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Thomas Nord-Larsen, Torben Riis-Nielsen, and Mathias Bo Ottosen

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Forest resource map of Denmark – Mapping of Danish forest resource using ALS from 2014-2015

Authors
Thomas Nord-Larsen, Torben Riis-Nielsen, and Mathias Bo Ottosen

Publisher
Department of Geosciences and Natural Resource Management
University of Copenhagen
Rolighedsvej 23
DK-1958 Frederiksberg C
Tel. +45 353 31500
ign@ign.ku.dk
www.ign.ku.dk

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Contents

Introduction

The Danish National Forest Inventory provides estimates of e.g. forest area, growing stock, biomass, and carbon stocks. National and regional estimates are reported nationally (e.g. Nord-Larsen et al., 2015) and internationally (e.g. FAO 2015, MCPFE 2015).

Airborne laser scanning (ALS) provides a good basis for assessing local forest resources as, for example, biomass, volume, or basal area (e.g. Nelson 1988; Næsset 1997; Næsset 2004a, 2004b; Lim and Treitz 2004, Næsset et al. 2009). In a previous study in Denmark, forest basal area, volume, aboveground biomass, and total biomass were successfully modelled using national forest inventory (NFI) and ALS data obtained in a countrywide scanning survey in 2006-07 (Nord-Larsen & Schumacher 2012). This ALS data was also used to model canopy height (Nord-Larsen & Riis-Nielsen 2010), classify tree types (Schumacher & Nord-Larsen 2014), estimate canopy water fluxes (Schumacher & Riis Christiansen 2015), and is currently part of a study towards high nature value forest detection. Information such as that derived from these studies is of high interest and value for forest owners, managers, planners and other professionals involved in the management of forest and nature.

Delineating forest stands

Forest stands are the basic units of forest mapping on which management decisions are made. A forest stand can be described as a group of trees that are more or less homogeneous with regard to species composition, stem density, tree size, and sometimes habitat. Traditionally, forest stands are delineated on a map by a forest manager in the field. To support this task, automatic stand delineation based on remote sensing data is desired.

Previous studies have used various types of remote sensing data to delineate forest stands. Leckie et al. (2003) used high-resolution airborne multispectral images for tree crown segmentation, and supervised classification of these segments into tree species. Diedershagen et al. (2004) calculated a canopy height model (CHM) based on airborne laser scanner data, and used the ISODATA algorithm to delineate forest stands. A problem with gaps in forests, and the difficulty of determining species mixture without additional spectral data was highlighted. A number of other studies used LiDAR based CHMs to delineate forest stands (Tiede et al. 2004; Leppänen et al. 2008; Mustonenet al. 2008; Koch et al. 2009; Sullivan et al. 2009).

Several approaches for forest stand delineation have been tested in previous studies. Baatz and Schäpe (2000) used eCognition's multi-resolution segmentation algorithm and raster images. Eysn et al. (2012) used local maxima on a CHM as nodes for a Delaunay triangulation. Within these triangles metrics were calculated, and classification into forest and non-forest areas was performed. Olofsson and Holmgren (2014) used a forest stand delineation algorithm based on Voronoi cells and region merging of LiDAR point-cloud data.

New remote sensing data for forest resource assessment

In a recent survey (2014-2015), new ALS data was collected for entire Denmark and is freely available (Geodatastyrelsen). The recently collected ALS data is of higher quality compared to the survey conducted in 2006-07 and would possibly yield improved estimates of forest variables and allow for increased resolution. Together with NFI data, this allows for new forest resource assessments and comparison with previous estimates.

The objective of this project is to use the new ALS data of entire Denmark in combination with NFI data for forest resource assessment, and make it easily available on forest stand level. Specifically, we (1) will use methods developed and models fitted with data from 2006/07, and re-fit them to the recent data from 2014/15. This will provide up to date information about forest resources, and will allow for change detection of various forest properties in this period. (2) We will automatically delineate forest stands based on ALS data, as performed in a current high nature value forest project. (3) We will extract tree types, biomass, volume, and basal area estimates for each forest stand polygon and 4) make this information available in an interactive online-platform, where each forest stand polygon can be selected by clicking and its properties can be displayed and compared to estimates based on the last survey from 2006/07.

Materials and methods

Data from the National Forest Inventory

Design of the Danish National Forest Inventory

The Danish National Forest Inventory (NFI) is a continuous, sample-based inventory, with partial replacement of sample plots based on a 2 x 2-km grid covering the Danish land surface.

Approximately one-third of the plots are permanent and are re-measured in every cycle of the NFI, whereas two-thirds are temporary and are moved randomly within the particular 2 x 2-km grid cells in subsequent cycles. The sample of permanent and temporary field plots has been systematically divided into five non-overlapping, interpenetrating panels that are each measured in a single year and constitute a systematic sample of the entire country. Hence all the plots are measured in a 5-year cycle.

In each square grid cell, a cluster of four circular plots (primary sampling unit, PSU) is placed at the corners of a square with 200-m side length. Each circular plot (secondary sampling unit, SSU) has a radius of 15 meters. When plots include different land-use classes or different forest stands, the individual plot is divided into tertiary sampling units (TSU). Based on an analysis of aerial photos, each sample plot (SSU) is assigned one of three categories, reflecting the likelihood of plot-level forest or other wooded land (OWL): (0) unlikely to contain forest or other wooded land cover, (1) likely to contain forest, and (2) likely to contain other wooded land. All plots in the last two categories are inventoried in the field.

Each plot is composed of three concentric circles with radii of 3.5, 10 and 15 m. Depending on their size, individual trees are measured in the different circles.

Field measurements

In the field, the centre of each sample plot is found using a Trimble GPS Pathfinder Pro XRS receiver mounted with a Trimble Hurricane antenna, fitted into a backpack. The equipment has an integrated differential beacon. Horizontal root mean squared accuracy of the equipment after postprocessing is 30 cm after 5 min of satellite tracking with a minimum of four satellites.

In the field a wide range of measurements are carried out to reflect the multitude of functions provided by the Danish forests. Of relevance to this study, forest stand level measurements include crown cover, mean stand height, and the height of individual canopy layers.

At plot level, a single calliper measurement of diameter is made at breast height for all trees in the 3.5 m circle. Trees with diameters larger than 10 cm are measured in the 10 m circle, and only trees with diameters larger than 40 cm are measured in the 15 m circle. For a random sample of 2-6 trees, further measurements of total height, crown height, age and diameter at stump height are made, and the presence of defoliation, discoloration, mast, mosses and lichens is recorded. The presence of regeneration on the plots is registered as well as the species, age and height of the young trees.

