Forest Plan - pilot project on mapping of forest resources

Nord-Larsen, Thomas; Tsatsakis, Michail; Li, Sizhuo; Avila, Linsey Marie; Brandt, Martin Stefan; Liu, Siyu; Morueta-Holme, Naia; Davison, Charles; Fensholt, Rasmus

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Thomas Nord-Larsen, Michail Tsatsakis, Sizhuo Li, Linsey Marie Avila, Martin Stefan Brandt, Siyu Liu, Naia Morueta-Holme, Charles Davison, and Rasmus Fensholt

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1 Preface

The project Forest Plan – pilot project on mapping of forests and forest resources represents part of the overall project "Forest Plan", which the Danish Parliament initiated on 4 December 2021:

"The parties to the agreement agree that a forest plan must be drawn up with the involvement of relevant stakeholders. The forest plan must be drawn up by the end of 2022. The parties to the agreement will be convened for discussions on this in spring 2022. DKK 10 million will be allocated in 2022 for the preparation of the forest plan."

The overall project was later specified in Specification of funds for the forest plan, including the pilot project on the creation of maps of forests and forest resources in Denmark.

The purpose of the forest resource mapping project is to create a pilot project for the establishment of a wall-to-wall map of the Danish forests and their resources. The project will support 1) monitoring and documentation of afforestation 2) climate reporting for the LULUCF sector to the EU and the UN, 3) analyses of forest development, 4) private and public forest management and 5) green transition of the forest sector. The mapping endeavor will further support national and international reporting, for example on EU biodiversity and forest strategies.

The report includes work that is expected to be published scientifically. In order not to stand in the way of a later scientific publication, the technical description in the report in some cases only includes a more general summary, while the detailed description will be made available in connection with the subsequent publication of the individual articles. This report has been prepared in English as a result of the international competences that have been included in its preparation. However, a comprehensive summary has been prepared in Danish.

The project on mapping forests and forest resources is based on a project proposal that was previously developed jointly by the Danish Environmental Protection Agency, the Danish Agency for Data Supply and Innovation and the Department of Geosciences and Natural Resource Management at the University of Copenhagen. This project had a similar purpose to the present pilot project and a duration of 2½ years with a basically infinitely expected continuous update of the mapping thereafter. In comparison, the current pilot project had a total of 4½ months available. The results obtained, despite the very limited time available for the pilot project, show the wide scope for development in this area. However, the differences in the time available for the two projects also underline the need for further development and validation before the methods can be fully implemented.
2 Forord

Projektet Skovplan – pilotprojekt om kortlægning af skovressourcer repræsenterer en del af det samlede projekt "Skovplan”, som Folketinget igangsatte den 4. december 2021:


Det samlede projekt blev senere specificeret i Udmøntning af midler til skovplanen, herunder Forprojekt for etablering af kort over skovressourcer i Danmark.


I rapporten indgår arbejder, der forventes udgivet videnskabeligt. For ikke at stå i vejen for en senere videnskabelig publikation omfatter den tekniske beskrivelse i rapporten i visse tilfælde alene en mere overordnet sammenfatning, mens den uddybede beskrivelse vil blive gjort tilgængelig i forbindelse med publiceringen af de enkelte artikler. Rapporten her er udfærdiget på engelsk som følge af de internationale fagkompetencer, der har indgået i dets udarbejdelse. Der er dog udfærdiget en omfattende sammenfatning på dansk.

3 Abstract

Forest ecosystems provide a variety of goods and services to society, including timber and other materials for industry, biodiversity conservation, carbon storage and sequestration, clean ground water, and recreational opportunities. In particular, the role of forests in biodiversity conservation and climate change mitigation have gained increasing international focus in recent years.

Competing objectives for the forest resource along with a growing demand for wood products and green biomass for energy exerts a mounting pressure on the forest resource. Simultaneous with these increasing demands there has been a desire to halt the loss of biodiversity imposed by deforestation and degradation of forest habitats, leading to the adaptation of multilateral conservation strategies such as the Aichi Targets and the New York Declaration on Forest as well as the implementation of national actions. Managing forests according to these multiple objectives and competing demands is a complex task and calls for sound data on the forest resource in adequate spatial and temporal resolution.

Traditionally forest inventories have been carried out as field-surveys, collecting data by sampling or complete inventory, depending on the required accuracy. Field inventory campaigns are, however, time consuming and expensive and the application of remotely sensed data, especially aerial photography, has long assisted the process of stand delineation and stratification. In recent decades, the possibility to map forests and forest resources remotely has increased dramatically due to improvements in both temporal, spatial, spectral, and radiometric resolution of remotely sensed data as well as advances in areas of statistical learning.

The scope of the project on mapping forest resources is to make a pilot project for establishing a system for reliable, consistent, and timely wall-to-wall mapping of the Danish forests and their resources. The project includes inter-comparison of an array of different data sources and techniques, from which experiences have been gained, ultimately serving as a basis for improved decision-making on selecting adequate mapping approaches in the years to come. The project will support 1) monitoring and documentation of afforestation 2) climate reporting for the LULUCF-sector to EU and UN, 3) analyses of forest development, 4) private and public forest management, and 5) the green transition of the forest and adjoining sectors. The mapping will further support the national and international reporting e.g., related to the EU biodiversity and forest strategies. Underlying this scope is an expectation that the mapping procedures will be implemented subsequently in consistent annual updates of the forest and forest resource maps to aid future sustainable forest management and the green transition of society.

3.1 Forest area and resource mapping methods

In relation to the ForestPlan project, we explored mapping of the forest area and subsequently mapping of forest resources in terms of volume, biomass, and carbon stocks. In some cases, the two different types of mapping rely on the same type of data and the same modelling approach. In other cases, data types and modelling approaches differ. The methods applied span well-proven methods previously used for mapping.
Danish forests and their resources as well as beyond state-of-the-art methodologies breaking new ground in the applied data products and statistical learning.

**Forest area mapping**

For the forest area mapping we explored three principally different approaches utilizing different types of data and applying different methodologies for the forest classification: 1) a segmentation-based method in which individual tree crowns are identified from aerial images in very high resolution (0.2 m) and subsequently joined to represent the forest area according to a given forest definition, 2) a segmentation-based approach in which the canopy area is identified from high resolution (3 m) PlanetScope satellite images using deep learning, and 3) an area-based approach in which individual pixels in medium resolution (10 m) Sentinel-1 and Sentinel-2 satellite images from the Copernicus programme are classified using a machine learning decision tree-based ensemble classifier.

**Segmentation of individual tree crowns.** For the tree segmentation approach, a deep learning model was trained on aerial images (RGB + NIR (near-infrared) + NDVI (normalized difference vegetation index)) at 20 cm resolution acquired during summer 2018 and a canopy height map projected from airborne LiDAR data at 40 cm resolution. For training of the model, we manually delineated 19,771 individual tree crowns from different forest and non-forest landscapes. The deep learning-based model was adapted from the U-Net architecture and was trained on the target references. The model trained on the 2018 aerial images was applied to both the 2018 and 2020 summer aerial images to form country-wide tree cover maps subsequently used for forest delineation. Owing to problems with a different normalization of the near-infrared band in the 2020 dataset, we opted to produce the 2020 mapping from a model solely trained with RGB+NIR data from 2018, i.e., without NDVI and height map, which was less prone to such differences. The output produced was evaluated against two types of test data: manual delineations of tree crowns not using in model training (for 2018 results) and NFI field plot data (for 2018 and 2020 results).

**Mapping canopy with PlanetScope data.** The mapping of canopy with PlanetScope data obtained during 2019 comprised more than 1000 individual cloud-free, orthorectified, and high-quality scenes of the format PSscene with 4 bands (NIR, red, green, blue). All images were from late summer where trees still have green leaves and are easily identified. To organize the large data volumes, we divided the world into a grid of 1x1 degree tiles and generated a custom mosaic of PlanetScope scenes for each tile. The software tools developed for the mosaic generation process were fully automated, such that with a single input of a study area, analysis ready custom mosaics can be generated anywhere in the world at an annual scale. A fully convolutional neural network based on the U-Net architecture was trained with LiDAR canopy height images (thousands of 1x1 km samples) to predict both tree cover and tree height from PlanetScope images at 3 m resolution. The work was done and evaluated for entire Europe, with the Danish LiDAR data being a crucial component, but also LiDAR data from Spain, Finland, Estonia, Netherland, Wales, and Switzerland were used.

**Pixel-based mapping with Sentinel-images.** For the pixel-based mapping of forest area, we produced two wall-to-wall cloud free images from all available data covering 1) the fall and winter 2019/2020 and 2) the
summer of 2020, from both Sentinel-1 (synthetic aperture radar) and -2 (optical), with global repeat cycles of six and five days, respectively. Initially, we aimed to include a higher temporal resolution likely leading to higher classification accuracy of tree species, but cloud cover made it difficult to produce the wall-to-wall images at shorter intervals.

Multispectral optical features were generated from the Sentinel-2 satellite images obtained during leaf-on and leaf-off conditions. The winter collection of optical images comprised a series of 1404 S-2 images acquired on 125 distinct dates between 20 December 2019 and 23 April 2020, while the summer collection comprised a series of 959 S-2 images acquired on 84 distinct days between 24 May and 16 August 2020. Cloud-free image composites were produced for each spectral band including bands within the visible (band 2–4), near infrared (NIR, band 5–8), and short-wave infrared (SWIR, band 10–12) parts of the electromagnetic spectrum for the winter and summer images, respectively. The 20 m resolution bands were resampled (nearest neighbour) to 10 m resolution. SAR features were generated from a series of C-band S-1 Level-1 Ground Range Detected images with a pixel size of 10 m. The winter collection comprised a series of 582 S-1 images acquired on 125 distinct dates between 20 December 2019 to 23 April 2020, while the summer collection comprised a series of 351 S-1 images acquired on 84 distinct days between 24 May and 16 August 2020. The images in each collection (summer and winter) were mosaicked to a composite for each of the two polarizations (VV and VH) of the area of interest by applying a mean function on the winter and summer collection, respectively. Using the optical and SAR mosaics, we trained the classification of forest from Sentinel satellite imagery using machine learning with random forest (RF), neural network (NNET), and support vector machine (SVM) employing national forest inventory data for labelling. We further, used this approach to classify the forest area into forest types (broadleaves/conifers).

Post-processing. All three methods produced maps of tree canopy cover which may not be coherent with international definitions of forest land. We consequently developed procedures to thin the forest area to be concurrent which such definitions for consistent reporting of the forest resources and their development. In this procedure the forest boundaries are drawn by expanding and unifying adjacent tree crowns or canopy groups by buffering outwards to reach to neighbouring tree crowns and connect these. While accumulating new space, next, is thinning the new gained area by buffering inwards to remove areas less than the limit width of forest areas. The spatial criteria of what is defined as forest is applied, hence, the definition of the forest sets the parameters to be used in a heuristic approach of solving the problem, by dilation and contraction as long as the area can grow on appending new tree crowns while expanding and withdrawing back to initial extent.

Forest resource mapping

For the forest resource mapping three different approaches were investigated for estimation of canopy height, forest growing stock, and above-ground biomass: 1) a method building upon deep learning-based segmentation of individual tree crowns from aerial images, combined with canopy height maps projected from airborne LiDAR scanning data, 2) a method based on the tree cover and canopy height information produced with PlanetScope satellite images and NFI data, and 3) a two-stage prediction of forest resources
from non-linear regression-based modelling of the relationship between airborne laser metrics and observed biomass on the NFI plots.

**Forest resource mapping from individual tree crowns.** For the estimation of above-ground biomass for single trees, we used the tree crown detections obtained from the summer 2018 aerial images and canopy height maps projected from LiDAR scanning data. Forest type was obtained from the Copernicus forest type map. A global dataset of tree measurements was used to establish allometric equations for the regression of above-ground biomass against crown diameter and height. Crown area and crown diameter was calculated for each individual tree and overlayed with the canopy height maps to derive the height for each detected tree crown. Above-ground biomass was then estimated for each tree crown based on the global allometric equations fitted on crown diameter, height, and forest type. The estimated above-ground biomass for individual trees were aggregated to above-ground biomass for individual national forest inventory reference plots. A quadratic function was fitted against the above-ground biomass references to calibrate for local and global dissimilarities caused by differences between allometric equations and underestimation caused by inability to capture understory vegetation. 1898 plots were used to fit the quadratic function.

**Forest resources from PlanetScope data.** Tree cover and canopy height produced with PlanetScope images from 2019 were used to estimate above-ground forest biomass. In this assessment, we used Danish national forest inventory plot data (about 1100 plots) to establish relationships between above-ground tree biomass and airborne canopy height (for vegetated areas above 1.3 m) from airborne LiDAR, both averaged at plot level for different forest types. This provided relationships between tree height and biomass, which can then be aggregated to the 3 m resolution of PlanetScope data. Different allometric equations were used for mixed forests (error = 13.4%), coniferous forests (error = 9.2%), broadleaf forests (error = 8.1%), and trees outside forests (error = 9.8%). The Copernicus forest map was used to distinguish the classes.

**Pixel-based forest resource mapping from LiDAR data.** Airborne laser scanning (ALS) produces point clouds, imaging the biophysical and structural properties of the forest. The direct representation of the forest properties renders data from ALS a promising tool for assessing forest resources among other things. As the third approach to forest resource mapping, we used a two-stage sampling procedure previously applied in Denmark and the Nordic countries. In the first step, normalized point cloud data corresponding to the National Forest Inventory sample plots were cut from the point cloud. A suit of point cloud metrics was calculated from the normalized point cloud including e.g. the mean height above ground of the pulse returns, various percentiles of return heights, and the ratio of laser pulses being reflected from the tree canopy relative to the total number of pulses. For predicting forest variables, we modelled the relationship between these point cloud 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. In the second step of the procedure, the country was divided into 25 x 25 m pixels. Normalized point cloud data was extracted from each pixel and a similar suit of point cloud metrics as for the NFI plots was calculated. Finally, canopy height, growing stock, and biomass was
estimated using the allometric equations derived from the first step on the pixel point cloud metrics to produce the final map.

### 3.2 Results of forest area and resource mapping

#### Forest area mapping

All three methods applied successfully identified forest canopies. In all cases, the forest area estimated prior to post-processing was much higher than the area reported from the national forest area. This was expected as the raw maps include tree covered areas not concurrent with the forest definition such as shelterbelts, parks, and areas with tree over in low build-up and summerhouse areas.

After postprocessing, the reported forest areas were generally smaller than the forest area reported by the national forest inventory, with the exception of the map produced from Sentinel data. This was as expected owing to the inability of the methods to identify tree-less temporarily unstocked and auxiliary areas as forest and likely difficulties in identifying very young afforestation and replanting as forest. The overall accuracies obtained from the mapping of the forest area were high for all tested methods (0.95-0.96) but slightly less than those reported from earlier studies. This was somewhat surprising since the classification from Sentinel images were almost identical but maybe due to minor differences in the calculation of the overall accuracy.

The satellite imagery from Sentinel data successfully classified the forest area into broadleaved and coniferous forest with an overall accuracy of 0.94. Since the method rests on a set of summer and winter images, the identification probably rests on the difference in colour due to the deciduous trees dropping their leaves in autumn. This generally causes the method problems in identifying species of larch, which occupy about 27,000 hectares or just over 4% of the forest area. The analysis could instead have been made on a division into deciduous/non-deciduous forest, but since larch in terms of wood quality, forest structure and opportunities for biodiversity is more similar to the conifers, the analyses were carried out based on the division into deciduous and coniferous forests. The user and producer accuracies differed much between different forest types with producer accuracies of 0.84-0.85 for the two dominant classes (broadleaved and coniferous forest) and corresponding user accuracies of 0.67-0.80.

The different methods demonstrated in this project utilize different data sources, applies different methodologies, and produce different results. In relation to future mapping of forest in Denmark, the different approaches consequently have different strength and weaknesses (Table 3.1). The final recommendation of a specific method relies on a dialogue with stakeholders based on private and public information needs in relation to the results from this pilot project.
Table 3.1. Strength and weaknesses of the different methods to forest area mapping. Classification ranges from bad/complex/expensive (+) to good/simple/cheap (+++). Versatility in this context refers to the capacity of the map products to be used in different areas, such as for mapping trees outside forests or for determining forest structure and its relationship to biodiversity.

<table>
<thead>
<tr>
<th>Method</th>
<th>Aerial images (section 7.1)</th>
<th>PlanetScope (section 7.2)</th>
<th>Sentinel (section 7.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Product</strong></td>
<td>Tree crown size and height at individual tree level for both forest and non-forest trees (can be converted to tree cover at any resolution)</td>
<td>Forest cover and height at 3 m resolution. Forest and large trees outside forests</td>
<td>Forest cover at 10 m resolution</td>
</tr>
<tr>
<td><strong>Method</strong></td>
<td><strong>Accuracy</strong></td>
<td>Deep learning</td>
<td>Deep learning</td>
</tr>
<tr>
<td></td>
<td>+++</td>
<td>+++</td>
<td>+++</td>
</tr>
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<td></td>
<td>++</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>+</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Spatial resolution</strong></td>
<td>+++</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td><strong>Temporal resolution</strong></td>
<td>+</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Data costs</strong></td>
<td>+++</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Computational costs</strong></td>
<td>+</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Method complexity</strong></td>
<td>+</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Continuity</strong></td>
<td>+++</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Versatility</strong></td>
<td>+++</td>
<td>++</td>
<td>+</td>
</tr>
</tbody>
</table>

Forest resource mapping

All three methods applied for mapping of forest resources produced low bias (0 to 7%) and high precision (R-squares ranging from 0.7-0.9). Measured on R-square and RMSE, the models were more accurate for conifers than for broadleaves, likely owing to the simpler structure of the coniferous trees.

The methods applied in forest resource modelling utilized different types of data with different properties in terms of spatial and temporal resolution and the structural information inherent in the data. This required the application of fundamentally different approaches to the modelling of forest resources and resulted in results with different properties. In relation to future mapping of forest in Denmark, the different approaches consequently have different strength and weaknesses (Table 3.2). As for the forest area mapping, the final recommendation of a specific method relies on a dialogue with stakeholders based on private and public information needs in relation to the results from this pilot project.
Table 3.2. Strength and weaknesses of the proposed methods for forest resource mapping. Classification ranges from bad/complex/expensive (+) to good/simple/cheap (+++).

