time period of applying DA the stronger was the effect of decreasing the variances. But in practice we have to expect disturbances, like clear-cutting or thinning, which will limit the length of the undisturbed periods in which DA is effective. Once a major change has occurred in a stand there is probably a need to restart or adapt the assimilation process.

In Paper II it was found that the empirical results were not as promising as those obtained with simulated data in Paper I. The results of taking the most recent estimate in general were almost as good as using DA. However, DA gave better results than using forecasts based on the initial state of the time series. A means to further increase the accuracy of the DA framework in practice could be to combine initial high quality data from, for example, field visits with new RS information instead of replacing the older information. In Sweden, the option to do this is currently very interesting due to the availability of almost wall-to-wall forest information from the recent national level LiDAR survey which would have a potential to be updated using DA.

In paper II all RS data were of the same type, in this case point cloud data from digital air photos. Although this type of data was not evaluated in Paper III, there is reason to believe that the correlations of prediction errors between subsequent predictions are strong. When this is the case the efficiency of DA decreases considerably, as shown in Paper III. This is a plausible explanation why DA did not perform much better than discarding old data and only using the newest estimate. In our study (Paper II) the assimilation period was rather short, 8 years only, compared to the rotation period of perhaps 80-100 years in Nordic forests. In our study raster cells of 18x18m size were used but maybe assimilation at stand-level would lead to better results. This is an issue that requires further attention. Since the modelling units for the growth forecast and the RS-based prediction preferably should correspond, a further evaluation of the appropriate area unit for DA must take into account both the RS-based inventories and the growth modelling. Due to this, raster based approaches to DA seem to be more straightforward than stand-based approaches (Nyström 2015). However, in summing up from raster cells to stands there is a need to know the correlations also between the prediction errors of spatially adjacent raster cells. This is another type of study involving error correlations that needs further attention in the development of cost-efficient stand-level DA approaches, and if the spatial autocorrelation of plot level prediction errors within stands is weak, DA has a potential to be more efficient at stand level than at plot level.

Paper III showed that the correlation between prediction errors at plot level was strong for all RS data sources investigated in our study, when predicting growing stock volume and mean height. So applying the standard Kalman filter which assumes the predictions to be independent might not be the best approach, but a non-standard filter approach might give better results (cf. Stewart *et al.* 2008). Error correlations otherwise cause severe misjudgements of the precision of the DA-based predictions, which can cause unfavourable decisions in the forest management (Saad *et al.* 2017), since the data quality is misjudged.

Since the provision of data about forest stands is likely to be frequent in the future, a mix of different types of data might improve the results from DA. Paper III showed that error correlations across sensors were smaller, which gives an indication that mixing different RS-sources would be a more efficient DA strategy than sticking to one single source of data. New types of field data may also become available, such as data from harvesters and ground based laser scanners (Holmgren *et al.* 2012). Even if some source of data would not be sufficient when used alone it may effectively contribute with information to the DA process. Using different types of RS data in the DA process, the error correlations will cause the weights to be incorrect (if a standard Kalman filter is used) and the estimated variances of the DA-based predictions will be incorrect as well. However, if the correlations are not too strong and the differences in standard deviations between the different sources of data are small, slightly incorrect weights will only slightly affect the (true) standard deviation of the DA-based predictions. But if the differences are larger it becomes necessary to handle the error correlations correctly.

By using different RS data sources the accuracy of the DA-based predictions might be increased. If the correlations between the different RS sources are weak and their accuracy is similar, the predictions will gain accuracy by the other source compared to using only one RS data source repeatedly. That means assuming several prediction of one RS data source will have lower accuracy than assuming one prediction less of the first RS source followed by a prediction by another RS source. To what extent the accuracy of the other RS source can be worth and still result in better DA predictions has to be investigated in further studies. It is, for example, not probable that a prediction based on the SPOT 5 satellite can increase the predictions of the mean height obtained by ALS since the accuracy of the mean height measurement by the satellite is much worse than the accuracy of the mean height by ALS, where the RSME is only 4-7% (e.g., Naesset *et al.* 2004).

In cases where the estimates have high accuracy the need and possibility to apply DA is not as strong as for cases where the accuracy is low. So, further research should concentrate on how to increase the accuracy also in those cases.

In our studies the assimilations were done for one variable at a time so further studies need to investigate the possibility of assimilating multiple variables simultaneously. Furthermore, it would be useful to implement a method (cf. Olsson 1994) to identify major disturbances and to break and restart the assimilation process accordingly.

The results of our studies are important first steps towards an operational DA system for forest variables. Such systems are important for the future to make best use of RS data for making forest inventories cost-efficient.

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Popular science summary

Good knowledge about forest stands is important for forest owners to manage the stand as effective as possible. To know the characteristics of the forest stand, e.g. the tree species, the number of trees, their heights or volumes, is important when it comes to decisions about management actions like fellings or thinnings. The traditional way to obtain the characteristics of a stand is to make field campaigns where the desired parameters are measured. Since this is quite expensive and time intensive, it is usually only done only every ten to twenty years. But a lot will happen under such a long time, e.g. management actions or damage by storms, so the old data from the last campaign is discarded when new data is acquired. If you are interested in what the forest will look like in a few years, the measured estimates can be forecasted by using functions that will predict how much the forest will grow. Since the growth functions are approximations of the real growth, the prediction will have errors (just like the measured values have). This results in predictions which can have quite large errors. But for a long time this was the best you could do.

In areas like meteorology similar problems could be solved by applying data assimilation because remotely sensed data from satellites are available several times per day so that the weather forecasts can be updated every few hours and became very accurate.

During the last decades remote sensing methods for forestry, e.g. using satellites, have been developed and nowadays forest characteristics can be obtained at short intervals and at low costs. So, now a possibility to update the measurements with short intervals turned up and offered a means to increase the accuracy of the predictions. One method to further increase the accuracy is to apply data assimilation. When a new measurement becomes available the old prediction is updated with the new measurement and a weighted average is obtained, i.e. the old data are not discarded. To combine the old data with the new measurements is the principal idea of data assimilation. Since by this no information is discarded a lot of data are available to obtain the new best estimates. Depending on the quality of the measured data, i.e. how large the error is, and how good the prediction is, they will contribute a lot or almost nothing to the new best estimates. If the measurement is very accurate, while the forecasting model is not so good, most of the weight of the final estimates will come from the measurements and not from the forecast. If the forecast is quite accurate but the measurement has large errors, you will trust the forecast more and the weight comes mostly from the forecast. In theory, data assimilation has the potential to increase the predictions in forestry which was shown in a study with simulated data. Using real data pointed out problems to reach the potential in practice. DA could only slightly increase the accuracy of the estimates, but no big gain was achieved, especially not for the predictions of the mean height. The mean height measured by laser scanning is very accurate so that no big gain is possible. Further studies that investigated the correlations of the prediction errors showed that the correlations have to be taken into account since correlated errors decrease the gain of data assimilation. Using the same remote sensing data source for several subsequent predictions results in correlated errors which implies that using different data sources with similar accuracies can increase the accuracy of the predictions.

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