Preparing NFI data

NFI data are collected from the individual forest stands (TSU's) for the entire sample plot (SSU'es). Forest canopy height is calculated as the maximum height measured on sample trees within the SSU, including height measurements of regeneration. In some cases, no sample trees are measured for height. In those cases the maximum canopy height obtained from the stand level measurements is used instead.

Individual tree volume and biomass is estimated, using the standard models of the Danish NFI[1]. The basal area, volume, and biomass of each tree is scaled according to the which concentric circle it was measured (i.e. divided by 38.5 m^2 (*dbh*<10 cm), 314.2 m^2 (40 cm>*dbh*>10 cm), or 706.9 m^2 (*dbh*>40 cm)). Subsequently, plot level estimates were calculated by summing the scaled variables. Consequently, in cases where plots are intersected by other landuses (e.g. agricultural land, roads etc.), estimates take into account that part of the area has no vegetation.

Crown cover of entire sample plots are estimated as the area weighted average of the crown cover in individual TSU's. Crown cover of TSU's with other landuse than forest (e.g. agricultural land, roads etc.) is assumed to be 0.

Laser scanning data

The laser scanning data was collected (predominantly) during leaf-off conditions in 2014 and 2015. The planned point density was 4.6 points/m^2 with a footprint size of xx m^2 (Table 1). The scanner recorded up to 5 return pulses from each pulse and the data included pulse scanning angle, return pulse coordinates, and return pulse intensity. Despite the intention to conduct the scanning during leaf-off conditions, part of the scanning was conducted during leaf-on conditions (May – October) (Figure 1).

[1]See: http://static-curis.ku.dk/portal/files/164970017/Danish_National_Forest_Inventory.pdf

Table 1. Specifications for the collection of the laser scanning data.

Equipment	
Airplane	Fixed wing
Scanner	Riegel LMS-680i
Flight specifications	
Flying height	680 AGL
Flying speed	130 kts
Side-lap (LiDAR)	30% (wrt 60 degrees FOV)
Strip distance	550 m
Minimum altitude	650 m AGL
Maximum altitude	710 m AGL
LiDAR	
Scan angle (half)	30 degrees (60 degrees full)
Scanner pulse rate	400 kHz
Mirror frequency	152 lines /sec
Point density	4.6 points/m^2
Horizontal accuracy	0.15 m
Vertical accuracy	0.05 m
GPS Base stations	
Permanent stations	Yes
Mobile stations	No

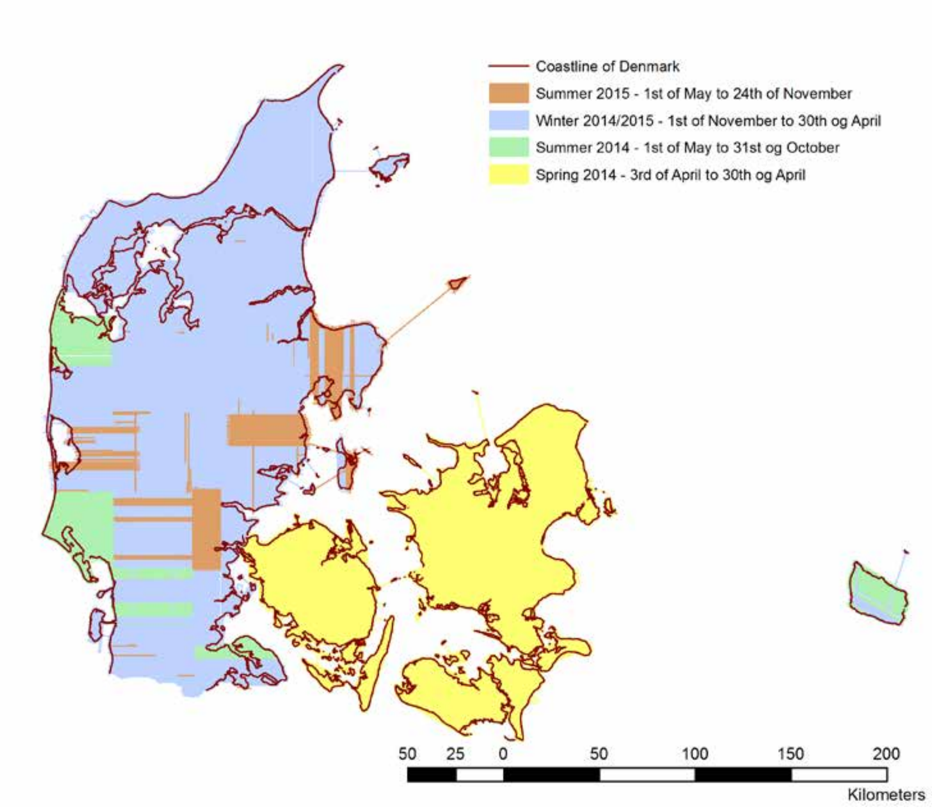

Figure 1. Flight lines and scanning times for LiDAR data.

Preparation of laser scanning data

A digital terrain model (DTM) was calculated for 1x1 km tiles covering the entire land surface area using Fusion. Return pulses were spatially assigned to NFI sample plots, excluding returns outside the 15 m radius of the plots. Based on the DTM, return pulses were normalized and all returns with a scanning angle exceeding 25° were excluded. Based on the normalized point cloud, the laser metrics were calculated for individual return numbers (r= 1 - 5) for both all return pulses (q=1) and above-ground return pulses only ($Dz>1$ m; $q=2$). The metrics included:

1. mean pulse height ($Dz_{mean;r,q}$)
2. variance parameters: variance ($Dz_{var;r,q}$), standard deviation ($Dz_{std;r,q}$) and coefficient of variation ($Dz_{cv;r,q}$)
3. distribution form parameters: skewness ($Dz_{skew;r,q}$) and kurtosis ($Dz_{kur;r,q}$)
4. percentiles of the distribution (5th, 10th, 25th, 50th, 75th, 90th, 95th, 99th percentile) ($Dz_{5;r,q}$, . . . , $Dz_{99;r,q}$)
5. overall interception rate (IR): $IR_r=n_{r,q=2}/n_{r,q=1}$, where $n_{r,q}$ is the total (q=1) or total above-ground (q=2) number r returns.

Prediction of forest variables

For predicting forest variables we modelled the relationship between laser metrics and observed canopy height, growing stock, and biomass on the NFI plots. In the analyses, we included only plots where the time between NFI measurements and collection of laser data was less than one year. We further excluded plots where e.g. harvesting had occurred between the two measurements. This part was in essence iterative as we estimated the canopy height model and evaluated the residuals to identify and remove outliers and then reestimated the model. Outliers were only removed after checking with updated aerial photographs.