<table>
<thead>
<tr>
<th>Method</th>
<th>Aerial images (7.1)</th>
<th>PlanetScope (7.2)</th>
<th>LiDAR (7.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>Deep learning model learns from NFI plots to predict biomass from aerial images. Can be converted to tree cover at any resolution.</td>
<td>Forest variables directly derived from tree cover and height maps using allometric equations from NFI data.</td>
<td>Canopy height, growing stock, and biomass estimated for 25x25 m pixels.</td>
</tr>
<tr>
<td>Method</td>
<td>Deep learning</td>
<td>Deep learning</td>
<td>Parametric models</td>
</tr>
<tr>
<td>Accuracy</td>
<td>++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>+++</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Temporal resolution</td>
<td>++</td>
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<tr>
<td>Data costs</td>
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<td>Computational costs</td>
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<td>Method complexity</td>
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<td>Continuity</td>
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<td>+</td>
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<tr>
<td>Versatility</td>
<td>+++</td>
<td>++</td>
<td>++</td>
</tr>
</tbody>
</table>

3.3 Pilot project discussion and conclusions

The three different approaches to forest and forest resource mapping involved different approaches and included different types of data and thereby also resulted in different outputs regarding accuracy and level of details in spatial resolution.

The overall accuracies obtained from the mapping of the forest area (0.95-0.96) were somewhat less than the overall accuracies (0.98) reported by Bjerreskov et al. (2021) for all of the methods tested. A likely reason for the differences is that the methods applied for assessing the accuracies differed. A common feature of all three methods tested was the inability of the underlying procedure to localize forest areas with no tree cover or with newly planted, small trees and hence the ability to map areas with young forest. This represents a common discrepancy between mapping of land cover and land use. The approaches presented all seek to classify forest from interpretation of the visual landscape, in this case specifically from the presence of trees. However, the definition of forest includes landscapes with absence of trees namely temporarily unstocked areas that are to be reforested as well as auxiliary areas needed for forest management such as firebelts, some forest roads, etc. Furthermore, the textural appearance of newly established forest may in many cases not allow detection with methods relying on detection of individual tree crowns or pixel-based methods such as the satellite imagery produced in this pilot study. However, in our study the models for detecting individual trees were trained with trees having somewhat large crowns to avoid confusion with smaller bushes. This training could be refined in subsequent applications to include smaller trees.

The classification of forest areas from aerial images provides the highest level of spatial details and the results are easy to interpret as trees are mapped as individual objects. Mapping of the individual tree crowns can serve as an attractive starting point as this represents one of the key building blocks for further
post-processing into forest cover, based on whatever definition of forest is applied. An advantage of this approach is the identification of non-forest trees, e.g. in urban areas and the open landscape offering a high degree of versatility in the use of resulting products.

Forest mapping from Sentinel 1 and 2 data based on classical machine learning represents an approach that can be performed rapidly and at low cost using cloud computing facilities. The methods applied are well-known, well documented, transparent, and may be deployed in standard software packages. However, the low level of spatial details produced makes the method unsuited for detecting trees outside forests and for aligning results with data from the national inventory forest plots. In this study, the classification of conifer/broadleaved forest from Sentinel data was based on only two wall-to-wall, cloud free images and we expect that accuracy could be improved by increasing the temporal resolution of the images. In particular, the high revisit frequency and the multi-spectral and multi-sensor observation capacity offers possibilities documented in other studies.

The classification of forest cover from PlanetScope data offers a compromise between the level of detail provided and the processing costs associated with high-detailed aerial images. The method produces a relatively high level of detail allowing alignment with national forest inventory sample plots. However, unlike the aerial images, the resolution of PlanetScope data does not allow for the detection of small trees outside forests. The constellation of PlanetScope nano-satellites is privately operated, but the mission is expected to be continued for many years to come. Unlike the two other data sets, this also means that the data from PlanetScope is not free of charge.

The forest resource mapping from aerial images produces an output of high spatial resolution, and the approach enables future assessment of biomass resources and carbon stocks outside the forest, hereby enhancing other parts of the LULUCF emissions accounting. The method yielded a high accuracy when tested with independent NFI plot data, but even this approach appears very promising it needs further scientific grounding before considered operational.

Pixel-based mapping of forest resources solely from LiDAR data is well-established and has been shown to produce reliable results across a wide range of studies conducted in the past three decades. It is unknown to what extent this approach can accurately predict the forest resources outside forests. Laser scanning data is currently captured for only a fifth of the country every year (resulting in a return-time of five years), which is not fully aligned with the annual reporting of climate gasses and for applications in general forest management.

Mapping of forest resources from PlanetScope data represents a compromise between the two other methods regarding the spatial resolution. An advantage of this approach is the frequent passing of the satellites (achieved by the constellation of multiple nano-satellites), that enables frequent updates of the mapping products and opens an interesting pathway towards improved woody species mapping from tracking the distinct phenological cycle of different species.
3.4 Future perspectives of forest area and resource mapping

Forest information is collected at many levels and for many purposes. Typically, sampling-based national forest inventories are carried out to provide national- and international-level statistics. The inventories are designed to meet these targets with a sufficient precision and at a reasonable price, consequently commonly using sample designs with around or less than one sample plot per square kilometre. Oppositely, at the forest holding level, spatially explicit forest data are needed to support forest owners in their strategic planning as well as for short-term decision-making and planning of forest management. Hence, the sample design used in the forest management inventories is commonly more detailed than the national forest inventories and is commonly focused on the mature and therefore valuable forest stands of importance to the forest owner.

The mapping products produced in relation to this pilot study may readily be implemented in forest management inventories. In this way they bridge the gap between national and regional level inventories and local forest management needs and support future sustainable management of the forest resource, providing detailed and multifaceted information on for example forest resources, forest development, carbon stocks, and habitat quality. As such, the information provided can play an important role in the sustainable procurement of resources for the transition to a future carbon neutral society. However, the costs associated with the implementation and use of the information provided in forest management programmes and routines requires that forest owners and managers may expect that such information will be available in the foreseeable future. Consequently, the gain of producing remotely sensed and detailed forest information for local and sustainable forest management is dependent on the frequent, reliable, and consistent updating of the forest resource maps.

Auxiliary variables, obtained by remote sensing and correlated with attributes of interest, are not only of importance to local forest management planning but may help improve the precision of national and regional estimates. Model-assisted (MA) and model-calibrated (MC) estimators have been shown to enable a reduction in standard error of the forest growing stock estimates with 44 and 41%. The precision gain corresponds to field sampling of almost three times as many sample plots annually in the national forest inventory. The result demonstrates that forest area and resource maps may have large potentials in reducing variance of estimates related to forest resources. This is of particular interest when contemplating the estimation of forest carbon stocks in relation to the climate gas emissions reporting. The reporting is assessing annual differences in carbon stocks to measure emissions from forests. As the annual change in forest carbon pools is small compared to the very large stocks, even small uncertainties in the estimates of the stocks result in large uncertainty in the estimate of emissions. Hence, reductions of uncertainties in the magnitude observed for model-assisted and model-calibrated estimates would largely improve certainty of emissions reporting. Such gains are however ultimately dependent on regular, accurate, and consistent updating of the forest and forest resource maps such as demonstrated in this report.
4 Resume

Skovkøsystemer leverer en række varer og tjenester til samfundet, herunder træ og andre materialer til industrien, bevarelse af biodiversitet, kulstofbinding og -lagring, rent grundvand og rekreative muligheder. Især skovenes rolle i bevarelse af biodiversitet og modvirkning af klimaændringer har haft stigende internationalt fokus i de senere år.


Traditionelt er taksation af skov blevet udført ved feltundersøgelser i form af stikprøve-baserede opgørelser på prøveflader, ved fuldtaksation eller ved en af de mange mellemformer afhængigt af den ønskede præcision. Taksation af skov er dog tidskrævende og dyrt, og anvendelsen af data fra remote sensing, især luftfotografi, har længe understøttet skovplanlægning eksempelvis i forbindelse med afgrænsning af skovbevoksninger. I de seneste år er det mulig for at kortlægge skove og skovressourcer ud fra remote sensing dog steget dramatisk på grund af forbedringer af både den tidsmæssige, rumlige, spektrale og radiometriske oplösning af remote sensing data samt fremskridt inden for statistisk læring.


4.1 Metoder til kortlægning af skovarealet og ressourcer

I forbindelse med SkovPlan-projektet undersøgte vi kortlægning af skovarealet og efterfølgende kortlægning af skovressourcer i form af volumen, biomasse og kulstoflægge. I nogle tilfælde er de to forskellige typer kortlægning afhængige af den samme type data og den samme metode. I andre tilfælde er datatyper og modelleringsmetoder forskellige. De anvendte metoder spænder fra velafprøvede metoder,
der tidligere er blevet brugt til kortlægning af danske skove og deres ressourcer til nye metoder, der præsenterer helt nye tilgange til statistisk læring.

**Kortlægning af skovareal**

Til kortlægningen af skovareal undersøgte vi tre forskellige tilgange ved brug af forskellige typer data og anvendelse af forskellige metoder til skovklassificeringen: 1) en segmenteringsbaseret metode, hvor individuelle trækroner identificeres ud fra luftfotos i meget høj oplysning (0,2 meter) ved hjælp af deep learning og efterfølgende sammenføjes for at repræsentere skovområdet i henhold til en given skovdefinition, 2) en segmenteringsbaseret tilgang, hvor sammenhængende trækronedækkede arealer identifieres fra PlanetScope-satellitbilleder i høj oplysning (3 m) ved hjælp af deep learning og 3) en pixel-baseret tilgang, hvor individuelle pixels i Sentinel-1- og Sentinel-2-satellitbilleder i medium oplysning (10 m) fra Copernicus programmet klassificeres ved brug af klassisk maskinlæring.


**Segmentering af kroendække med PlanetScope data.** Kortlægningen ud fra kroendække med PlanetScope-data optaget i løbet af 2019 omfattede mere end 1000 individuelle skyfröje, ortho-korrigerede og højkvalitetsbilleder i formatet PSscene med 4 bånd (NIR, rød, grøn, blå). Alle billeder er fra sensommeren, hvor trær stadig har grønne blade og er lette at identificere. For at organisere de store datamængder opdelte vi de globale data i gridceller af 1x1 graders dækning og genererede en brugerdefineret mosaik af PlanetScope-scener for hver gridcell. De softwareværktøjer, der blev udviklet til mosaikgenereringsprocessen, var fuldt automatiserede, således at der med et enkelt input fra et projektområde kan genereres klargjorte brugerdefinerede mosaikker overalt i verden. Et fuldt konvolutionelt neuralt netværk baseret på U-Net-arkitekturen blev trænet med en LiDAR-baseret højdemodel (tusindvis af 1x1 km-prøver) for at forudsige både trædække og træhøjde fra PlanetScope-billeder i 3 m oplysning. Arbejdet blev udført og evaluere for hele Europa, hvor de danske LiDAR-data var en afgørende komponent, men også LiDAR-data fra Spanien, Finland, Estland, Holland, Wales og Schweiz blev brugt i denne proces.

Postprocessering. Alle tre metoder producerede kort over trækroner, som muligvis ikke er i overensstemmelse med internationale skovdefinitioner. For at sikre en konsistent rapportering af skovarealet og -ressourcer og deres udvikling, designede vi en procedure til at kortlægge kronedækkede arealer, der er konsistent med internationale skovdefinitioner. I denne procedure trækkes skovgrænserne først ved at lægge en 10 m buffer omkring træ-dækkede polygoner og forene overlappende arealer. Herved forenes tilstødende trækroner med en indbyrdes afstand på mindre end 20 m. Herefter fratrækkes en buffer på 10 m for at gendanne den oprindelige ydre skovafgrænsning samt yderligere 10 m. Herved forsvinder kronedækkede polygoner med en brede på mindre end 20 m i overensstemmelse med FAO’s skovdefinition (FAO, 2020). Processen med at udvide og sammentrække kronedækkede polygoner gentages indtil skovarealet stabiliseres. Slutteligt fjernes sammenhængende polygoner med et areal på mindre end 0,5 ha i overensstemmelse med FAO’s skovdefinition og skovkortet filteres med anden kortlagt information for at fjerne arealer med eksempelvis sommerhuse, frugtplantager og rekreative arealer, der kan have kronedække, men ikke lever op til FAO’s skovdefinition.

Kortlægning af skovressourcer

Til kortlægningen af skovressourcen blev tre forskellige tilgange til estimering af kronehøjde, vedmasses og overjordisk biomasse undersøgt: 1) en metode, der bygger på deep learning-baseret segmentering af individuelle trækroner fra luftfotos kombineret med højdekrone produceret fra luftbårne LiDAR-scanningsdata, 2) en metode baseret på trædække og kronehøjde produceret med PlanetScope satellitbilleder og NFI-data, og 3) en pixel-baseret estimation ved hjælp af non-lineær regression baseret på sammenhængen mellem luftbårne lasermålinger og målinger på prøveflader fra Danmarks Skovstatistik.

Trædække og kronehøjde produceret med PlanetScope data. Trædække og kronehøjde produceret med PlanetScope-billeder fra 2019 blev brugt til at estimere overjordisk skovbiomasse. I denne model brugte vi data fra den nationale skovstatistik (ca. 1.100 plots) til at etablere forholdet mellem overjordisk træbiomasse og luftbåren kronehøjde fra LiDAR på plotniveau for forskellige skovtyper. Dette skabte en sammenhæng mellem træhøjde og biomasse, som derefter kan aggregeres til 3 m opløsning af PlanetScope-data. Der blev anvendt forskellige allometriske ligninger for blandede skove (standard fejl = 13,4%), nåleskove (standard fejl = 9,2%), løvskove (standard fejl = 8,1%) og træer uden for skove (standard fejl = 9,8%). Copernicus skovkortet blev brugt til at skelne klasserne.

4.2 Resultater af skovareal og ressourcekortlægning

Kortlægning af skovareal

Alle tre anvendte metoder identificerede med succes kronedækkede arealer. I alle tilfælde var det beregnede kronearal, væsentligt højere end det areal, der blev rapporteret fra den nationale skovstatistik. Dette var forventet, da de rå kort inkluderer trædækkede områder, der ikke er i overensstemmelse med FAO’s skovdefinition, såsom læbælter, parker og områder med træ-dække i lav bebyggelse og sommerhusområder.

Efter efterbehandlingen var de indberettede skovarealer som forventet generelt mindre end det skovareal, der bliver indberettet i den nationale skovopgørelse med undtagelse af kortet baseret på Sentinel data. Dette skyldes, at metoderne har svært ved at identificere ikke-trædækkede, midlertidigt ubevoksede arealer og hjælpearealer i skov (eksempelvis brandbælter, læggepladser mv.) og sandsynligvis vanskeligheder med at identificere meget ung skovrejsning og gentilplantning af skov. Den samlede nøjagtighed opnået ved kortlægningen af skovområdet var høj for alle testede metoder (overordnet nøjagtighed 0,95-0,96), men lidt mindre end den, der blev rapporteret fra tidligere undersøgelser. Dette var noget overraskende, da klassificeringen fra Sentinel-billeder var næsten identisk med disse, men skyldes sandsynligvis forskelle i beregningen af overordnet nøjagtighed.

Satellitbillederne fra Sentinel-data klassificerede med en overordnet nøjagtighed på 0,94 skov som enten løv- eller nåleskov. Da metoden hviler på et sæt af sommer- og vinterbilleder, hviler identifikationen sandsynligvis på forskellen i farve som skyldes at løvtræerne taber bladene om efteråret. Dette giver generelt metoden problemer med at identificere arter af lærk, der optager ca. 27.000 ha eller godt 4% af skovarealet. Analysen kunne således i stedet være lavet på en opdeling i løvfældende/ikke-løvfældende skov, men da lærk med hensyn til veddets kvalitet, skovstruktur og muligheder for biodiversitet minder mere om nåletræerne blev analyserne gennemført ud fra opdelingen i løv- og nåleskove. Bruger- og producentnøjagtighederne varierede en del mellem forskellige skovtyper med producentnøjagtigheder på 0,84-0,85 for de to dominerende klasser (løvskov og nåleskov) og tilsvarende brugernøjagtigheder på 0,67-0,80.

De forskellige metoder, der demonstreres i dette projekt, bruger forskellige datakilder, anvender forskellige metoder og producerer forskellige resultater. I forhold til fremtidig kortlægning af skov i Danmark har de forskellige tilgange derfor forskellige styrker og svagheder (Tabel 4.1). Den endelige anbefaling af en specifik metode bygger på en dialog med interessenter baseret på private og offentlige informationsbehov i forhold til resultaterne fra dette pilotprojekt.

<table>
<thead>
<tr>
<th>Metode</th>
<th>Luftfotos (afsnit 7.1)</th>
<th>PlanetScope (afsnit 7.2)</th>
<th>Sentinel (afsnit 7.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Produkt</td>
<td>Trækronestørrelse og højde på individuelt træniveau for både skov- og ikke-skovtræer (kan konverteres til trædække i enhver opløsning)</td>
<td>Skovdække og højde ved 3 m opløsning. Skov og store træer uden for skovene</td>
<td>Skovdække i 10 m opløsning</td>
</tr>
<tr>
<td>Metode</td>
<td>Deep learning</td>
<td>Deep learning</td>
<td>Random Forest</td>
</tr>
<tr>
<td>Nøjagtighed</td>
<td>++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Rumlig opløsning</td>
<td>+++</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Tidsmæssig opløsning</td>
<td>+</td>
<td>+++</td>
<td>++</td>
</tr>
<tr>
<td>Dataomkostninger</td>
<td>+++</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td>Beregningsomkostninger</td>
<td>+</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td>Metode kompleksitet</td>
<td>+</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>Kontinuitet</td>
<td>+++</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>Alsidighed</td>
<td>+++</td>
<td>++</td>
<td>+</td>
</tr>
</tbody>
</table>

**Kortlægning af skovressourcer**

Alle tre metoder, der blev anvendt til kortlægning af skovressourcer, producerede lav bias (0 til 7 %) og høj nøjagtighed (R-kvadrater fra 0,7-0,9). Målt på R-kvadrat og RMSE var modellerne generelt mere nøjagtige for nåletræer end for løvtræer, sandsynligvis på grund af nåletræernes enklere struktur.

De metoder, der blev anvendt i skovressourcemodellering, udnyttede forskellige typer data med forskellige egenskaber med hensyn til rumlig og tidsmæssig opløsning og den strukturelle information, der er forbundet med dataene. Dette krævede anvendelse af fundamentalt forskellige tilgange til modellering af skovressourcer og resulterede i resultater med forskellige egenskaber. I forhold til fremtidig kortlægning af skov i Danmark har de forskellige tilgange derfor forskellige styrker og svagheder (Tabel 4.2). Hvad angår kortlægningen af skovressourcer, bygger den endelige anbefaling af en specifik metode på en dialog med interessenterne baseret på private og offentlige informationsbehov i forhold til resultaterne fra dette pilotprojekt.
Tabel 4.2. Styrke og svagheder ved de foreslåede metoder til kortlægning af skovressourcer. Klassificering spænder fra dårlig / kompleks / dyr (+) til god / enkel / billig (+++).

<table>
<thead>
<tr>
<th>Metode</th>
<th>Produkt</th>
<th>Luftpotos (7.1)</th>
<th>PlanetScope (7.2)</th>
<th>LiDAR (7.3)</th>
</tr>
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<tbody>
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<td>Metode</td>
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<td>Deep learning</td>
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<td>Parametriske modeller</td>
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<td>Dataomkostninger</td>
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<tr>
<td></td>
<td>Beregningsomkostninger</td>
<td>+</td>
<td>++</td>
<td>+++</td>
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<tr>
<td></td>
<td>Alsidighed</td>
<td>+++</td>
<td>++</td>
<td>++</td>
</tr>
</tbody>
</table>

4.3 Diskussion og konklusioner fra pilotprojektet

De tre forskellige tilgange til kortlægning af skov- og skovressourcer involverede forskellige tilgange og omfattede forskellige typer data og resulterede derved også i forskellige output med hensyn til nøjagtighed og detaljeringsgrad i rumlig og tidslig opløsning.

Den samlede nøjagtighed fra kortlægningen af skovarealet (0,95-0,96) var noget mindre end den samlede nøjagtighed (0,98), der blev rapporteret fra Bjerreskov et al. (2021) for alle de testede metoder. En sandsynlig årsag til forskellene er, at de metoder, der blev anvendt til vurdering af nøjagtighederne, var forskellige.


Laserscanningsdata registreres i øjeblikket kun for en femtedel af landet hvert år (hvilket resulterer i en "returtid" på fem år), hvilket ikke er helt i overensstemmelse med den årlige rapportering af klimagasser og til anvendelser inden for generel skovforvaltning. Kortlægning af skovressourcer fra PlanetScope-data repræsenterer et kompromis mellem de to andre metoder med hensyn til den rumlige opløsning. En fordel ved denne tilgang er den hyppige passage af satellitterne (opnået ved konstellationen af flere nanosatellitter (>100), der muliggør hyppige opdateringer af kortlægningsprodukterne og åbner en interessant vej for forbådet kortlægning af træarter ud fra deres fænotypiske profil vurderet ud fra eksempelvis udspringstidspunkter.
4.4 Fremtidsperspektiver for skovareal og ressourcekortlægning

Skovinformation indsamles på mange niveauer og til mange formål. Typisk udføres stikprøvebaserede nationale skovopgørelser for at levere statistikker på nationalt og internationalt plan. De nationale opgørelser er således udført med henblik på at opfylde disse mål med tilstrækkelig nøjagtighed og til en rimelig pris. Det er derfor almindeligt at anvende stikprøvedesign med mindre end ét prøveområde pr. kvadratkilometer. På ejendomsniveau er der modsat behov for rumligt eksplicitte skovdata for at støtte skovejere i deres strategiske planlægning samt i kortsigtet beslutningstagning og planlægning af skovforvaltning. Derfor er det sampling-design, der anvendes i opgørelserne på ejendomsniveau, almindeligtvis langt mere detaljeret end de nationale skovopgørelser og er almindeligt fokuseret på de modne og derfor værdifulde skovbevoksninger af betydning for skovejeren.


Skovressourcekortene er ikke kun af betydning for lokal skovforvaltning og -planlægning, men kan bidrage til at forbedre præcision og nøjagtighed af nationale og regionale estimater af skovressourcerne. Modelassisterede (MA) og modelkalibrerede (MC) estimatorer har vist sig at muliggøre en reduktion i standardfejlen på estimaterne for skovbiomassen med henholdsvis 44 og 41%. Gevinsten i præcision svarer til en forøgelse af stikprøvestørrelsen i den nationale skovstatistik med måling af næsten tre gange så mange prøveprøveflader som i dag. Dette er af særlig interesse i forhold til beregningen af skovenes kulstoflagre i forbindelse med rapporteringen af klimagas-emissioner. Rapporteringen anvender årlige forskelle i skovenes kulstoflagre til at måle emissioner fra skove. Da den årlige ændring i skovenes kulstofpuljer er lille sammenlignet med de meget store lagre, medfører selv små usikkerheder i estimaterne for lagrene stor usikkerhed i beregningen af emissionerne. Derfor vil reduktioner af usikkerheder i det omfang, der observeres for modelstøttede og modelkalibrerede estimatorer, i vid udstrækning forbedre sikkerheden ved emissionsrapportering. Sådanne gevinsten afhænger dog i sidste ende af regelmæssig, nøjagtig og konsistent opdatering af skov- og skovressourcekortene, som det fremgår af denne rapport. Således har dette pilotprojekt alene en værdi i det omfang at kortlægningen gentages fremover.
5 Introduction

Forest ecosystems provide a variety of goods and services to society, including timber and other materials for industry, conservation of biodiversity, carbon storage and sequestration, clean ground water, and recreational opportunities (Angelstam et al., 2022). In particular, the role of forests in biodiversity conservation and climate change mitigation have gained increasing international focus in recent years.

Competing objectives for the forest resource along with a growing demand for wood products and green biomass for energy exerts a mounting pressure on the forest resource. Simultaneous with these increasing demands there has been a desire to halt the loss of biodiversity imposed by deforestation and degradation of forest habitats, leading to the adaptation of multilateral conservation strategies such as the Aichi Targets (CBD, 2010) and the New York Declaration on Forest (NYDF, 2015) as well as the implementation of national actions (Miljøministeriet, 2021). Managing forests according to these multiple objectives and competing demands is a complex task and calls for sound data on the forest resource in adequate spatial and temporal resolution.

Quantifying important biophysical attributes through forest inventory remains a key element in effective and sustainable forest management and planning, as knowledge of the forest resource such as tree properties, forest structure, composition, and growth form the basis of forestry related decision-making on the operational, tactical, and strategic level (Bettinger et al., 2017). Beside the local inventories on estate level, national forest inventories (NFIs) enable strategic considerations regarding the forest resources and policy development at the national level, while estimates are reported internationally in the context of, e.g. Forest Europe (Forest Europe, 2020), the Global Forest Resources Assessment (FAO, 2020), and The United Nations Framework Convention on Climate Change (UN General Assembly, 1994). Depending on the

FOREST DEFINITION (FAO, 2020)

Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.

The definition includes:

- areas with young trees that have not yet reached but which are expected to reach the height and crown cover criteria,
- areas that are temporarily unstocked due to clear-cutting as part of a forest management practice or natural disasters,
- forest roads, firebreaks, and other small open areas,
- windbreaks, shelterbelts, and corridors of trees that meet the above criteria, and
- rubberwood, cork oak and Christmas tree plantations.
inventory objectives, information of interest includes forest tree species, tree size, growing stock, biomass, and forest cover along with more complex measures such as timber quality, carbon balance, mapping of key habitats, and registration of biodiversity indicators.

Traditionally, forest inventories have been carried out as field-surveys, collecting data by sampling or complete inventory, depending on the required precision (Gschwantner et al., 2022). Field inventory campaigns are however time consuming and expensive and the application of remotely sensed data, especially aerial photography, has long assisted the process of stand delineation and stratification (McRoberts et al., 2010). However, in recent decades, the possibility to map forests and forest resources has increased dramatically due to improvements in temporal, spatial, spectral, and radiometric resolution of remotely sensed data, the combination of multiple sensor systems, increasing processing capacity, as well as advances in areas of statistical learning. A prominent feature of recent advances in classification is the fusion of multi-sensor data (Wolter and Townsend, 2011; Lu et al., 2017; Fortin et al., 2020). Different sensors vary in terms of spatial and temporal resolution as well as in the properties of data collected. Combining different sensors have been shown to overcome shortcomings of individual sensors, providing improved classification results (Poortinga et al., 2019).

A vast number of studies have used fusing of various sources of earth observation data for different aspects of land use and land cover classification (Zhang, 2010; Mahyoub et al., 2019). In an analysis including 32 studies reviewing the advantages of fusing optical and radar data for land use analysis, the vast majority concluded that the fusion of RS data improved forest classification compared to using a single source (Joshi et al., 2016). Fusion of data from different sensor systems may provide means to characterize other elements of the forest environment. For example, combining multispectral images containing specific reflectance attributes of plants and LiDAR data providing understanding of structural canopy properties may be used for characterizing forest habitats (Asner et al., 2015; Dutta et al., 2017; Martin et al., 2018), while the combination of SAR and LiDAR may yield accurate estimates of biophysical quantities, such as biomass (Treuhaft et al., 2004).

Adding a temporal dimension, fusion of multi-temporal acquisitions remote sensing data provide opportunities to detect changes in for example forest cover over time (Brovelli et al., 2020). However, in the nemoral forest zone, multi-temporal data may further detect seasonal variation in spectral signature and radiometric backscatter specific to e.g., individual tree species or forest types. With a common denominator of detecting seasonal changes in spectral signatures, several studies have used multi-temporal data for mapping forest types, growing stocks, and habitats (Guyot et al., 1989; Ahern et al., 1993; Pulliainen et al., 1999; Sharma et al., 2005; Santoro et al., 2009). However, until recently, factors unrelated to forest properties such as weather and ground conditions caused anomalies in annual signal variations, inhibiting applications such as land cover typing (Dostálová et al., 2018).

The recent advances in forest classification and mensuration have resulted in significant increase in the precision and accuracy of estimates and increased the range of properties that may be assessed and measured from earth observation. More importantly, resulting mapping products have gained a quality that allows them to be readily implemented in forest planning systems and aid future sustainable forest
management planning, bridging the gap between national forest inventories and local knowledge of the forest ecosystem (Kangas et al., 2018b). Furthermore, the mapping products may be employed as auxiliary data to improve national and regional estimates of e.g. growing and carbon stocks (Magnussen et al., 2018; Breidenbach et al., 2020), aiding climate and ecosystem reporting and policy development. However, in all cases, successful implementation of the mapping products in commercial forest planning and government support systems, requires reliable and consistent updates over time.

Previous efforts on remote sensing and mapping of forest and forest resources in Denmark (e.g. Nord-Larsen and Riis-Nielsen, 2010; Nord-Larsen and Schumacher, 2012; Bjerreskov et al., 2021) may be characterized as individual research projects, which due to inconsistency of methods applied and the time between individual campaigns have not been generally implemented in practical applications. Hence, when aiming to gain from recent scientific advances of remote sensing in relation to climate change mitigation, sustainable forest management, and the green transition of society there is a need to 1) develop consistent methods 2) for assessing a relevant set of indicators, 3) applied and disseminated at a suitable rate 4) over a considerable time.

5.1 Scope

The scope of the project on mapping forest resources is to make a pilot project for establishing system for reliable, consistent, and timely wall-to-wall mapping of the Danish forests and their resources. The project will support 1) monitoring and documentation of afforestation 2) climate reporting for the LULUCF-sector to EU and UN, 3) analyses of forest development, 4) private and public forest management, and 5) the green transition of the forest sector. The mapping will further support the national and international reporting e.g. related to the EU biodiversity and forest strategies. Underlying this scope is an expectation that the mapping procedures will subsequently be implemented in consistent annual updates of the forest and forest resource maps to aid future sustainable forest management and the green transition of society.
6 Data for forest classification and forest resource assessment

6.1 National forest inventory data

Currently, Danish forest statistics are produced and reported mainly from the Danish National Forest Inventory (DNFI) (Nord-Larsen and Johannsen, 2016; Nord-Larsen et al., 2020). The DNFI represents a large and multifaceted source of information of the forest environment. Moreover, most remote sensing classification efforts are based on supervised machine learning which relies on labelled training data, unlike unsupervised learning processes that rely only on unlabelled or raw data. In this context, the DNFI represents a large source of labelled data, which has previously been extensively used in remote sensing studies (Nord-Larsen and Riis-Nielsen, 2010; Nord-Larsen and Schumacher, 2012; Schumacher and Nord-Larsen, 2014; Kangas et al., 2018b; Breidenbach et al., 2020; Bjerreskov et al., 2021).

The DNFI 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 (Nord-Larsen and Johannsen, 2016). Approximately one-third of the plots are permanent and are re-measured in every cycle of the DNFI, whereas two-thirds are temporary and are moved randomly within the 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 (Figure 6.1). Based on an analysis of aerial photos, each sample plot (secondary sampling unit, SSU) is assigned to 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 clusters with one or more sample plots in the last two categories are inventoried in the field.

Each circular plot (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).

Figure 6.1. NFI sample design. Top image: 2 x 2 km grid covering all the county. Bottom: clusters of four sample plots in a 200 x 200 m square within each grid cell.
**Field measurements**

NFI field measurements are described in the field manual (Alban et al., 2019). 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, measurements include delineation of different land use (e.g. forest or agricultural land), stem diameter at breast height, individual tree height, crown cover, mean stand height, and the height of individual canopy layers.

Each plot is composed of three concentric circles with radii of 3.5, 10, and 15 m. 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 occurrence 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. Furthermore, of relevance to this study, a number of stand level forest properties are registered including crown cover, mean stand height, and the height of individual canopy layers.

**Preparing NFI data**

The NFI data structure is described in the appendix (11.1 NFI data structure) and the description of individual data tables may be found in Riis-Nielsen (2016).

Forest canopy height is calculated as the maximum height measured on sample trees (Tables DOMTREE, SAMPTREE) within the SSU, including height measurements of regeneration (Table TSUREGEN). 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 (Tables TSULAYER).

Individual tree volume and biomass is estimated, using the standard models of the Danish NFI (Nord-Larsen and Johannsen, 2016). The basal area, volume, and biomass of each tree is scaled according to the concentric circle in which it was measured (i.e. divided by 38.5 m² (dbh<10 cm), 314.2 m² (40 cm>dbh>10 cm), or 706.9 m² (dbh>40 cm)) (Tables TSUBORDER, TSUTREE). Subsequently, plot level estimates are 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 (Table TSUCROWN). Crown cover of TSU’s with other landuse than forest (e.g. agricultural land, roads etc.) is assumed to be 0.

6.2 Aerial images

The Danish Agency for Data Supply and Infrastructure has been responsible for the recording of aerial photos for many years and therefore has an extensive collection of photos dating back to 1945. Today, aerial photographs are produced in the GeoDanmark collaboration with the country's municipalities. The aerial photos are used for the production of GeoDanmark vector data as well as for the production of orthophotos. Both products form the basis for public case processing and are exhibited as free data via the data distributor.

Orthophotos are aerial photos in which each pixel is adjusted according to the camera's position and the terrain height model of the earth’s surface. In this way, the orthophoto produced is angle- and dimensionally fixed at the terrain level. Thus, distances at the terrain can be measured in the images, just as you can in a map with a fixed scale. In relation to this project, we discussed the possibility to use true orthophotos to improve the delineation of individual tree crowns, where the correction is made with a surface model, but this was not possible within this project.

The aerial images are procured in the spring before flushing, typically from March 8 to May 1. They are recorded with a longitudinal overlap of 60% and a side overlap of 20%. This ensures a high accuracy so that the images can be used to produce orthophotos and for updating Geodanmark_vektor. The photos are obtained from external operators. For this purpose, Denmark is divided into 53 geographical blocks, which typically are divided into 5 areas, each assigned to an external photo company. In even years, the spring orthofotos are supplemented by summer orthofotos with similar properties.

By default, the images are captured at 15 cm Ground Sample Distance (GSD), after which the orthophoto is resampled to the pixel size of 12.5 cm. However, municipalities can instead choose to have images recorded in 10 cm GSD, which is produced for orthophoto in the pixel size 10.0 cm. Orthophotos are produced as 4-channel, 32 bit RGB/NIR, the projection UTM32_ETRS89, DVR90 (EPSG: 25832). The orthophoto’s produced by GeoDanmark are further processed in terms of colors, contrast, and lighting conditions, among other things to remove visible transitions between the individual images.
6.3 Sentinel images

Copernicus is a European initiative for the implementation of information services dealing with environment and security. It is based on observation data received from Earth Observation satellites and ground-based information. Of special interest to the mapping of forests and forest resources are the Sentinel 1 and 2 missions, obtaining Synthetic Aperture Radar (SAR) and optical images, respectively.

**Sentinel 1**

The Sentinel-1 mission is the European Radar Observatory for the Copernicus joint initiative. The mission is composed of a constellation of two satellites, Sentinel-1A and Sentinel-1B, sharing the same orbital plane. Synthetic Aperture Radar (SAR) has the advantage of operating at wavelengths not impeded by cloud cover or a lack of illumination and can acquire data over a site during day or night-time under all weather conditions.

The Sentinel-1 mission includes C-band imaging operating in four exclusive imaging modes with different resolution (down to 5 m) and coverage (up to 400 km). It provides dual polarisation capability and a revisit time of only 6 days. However, the effective repeat cycles are shorter in Denmark due to partial scene overlaps.

**Sentinel 2**

The Copernicus Sentinel-2 mission comprises a constellation of two polar-orbiting satellites placed in the same sun-synchronous orbit, phased at 180° to each other. It aims at monitoring variability in land surface conditions. The wide swath width (290 km) and high revisit time of 10 days at the equator with one satellite, and 5 days with 2 satellites under cloud-free conditions results in 2-3 days at mid-latitudes (5 days in Denmark and effective repeat cycles are shorter in Denmark due to partial scene overlaps) supporting monitoring of Earth’s surface changes.
Sentinel-2 carries an optical instrument payload that samples 13 spectral bands: four bands at 10 m, six bands at 20 m and three bands at 60 m spatial resolution (Table 6.1). Some bands are no longer in service, and thus were omitted from the sentinel forest classification procedure. These can be seen in Table 6.1. The orbital swath width is 290 km.

Table 6.1. Data for forest classification and forest resource assessment. Spectral bands for the SENTINEL-2 sensors (S2A & S2B). ** indicates bands that are no longer in operation, and therefore were omitted from the sentinel forest classifications.

<table>
<thead>
<tr>
<th>S2A Band Number</th>
<th>Central wavelength (nm)</th>
<th>Bandwidth (nm)</th>
<th>S2B Central wavelength (nm)</th>
<th>Bandwidth (nm)</th>
<th>Spatial resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1**</td>
<td>442.7</td>
<td>20</td>
<td>442.3</td>
<td>20</td>
<td>60</td>
</tr>
<tr>
<td>2</td>
<td>492.7</td>
<td>65</td>
<td>492.3</td>
<td>65</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>559.8</td>
<td>35</td>
<td>558.9</td>
<td>35</td>
<td>10</td>
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<td>4</td>
<td>664.6</td>
<td>30</td>
<td>664.9</td>
<td>31</td>
<td>10</td>
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<tr>
<td>5</td>
<td>704.1</td>
<td>14</td>
<td>703.8</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>740.5</td>
<td>14</td>
<td>739.1</td>
<td>13</td>
<td>20</td>
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<tr>
<td>7</td>
<td>782.8</td>
<td>19</td>
<td>779.7</td>
<td>19</td>
<td>20</td>
</tr>
<tr>
<td>8</td>
<td>832.8</td>
<td>105</td>
<td>832.9</td>
<td>104</td>
<td>10</td>
</tr>
<tr>
<td>8a</td>
<td>864.7</td>
<td>21</td>
<td>864.0</td>
<td>21</td>
<td>20</td>
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<tr>
<td>9**</td>
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<td>19</td>
<td>943.2</td>
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<td>10**</td>
<td>1373.5</td>
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<td>1376.9</td>
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<tr>
<td>11</td>
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<td>94</td>
<td>20</td>
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<tr>
<td>12</td>
<td>2202.4</td>
<td>174</td>
<td>2185.7</td>
<td>184</td>
<td>20</td>
</tr>
</tbody>
</table>
6.4 PlanetScope data

Companies such as Planet Labs (based in Inc., San Francisco, CA, USA) have been revolutionizing Earth observation by developing miniature satellites, that can be produced and launched much faster than traditional satellites (Frazier and Hemingway, 2021). The satellites are small (approximately the size of a loaf of bread) allowing them to be rapidly and easily built and launched as part of other deployments as a secondary payload. As a result, such miniature satellites are emerging as a key resource for Earth imaging.