Based on experiences with the ALS data collected in 2006-07 we expected that forest canopy height could be predicted with linear functions of various percentiles of the normalized point cloud. We further expected that growing stock and forest biomass could be predicted using a log-log transformation of the response and predictor variables. We thus transformed both response and predictor variables for an initial screening of potential candidate models.

To find suitable models we used PROC GLMSELECT of SAS institute, using different methods for model selection (including backward, forward, stepwise, and LASSO) and AICC as the model selection criteria. In the selection procedure we allowed first order interaction terms between the model parameters.

The models for growing stock and biomass found using the automated approach in all cases performed worse (in terms of AICC) than the models developed during the work with the 2006-07 data (Nord-Larsen and Riis-Nielsen, 2009; Nord-Larsen and Schumacher, 2010). We thus settled with a few candidate models, of the general form $y = a_0 x_1^{a_1} x_2^{a_2} \cdots x_n^{a_n}$, which included IR_1, $Dz_{mean;1,2}$, $Dz_{50;1,2}$, $Dz_{90;1,2}$, $Dz_{95;1,2}$, and $Dz_{99;1,2}$, and made the final model selection using backward selection.

We modelled crown cover solely from the interception ratio of first pulses (IR_1). For estimating crown cover we chose a model that was restricted with an upper asymptote of 100 % and where an interception ratio of 1 would yield a crown cover of 100 %. Based on these criteria we chose a modified version of Schnute's function: $CC = 100 \times \left(\frac{1-\exp(-c_1 \cdot IR_1)}{1-\exp(-c_1 \cdot 1)}\right)^{c_2}$.

The models for predicting crown cover, canopy height, growing stock, and biomass stock were estimated using non-linear regression with the MODEL procedure in SAS. To account for contemporaneous correlations among the different models, the final model system was estimated using iterated seemingly unrelated regression (the ITSUR of the MODEL procedure in SAS).

Making a forest resource map

In a first step, we used the forest map developed in relation to the project "Developing a High Nature Value – HNV – forest map for Denmark" (Johannsen et al. 2015), as a mask to identify 1x1 km tiles with forest. The forested 1x1 km tiles were extracted and normalized using Fusion. The resulting LAS files were read into SAS and returns with a scanning angle exceeding 25° were excluded. Finally, point cloud metrics of the normalized data was calculated for 25x25 m tiles, and canopy height, growing stock, above ground biomass, and total biomass was calculated according to the models developed from the NFI data. Since many of the point cloud metrics are not scale invariant, the pixel size (725 m^2) was determined from the NFI plot size (706 m^2) and practical considerations when working with tiles with a 1x1 km size. The point estimates were converted into a wall-to-wall raster map of forest resources.

Making a segmented forest map

The aim of this study was to automatically delineate forest stands based on a normalized digital surface model (nDSM) obtaind from the 2014 LiDAR survey of entire Denmark. The multi-resolution segmentation algorithm of the software eCognition was used to delineate forest stands. These were subsequently classified and combined based on vertical structure (height classes) and horizontal structure (homogeneous or heterogeneous stands).
A digital surface model (DSM) and a digital terrain model (DTM) were calculated with 0.4 m ground resolution based on the 2014 LiDAR survey of entire Denmark and provided by the contractor who conducted the survey. A nDSM was obtained by subtracting the DTM from the DSM. The nDSM with 0.4 m ground resolution was the primary input for the forest stand segmentation.

The nDSM was re-sampled using a 9 by 9 cells median filter resulting in nDSMres. Furthermore, within a 9 by 9 cells window standard deviation of the nDSM was calculated resulting in nDSMstd. Based on nDSMres and nDSMstd forest stands were segmented using the multi-resolution segmentation algorithm of the software eCognition. Within this algorithm, a scale factor (sc) controls how large segments can be. The scale factor was set to 300. The shape and compactness criterions control how much influence the spectral data have, and how compact segments are allowed to be. These two criterions were set to 0.3 and 0.9, respectively. Fundamental references for the multiresolution segmentation can be found in Baatz and Schäpe (2000).

Results

A total of 6,910 NFI sample plots were aligned with LiDAR data, of which 2,743 were sampled within one year from the laser scanning. A total of 409 plots were identified as outliers due to e.g. harvesting between the time of NFI plot measurements and the laser scanning or obvious errors in the NFI plot sampling. The resulting dataset for modelling forest resources thus included a total of 2,334 plots (Table 1). Of the total number of plots, 35 % were dominated by broadleaves (i.e. broadleaves take up more than 25% of the basal area), 30 % were dominated by conifers, and 38 % were mixtures of broadleaves and conifers.

Table 2. Number of plots and mean values of the modelled forest variables for all NFI plots used in the modelling and according to the main species on the plots. For plots with mixtures of broadleaves and conifers, no species type take up less than 25 % of the basal area. Standard deviations are provided in italics

Species type	Plots	Canopy height	Growing stock	Above-ground biomass	Total biomass
		dm	m^3/ha	tons/ha	tons/ha
Total	2334	177	198.3	106.3	129.1
		86	*182.1*	*97.8*	*118.9*
Mixed	883	165	173.6	92.1	111.8
		90	*170.0*	*89.1*	*107.9*
Broadleaf	823	203	232.8	130.1	159.1
		85	*195.3*	*113.0*	*137.5*
Conifer	628	160	187.6	94.9	114.2
		74	*173.9*	*80.7*	*97.9*

The forest variables (canopy height, growing stock, and biomass) were strongly correlated with many of the laser scanning variables, such as the interception ratio (Figure 2) and the 95th percentile (Figure 3). A wide range of different both linear and non-linear models were tested to select the best possible model. The final model system included only variables calculated with the first return pulses such as the pulse mean height and height of the 95th percentile. The models and parameter estimates for estimation of growing stock and biomass were quite similar (Table 3):

$$CC = 100 \times \left(\frac{1-\exp(-c_1 \cdot IR_1)}{1-\exp(-c_1 \cdot 1)}\right)^{c_2} \qquad \text{Equation (1)}$$
$$H_{canopy} = h_0 + h_1 Dz_{95,1,2} + h_2 Dz_{95,1,2} IR_1$$
$$V = v_0 Dz_{mean,1,2}^{v_1} \cdot Dz_{95,1,2}^{v_2} \cdot IR_1^{v_3}$$
$$B_{Above-ground} = b_0 Dz_{mean,1,2}^{b_1} \cdot Dz_{95,1,2}^{b_2} \cdot IR_1^{b_3}$$
$$B_{Total} = c_0 Dz_{mean,1,2}^{c_1} \cdot Dz_{95,1,2}^{c_2} \cdot IR_1^{c_3}$$

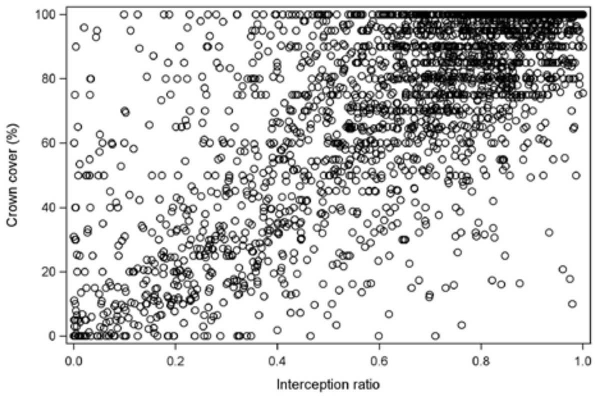

Figure 2. Relation between the interception ratio of above-ground laser returns and crown cover for 2334 NFI sample plots.