The Planet Scope constellation currently includes three generations of satellites (called “doves”) relevant to remote sensing: Dove Classic, Dove-R, and SuperDoves. Each generation comprises multiple groups of satellites launched and placed into similar orbit around the same time. All satellites are in sun-synchronous orbit at 475 km, a 98-degree inclination, and capture data ±81.5°, depending on the season.

The first flocks of Dove Classic satellites were launched in 2016, with a payload that included a 4-band (RGB-NIR) ‘PS2’ sensor. These satellites were launched primarily from the International Space Station (ISS) into an orbit at 375 km with a 52-degree inclination. Therefore, coverage during the demonstration period includes gaps.

In 2018, a second generation of sensors with improved spectral characteristics, known as Dove-R, were added to the constellation. Like the Dove classic, the PS2.SD sensors carried onboard the Dove-R platforms has a 4-band (RGB-NIR) spectral resolution, but band separation and definition was improved.

In 2019, a third generation of sensors, SuperDoves, were launched. The SuperDoves carry a new generation PSB.SD sensor, which can capture eight bands including Blue, Green II, Red, NIR, Coastal Blue, Green, Yellow, and Red-Edge. The first four bands are generally compatible with those of the former PS2.SD sensor.

For all products, the spatial resolution is around 3 m and images are provided in 12-bit (digital number) and 16-bit (radiance). All PS products undergo some level of geometric correction by Planet, which varies by processing level. Post-correction positional accuracies are officially reported as less than 10 m root mean square error at the 90th percentile, which can mean considerable image-to-image pixel shifts in comparison to other spatially referenced data.
Planet images combine advantages of very high spatial resolution commonly associated with aerial or commercial satellite images, allowing to map trees outside forests and exact forest boundaries, with low costs, low data processing demands, and high availability at multiple time-scales. The high temporal resolution allows to create large scale, cloud-free mosaics for narrow time windows. Planet images are low cost but not free of charge. The University of Copenhagen has a license allowing the almost unlimited download of images in the coming years.

6.5 Airborne laser scanning data (ALS)

Light Detection and Ranging (LiDAR or commonly laser scanning) is a remote sensing technique that uses light in the form of a pulsed laser to measure ranges. Airborne Laser Scanning (ALS) data is collected by emitting near infrared beams of light from an aircraft towards the ground. Upon hitting solid objects, the beams are reflected back to a sensor on the aircraft. Elevation data are subsequently calculated by measuring the time required for the light to travel to the object surface and back to the sensor, knowing the position of the aircraft and the angle of the emitted pulse. The resulting data is referred to as a “point cloud”.

The scanner may record return signals from multiple surfaces hit by the individual beam (e.g. from different branches and the ground). In early studies the scanners typically recorded the first and last return signal from the scanner (Næsset, 2004b, a; Næsset et al., 2004) but more recently the scanners may record 5-10 return signals or even the full waveform of return energy from the emitted pulse. The more return signals that are recorded e.g. when passing over a forested area, the more dense a point cloud is produced and a more detailed picture of the canopy structure is obtained.

In Denmark, airborne laser scanning was first performed in 2006-07 (Table 6.2), covering the entire area mainly during leaf-off conditions. Scanning during leaf off conditions is commonly preferred since the better penetration of tree crowns increase precision and coverage of the terrain model. In relation to forest and forest resource assessment, leaf off conditions is also generally preferred providing a better profile of the crown layer density and hence also better understanding of forest growing stocks.

The wall-to-wall scanning was repeated in 2014-15 with improved settings in terms of scanning height, pulse frequency, and hence also point density (Nord-Larsen et al., 2017). Furthermore, this scanning captured the four first returns and the last, potentially adding to the above ground point density. The
scanning was mainly conducted during leaf-off conditions, but parts were captured after flushing in the spring and before shedding of leaves in the fall (Nord-Larsen et al., 2017).

In 2018, 2019, 2020, 2021, and 2022, the scanning was again repeated each of the scanning’s covering one fifth of the country area. The scans were carried out during leaf-off conditions. It is at present unknown if the intention is to repeat the partial scanning of the country each year hereafter.

Table 6.2. Details on different scanning campaigns.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<td>Fixed wing</td>
<td>Fixed wing</td>
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<tr>
<td></td>
<td>Optech 3100</td>
<td>Riegel LMS-680i</td>
<td>Rieg VQ780i</td>
<td>Rieg VQ780i / Rieg VQ1560i</td>
<td>Rieg VQ780i / Rieg VQ1560i</td>
<td>Rieg VQ780ii / Rieg VQ780ii</td>
<td>Rieg VQ780iiS</td>
</tr>
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<td>Wall-to-wall</td>
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<td>1/5 of country</td>
<td>1/5 of country</td>
<td>1/5 of country</td>
<td>1/5 of country</td>
</tr>
<tr>
<td>Flight specifications</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Flying height (m AGL)</td>
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<td>680</td>
<td>800</td>
<td>800-1000</td>
<td>800</td>
<td>800</td>
<td>1000</td>
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<tr>
<td>Flying speed (kts)</td>
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<td>130-140</td>
<td>130</td>
<td>130</td>
<td>130</td>
<td>140</td>
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<td>30% (wrt 60 degrees FOV)</td>
<td>30% (wrt 60 degrees FOV)</td>
<td>30% (wrt 60 degrees FOV)</td>
<td>30% (wrt 60 degrees FOV)</td>
<td>30% (wrt 60 degrees FOV)</td>
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<td>LiDAR Scan angle (degrees)</td>
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<tr>
<td>Vertical accuracy</td>
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<td>0.1 m</td>
<td>0.1 m</td>
<td>0.1 m</td>
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</table>
7 Forest area mapping

In relation to the ForestPlan project, we explored three principally different approaches to forest classification and forest area mapping: 1) a segmentation-based method in which individual tree crowns are identified from aerial images and joined to represent the forest area, 2) a segmentation-based approach in which the canopy area is identified from high resolution PlanetScope satellite images using deep learning, and 3) an area-based approach in which individual pixels in medium resolution satellite images from the Copernicus programme are classified using a decision tree-based ensemble classifier.

7.1 Object-based forest area mapping with aerial images

Satellite-based monitoring of forests enables low-cost (Turner et al., 2015) and wall-to-wall assessments that can be rapidly repeated at a high temporal frequency and a large scale. Yet these assessments are typically limited to the variable “forest cover” (Hansen et al., 2013; EEA, 2018). This variable has a long tradition in forest monitoring but has little use from a management perspective. Moreover, forest biomass estimations based on “cover” information and spatially aggregated height or volume proxies ignore the diversity of trees, i.e., the fact that trees generally have different height and crown sizes, leading to highly uncertain carbon stock estimations (Santoro et al., 2021). Forest cover also ignores trees outside forests, which can constitute a considerable woody resource and provide a variety of ecosystem services (Schnell et al., 2014; Skole et al., 2021). Finally, the provisioning of ecosystem services, such as forest resources and habitats as well as climate change mitigation and adaptation, is closely related to the distribution and size of individual trees, which are difficult to measure by traditional optical satellite systems.

Mapping individual tree crowns has been made feasible owing to the high quality and ultra-high resolution of the latest remote sensing data. Several studies applied Gaussian edge detection and watershed segmentation-based approaches using high-resolution aerial images (Wang et al., 2004; Jing et al., 2012; Yun et al., 2021). Machine learning methods such as random forest have also been used frequently for similar studies (Yu et al., 2010; Yu et al., 2011; Maschler et al., 2018). More advanced, yet challenging techniques, involves tree crown delineation directly from airborne LiDAR data (Zhen et al., 2016; Chen et al., 2021).

Ultra-high resolution summer aerial imagery is available annually for Denmark. Identifying single tree crowns from these images is not difficult for the human eye, and deep learning methods have achieved great success in solving similar problems. Here, we present an automatic and scalable airborne tree mapping approach based on state-of-the-art convolutional neural networks (Ronneberger et al., 2015; Oktay et al., 2018). We define trees as woody plants with shadow and visible from an aerial view, which exclude understory trees.

In relation to the ForestPlan project, the method allows for detection and analysis of trees growing in diverse landscapes including dense forests, open fields, and urban areas. Subsequent aggregation of tree crowns allows for accurate estimates of forest area according to international forest definitions at larger scale, while providing additional information on trees outside the forest. We expect this framework to
meet multiple demands for differentiated knowledge on forests as well as individual trees, becoming an important complement to inventories supporting forest management and policy planning.

**Materials and methods**

Developing a deep learning model requires input data and the corresponding reference or target data. As input data, we used aerial images (RGB + NIR (near-infrared) + NDVI (normalized difference vegetation index)) at 20 cm resolution acquired during summer 2018 and a canopy height map projected from airborne LiDAR data at 40 cm resolution. On 75 variable size plots across Denmark, we manually delineated a total of 24,466 individual tree crowns distributed over Denmark, among which 19,771 crowns (49% in dense deciduous forests, 30% in dense coniferous forests, and 21% in non-forest areas) were assigned to the training dataset, 2,016 crowns (46% in dense deciduous forests, 38% in dense coniferous forests, and 15% in non-forest areas) to the validation dataset, and 2,679 crowns (48% in dense deciduous forests, 32% in dense coniferous forests, and 20% in non-forest areas) to the final test dataset.

The deep learning-based model was adapted from the U-Net architecture (Ronneberger et al., 2015) and was trained on the target references, i.e. the labelled tree crowns (Figure 7.1). The output produced was evaluated against two types of test data, one being manual delineations of tree crowns that the model never visited during training (for 2018 results), and another being the NFI field plot data (for 2018 and 2020 results).

The model trained on the 2018 aerial images was applied to both the 2018 and 2020 summer aerial images to form country-wide tree cover maps that were subsequently used for forest delineation. During the preliminary testing of the model, we noted large differences in the identification of tree crowns between the 2018 and 2020 datasets, owing to differences in the NDVI values caused by different normalization of the near infrared band. We therefore opted to produce 2020 results using a model solely trained with RGB+NIR data from 2018, i.e., without NDVI and height map, which was less prone to such differences.

![Figure 7.1. Overview of the deep learning model for individual tree crown segmentation.](image-url)
Results

The model was evaluated against an independent test dataset with 2,679 delineated tree crowns collected in randomly sampled plots distributed all over Denmark. Three major types of landscapes were included in the evaluation set (EEA, 2018), including high-density deciduous forests, high-density coniferous forests, and open fields (non-forest) involving trees outside forest in hedgerows and small patches. The F1-score was 0.77 globally (0.80 for deciduous trees, 0.76 for coniferous trees, and 0.74 for non-forest trees). The tree counting performance was relatively high, with a coefficient of determination (or R²) score of 0.93 and a relative mean absolute error (MAE) of 16.0% (MAE = 35 trees/ha, relative bias = 10.3%). The model underestimated the crown area by approximately 20% (Figure 7.2c), which was likely caused by the separation of individual trees. For country-wide applications, we corrected for this underestimation by rescaling the predicted crown area according to the fitting curves. Note that the above evaluation was only done for the 2018 results, as a similar analysis for the 2020 would require additional labelling of tree crowns from the 2020 aerial images.

Figure 7.2. Independent evaluation of individual tree crown segmentation against manually delineated tree crown reference. a) Examples for three major landscape/forest types. The manual crown delineations are shown in thin blue lines and our predictions are shown in gray-blue color. b) Comparison between predicted tree counts and reference tree counts. c) Comparision between predicted individual tree crown areas and reference areas.

The model was further evaluated for tree counts obtained from 2018 aerial data against 914 field plots from the 2018 Danish NFI. The relative bias (Relative bias = \[ \frac{1}{N} \sum_{i=1}^{N} \frac{\text{prediction} - \text{actual}}{\text{actual}} \]) was 10.7% for all plots. For deciduous forest plots (plots with more than 75% deciduous tree cover, 370 plots), the bias was
higher (18.2%), while for coniferous forest plots (plots with more than 75% conifer tree cover, 436 plots) and mixed broadleaved and coniferous forest plots (plots that are not deciduous or coniferous, 92 plots), the bias was lower (3.2% and 0.3%, respectively). Note that small trees were not systematically counted on the field within these plots, so above numbers quantified the errors for larger trees. To evaluate our underestimation of small trees, we used additional plot data that included estimates of small trees numbers counted in the inner circle of the plot (3.5 m radius for trees with dbh< 10 cm and 10 m radius for trees with dbh< 40 cm) and extrapolated to the entire plot, assuming an even distribution of the stems.

Comparing our predicted tree counts with the extrapolated tree counts from the NFI, the bias was higher (44.7%, Figure 7.3a). We observed that biases tended to decrease as more large trees (dbh >10 cm) dominated the plot (Figure 7.3b), implying a potentially large underprediction of small trees, which were largely outshaded by tall trees. This was confirmed by the size distribution shown in Figure 7.3c, where the number of detected trees dropped for trees smaller 6 m, while an increase would be expected, as seen in the NFI counts.

Figure 7.3. Independent evaluation of individual tree crown segmentation against NFI plot data. a. Relative bias for tree counts, evaluated for 2018 and 2020 respectively. The first two bars represent relative bias against all measured trees from the NFI, and the last two bars represent relative bias against total tree count estimates from NFI by extrapolating smaller trees not measured on the field. b. Relative bias plotted against the large tree fraction in each field plot. Here, the large tree fraction refers to the
proportion of large trees (dbh > 10 cm) relative to the total number of trees in each plot (extrapolated). c. Comparison of total forest tree counts in Denmark (2018) distributed to 2 m height classes. d. Examples of plots with low bias (<30%). e. Examples of plots with high bias, reflecting model uncertainties and limitations.

Additionally, we evaluated the tree counts obtained from the 2020 aerial data against 1101 field plots from the 2020 NFI. The bias was 20.8% for all plots (Figure 7.3a). The bias was 24.5% for plots with deciduous trees (523 plots), 22.7% for plots with coniferous trees (434 plots), and 27.4% for mixed type (129 plots). When comparing our tree counts with the extrapolated tree counts from NFI (explained above), the bias was much higher (62.0%, Figure 7.3a). Similarly, as the 2018 evaluation against NFI, we noticed a decreasing tendency of bias as more large trees (dbh > 10 cm) dominated the plot (Figure 7.3b). Though higher biases were noted consistently in the 2020 results compared with the 2018 results.

The plot-level comparison against the NFI data across various landscapes reflected robustness or limitations of our framework in different scenarios. The biases tended to be low for trees with rather clear crown structures (Figure 7.3d). Meanwhile, we noticed severe biases for meadows with tree-like structures, sparse and tall trees with highly inclined shadows, trees with ambiguous or multiple branches, exceedingly dense forest with no crown gaps, or trees with tiny crowns (Figure 7.3e).

We applied the model to aerial images captured in 2018 and 2020 and produced country-wide tree cover maps featured with tree counts for both years (Figure 7.4). In 2018, a total of 312 million overstorey trees were detected with a total crown area of 0.47 million hectares (Table 7.1). The results revealed a surprisingly large number of non-forest trees (91 million), which represents around 30% of the national tree crown coverage. Compared with the NFI forest tree count from 2018 (Nord-Larsen et al., 2020), which upscaled field measured plot information to nation-wide forest areas, our predictions showed an underestimation of 68.8%. Note that 89.4% of tree counts from NFI estimates belonged to the 10 cm diameter class, which was likely to be missed out from this method. In 2020, a total of 271 million trees were detected with a total crown area of 0.41 million hectare (Table 7.2) and 69 million trees were found in non-forest areas, which contributes to 30% of national tree crown coverage. Compared with the NFI forest tree counts from 2020 (Nord-Larsen et al., 2021), the bias was 73.3%. Note that 89.3% of the NFI count estimates belonged to the 0-20 cm diameter class. The rather high biases against NFI tree counts can be partly explained by the fact that small trees or understory in dense forests cannot be seen in aerial or satellite images (Melin et al., 2017).
Figure 7.4. Examples of tree crown segmentation, coloured by heights.

Table 7.1. Tree count and total crown area predictions for Denmark in 2018, grouped in three major forest/landscape types.

<table>
<thead>
<tr>
<th>Forest/Landscape type</th>
<th>Tree count</th>
<th>Tree crown area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deciduous Forest</td>
<td>136,467,589 (43.7%)</td>
<td>233,720 (50.0%)</td>
</tr>
<tr>
<td>Coniferous Forest</td>
<td>85,023,211 (29.1%)</td>
<td>92,352 (19.8%)</td>
</tr>
<tr>
<td>Non-forest</td>
<td>91,014,130 (27.2%)</td>
<td>141,186 (30.2%)</td>
</tr>
<tr>
<td>Total</td>
<td>312,504,930 (100%)</td>
<td>467,257 (100%)</td>
</tr>
</tbody>
</table>
Table 7.2. Tree count and total crown area predictions for Denmark in 2020, grouped in three major forest/landscape types.

<table>
<thead>
<tr>
<th>Forest/Landscape type</th>
<th>Tree count</th>
<th>Tree crown area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deciduous Forest</td>
<td>117,846,612 (43.4%)</td>
<td>207,287 (50.7%)</td>
</tr>
<tr>
<td>Coniferous Forest</td>
<td>84,707,198 (31.2%)</td>
<td>79,781 (19.5%)</td>
</tr>
<tr>
<td>Non-forest</td>
<td>68,641,486 (25.3%)</td>
<td>121,555 (29.7%)</td>
</tr>
<tr>
<td>Total</td>
<td>271,411,031 (100%)</td>
<td>408,623 (100%)</td>
</tr>
</tbody>
</table>

Discussion

We established a novel, end-to-end deep learning-based model for individual overstory tree mapping in forest and non-forest areas from high-resolution aerial images. We propose such an individual tree localization and characterization approach as the means to produce a comprehensive tree database that concerns not only forest but also non-forest trees, which are essential yet often neglected by the conventional forest inventories (Schnell et al., 2015). Such a tool may serve as the new standard for supporting local or national forest management. A database on individual trees could serve as a digital twin of global forests, where each tree could be traced, for example, from the forest to the factory. Such detailed information would allow more sophisticated and attentive utilization of the wood material as wood properties are influenced by the local growing conditions, leading towards resource efficiency and sustainable utilization of forests.

The resulting individual tree crown map reflect the vegetation structure more accurately than existing forest cover maps, and the products can be intuitively interpreted and validated by the human eye. Our method unambiguously determined trees as objects, whilst other well-known methods estimate the percentage canopy cover from spectral colours at relatively coarse resolution (10 - 30 m) (Hansen et al., 2013; EEA, 2018).

The localization of individual trees is particularly important for the monitoring of tree mortality, which would not be based on plot-scale estimations, but on actual counts with wall-to-wall coverage. Moreover, carbon stocks could be reported at the level of individual trees in the frame of climate agreements. Using local or global allometric equations (Jucker et al., 2017), crown diameter and height can be directly converted to carbon stocks, so the upscaling from inventory plots would remain at the level of single trees. Going beyond areal variables and towards single tree assessments also reduces uncertainties related to forest area definitions. We found that following existing forest maps and definitions, approximately one million trees in Denmark were missed by the NFI statistics (Melin et al., 2017), as they were growing outside of forests. Note however that short trees growing under the top canopies are underestimated and NFI data needs to be used to correct for the undercount bias.

The model can be applied to aerial images from different years with comparable image quality. This allows for annual wall-to-wall airborne tree mapping with marginal efforts. Notably, the aerial images need to be taken during the leave-on seasons when the tree crowns are visible from above. Here, we tested the model preliminarily using aerial images captured from a different year (2020). Expectedly, we noticed a performance drop when the model trained using data from 2018 was directly applied to data from 2020. There are several obvious reasons behind this. Firstly, owing to the fact that aerial images captured in 2020
was not normalized in the same way as aerial images captured in 2018, we opted to apply a slightly different model for the 2020 data. Evaluated against the same test data, the model used for generating 2018 products had a counting bias of 2%, while the model used for generating 2020 products had a counting bias of 16%. Secondly, aerial images were captured using different devices and the raw data was processed differently in these two years. Through visual interpretation, we observed clear dissimilarities in pixel intensities and brightness between the images. This could challenge the robustness of the model, considering that deep learning models cannot deal with situations it has never seen. This demonstrated that meticulous quality control for consistency of images is needed. However, the model could be tuned to fit for dissimilar input images by transfer learning. Normally this can be done by continuing training the model using a small training set from the new data. Owing to time limitation, such experiments could not be finished for this study, but experiments on transferring the model to a dataset from Finland showed promising results (Li et al., 2022).

Nevertheless, individual tree crown segmentation could be subject to several uncertainties and limitations, mainly due to the manually delineated tree crown references. Firstly, we excluded small trees, shrubs, and bushes with no visible shadow or with a crown area below 0.08 m². Secondly, labelling individual trees was not always obvious, in particular for touching or overlying crowns, heavily shadowed crowns induced by non-vertical shooting angles, and the coexistence of single and multi-branched trees. Though the model reached relatively high scores for the evaluation against manual delineations, the bias was much higher compared with the field data from NFI, indicating high uncertainties and limitations particularly for the small or understory trees. Such limitations are inherent in the formulation of the problem, since small trees or understory trees are hard to identify from aerial data.

In conclusion, high-resolution aerial images and deep learning open the gate for human-interpretable tasks of various types. For instance, a model can be trained to detect forest area given examples of manually delineated forest blocks, a model can be trained to detect trees of certain species given examples of such trees, and a model can be trained to predict landscape classes given examples of different landscape types. The quality and quantity of reference labels are the crucial part of any deep learning model. The amount of training labels needed for establishing a well-performing model varies from task to task. For tasks with exhaustive details such as individual tree crown detection, a huge training dataset is required to inclusively reflect trees of various shapes standing in dissimilar landscapes. Building such a dataset took several weeks and involved a diligent search for all possible scenarios. For tasks such as detecting closed forest areas, a smaller dataset would be expected and the training data could be potentially prepared faster (days or hours), considering that the task is easier, and the labels are simpler to prepare. While for more complex tasks such as predicting tree species, a highly precise training dataset with field data and expert knowledge would be expected. In practice, developing deep learning models for country-level analysis usually requires dynamic adjustments of preliminarily trained models by adding new training samples where the model fails until it learns efficiently well.
7.2 Forest mapping with PlanetScope data

PlanetScope images combine advantages of very high spatial resolution comparable to aerial or commercial satellite images with a detail sufficient to map trees outside forests and exact forest boundaries or removal of single large trees, with advantages of low costs, low data processing demands, and high availability at multiple timescales.

Former studies have demonstrated that the high resolution obtained from the PlanetScope constellation are specifically suitable for object-based classification purposes. In a land classification study in central Brazil an overall accuracy of 67% was obtained when applying a random forest classifier in a pixel-based approach (Vizzari, 2022). Adopting an object-based approach on the same dataset resulted in a very high accuracy of 82%, underpinning the ability to distinguish individual objects of the high-resolution images. The integration of the PlanetScope data with Sentinel 2 and Sentinel 1 datasets improved overall accuracy of both the pixel-based (82 vs. 67%) and object-based (91 vs. 82%, respectively) approach.

In this study, we developed a deep learning-based framework, which uses PlanetScope images to map forests and trees outside forests at annual scale, including tree height and cover at 3 m resolution (Liu et al., 2023). The high level of detail and the inclusion of the canopy height makes it straightforward to apply the FAO definition for forests, although the method may not allow assessment of temporarily unstocked areas or resent establishment of forest able to grow taller than 5 m in situ. Maps can not only be used for an annual mapping of forests, but also urban trees and trees on farmland and grassland can be monitored and their resources quantified. The framework has a high potential to complement or replace low resolution imagery (e.g. satellite imagery) and/or ultra-high resolution imagery (e.g. aerial photo imagery) approaches in the future.

Materials and methods

For this study we used Planet Data obtained during 2019; more recent years will be added in future versions. The data comprised more than 1000 individual cloud-free, orthorectified and high-quality scenes of the format PSscene with 4 bands (NIR, red, green, blue) mixing all Dove satellites. All images are from late summer where trees still have green leaves and could be easily identified. In addition to strict filtering using the available meta-data, we tested images for sharpness using a blur kernel and rejected images with a low standard deviation of the reflectance values, as these images are often of low quality, which is not obvious from the meta-data.

To organize the large data volumes, we divided the world into a grid of 1x1 degree tiles and generated a custom mosaic of PlanetScope scenes for each tile (Figure 7.5). The creation of custom mosaics instead of available Planet basemap imagery was pivotal, as the provided basemaps are designed to maximize visualization by combining scenes from many different days, which limits the consistent detection of tree
crowns. Instead, we developed an automated algorithm to download and mosaic PlanetScope scenes based on the local phenological conditions of each grid tile.

For best visibility of tree cover, a date range was selected where both evergreen and deciduous trees were in full foliage, which is late summer in Denmark. We used the MODIS/Terra phenology product to determine the local mean days for senescence, mid-greendown, and dormancy thresholds. We also included an indicator if the majority of the tile was dominated by deciduous or evergreen vegetation; this information was derived from the Copernicus forest type map from 2018 (European Environment Agency, 2018). After filtering by date range, we then used a dynamic scene-placing algorithm to select scenes and partial scenes until the entire mosaic tile was filled. The selected scenes per tile were clipped to their partial footprints, downloaded in parallel, reprojected to WGS84 and merged into a mosaic. To reduce the sharp edges between scenes, a histogram matching algorithm was then applied using Landsat reference images. The software tools developed for the mosaic generation process were fully automated, such that with a single input of a study area analysis ready custom mosaics can be generated anywhere in the world at an annual scale.

We then used a fully convolutional neural network based on the U-Net architecture trained with LiDAR derived canopy heights sampled across Europe (10,000 1x1 km samples from Denmark, the Netherlands, Wales, Switzerland, Estonia, Finland and Spain) to predict both tree cover and tree height from PlanetScope images at 3 m resolution. We used a height threshold of 3 m for the LiDAR canopy height images and the tree cover map was a binary canopy/-no-canopy map that was used to mask vegetated areas; height was only predicted in areas classified as canopy cover.

We will contribute our network to an open access library upon acceptance of the manuscript being prepared based on our findings.

**Results**

Both tree cover and height can be predicted with a fairly high accuracy, demonstrated with thousands of 1x1 km samples from LiDAR canopy height data that was not used for training the model. The error in the canopy cover prediction based on the evaluation with LiDAR data was 3%. We also evaluated the canopy cover with NFI data on fractional forest cover, showing a good agreement (Figure 7.6). For Denmark, the RMSE of the canopy height estimation was 4 m and the MAE 2.81 m, the overall error was 8%, which is comparable to results of predicted canopy height from aerial images trained by LiDAR (see section 8.1).
Figure 7.6. Evaluation using Danish NFI data and comparison with other biomass products. a, Normalized confusion matrix comparing NFI plots (classified as forest or non-forest) with PlanetScope tree cover predictions. Here we followed the FAO forest definition using a 10% tree cover threshold combined with land use data to define if the area of the plot was predicted as forest or non-forest. b, Scatter plot between tree height recorded per NFI plot (n = 3451) and our PlanetScope predicted top height. c, Same but for biomass. Number of samples: 13,638 collected between 2018-2020 for forest (3451) and non-forest (10187) plots. We applied a 3 m height threshold and 3 Mg/ha biomass density threshold to (b) and (c).
Figure 7.7. Planet based height and cover prediction across Europe. a, Planet imagery displayed in near infrared, red and green false color composite. b, Corresponding canopy height reference from airborne LiDAR. c, Corresponding canopy height prediction from a. d, Scatter plots between average height of b and c. e, Same as d but for canopy cover percentage. Number of 1x1 km samples across Europe: 7136.

Figure 7.8. Left: PlanetScope false color composite (NIR, green, blue). Middle: airborne LiDAR canopy height at 0.5 m. Right: PlanetScope based prediction of canopy height. Note that also trees outside forests are captured and the different height structures within the forest are captured as well. Background map: Google Earth. Tree over and height can be used to upscale NFI above-ground biomass estimations to national level, including trees outside forests.

The overall tree crown area was higher as compared to results from the aerial images (Table 7.3) because gaps between tree crowns are not mapped using Planet and forest areas are mapped as canopy objects and not individual tree objects. The areas mapped as non-forest tree cover match well with the aerial photo-based approach (section 7.1 Object-based forest area mapping with aerial images).

Table 7.3. Comparison between results from aerial images and Planet images for the Danish 2018 forest area. The overall forest numbers are higher from Planet, because gaps between trees are not considered. The non-forest tree cover matches relatively well. Forest classes were derived from the Copernicus map (2018)

<table>
<thead>
<tr>
<th>Forest type</th>
<th>National forest inventory</th>
<th>Aerial images</th>
<th>Aerial images</th>
<th>PlanetScope</th>
<th>PlanetScope</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forest area (ha)</td>
<td>Tree crown area (ha)</td>
<td>Tree height (m)</td>
<td>Tree crown area (ha)</td>
<td>Tree height (m)</td>
</tr>
<tr>
<td>Deciduous</td>
<td>310,164 (49%)</td>
<td>233,720 (50%)</td>
<td>12.5 [3.6-24.8]</td>
<td>326,401 (49.3%)</td>
<td>15.3 [5-25.3]</td>
</tr>
<tr>
<td>Coniferous</td>
<td>292,317 (46%)</td>
<td>92,352 (19.8%)</td>
<td>12.9 [5.1-17.2]</td>
<td>182,800 (27.6%)</td>
<td>14.9 [5-24.8]</td>
</tr>
<tr>
<td>Non-forest</td>
<td>28,341 (4%)</td>
<td>141,186 (30.2%)</td>
<td>6.7 [0.5-17.2]</td>
<td>152,784 (23.1%)</td>
<td>9.2 [5-15.4]</td>
</tr>
<tr>
<td>Total</td>
<td>632,711 (100%)</td>
<td>467,257 (100%)</td>
<td>11.6 [2.7-23.6]</td>
<td>661,985 (100%)</td>
<td>13.8 [5-24.2]</td>
</tr>
</tbody>
</table>
**Discussion**

We developed a processing chain, including data downloading, quality filtering, mosaicking as pre-processing steps used to produce tree cover and canopy height maps at 3-m resolution. Maps are produced for all Europe, with a specific focus on Denmark. Individual trees can only reliably be identified if they are isolated and have a crown area of at least 20 m²; other trees are merged into canopy objects, which impedes the use of Planet based products for applications requiring a very high level of detail, such as tree count and crown area. However, the 3-m spatial resolution allows to recognise tree crown structures also within forests, which enables a deep learning model to learn and estimate/predict the height of canopies both for forest and non-forest trees. Both cover and height maps have a high accuracy, and the daily availability of Planet images allows for cloud free mosaics at national level and at an at least annual scale. Once the model is trained, tree cover and height can be predicted for each year, and both variables can be used to upscale NFI biomass data, that is to estimate resources of both forest and non-forest trees at national level. The high temporal combined with the high spatial resolution of PlanetScope images also opens doors to go beyond the mapping of tree cover. Phenological profiles of woody vegetation combined with visible crown structure and spectral reflectance can be used to differentiate forest types, such as coniferous and broad-leaved.

### 7.3 Area-based Forest mapping with Sentinel data

Former research has shown that high acquisition frequencies of Sentinel 1 and Sentinel 2 have provided innovative applications for multi-temporal data in forest classification. In a study conducted in Switzerland, researchers were able to run a classification for broadleaf and coniferous forests as well as a tree species classification using seasonal variations in vertical-horizontal backscatter. This yielded rather favourable results with an accuracy of 0.86 for forest type, but a slightly reduced accuracy for forest species since differences between some deciduous species were less pronounced (Rüetschi et al., 2018). Similarly, in a Danish study by Bjerreskov et al. (2021) using a random forest model coupled with sentinel data for tree type classification, they were able to achieve an accuracy of 95% and 96% for confer and deciduous forests, respectively. When they performed the random forest classification for forest cover, they attained a total classification accuracy of 98%, forest accuracy of 90%, and non-forest accuracy of 98% further supporting the likelihood for highly productive and robust forest map creation when using Sentinel-based classification methods.

For this part of the forest area mapping, we implemented a supervised classification approach that has already been highly successful in mapping forest areas within Denmark using Sentinel 1 and 2 images with NFI training data. Since these methods have already been well established, defining forest area parameters was quite simple and compared well to previous study years. While the output of these methods can easily be used for creating general forest area maps annually, mapping can also be extended to tree type and even tree species if desired making the possible future applications of this approach highly appealing.
Materials and methods

Sentinel-1 and -2 data processing were conducted using the GEE cloud computing platform (https://earthengine.google.org/), which enables parallel computing and big data handling and processing. We used all available data covering the year of 2020, from both Sentinel-1A and B as well as Sentinel-2A and 2B, achieving a global repeat cycle of six and five days, respectively.

Multispectral optical features were generated from a series of S-2 Level-2A BOA (bottom-of-atmosphere) satellite images covering the study area. The winter collection of optical images comprised a series of 1404 S-2 images acquired on 125 distinct dates between 20 December 2019 and 23 April 2020 (Figure 7.10, left), while the summer collection comprised a series of 959 S-2 images acquired on 84 distinct days between 24 May and 16 August 2020 (Figure 7.10, right).

![Figure 7.9. Cloud assessment for sentinel 2 image acquisition for winter (left) and summer (right) from google earth engine where images with cloud cover of less than 2% per pixel were selected.](image)

The normalized difference vegetation index (NDVI) was calculated for all images. Cloud-free image composites of each spectral band and the NDVI covering the entire land surface of Denmark was derived by applying a median compositing function on the winter and summer images, respectively (Figure 7.10). The median composite function removes any anomalous dark pixels (shadows) as well as bright, saturated pixels. Initially, we aimed to produce several mosaics to represent the phenological profile of different tree species, but cloud cover rendered this impossible. All bands with a resolution of 10–20 m were selected, including bands within the visible (band 2–4), near infrared (NIR, band 5–8), and short wave infrared (SWIR, band 10–12) parts of the electromagnetic spectrum. The 20 m resolution bands were resampled (nearest neighbour) to 10 m resolution.
Figure 7.10. RGB composite of winter images (20 December 2019 to 23 April 2020, left) and RBG composite of summer images (24 May 2020 to 16 August 2020, right) for all of Denmark captured using google earth engine.

To add a textural component to the image set, seven rotation-invariant Haralick texture features were calculated and added using a 3 x 3 window on the NDVI summer composite, including mean, variance, homogeneity, contrast, dissimilarity, entropy, and second moment (Figure 7.11).
SAR features were generated from a series of C-band S-1 Level-1 Ground Range Detected images with a pixel size of 10 m. The data were recorded in Interferometric wide swath mode (IW), with incidence angels between 30 and 45 degrees (both ascending and descending) and delivered in dual polarization, both vertical–vertical (VV) and vertical–horizontal (VH). The winter collection comprised a series of 582 S-1 images acquired on 125 distinct dates between 20 December 2019 to 23 April 2020, while the summer collection comprised a series of 351 S-1 images acquired on 84 distinct days between 24 May and 16 August 2020. The images in each collection (summer and winter) were mosaicked to a composite for each of the two polarizations (VV and VH) of the area of interest by applying a mean function on the winter and summer collection, respectively. Using temporal mean on the SAR data helps reduce speckle noise, which can otherwise be problematic.

Preparation of NFI data

The reference dataset was restricted to SSUs measured in the field season of 2020 to reduce the temporal span between the field measurements of the NFI and the collection of satellite data, resulting in a total of
3404 sample plots (SSU’s). Aiming for the highest possible accuracy and unwilling to include areas with newly planted trees not discovered on the aerial images, we included only plots visited in the field by NFI measurement crews.

The forest definition applied in the NFI follows the definition of FAO employed in the Global Forest Resource Assessment (FRA, 2018) as well as in the climate gas reporting (IPCC, 2006b). The definition includes areas where the vegetation has the potential of reaching the aforementioned criteria as well as temporarily unstocked areas and permanent unstocked areas designated to forest management. The adoption of land-use and potential criteria in the forest definition is problematic in the perspective of pixel-based classification of remotely sensed imagery as only the actual land cover is directly observable by the sensors. To reduce ambiguity on pixel level in the reference data a stricter definition of forest was applied aiming at reducing instances were land cover and land-use conflicts e.g. unstocked SSUs labeled as forest and SSUs only partly covered by forest. A SSU was labeled as forest if a fraction of more than 75% was characterized as forest and the estimated crown cover exceeded 10%. A SSU was labeled as non-forest if 0% of the plot was characterized as forest and the estimated crown cover equals 0%. SSUs falling between these thresholds were labelled as ambiguous and removed from the reference data (Table 7.4). For tree type classification only SSUs dominated by coniferous and broadleaved species respectively were included (Table 7.4).