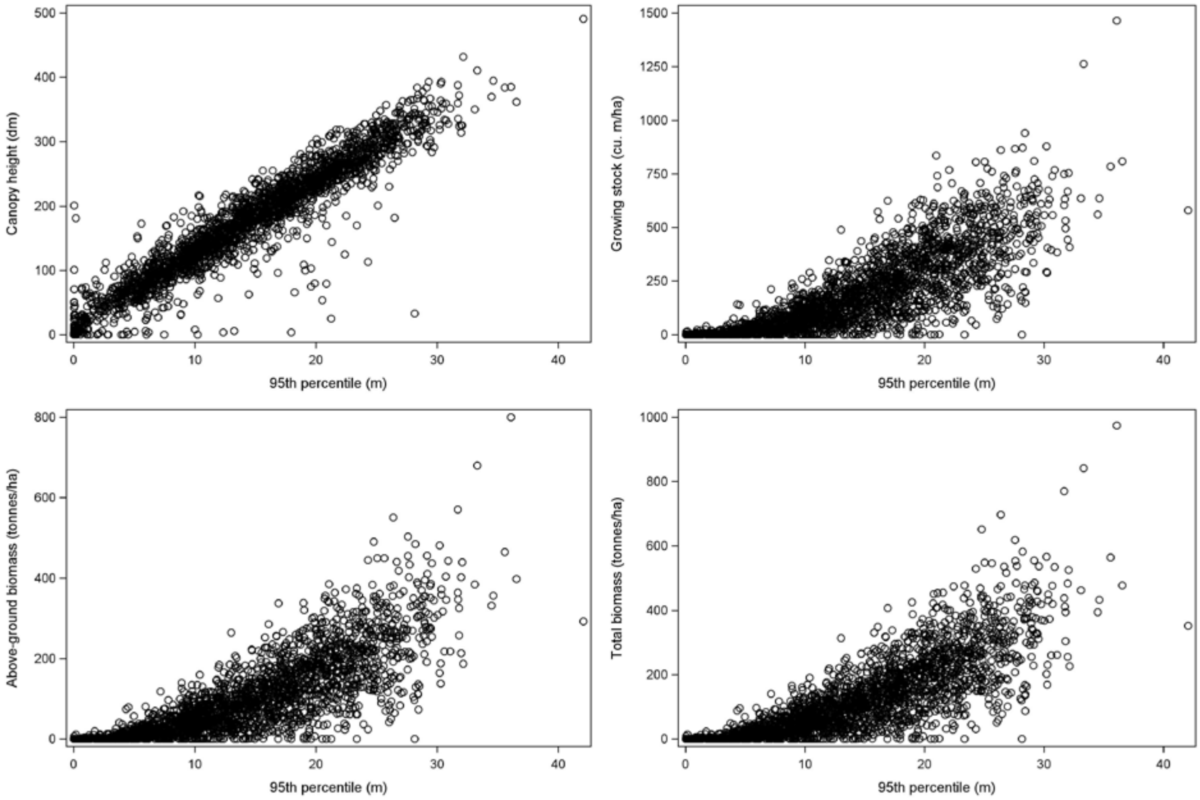

Figure 3. Relation between the 95th percentile of above-ground laser returns and canopy height, growing stock, above-ground biomass, and total biomass for 2334 NFI sample plots.

Table 3. Parameterestimates for the four forest resource models. Suffixes refer to the suffix numbers in the equation 1.

Parameter suffix	Estimate	Std Err	t Value	Approx Pr > |t|	Estimate	Std Err	t Value	Approx Pr > |t|
	Crown cover							
1	-0.43046	0.2788	-1.54	0.1228				
2	0.57897	0.0531	10.91	<0.0001				
	Canopy height				Growing stock			
0	18.85693	1.2733	14.81	<0.0001	15.72768	1.3192	11.92	<0.0001
1	10.57761	0.1796	58.89	<0.0001	1.22536	0.0551	22.24	<0.0001
2	0.44723	0.1935	2.31	0.0209	-0.01384	0.0672	-0.21	0.8369
3					0.90492	0.0356	25.40	<0.0001
	Above-ground biomass				Total biomass			
0	7.52367	0.6514	11.55	<0.0001	8.79430	0.7760	11.33	<0.0001
1	1.24619	0.0564	22.11	<0.0001	1.20752	0.0571	21.16	<0.0001
2	-0.00057	0.0588	-0.01	0.9934	0.04624	0.0698	0.66	0.5075
3	0.84534	0.0356	23.72	<0.0001	0.84400	0.0363	23.28	<0.0001

The final model system explained more than 90 pct. of the total variation in forest canopy height, but less (~80 pct.) of the variation in growing stock and forest biomass (Table 4). The models were unbiased, but the variance was heteroscedastic. As seen from the residual plots (Figure 4), deviations from the model mean were in some cases large, exceeding the predicted values, which has implications for model predictions on individual pixels.

Table 4. Fit statistics of the four forest resource models.

Fit statistic	Variable				
	Crown cover	Canopy height	Growing stock	Above-ground biomass	Total biomass
RMSE	19.4883	27.7815	82.1040	44.9766	55.5574
AB	-0.6425	-0.1557	-1.9002	-0.7114	-0.7977
AAB	14.6670	18.6463	55.8846	30.0493	36.7780
R sq	0.5724	0.9019	0.8048	0.7967	0.7902

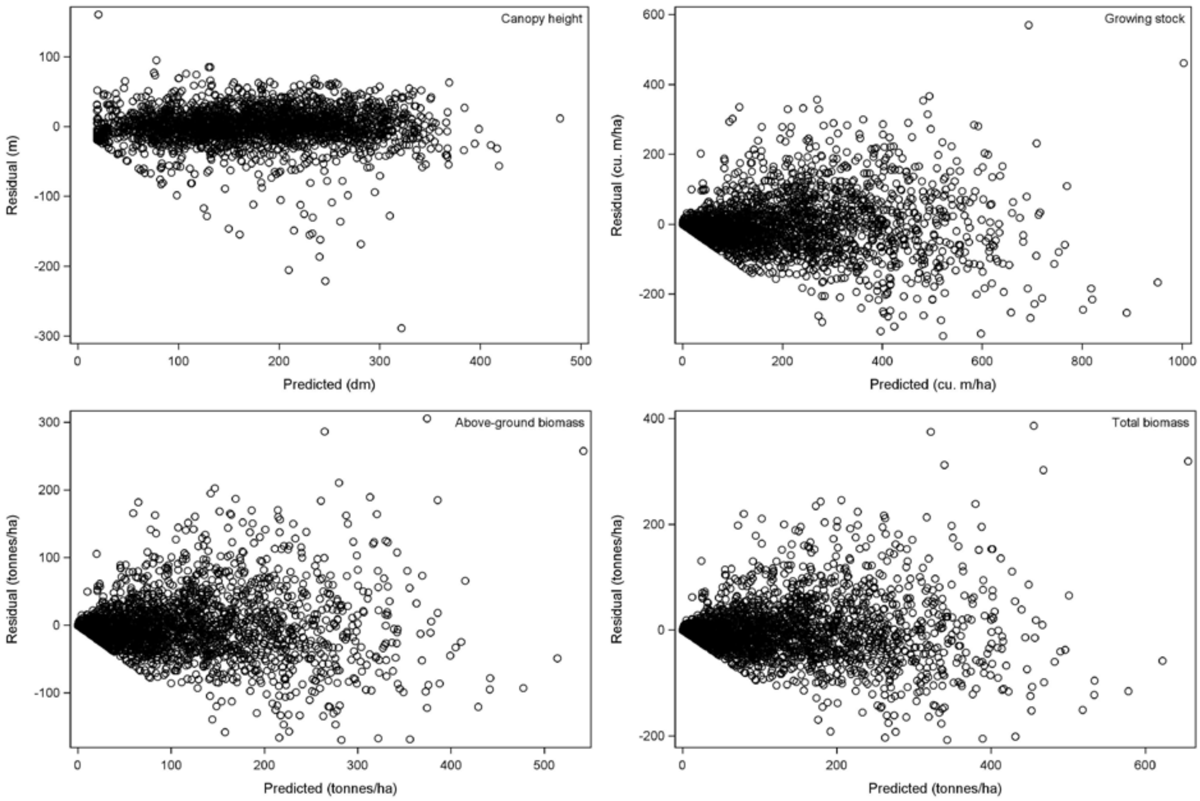

Figure 4. Residuals of the four forest resource models for predicting forest canopy height, growing stock, above-ground biomass, and total biomass.

Developing forest type specific models

When evaluating residuals of the general model it became evident that although predictions were generally unbiased, predictions for broadleaved and coniferous forests were biased. The bias is likely caused by differences in crown structure and could possibly be mitigated by applying forest type specific models when knowledge of the forest type is available. Consequently a set of models similar to equation 1 were estimated separately for broadleaved, coniferous and mixed forests (Table 5). Estimation of the models for individual forest types led to a slight improvement of the fit statistics for all the five forest resource models in equation 1.

Table 5. Parameter estimates for the four forest resource models estimated for forest types individually. Suffixes refer to the suffix numbers in the equation 1.

Broadleaves (N=1044)								
Parameter suffix	Estimate	Std Err	t Value	Approx Pr > |t|	Estimate	Std Err	t Value	Approx Pr > |t|
	Crown cover							
1	-1.27804	0.5945	-2.15	0.0318				
2	0.39796	0.0700	5.68	<0.0001				
	Canopy height				Growing stock			
0	22.12812	2.1420	10.33	<0.0001	12.53309	1.8962	6.61	<0.0001
1	10.90039	0.2632	41.42	<0.0001	1.053875	0.0806	13.07	<0.0001
2	-0.19002	0.2766	-0.69	0.4922	0.19618	0.1041	1.88	0.0599
3					0.69689	0.0522	13.34	<0.0001
	Above-ground biomass				Total biomass			
0	5.77232	0.9023	6.40	<0.0001	7.38998	1.1708	6.31	<0.0001
1	1.07476	0.0820	13.10	<0.0001	1.03133	0.0831	12.41	<0.0001
2	0.24306	0.1065	2.28	0.0226	0.26763	0.1079	2.48	0.0133
3	0.72799	0.0537	13.55	<0.0001	0.73857	0.0549	13.46	<0.0001

Conifers (N=935)								
Parameter suffix	Estimate	Std Err	t Value	Approx Pr > |t|	Estimate	Std Err	t Value	Approx Pr > |t|
	Crown cover							
1	-1.31676	0.5638	-2.34	0.0197				
2	0.45308	0.0779	5.82	<0.0001				
	Canopy height				Growing stock			
0	15.63567	1.8129	8.62	<0.0001	15.46126	1.6157	9.57	<0.0001
1	11.23927	0.2661	42.24	<0.0001	1.52687	0.0874	17.47	<0.0001
2	-0.21086	0.2767	-0.76	0.4462	-0.25548	0.0988	-2.58	0.0099
3					1.13032	0.0585	19.32	<0.0001
	Above-ground biomass				Total biomass			
0	12.03687	1.2070	9.97	<0.0001	13.26713	1.3548	9.79	<0.0001
1	1.39158	0.0847	16.42	<0.0001	1.38750	0.0857	16.19	<0.0001
2	-0.29117	0.0962	-3.03	0.0025	-0.25824	0.0973	-2.65	0.0081
3	1.05044	0.0557	18.86	<0.0001	1.03879	0.0563	18.46	<0.0001

Mixed forest (N=248)								
Parameter suffix	Estimate	Std Err	t Value	Approx Pr > |t|	Estimate	Std Err	t Value	Approx Pr > |t|
	Crown cover							
1	-1.19656	1.2038	-0.99	0.3212				
2	0.42941	0.1625	2.64	0.0088				
	Canopy height				Growing stock			
0	14.41520	3.2554	4.43	<0.0001	17.95824	4.2788	4.40	<0.0001
1	12.55502	0.5030	24.96	<0.0001	1.51280	0.1699	8.91	<0.0001
2	-1.22236	0.5248	-2.33	0.0207	-0.34186	0.2014	-1.70	0.0909
3					0.68634	0.1093	6.28	<0.0001
	Above-ground biomass				Total biomass			
0	11.88952	2.8263	4.21	<0.0001	14.58410	3.4461	4.23	<0.0001
1	1.49337	0.1722	8.67	<0.0001	1.44763	0.1712	8.46	<0.0001
2	-0.40279	0.2043	-1.97	0.0498	-0.36524	0.2032	-1.80	0.0735
3	0.66886	0.1087	6.15	<0.0001	0.68109	0.1087	6.27	<0.0001

Table 6. Fit statistics of the five forest resource models for individual forest types and across all forest types.