Table 7.4. Distribution of plots to forest cover and species type classes. Non-forest plots have a forest fraction or crown cover of 0 percent and forest plots has a forest fraction of more than 75 percent and a canopy cover of more than 10 percent. Other plots are ambiguous regarding forest cover. Plots regarded as either broadleaved or coniferous have a more than 75 percent cover of the particular species type.

<table>
<thead>
<tr>
<th>Forest cover</th>
<th>Broadleaf</th>
<th>Conifer</th>
<th>Mixed/none</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-forest</td>
<td>0</td>
<td>0</td>
<td>1606</td>
<td>1606</td>
</tr>
<tr>
<td>Forest</td>
<td>351</td>
<td>275</td>
<td>370</td>
<td>996</td>
</tr>
<tr>
<td>Ambiguous</td>
<td>115</td>
<td>38</td>
<td>649</td>
<td>802</td>
</tr>
<tr>
<td>Total</td>
<td>466</td>
<td>313</td>
<td>2625</td>
<td>3404</td>
</tr>
</tbody>
</table>

Training and validation data

The reference data was created by stacking all 33 input layers (both optical and SAR) into one raster brick and subsequently sampling all band values from pixels with a centroid covered by a 10-meter circular buffer of every labelled SSU center coordinate resulting in a total of 7686 unambiguous pixel samples for forest classification and 1839 pixel samples for tree type classification (Table 7.5). A previous study, using the same methods and input layers showed that the most important features in predicting forest cover were the summer and winter SAR images in VH polarization (VHs and VHw) (Bjerreskov et al., 2021). Among the optical bands, the most important feature were the green band of the summer composite (B3s) and the SWIR band of the winter composite (B12w). In general, the most important features for classification of forest/non-forest were obtained from the S-1 SAR images (3 out of the 4 most important features), while textural features from the optical data were shown to have a moderate importance when classification forest vs non-forest.
Regarding classification of forest types, the previous study found all 33 input features to be significant (Bjerreskov et al., 2021). Here, the most important feature in predicting tree type was the winter NDVI image (NDVIw) followed by the SAR VH polarization summer image (VHs), and the band 11 SWIR summer image (B11s). When considering the individual types of data, the summer image was in most cases markedly more important for the classification than the winter image. Most of the textural features were less important for this type of classification.

For the training the forest classification, 80% of the observations were sampled with a stratified procedure securing the original balance between classes. The remaining 20% constituted the evaluation data (Table 7.5).

Table 7.5. Distribution of pixels within 10 m of the NFI plot centre to forest cover and species type classes. Non-forest plots have a forest fraction or crown cover of 0 percent and forest plots has a forest fraction of more than 75 percent and a canopy cover of more than 10 percent. Other plots are ambiguous regarding forest cover. Plots regarded as either broadleaved or coniferous have a more than 75 percent cover of the particular species type. Only non-ambiguous pixels were used in the forest classification.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Forest cover</th>
<th>Broadleaf</th>
<th>Conifer</th>
<th>Mixed/none</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-forest</td>
<td>0</td>
<td>0</td>
<td>3768</td>
<td>3768</td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>847</td>
<td>625</td>
<td>909</td>
<td>2381</td>
<td></td>
</tr>
<tr>
<td>Ambiguous</td>
<td>273</td>
<td>83</td>
<td>1572</td>
<td>1928</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1120</td>
<td>708</td>
<td>6249</td>
<td>8077</td>
<td></td>
</tr>
<tr>
<td>Validation</td>
<td>Non-forest</td>
<td>0</td>
<td>0</td>
<td>956</td>
<td>956</td>
</tr>
<tr>
<td>Forest</td>
<td>212</td>
<td>155</td>
<td>214</td>
<td>581</td>
<td></td>
</tr>
<tr>
<td>Ambiguous</td>
<td>73</td>
<td>22</td>
<td>386</td>
<td>481</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>285</td>
<td>177</td>
<td>1556</td>
<td>2018</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>Non-forest</td>
<td>0</td>
<td>0</td>
<td>4724</td>
<td>4724</td>
</tr>
<tr>
<td>Forest</td>
<td>1059</td>
<td>780</td>
<td>1123</td>
<td>2962</td>
<td></td>
</tr>
<tr>
<td>Ambiguous</td>
<td>346</td>
<td>105</td>
<td>1958</td>
<td>2409</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1405</td>
<td>885</td>
<td>7805</td>
<td>10095</td>
<td></td>
</tr>
</tbody>
</table>

Results

Using training data from the National Forest Inventory (NFI) coupled with calculated texture variables the forest classification from Sentinel produced similar results for the three different forest classification models at a 10 m resolution for all of Denmark (Figure 7.12).
Figure 7.12. Forest classification results of forest (green, 2) above 0.5 hectares with built-up areas removed and non-forest (beige, 1) from a) random forest model, b) support vector machine model, and c) neural network model for all of Denmark before post-processing.

The random forest ensemble classifier (RF) performed best in terms of producing a median accuracy prior to post-processing of 97% followed by 96% and 89% for the support vector machine model (SVM) and the neural networks model (NNET), respectively (Figure 7.13). Prior to post-processing the three different methods yielded similar total forest areas, which were however, much larger than the forest area provided by the Danish national forest inventory (Table 7.6), likely due to the inclusion of small patches with tree cover, not in agreement with the forest definition, and tree covered areas with non-forest land-use such as summer house areas, parks, and fruit orchards.
Figure 7.13. Accuracy and kappa scores for three forest classification models: support vector machine (SVM), neural network (NNET), and random forest (RF) for the Bornholm region.

Table 7.6. Land-cover percentage and land-cover area predictions for Denmark in 2020 for random forest, support vector machine, and neural network forest classification models before post-processing where built-up areas and forest cover < 0.5 hectares are reclassified.

<table>
<thead>
<tr>
<th>Model</th>
<th>Land-cover type</th>
<th>Land-cover percentage (%)</th>
<th>Land-cover area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>Non-forest</td>
<td>81.3</td>
<td>3,484,254</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
<td>18.7</td>
<td>803,115</td>
</tr>
<tr>
<td>Support Vector Machine</td>
<td>Non-forest</td>
<td>81.8</td>
<td>3,505,088</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
<td>18.2</td>
<td>782,189</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>Non-forest</td>
<td>81.1</td>
<td>3,476,362</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
<td>18.9</td>
<td>810,915</td>
</tr>
</tbody>
</table>

The random forest classification model was selected to classify forest by tree type (Figure 7.14) since it had the highest accuracy when classifying forest and non-forested areas. The model was trained with NFI data for coniferous, deciduous, and mixed forest plots as well as coniferous and deciduous forest only plots. When the model was trained also with mixed forest plots, it had a tendency to classify forest areas along the edges between the conifer and deciduous forest areas as mixed (Figure 7.14a, black markings). Furthermore, the error was higher for all three classes when mixed forest was included in the model training compared to the method that used only coniferous and deciduous forest training plots. Prior to post-processing, the total error for the forest type classification using all three classes was 13.3% with 7.3% for the conifer class, 5.2% for the deciduous class, and a large error of 65.7% for the mixed class. When only
the conifer and deciduous tree types were included, the total error was much lower at 5.2% with 6.6% for the conifer class and 4.0% for deciduous class. For these reasons, the random forest tree type classification with only deciduous and conifer training plots was selected as the best method for tree type classification (Figure 7.14b).

According to the mapping, 43.4 percent of the canopy cover is coniferous and 56.6 percent is broadleaved (Table 7.7). As this expectedly includes areas outside the forest definition, these figures are incomparable to the estimates obtained from the national forest statistics (Nord-Larsen et al., 2021). The maps clearly show the expected larger share of conifer forest in western Denmark compared to eastern Denmark (Figure 7.14c).

Table 7.7. Tree-type cover percentage and tree-type area predictions for 2020 estimated from the random forest model before post-processing where built-up areas and forest cover < 0.5 hectares are reclassified.

<table>
<thead>
<tr>
<th>Land-cover type</th>
<th>Land-cover percentage (%)</th>
<th>Land-cover area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conifer</td>
<td>43.4</td>
<td>345,564</td>
</tr>
<tr>
<td>Deciduous</td>
<td>56.6</td>
<td>449,861</td>
</tr>
</tbody>
</table>

Figure 7.14. Random forest classification prior to post-processing zoomed in for a) conifer (green), deciduous (orange), and mixed (black), zoomed in for b) conifer (green) and deciduous (orange) and the whole map of c) deciduous (orange) and conifer (green) with non-forest masked for all of Denmark in 2020.
Discussion

The use of Sentinel data for forest classification and mapping presents several advantages. Firstly, Sentinel satellites have been in operation since April of 2014 and the image packages these satellites produce are accessible, widely used, open source, and cover the entire world. Consequently, straightforward classification is possible at no cost to users and with adequate precision at 10 m resolution. Classification protocols can also be replicated over several years, past or present, since these satellites have been operational for over seven years, and since they will likely continue to run for many years to come, research methods can be repeated in a highly uniform fashion making comparisons over long periods of time possible. Additionally, because Sentinel images have a coarser resolution than commercial grade satellite images, the data processing times can be reduced. A caveat of Sentinel's tenure, however, is that some bands have already been decommissioned which could threaten reproducibility of research between study years. In the present study, we opted to produce full wall-to-wall cloud free images to be in conformity with previous studies. In this case, the restricted satellite pass schedules of the Sentinel may require inclusion of longer study periods to create the cloud-free image during periods of frequent cloud cover of interest in order to ensure that quality, cloud-free data acquisition is feasible. However, as image pixels can be analysed individually with much higher frequency, proper cloud-masking of individual images and possible time-series filtering/smoothing would allow analysis of data with much higher temporal resolution in future analyses.

While the resolution of the Sentinel maps is coarser than the Planet images, the overall accuracy of supervised classification using Sentinel imagery allows for replicable assessment of national forest structure to a reliable degree since images can be acquired annually in a uniform fashion. When comparing the error of Sentinel classification versus the other methods, the results appeared rather comparable. This makes Sentinel classification a favourable method for forest and tree type classification since Sentinel data is open source and readily available with model procedure being the easiest to recreate across years and between researchers.

However, there are some limitations at this spatial resolution where the classification of trees outside forested areas becomes less straightforward when compared to e.g. PlanetScope data methods. Additionally, since Sentinel satellites pass over the area of interest less frequently, limitations in the temporal scale means that the quality of images captured can be less than ideal when compared to the PlanetScope data. Namely this issue is most pronounced when there is high cloud cover in several consecutive satellite passes. This can mean that long sessional periods might be necessary for running the Sentinel forest classifications, which ultimately limits how many seasons can be used when producing the training data for the model(s) and creates higher spatial variability within each seasonal image composite.

7.4 Forest area delineation

In the “Skovplan”-project, we applied three different methods aiming at different resolution mapping of the forest area using object- and pixel-based methods. In each case, the mapping results in the classification of canopy cover rather than a segmentation of forest in accordance with the international
definition provided by FAO (2020) and used in the climate gas reporting (IPCC, 2006a). Among the underlying objectives of the SkovPlan-project, supporting future carbon accounting holds a prominent position. Hence, further post-processing of the canopy maps is necessary to produce forest maps that are concurrent with the international forest definitions. In summary, such post-processing should be aiming at delineating areas larger than 0.5 ha with a minimum width of 20 m grown with trees taller than 5 m and a crown cover of more than 10 % or trees that can obtain these criteria in situ. The latter criterium is not addressed here specifically but is implicitly included in the training of the models for detecting tree cover as samples with less tree cover were not labelled as forest.

The three methods applied in forest classification resulted in two different types of output, but the post-processing of the data is quite similar. The starting point of the forest delineation are tree crown or canopy polygons or pixels spatially scattered or clustered. Whether the canopies form a forest depends on the dispersal of the tree crowns or canopies. The assessment depends on whether something breaks the continuity of the canopy dispersal and introduces a boundary as well as the distance between canopy patches areas is too large to maintain 10 % coverage (Figure 7.15). In the following, we aim to describe the post-processing applied to the results of the three different forest classification methods to form forest maps.

![Figure 7.15. Tree crowns on the left and delineated forest area on the right. The forest area disregards tree crowns of forming canopies with a width less than 20 m, like hedgerows and others, and a continuous forest area of less than 0.5 ha.](image-url)
Methods

There were two approaches, mainly investigated, to solve the problem of the tree and canopy area aggregation into forest. The first one was with the use of the Concave Hull Alpha Shapes Algorithm, which utilizes the Delaunay Triangulation to enclose a set of neighbouring points. The method connects all possible first neighbouring points, calculating distances, area, and the radius of each area of triangles formed so that in the end to produce the cascade union of the triangles in bigger polygons (Figure 7.16).

![Figure 7.16. Example of the Concave Hull Alpha shapes for various values for α in figure on the left (reproduced from Asaeedi et al., 2017), on the right figure calculation process with α parameter set to 0.3 (reproduced from Dwyer, 2014).](image)

The algorithm executed from Python 3.8.10 QGIS 3.18.3 API produced very satisfying results, with highly detailed delineation of the tree crowns in forest areas. Nevertheless, the method came out very expensive computationally even for mere test executions with small subsets. Furthermore, the approach required extra steps of pre-processing. Specifically, the tree crown data are acquired as polygons, whilst the concave hull alpha shapes require vector point data as input. Consequently, the points must be extracted from the polygon vertices as an extra step before the execution of the algorithm (Figure 7.17). The vertices resulting from this extraction was counted in billons and posed a major challenge in terms of data handling. Consequently, we found that the concave hull does not yet provide a feasible solution to the forest delineation problem but could be reassessed in future applications, when computational power likely increases to a level making the size of the problem less relevant.

![Figure 7.17. Extracted vertices from polygons. Billions of points would be required for whole Denmark.](image)
In place of using convex hulls, we opted to use buffering of the polygons produced in the classifications as more efficient means to delineate the forest area. In this procedure the forest boundaries are drawn by expanding and unifying adjacent tree crowns or canopy groups by buffering outwards to reach to neighbouring tree crowns and connect these. While accumulating new space, next, is thinning the new gained area by buffering inwards to remove areas less than the limit width of forest areas. The spatial criteria of what is defined as forest is applied, hence, the definition of the forest sets the parameters to be used in a heuristic approach of solving the problem, by dilation and contraction as long as the area can grow on appending new tree crowns while expanding and withdrawing back to initial extent.

Due to the large number of small polygons and their associated processing demands, the 1st dilation and union of polygons could not be executed on the full dataset. Consequently, we initially split the data in 1,000 x 1,000 m grid cells and made the first dilation and union of polygons on these grid cells separately (Figure 7.18). Subsequently, the grid cells were merged into one tabular data and then the next steps of retraction and dilation were made on the full data set to create one nation-wide forest map. Specifically for the tree crown delineation, data was supplied in 53 individual blocks and following steps were conducted on these blocks individually.

In a first step of the forest delineation, adjacent tree crowns or canopy groups are joined into larger units by buffering individual tree crown or canopy polygons outwards to reach neighbouring tree crowns and merge overlaying polygons (Figure 7.19). In this step we applied a 10 m outward buffer to the tree or canopy polygons and overlapping polygons were merged to join adjacent polygons less than 20 m apart, in line with the forest definition.
The second step aimed at removing canopies with a width of less than 20 m. To do this we added an inward buffer of 20 m, which both retracted the areas to the original boundary (i.e. countering the first 10 m outward buffer) and added an additional 10 m inward buffer (Figure 7.20). By this procedure, shelterbelts, single trees, or smaller groups of trees with a width of less than 20 m were deleted.

The procedure was iteratively repeated, by sequential dilation and contraction as long as the area is growing by appending new trees in accordance with the forest definition (Figure 7.21). Finally, a buffer 10 m inwards was applied to get to the initial extent of the outer most tree crown boundaries (Figure 7.23).
In the final step of the procedure, irrelevant areas were removed by overlaying with a “non-forest” layer, comprising high- and low built-up areas, summerhouses, enterprises, recreational areas, and areas categorized as crop land (“Afgroede”) in the cadastral map (Figure 7.22). The selection of non-forest crops was based on the codes from Landbrugsstyrelsen (2022, Bilag 11). Crop codes for areas that could have forest cover are provided in the appendix (Table 11.2).

The removal of non-forest areas in some cases created small polygons insufficient in width to apply to the forest definition (Figure 7.22) and a final retraction and expansion of the polygons was made with a 10 m buffer to erase such areas. Finally, resulting polygons with an area of less than 0.5 ha were filtered out to be in concordance with the forest definition.

Specifically for the tree crown data, the original 53 blocks were lastly merged, and a final 10 m outward and inward buffer was made to union forest areas from different blocks. In this case, the deletion of forest areas less than 0.5 ha was made after the union of the blocks (Figure 7.24).

Figure 7.23. Final buffer inwards bringing forest boundary to outer most tree crown border.

Figure 7.22. Non forest erasing layer creating small in between areas that need to be cleared with a final buffer inward and outward.
Figure 7.24. Last process of merging the 53 forest blocks and connecting their adjacent boundaries.

The buffering method proved to be very simple and cost effective. The “Buffer” tool is provided by all spatial libraries giving the possibility that the method can be deployed in numerous programming languages and API’s of them. In the initial stages of the wok, we applied the methodology in Desktop ArcGIS but due to the extent of the processing problem, we shifted to other programmes as ArcGIS is not provided for Linux operational systems. Instead, we opted to use, Python 3.8. QGIS 3.18.3 API on a Linux Desktop machine, deployed in the “Anaconda” virtual environment. To further enhance computing power, we finally deployed the Python scripts on GeoPandas 0.10.2 API in cluster machines of cloud computing on Databricks 10.5 ML. As the application had to deal with large amounts of data, Big Data handling solutions had to be investigated that introduce different data structures that optimize computing architectures such as distributed ones and parallel computing, namely for future reference Apache Sedona, GeoMesa, Mosaic, and Dask GeoPandas. The selection of these API’s was due to their capabilities in large datasets where other API fail.