Fit statistic	Variable				
	Crown cover	Canopy height	Growing stock	Above-ground biomass	Total biomass
Across forest types					
RMSE	19.0596	26.6912	80.1413	43.6338	53.8954
AB	-0.5178	0.0216	-0.3008	-0.2177	-0.2041
AAB	14.3601	18.4307	53.2304	28.6223	35.0553
R sq	0.5910	0.9095	0.8140	0.8087	0.8026
Broadleaves					
RMSE	21.1533	27.1267	97.1874	55.0685	68.4503
AB	-0.4069	-0.1099	-1.5386	-0.8117	-0.9902
AAB	16.3074	19.4670	69.505	38.9423	48.1860
R sq	0.3727	0.8993	0.7607	0.7665	0.7564
Conifers					
RMSE	16.6905	22.7970	68.5675	33.9890	41.4698
AB	-0.6623	0.1336	1.2491	0.5300	0.7949
AAB	12.5453	14.9928	46.5778	23.4064	28.2109
R sq	0.5090	0.9072	0.8340	0.8157	0.8129
Mixed forest					
RMSE	16.9051	19.9220	70.4373	37.3150	45.1450
AB	-0.8051	-0.0299	-1.1628	-0.7177	-0.8422
AAB	12.9994	15.4272	48.9941	26.0754	31.5800
R sq	0.3966	0.9368	0.7983	0.7854	0.7841

Segmentation of the forest into stands

Segmentation of the forest area into forest stands resulted in a total of 367775 forest polygons with an average area of 1.6 ha and a median of 0.03 ha. Although many forest stands in the Danish forests are small, the "typical" forest stand originating from the analyses seems to be too small. The ability to detect stand delineations was evaluated using a visual appraisal of aerial photographs (Figure 5). Judging from the analyses, the method may be used for an initial assessment of the spatial forest structure.

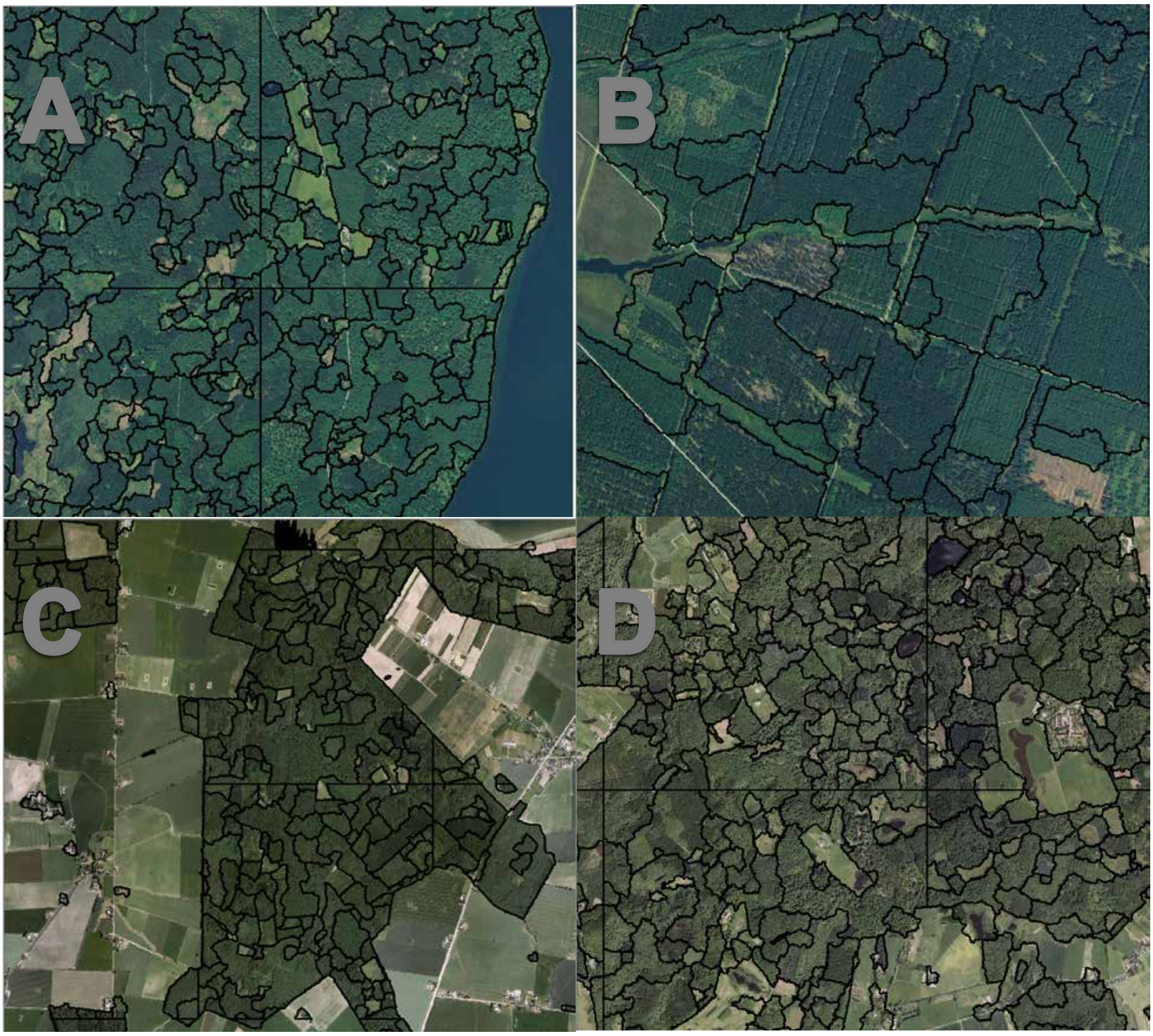

Figure 5. Examples of the segmented forest map. A: Gribskov, B: Klosterheden Plantage, C: Forest on Lolland, D: Forest close to Hvalsø.

Discussion

The models for predicting canopy height, growing stock, and biomass yielded a satisfactory level of precision, explaining around 90 % of the variation in canopy height and around 80 % of the variation in volume and biomass. This level of precision is comparable with similar studies in boreal and temperate regions (e.g. Heurich and Thoma 2008, Næsset2004a,b, Næsset2002, Nilsson 2016). As mentioned, due to economic constraints only the largest trees (*dbh* > 40 cm) are measured within the full 15 m radius plots in the NFI. Smaller trees are measured in the 3.5 m (*dbh*<10 cm) and 10 m (*dbh*<40 cm) circles, respectively. This stratification of measurements in the

NFI introduces additional error to the dependent variables affecting the observed model precision negatively, while the actual effect on predictions is unknown.