The choice of API brought some additional processes to successfully complete the whole workflow of buffer in and out iterations. Shortly on the data structure of the used API, Geopandas can read spatial data, which it brings down as tabular data called Geodataframes that hold a Geoseries as a vector where the geometry is stored and is what is being manipulated. It was revealed that a series of manipulations had to be repeated after every GeoPandas geometric operation as that would affect the tabular data in ceasing to have a Geoseries or GeodataFrame structure and these had to be recreated. Firstly, buffers after implementing them, with embedded defined CRS, result in disrupted tabular data, no longer formed as Geoseries, which is needed for the following operations. Secondly, the Geopandas buffer will not connect the geometry of the polygons that come to overlap from the buffer, so after every buffer outward the
GeoSeries must be created again. With the GeoSeries in place a unary union property is applied that will unify the overlapping buffers and polygons and then CRS has to be set. The following outcome of buffer inwards is that it will also create one individual bigger multi-part unified polygon. The unified polygons must be split into multiple single polygons when they are separate geometries and that is achieved by applying the explode operation on the GeodataFrame followed by recreating the GeoSeries and lastly to rename the geometry column as ‘geometry’.

Evaluation of final maps

The post processing evaluation of the produced maps from the three different methods was made with NFI data sampled within one year of the mapping year, i.e. data collected in 2019-2021. Unlike the evaluation of the original pre post-processed results, we used all sample plots in the evaluation, no matter if they were included in the training of the different mapping procedures; including also plots not visited in the field but evaluated as non-forest from aerial photographs in accordance with NFI procedures. This was to use the same plots in the evaluation of all three approaches and to better reflect the distribution of forest/non-forest area in Denmark. We evaluated the performance in terms of producer, user, and overall accuracy:

\[
\text{Overall accuracy} = \frac{\text{The number of correctly classified samples}}{\text{The total number of samples}}
\]

\[
\text{Producers accuracy} = \frac{\text{The number of correctly classified samples in one category}}{\text{The number of samples in that category}}
\]

\[
\text{Users accuracy} = \frac{\text{The number of correctly classified samples in one category}}{\text{The number of samples labelled in that category}}
\]

Results

The forest mapping from crown delineation based on aerial photographs made in section 7.1 yielded an overall accuracy of 0.95 and a user and producer accuracy of 0.89 and 0.76, respectively, for the forest classification (Table 7.8). The total forest area amounted to 581,262 ha with the highest density in Central Jutland and Northern Zealand (Figure 7.25).
Table 7.8. Confusion matrix based on the crown delineations from 2020 ortho-photos (Section 7.1) and NFI-data from 2019-2021. Numbers represent NFI sample plots.

<table>
<thead>
<tr>
<th>Actual forest cover</th>
<th>Total</th>
<th>Predicted forest cover</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forest</td>
<td>Non-forest</td>
<td>Total</td>
</tr>
<tr>
<td>Forest</td>
<td>2,762</td>
<td>867</td>
<td>3,629</td>
</tr>
<tr>
<td>Non-forest</td>
<td>353</td>
<td>21,326</td>
<td>21,679</td>
</tr>
<tr>
<td>Total</td>
<td>3,115</td>
<td>22,193</td>
<td>25,308</td>
</tr>
<tr>
<td>User accuracy</td>
<td>0.89</td>
<td>0.96</td>
<td>Overall accuracy</td>
</tr>
</tbody>
</table>

Figure 7.25. Danish Forest Map, Delineation Results from summer 2020 data.

The delineation of the PlanetScope data returned a total area of 600,930 ha forest with an overall accuracy of 0.95, and a user and producer accuracy of 0.87 and 0.91, respectively, for the forest classification (Table 7.9).
Table 7.9. Confusion matrix based on forest area delineations from 2019 PlanetScope data and NFI-data from 2018-2020.

<table>
<thead>
<tr>
<th>Actual forest cover</th>
<th>Total</th>
<th>Predicted forest cover</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3,187</td>
<td>0.91</td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>2,914</td>
<td>709</td>
<td></td>
</tr>
<tr>
<td>Non-forest</td>
<td>436</td>
<td>21,299</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>3,350</td>
<td>22,008</td>
<td></td>
</tr>
</tbody>
</table>

The delineation of the forest map produced from Sentinel data produced results with total area of 690,251 ha, an overall accuracy of 0.96 and a user and producer accuracy of 0.84 and 0.88, respectively, for the forest classification (Table 7.10).

Table 7.10. Confusion matrix based on forest area delineations from 2020 Sentinel data and NFI-data from 2019-2021.

<table>
<thead>
<tr>
<th>Actual forest cover</th>
<th>Total</th>
<th>Predicted forest cover</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3,629</td>
<td>0.88</td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>3,191</td>
<td>438</td>
<td></td>
</tr>
<tr>
<td>Non-forest</td>
<td>610</td>
<td>21,069</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>3,801</td>
<td>21,507</td>
<td></td>
</tr>
</tbody>
</table>

The overall accuracy of the tree type classification was 0.94 (Table 7.11). Seemingly, the random forest algorithm distinguishes between broadleaved and coniferous forest from the phenological change associated with the loss of leaves for the broadleaved trees at wintertime. Consequently, the algorithm has difficulties in distinguishing larch species as conifers being the only coniferous species shedding needles during wintertime.

Table 7.11. Confusion matrix for the classification of forest types, based on the three forest type classification of broadleaved (B), coniferous (C), and mixed (M) forest. Based on 2020 Sentinel data and NFI-data from 2019-2021.

<table>
<thead>
<tr>
<th>Actual forest cover</th>
<th>Total</th>
<th>Predicted forest cover</th>
<th>Non-forest</th>
<th>Total</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>C</td>
<td>B</td>
<td>M</td>
<td>1,395</td>
</tr>
<tr>
<td>C</td>
<td>1,183</td>
<td>64</td>
<td>25</td>
<td>123</td>
<td>0.84</td>
</tr>
<tr>
<td>B</td>
<td>1,333</td>
<td>58</td>
<td>140</td>
<td>1,558</td>
<td>0.85</td>
</tr>
<tr>
<td>M</td>
<td>137</td>
<td>89</td>
<td>25</td>
<td>145</td>
<td>0.36</td>
</tr>
<tr>
<td>Non-forest</td>
<td>136</td>
<td>444</td>
<td>9</td>
<td>21,286</td>
<td>21,875</td>
</tr>
<tr>
<td>Total</td>
<td>1,466</td>
<td>1,978</td>
<td>206</td>
<td>21,574</td>
<td>25,358</td>
</tr>
</tbody>
</table>

The overall accuracy of the tree type classification was 0.94 (Table 7.11). Seemingly, the random forest algorithm distinguishes between broadleaved and coniferous forest from the phenological change associated with the loss of leaves for the broadleaved trees at wintertime. Consequently, the algorithm has difficulties in distinguishing larch species as conifers being the only coniferous species shedding needles during wintertime.
Discussion

The overall accuracies obtained from the mapping of the forest area were very similar across the different methods (0.95-0.96) but slightly less than the overall accuracies (0.98) reported by Bjerreskov et al. (2021). This was somewhat surprising since the classification from Sentinel images were almost identical to the classification made by Bjerreskov et al. (2021). A likely reason for the differences is that the methods applied for assessing the accuracies are different. In this report, we assumed that all NFI-plots with more than 50% forest cover were forest and compared these point classifications corresponding the centre of the NFI plots to the classification obtained from the raster cell. However, this approach may lead to excessive error along the forest edges. Indeed, a visual inspection demonstrated that wrongfully classified NFI-plots were in almost every case close to the forest border. To accommodate edge effects due to discrepancy between the reference data from the NFI, i.e. circular plots with a radius of 15 m, and the classification output map, i.e. raster pixels with a resolution of 10 x 10 m, Bjerreskov et al. (2021) implemented a slightly different evaluation procedure. Instead of using the SSU centre point as evaluation reference, they assessed the forest cover status of pixels within a 15 m radius from the plot centre (corresponding to the SSU plot). Evaluation of class agreement was then based on the majority of the mapped class inside the circle. In relation to future implementation of the results from this pilot study, consistent methods for error assessment should be implemented.

A common feature of all three methods tested was the inability of the underlying procedure to localize forest areas with no tree cover or with newly planted, small trees and hence the ability to map areas with young forest. This represents a common discrepancy between mapping of land cover and land use. The approaches presented all seek to classify forest from interpretation of the visual landscape, in this case specifically from the presence of trees. However, the definition of forest includes landscapes with absence of trees namely temporarily unstocked areas that are to be reforested as well as auxiliary areas needed for forest management such as firebelts, some forest roads, etc. Furthermore, the textural appearance of newly established forest may in many cases not allow detection of either methods relying on detection of individual tree crowns or pixel-based methods such as the satellite imagery produced in this pilot study. Consequently, it is expected that the mapped forest area before post-processing is larger than the actual forest area, owing to areas with tree cover but an alternative land use, and smaller than the actual after post-processing owing to the failure to detect forest areas with no or little tree canopy cover.

For example, for the delineation of forest from tree crowns (section 7.1), the total mapped forest area was 581,262 ha, which may be compared to the 632.711 ha forest area found by the national forest inventory (Table 6.11, Nord-Larsen et al., 2021). The difference of 51,449 ha is likely in part due to the forest definition including temporarily unstocked areas such as clear-cuts as well as auxiliary areas such as fire belts, forest roads etc. These areas make up a total of 41,605 ha according to the national forest statistics and cannot be captured by the mapping of tree crowns and are therefore likely not part of the forest area map. Secondly, the results of the current study is in part dependent on the definitions in the non-forest layer. The introduction of this layer is supposed to bring a higher accuracy and detail as it has not been used in forest mapping attempts such as in Copernicus (European Environment Agency, 2021) where areas
of “summerhouses” in many cases have been mapped as forest. However, as the forest definition is indifferent to the land-use, the national forest area includes some areas no matter that they are placed in areas designated for e.g., summer houses. The consequence of the difference in perceptions between land-cover and land-use, is a likely small underestimation of the forest area by the mapping compared to the inventory data. Finally, even at the high resolution (12.5 cm) available in the aerial images, it is not possible to delineate small tree crowns. Consequently, the tree will have to attain a certain (but unknown) size before they may be detected. Currently, 49,400 ha of the forest area is less than 10 years old and may be difficult to capture with remote sensing.

Despite the apparent similarities regarding overall accuracies, the differences in forest area obtained with the different mapping methods are relatively large, ranging from 581,262 ha to 690,251 ha (Table 7.12). From our evaluation of the mapping, it became evident that the imagery based on Sentinel-data contained more false-positives and less false negatives for forest cover than the two other methods. This may be because we only included plots visited in the field in the training with Sentinel data. This meant that a large number of plot locations identified as non-forest on aerial images, where none of the NFI plots in the cluster contained forest, were omitted from the analysis. We suspect that this may have hampered the ability of the algorithm to detect non-forest. Furthermore, we noted that in most cases, the wrongly identified forest was close to the forest edge likely as a result of the coarser resolution of the Sentinel-mapping compared to the other methods.

Table 7.12. Forest area and comparison with the area obtained from the NFI.

<table>
<thead>
<tr>
<th>Method/Data type</th>
<th>Forest area ha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial ortho-photos</td>
<td>581,262</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>600,930</td>
</tr>
<tr>
<td>Sentinel</td>
<td>690,251</td>
</tr>
<tr>
<td>NFI</td>
<td>632,711</td>
</tr>
<tr>
<td>NFI (with forest cover)</td>
<td>604,369</td>
</tr>
<tr>
<td>NFI (with forest cover older than 10 yrs)</td>
<td>554,966</td>
</tr>
</tbody>
</table>

7.5 Forest mapping discussion and conclusions

The three different methods for mapping forest presented in this report were all able to identify tree canopies as a prerequisite for mapping forest and produced similar high overall accuracies ranging between 0.95-0.96. Consequently, the difference in expected accuracy of the three different methods for forest classification and mapping based on aerial images, data from the constellation of PlanetScope nano-satellites, and data from the Copernicus Sentinel 1 and 2 satellites may not be important when deciding the future method of choice.

The evaluation of which method is ‘best’, depends not only on the methods ability to classify forest, but also on the spatial and temporal resolution, data costs, computational costs, complexity of the method, the
expected continuity of data sources and methods, as well as the versatility of the product in terms potential use of the product outside the mere classification of forest (Table 7.13). In the following, we elaborate on the strengths and weaknesses of the different methods.

Classification of forest from aerial images

The classification of forest from freely available aerial images provides the highest level of detail and the results are easy to interpret as trees are mapped as individual objects. In our study, the deep learning algorithm used for identifying trees was trained on larger forest trees, but the method is customizable by applying different training datasets to detect e.g., also new plantations or different species. This could be done by simply including also smaller trees and labelling the individual trees with species or species type information and including this in the training of the model. The high precision produced by this method allows alignment with NFI plots and we expect a high degree of continuity as annual collection of aerial images is expected to be continued. The high level of detail provided by this method allows counting of trees and direct assessment of forest structure. Once a model is trained, the method further allows application to historical aerial images allowing to detect temporal changes in the forest structure and distribution. This may be particularly important in mapping forest habitat development e.g., from crown size distribution in relation to biodiversity. An important byproduct is the identification of non-forest trees, e.g. in urban areas and the open landscape offering a high degree of versatility in the use of resulting products.

The high spatial resolution data used in the classification of forest trees and forests from aerial images require processing of large amounts of data with complex, custom coded deep learning algorithms. Processing costs in terms of hardware and time are consequently considerable. The complexity of the deep learning algorithms means that the underlying models may not be easily interpretable. Images are captured once a year and the low temporal resolution (compared to satellite images) offers little possibility to assess phenological profiles of flushing to detect individual tree species. Experiences with the method during our project demonstrated that the method may require retraining for forests, which require manual delineation of canopies for training. Although the method produced high accuracy compared to the manually delineated crowns and larger measured trees (stem diameter > 10 cm), comparison with national forest inventory data demonstrated that the methods frequently fail to identify understory trees under dense canopies in forests.

Classification from PlanetScope

The classification of forest canopies offers a compromise between the level of detail provided and the processing costs associated with high-detailed aerial images. The method was demonstrated to produce reliable estimates across a wide range of forest types across Europe. The method produces a high level of detail allowing alignment with national forest inventory sample plots. Compared to other satellite image products, the high temporal resolution potentially allows cloud-free images during the critical leaf-on period and general tracking of phenology to better detect individual tree species. The method further allows estimation of forest cover and canopy height, which again may allow estimation of forest biomass.
resources. The constellation of PlanetScope nano-satellites is privately operated, but the mission is expected to be continued for many years to come.

The data from PlanetScope is, unlike the two other data sets, not free of charge. The price for acquiring the data depends on a case-to-case negotiation with the Planet Labs Company. The maximum commercial price for national coverage would be around 55,000 EUR annually but may in reality be much lower. The data provided requires pre-processing with custom made code and the deep learning algorithms means that the underlying models may not be easily interpretable. Unlike, the aerial images, the resolution of the data does not allow for the detection of small trees outside forests that are not detected with a nominal pixel resolution of 3 meter. Also, neighbouring tree crowns are commonly merged into larger canopy objects and hence does not allow the assessment of canopy structure. Nevertheless, the total area covered by trees outside forests is similar for the Planet (153,000 ha) and aerial image (141,000 ha) derived results, when considering that the tree crown delineations does not include the areas between tree crowns and hence underestimate total cover.

**Classification from Sentinel data**

The Sentinel data are free of cost and may be rapidly pre-processed in cloud computing facilities like Google Earth Engine or the Copernicus DIAS (Data and Information Access Services) services, the latter one used by the Environmental Agency. The methods applied are well-known, well documented, transparent, and may be deployed in standard software packages. The Sentinel missions are expected to be continued for a long time and mapping products can be reproduced annually with a high level of consistency in the future. The temporal resolution with overpasses every 5-6 days allows to some extent tracking of phenology and hence tree species detection, but our pilot study demonstrated that it may be problematic to obtain sufficient cloud-free images from Sentinel-2 for this purpose, when aiming at producing wall-to-wall cloud free images as basis for the classification. This may be dealt with by training on a larger stack of individual images after removal of clouds, rather than relying on classification from single, wall-to-wall, cloud free images. In future, such approaches may allow for higher temporal resolution and hence improved ability to capture phenotypical development of the trees across the year to allow for improved species classification.

Compared to the other methodologies, the classification of forests from Sentinel images in this study did not make full use of novel technological advances in for example area of statistical learning. This was intentional as this part of the study served as a baseline for comparison. However, future development of the methods should include deep learning approaches, such as those demonstrated on the alternative approaches in this report, to make full use of the tempo-spatial distribution observed in the images underlying the classification. Such classification could furthermore include the full radiometric resolution offered by the Sentinel system to better capture species and forest structure as basis for improved classification and increasing the number of features that could be remotely sensed e.g. by assessing forest carbon stocks or habitat quality related to forest structure.
The low level of detail produced makes the method unsuited for detecting trees outside forests and for aligning results with data from the national inventory forest plots. Also, the spatial resolution of 10 meter, which does not allow to resolve spatial features of single tree crowns, makes the use of novel advanced deep learning classification techniques less powerful. In the case of Sentinel 1 and 2 data-based forest mapping, more classical machine learning approaches like the Random Forest performs at a comparable level of accuracy.

Table 7.13. Strength and weaknesses of the proposed methods for forest area classification and mapping. Classification ranges from bad/complex/expensive (+) to good/simple/cheap (+++).

<table>
<thead>
<tr>
<th>Method</th>
<th>Aerial images (7.1)</th>
<th>PlanetScope (7.2)</th>
<th>Sentinel (7.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>Tree crown size and height at individual tree level for both forest and non-forest trees (can be converted to tree cover at any resolution)</td>
<td>Forest cover and height at 3 m resolution. Forest and large trees outside forests</td>
<td>Forest cover at 10 m resolution</td>
</tr>
<tr>
<td>Method</td>
<td>Deep learning</td>
<td>Deep learning</td>
<td>Random forest</td>
</tr>
<tr>
<td>Accuracy</td>
<td>++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>+++</td>
<td>++</td>
<td>+</td>
</tr>
<tr>
<td>Temporal resolution</td>
<td>+</td>
<td>+++</td>
<td>++</td>
</tr>
<tr>
<td>Data costs</td>
<td>+++</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td>Computational costs</td>
<td>+</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td>Method complexity</td>
<td>+</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>Continuity</td>
<td>+++</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>Versatility</td>
<td>+++</td>
<td>++</td>
<td>+</td>
</tr>
</tbody>
</table>

The 'best' path to future forest maps

Assessing which of the three methods that is best in producing future forest maps is not possible without defining what such a map will be used for and consequently what demands it should satisfy. With the likely many usages, this is no trivial task.

In general, the method of choice should allow high accuracy and a spatial resolution that is equal to or less than the size of a tree crown. In all three cases, we found that the accuracy produced was sufficient and in terms of mapping forest, the 10 m resolution of the Sentinel images is adequate. However, to the extent that mapping of trees outside forests is desirable, only the product made from delineation of tree crowns from aerial images is adequate. Importantly, forest mapping with satellite imagery allows the combination of multiple scenes and hence the classification of forest into forest types (broadleaved and coniferous) and even species.