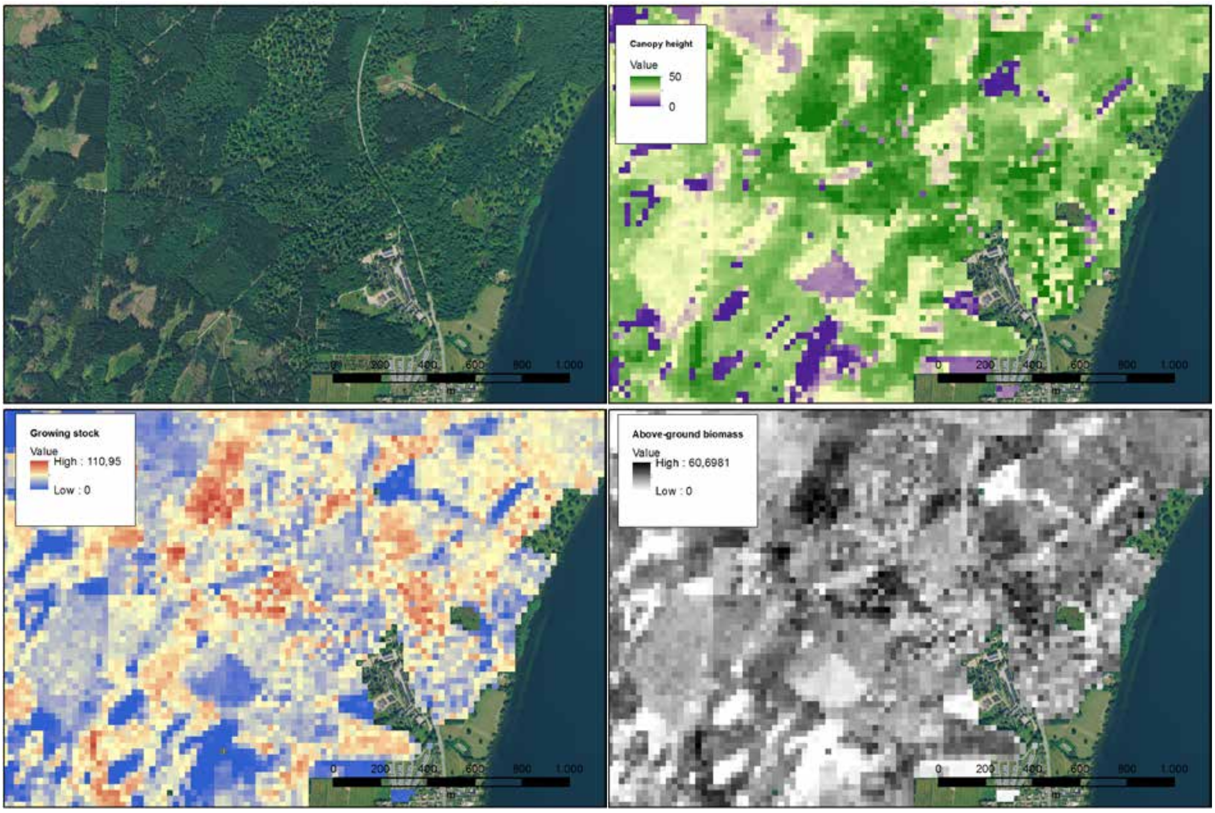

Figure 6. Forest resources estimated for an area north of Nødebo in northern Zealand. Upper left: aerial photograph summer 2015. Upper right: Estimated canopy height. Lower left: estimated growing stock. Lower right: estimated above ground biomass.

The dataset used in this study had a considerable higher resolution (4.6 pts/m^2) compared to similar studies (0.5-1 pts/m^2), but the precision obtained in this and other studies was quite similar. This is in line with a study (Gobakken et al. 2008) where average standard deviation showed only a minor increase by decreasing point density. Oppositely, the scanning angles used in our study were comparatively large (>30°) to other studies (<20°). This may have implications for estimation of canopy cover, as the view angle has a negative influence on canopy closure estimates, but not on tree height measurements (Holmgren et al. 2003). Based on these considerations it may be argued that, from a forestry perspective, a higher flight altitude and a lower scanning angle resulting in lower point density but the same swath width would be preferable.

Using the forest resource map in actual forest planning

In relation with forest management planning at Frederiksdal Skovdistrikt, 236 circular sampleplots with a radius of 15 m, were established in 2014 (Figure 7). All trees with dbh larger than 10 cm were measured for diameter and the total tree height was measured on a subsample of the trees. Forest variables such as stand height and growing stocks were estimated similar to the procedures in the Danish NFI (Nord-Larsen and Johannsen, 2016). To evaluate the performance of the map in relation to practical forest management, we compared estimates from the forest inventory to estimates obtained form the forest resource map.

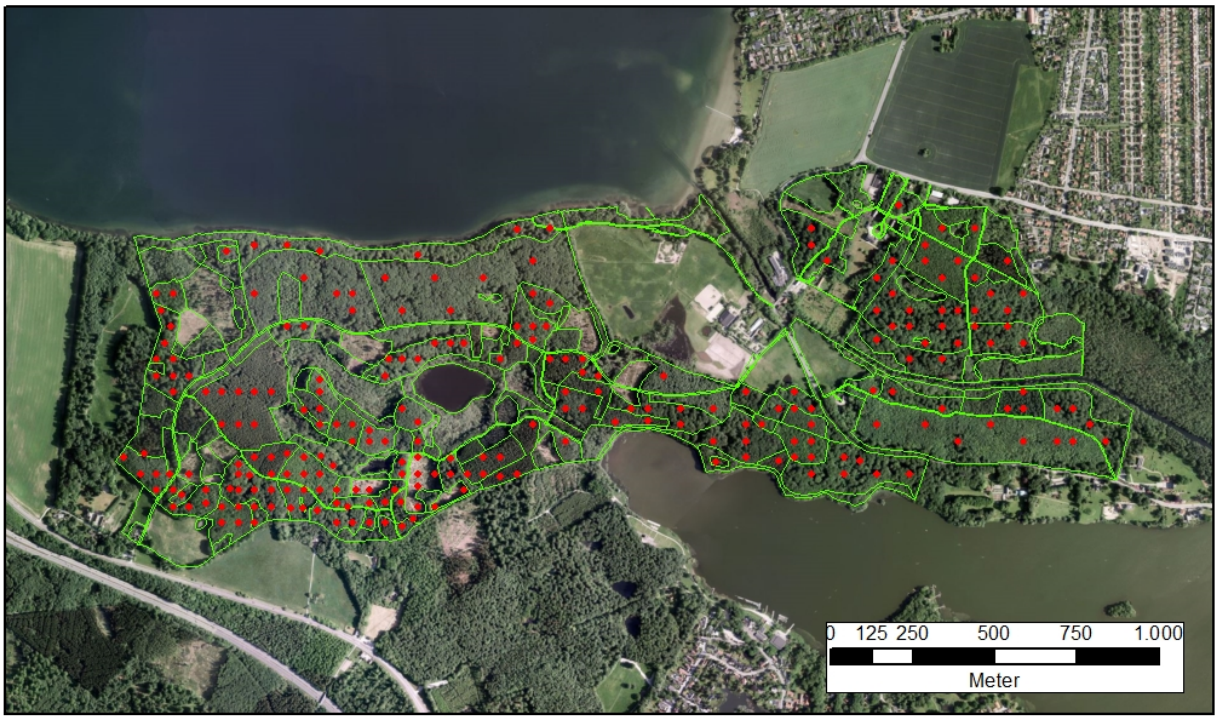

Figure 7. Sampled inventory plots in relation to the management planning at Frederiksdal Skovdistrikt 2014.

Looking at the forest canopy height obtained from the forest resource map (Figure 8, left), the heights correspond well with known differences in strand height. Comparing the stand heights (height of the tree corresponding to the mean basal area tree, H_g) obtained from the forest inventory, the forest resource map consistently overestimates stand height (Figure 8, right). The obvious reason for this is that the height obtained from the laser scanning corresponds to the dominant height (H_{100}) and thus should be larger than the measured stand H_g. This should be taken into account when using the forest resource map for obtaining e.g. site index, using yield tables based on H_g rather than dominant height.

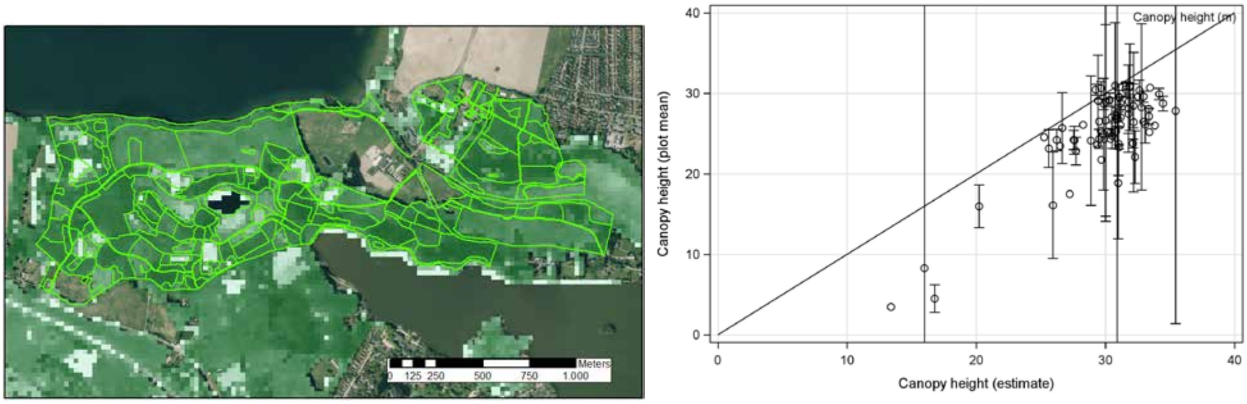

Figure 8. Comparing forest stand height obtained from the 2014 forest inventory at Frederiksdal Skovdistrikt with the canopy height obtained from the forest resource map.

Again, a simple look at the forest resource map of Frederiksdal Skovdistrikt, the colouring corresponds well with known stand differences in stocking (Figure 9, left). The comparison of measured and estimated volumes (Figure 9, right), show a strong correlation between the two and no obvious deviations from the 1:1 line in the plot. In most cases the estimates from the forest resource map is within the 95% confidence interval of the plot measurements, meaning that there are no significant difference between actual measurements and estimates obtained from the forest resource map.

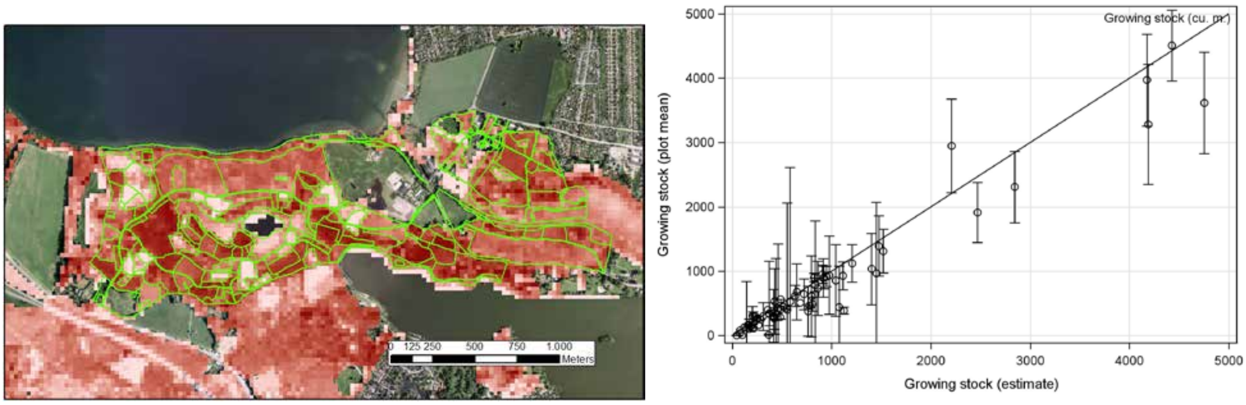

Figure 9. Comparing forest stand growing stock obtained from the 2014 forest inventory at Frederiksdal Skovdistrikt with the growing stock obtained from the forest resource map. Box-and -whiskers displays the 95% confidence interval of the estimate obtained from plot measurements.

Forest inventory and management planning is in Denmark becoming less frequent and is to a lesser extend based on actual measurements. Consequently, strategic and tactical decisions are commonly taken from uncertain knowledge about the forest. The uncertainty of forest attributes such as growing stock presented by the forest resource map is expected to much less than the uncertainty associated with current inventory practises. Consequently, it is our hope and expectation that the forest resource map will increase the knowledge of the forest and lead to improved decisions in forest management.

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UNIVERSITY OF COPENHAGEN

DEPARTMENT OF GEOSCIENCES
AND RESOURCE MANAGEMENT

ROLIGHEDSVEJ 23
DK-1958 FREDERIKSBERG

TLF. +45 35 33 15 00
IGN@IGN.KU.DK
WWW.IGN.KU.DK