The frequent and consistent update of the maps is essential for the implementation in public and private forest management and analysis. In general forest development and growth is slow. Hence annual differences in forest cover will be small and there is a risk of errors in the map being larger than the actual
change (known as a small signal-to-noise ratio). Such problems may result in large overestimation of change (Ceccherini et al., 2020), not least because areas with wrong classification are prone to erratic changes in subsequent campaigns. We find that the yearly update possible with all three methods is more than sufficient for most purposes, although the precise tracking of deforestation may require annual updates. Furthermore, catastrophic events such as occasional large-scale windthrow, may necessitate the possibility for even higher update frequency to enable assessment of the extent of the damage (Tøttrup et al., 2014). A likely compromise is bi-annual updating of the forest maps, but efforts should be made to adjust for overestimation of change when comparing subsequent maps and it may be considered that the method selected should allow for on demand mapping in the wake of a critical events.

The costs in terms of data purchase and computation differ among the three approaches. Considering the effort vested in the overall forest mapping, these costs however seem small; not least when contemplating the development in computational power. Hence, these considerations do not seem detrimental to the choice of method. This conclusion, however, depends to some extent on the expected processing environment, as the methods differ vastly in complexity and may not be readily implemented everywhere.

Continuity and consistency are pivotal to the choice of method for future forest mapping. Hence, only methods relying on data sources expected to be available in the medium to long term (15-30 years) should be considered. We expect the data collection underlying all three approaches to continue in the medium to long term, but the PlanetScope data is obtained from a private operator and there is no guarantee that these data will be collected consistently over such long timespans.

In conclusion, all three methods fulfil the aim of mapping forest with the ability to attain sufficient accuracy at a reasonable temporal and spatial resolution. The final choice of method hence depends on further analyses of stakeholder needs.
8 Forest resource map

8.1 Forest resource mapping from delineated tree crowns

Above-ground biomass (AGB) is normally estimated based on tree characteristics including stem diameter, height, and species (Xiao and Ceulemans, 2004; Návar, 2009). Such calculation heavily relies on in situ measurement of trees. Field-based estimates of AGB reflect the most accurate estimation of carbon stocks, but collecting such data is time consuming and often limited to plot-scale (Kumar and Mutanga, 2017). Individual tree crowns detected from aerial images offer the crown area, a tree characteristic correlated with stem diameter (Hemery et al., 2005). Such alternative paves the way to upscalable estimation of AGB at single-tree-level based on aerial data.

In the previous section on forest area mapping from identification of tree crowns from aerial images (section 7.1), a large set of training labels enabled the successful detection and delineation of individual tree crowns. As the size of individual tree crowns are likely highly correlated with tree volume or biomass, the resulting maps may be a valuable source of information to also map forest resources. In this study, we aim to use the delineated tree crowns from section 7.1 to estimate forest biomass.

Materials and methods

Aerial images and a deep learning-based model enable the segmentation of individual tree crowns, as shown in section 7.1. For the estimation of AGB for single trees (Figure 8.1), we used the tree crown detections obtained from summer 2018 aerial images and a digital canopy height model (DSM) projected from LiDAR scanning data obtained mainly during leaf-off conditions in different campaigns across the country (Section 6.5). The individual tree crowns were post processed to derive the crown area and crown diameter for each individual tree. The crown segmentation map was overlayed with the canopy height model to derive the height for each detected tree crown. AGB was then estimated for each tree crown, based on a set of forest type (broadleaved or coniferous) specific allometric equations fitted on a global dataset for the regression of AGB against crown diameter and height (Jucker et al., 2017). For this, forest type was obtained from the 2018 Copernicus forest type map (European Environment Agency, 2018, 2021).

In the NFI database, AGB was calculated for each measured tree using local allometric equations fitted on the stem diameter, height, and species (section 6.1). Here, we used the aggregated AGB across the entire plot (15 m radius) as the ground reference, since it was not possible to match trees measured on the field with trees detected from the aerial data precisely. Note that local allometric equations could not be used to derive AGB since stem diameter could not be directly obtained from the tree crown segmentation. 2257 NFI field plots randomly distributed across the country, were used for the analysis, among which 1989 plots were used for fitting the model and 268 plots were used as the test data for evaluation.

The estimated AGB for individual trees were aggerated to AGB per plot and a quadratic function was fitted against the AGB references from NFI to calibrate for local and global dissimilarities, the differences
between allometric equations and underestimation for understory vegetation (Figure 8.1). 1898 plots were used to fit the quadratic function (Figure 8.2a).

Figure 8.1. To estimate above-ground biomass, individual tree crowns were post processed to derive the crown area and crown diameter for each individual tree. The crown segmentation map was overlayed with the canopy height model to derive the height for each detected tree crown. AGB was then estimated for each tree crown, based on a set of forest type (broadleaved or coniferous) specific allometric equations fitted on a global dataset for the regression of AGB against crown diameter and height.

Table 8.1. Basics for the modelling of forest resources from individual tree crowns. A flow-diagram of the process may be found in the appendix (Figure 11.6).

<table>
<thead>
<tr>
<th>Coding language</th>
<th>Python</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main environmental dependencies</td>
<td>Rasterio, Gdal, Scipy</td>
</tr>
<tr>
<td>Processing speed</td>
<td>Approx. 30 seconds per 1km*1km grid</td>
</tr>
</tbody>
</table>

Results

We evaluated the model using 268 NFI plots that were not used for fitting the model. The model achieved an R² score of 0.7 and an overall bias of 4%. The predictions were rather scattered (Figure 8.2), while the overall bias was relatively low, implying reasonable aggregated results for large-scale applications. Examples of predictions are shown in Figure 8.3. We tested the model for northwestern Jylland, and examples are shown in Figure 8.4.
Figure 8.2. a. Fit allometric-based AGB estimates to NFI references respectively for different forest types. b. Evaluation on the test data.

Figure 8.3. Examples of above-ground biomass prediction on the testing plots (unit: Mg/ha). The 15 m radius circle represents the extent of the NFI sample plot, and the 18 m circle represents the likely inclusion radius of trees neighbouring and reaching into the plot.
Discussion

Individual tree crowns detected from aerial images and tree heights derived from LiDAR data open the gate to large-scale automatic AGB estimation down to the level of individual trees. This allows us to track carbon stock in trees and its changes efficiently for any regions of interest. It should however be noted that estimating AGB for individual trees from aerial data can be extremely difficult considering the variations of tree crowns, differences in allometric equations for different tree species and surrounding environments, and limitations for understory vegetation. The uncertainty and instability of the model is effectively revealed by the scattering of the predictions against NFI references. As a consequence of the uncertainty of especially small-area estimates, assessment of change in above-ground biomass stocks may be uncertain due to the relatively small changes compared to the often-large pools creating small signal-to-noise ratio.

The rather low overall bias observed on the validation and test datasets suggests great potentials for large-scale applications of the method. Such method may serve as a supplementary tool for field inventory to upscale field measurements to broader scales. Note that local NFI data lays the foundation for this method and a performance gain is expected with increased amount of field data.

8.2 Forest resource mapping from PlanetScope data

Tree height is closely related to the volume of trees, and recent research has used point data from a spaceborne LiDAR sensor (GEDI) to produce global tree biomass maps (Duncanson et al., 2022). These
global maps have however a coarse spatial resolution (1x1 km), have gaps where no GEDI data are available, and lack local calibrations, limiting their application to quantify forest resources at national scales. Moreover, the global maps are snapshots in time or merge input data from multiple years, and thus cannot be used for specific years, or track biomass changes over time. In section 7.2, we have shown that it is possible to derive tree height and tree cover maps from PlanetScope images at 3 m resolution, which would be sufficient for a detailed assessment of forest and non-forest tree resources for Denmark. PlanetScope images are not limited to single years, so assessments can be repeated at a frequent basis. Moreover, Denmark has an extensive coverage with NFI plots, providing a strong basis for a local calibration between tree height and biomass.

Materials and methods

Here we applied the tree cover and canopy height produced with PlanetScope images from 2019 (see section 7.2) to estimate above-ground biomass for Denmark’s trees. We used NFI plot data (about 1,100 plots) from Denmark to establish relationships between above-ground tree biomass and canopy height measured with airborne laser scanning (see section 6.5 Airborne laser scanning data (ALS)) mosaiced from data collected in 2018-2021 mainly during leaf-off conditions and averaged at plot level for different forest types. This provides relationships between tree height and biomass per m², which can then be aggregated to the 3 m resolution of PlanetScope data, resulting in biomass maps with the unit kg per m². Different allometric equations were used for mixed forests (error = 13.4%), coniferous forests (error = 9.2%), broadleaf forests (error = 8.1%), and trees outside forests (error = 9.8%). The 2018 Copernicus forest type map (European Environment Agency, 2018) was used to distinguish the classes. We used these relationships to convert the estimated tree height to estimate above-ground biomass at 3 m resolution. The tree cover map was subsequently used to limit the predictions to areas that are actually covered by trees. We will contribute our network to an open access library upon acceptance of the manuscript being prepared based on our findings.

Results

Results are available both at 3 m resolution in kg per m² and also aggregated to hectare scale. When comparing aggregated biomass estimates at national level with FAO statistics for 30 European countries, we found a bias of 7.6 %, which is a magnitude lower as compared to previous biomass products (17.3% for Santoro et al., 2021), and also the correlation was high (R=0.98). At the European scale, the results match relatively well with existing biomass maps using GEDI data at 1x1 km (bias -1.8%, NASA, 2022), with the advantage that the Planet based maps provides much more detail. For Danish NFI plots, the correlation at plot scale was moderate (r = 0.53, bias = -23%), which was expected due to a large uncertainty related to both satellite and field data, such as geolocation and image quality errors. Importantly, these errors were found to be not systematic, as demonstrated by a comparison of statistics aggregated to country scale, both from NFI and satellites. Here, the systematic bias was -10% (underestimation) for Denmark, which can be explained by the fact that clearcut areas and young tree plantations are part of the national statistic, but are not mapped in our product. Comparing forest and non-forest biomass, Denmark has the 4th highest
proportion of non-forest tree biomass from 30 European countries (after Ireland, UK, Netherlands); most of the non-forest biomass is found in urban areas.

Figure 8.5. Example how AGB from a NFI plot was related with canopy height from airborne LiDAR. The relationship was used to estimate AGB from canopy height modelled with PlanetScope images.

Figure 8.6. Planet based above-ground tree biomass predictions for Denmark (2019) at hectare scale (left) and 3-m scale (right). The background image is Google Earth.

Discussion

The high resolution of the biomass maps allows the quantitative assessment not only of forest resources but also of resources from trees outside forests. Moreover, once the model is trained using LiDAR and NFI data, no additional data sources are required, and forest and non-forest tree resources can theoretically be
estimated at an annual scale, only from PlanetScope imagery. The validity of temporal dynamics was however not yet tested, and it will require thorough validation using multi-year NFI and LiDAR data to quantify the uncertainty when estimating temporal changes in biomass. Nevertheless, the combination of high temporal and spatial resolution with a low cost, low data volume and fast processing time makes biomass maps derived from PlanetScope images a promising alternative to aerial and Sentinel image-based maps. LiDAR and NFI data are still required to train and validate the models, but Planet images may be a quick and cost-efficient way to upscale plot or patch-based data to national scales.

8.3 Pixel-based mapping of forest resources from laser scanning data

Airborne laser scanning (ALS) produces point clouds, imaging the biophysical and structural properties of the forest. The direct representation of the forest properties renders data from ALS a promising tool for assessing forest resources among other things.

In early studies, forest properties were estimated using a practical two-stage procedure (e.g., Nelson et al., 1988; Næsset, 1997; Næsset, 2004b, a; Næsset et al., 2004). In the first step, laser scanning data from profiling or scanning lasers were obtained from smaller sample plots also measured by common inventory methods in the field. Statistical variables such as maximum, minimum, and mean pulse height above ground and different percentiles of the point cloud were then regressed against the forest properties of interest such as stand height, basal area, or growing stock. In the final step, the regression model developed was used on pixels across the investigated area. Such an approach has been shown to produce accurate results at low cost compared to traditional stand-wise inventory (Hummel et al., 2011).

In similar studies in Denmark, forest basal area, volume, above-ground biomass, and total biomass were successfully modelled using national forest inventory (NFI) and ALS data obtained in countrywide scanning surveys in 2006-07 and 2014-15 (Nord-Larsen and Schumacher, 2012; Nord-Larsen et al., 2017). The current study aims to produce a forest resource map including canopy height, growing stock volume, and biomass for the area included in the latest available laser scanning of Denmark from 2020, using the same method as applied in the former forest resource mapping efforts in Denmark. Hereby this study serves as a baseline for other approaches to forest resource mapping.

Materials and methods

Wall-to-wall laser scanning of Denmark was carried out in 2006-07 and 2014-15. Since 2018, scanning covering about 1/5 of the country has been carried out with the intention to cover the entire country in a 5-year period (Figure 8.7). The laser scanning data has been collected (predominantly) during leaf-off conditions with a planned point density of 6-8 points/m² (Table 6.2). The scanner recorded multiple return pulses from each emitted pulse and the data included pulse scanning angle, return pulse coordinates, and return pulse intensity.
Prediction of forest variables

The point cloud data is delivered in 1 km x 1 km tiles. When processing the data, point cloud data were normalized with a digital terrain model (DTM) using R (R version 4.2.1 (2022-06-23 ucrt), R Core Team, 2021, procedure LidR) for each tile. In the first step of the procedure, normalized point cloud data corresponding to the National Forest Inventory sample plots were extracted and a suit of point cloud metrics were calculated on the extracted sample. The metrics included:

1. mean pulse height above ground ($Dz_{\text{mean},r,q}$)
2. variance parameters: variance ($Dz_{\text{var},r,q}$), standard deviation ($Dz_{\text{std},r,q}$) and coefficient of variation ($Dz_{\text{cv},r,q}$)
3. distribution form parameters: skewness ($Dz_{\text{skew},r,q}$) and kurtosis ($Dz_{\text{kurt},r,q}$)
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 ($IR_r$): $IR_r=n_{r,q=1}/n_{r,q=2}$, where $n_{r,q}$ is the total ($q=1$) or total above-ground ($q=2$) number $r$ returns.

The point cloud metrics calculated for different groups of returns ($r$), including all returns, vegetation returns only, and for first returns only. Furthermore, these statistics were calculated for both all returns irrespective of return height ($q=0$) as well as for pulses reflected from above 1 m ($q=1$).

For predicting forest variables, we modelled the relationship between point cloud 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 re-estimated the model. Outliers were only removed after checking with updated aerial photographs.

Based on experiences with the ALS data collected in 2006-07 and 2014-15, forest canopy height can readily be predicted with linear functions of various percentiles of the normalized point cloud, while the relationships between the other forest variables are best described by power functions easily linearized by log-log transformation of the response and predictor variables.

In the previous studies, suitable models were explored using the PROC GLMSELECT procedure 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, only first order interaction terms between the model parameters were allowed. However, for 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 (Nord-Larsen and Riis-Nielsen, 2010; Nord-Larsen and Schumacher, 2012). We therefore opted for a simple re-estimate the non-linear power models developed on the 2006-07 and 2014-15 data (Equation 1). However, we found a minor improvement when using vegetation returns rather than returns reflected from above one meter from the ground.

Equation 1

$$H_{canopy} = h_0 + h_1 Dz_{95,v,0} + h_2 Dz_{95,v,0} I R_1 + \varepsilon_H$$

$$V = v_0 Dz_{mean,v,0} Dz_{95,v,v} I R_{v}^{v_3} + \varepsilon_V$$

$$B_{Above-ground} = b_0 Dz_{mean,v,0} Dz_{95,v,0} I R_{v}^{b_3} + \varepsilon_{Bag}$$

$$B_{Total} = c_0 Dz_{mean,v,0} Dz_{95,v,0} I R_{v}^{c_3} + \varepsilon_{Btot}$$

The models for predicting canopy height, growing stock, and biomass stock were estimated using non-linear regression with the MODEL procedure in SAS (ver. 9.4, SAS Institute, 2015). 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).

For validating the models and investigating their stability, we randomly split the dataset into an estimation (80%) and a validation data set (20%). For the final model estimation, however, we used the full dataset to utilize as much information as possible.
Making a forest resource map

In the second step of the procedure, we applied the models estimated on NFI plots to pixels covering the entire landscape. The original data was delivered in 1 x 1 km tiles in laz-format. When producing the map, the tiles were processed individually in much the same manner as the point cloud data from the National Forest Inventory sample plots. First, a DTM was developed for the tile and the point cloud normalized. Subsequently, the point cloud data was rasterized into 25 x 25 m pixels and point cloud metrics were calculated for each pixel.

When producing the final map, the model estimated from Equation (1) was applied to the point cloud metrics of the individual 25 x 25 m pixels. Since many of the point cloud metrics are not scale invariant, the pixel size (625 m²) was determined from the NFI plot size (706 m²) 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.

A work-flow for the entire procedure is provided in Appendix; Figure 11.8. Work-flow diagram of the mapping of forest resources from laser scanning data.

Forest resource mapping results

A total of 1,146 NFI sample plots were sampled within one year from the laser scanning across all available scanning data from 2018-21 (Table 8.2). When using only laser scanning data from 2020, a total of only 174 plots were available for modelling, owing to the lower forest cover in western and southern Jutland. We evaluated that this would result in too limited data for training and opted to use data from all available scanning years.

Across the data from 2018-21, 49% were dominated by broadleaves (i.e. broadleaves take up more than 25% of the basal area), 34 % were dominated by conifers, and 11 % were mixtures of broadleaves and conifers. Showcasing the dominance of conifers in the western part of Jutland, in the 2020 data 30% were dominated by broadleaves, 49 % were dominated by conifers, and 9 % were mixtures of broadleaves and conifers (Table 8.2).
Table 8.2. Metadata on the National Forest Inventory data used for modelling forest resources. Number of plots and mean values of the modelled forest variables for all NFI plots used in the modelling are provided according to the main species on the plots. For plots with mixtures of broadleaves and conifers, no species type takes up less than 25% of the basal area. 64 plots were not assigned any forest type. Standard deviations are provided in italics.

<table>
<thead>
<tr>
<th>Species type</th>
<th>Plots</th>
<th>2018-2021 data</th>
<th>2020 data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Canopy height</td>
<td>Growing stock</td>
</tr>
<tr>
<td></td>
<td>m</td>
<td>m³/ha</td>
<td>tons/ha</td>
</tr>
<tr>
<td>Total</td>
<td>1146</td>
<td>19,6</td>
<td>229,3</td>
</tr>
<tr>
<td>Broadleaf</td>
<td>564</td>
<td>9,4</td>
<td>200,5</td>
</tr>
<tr>
<td>Conifer</td>
<td>391</td>
<td>22,3</td>
<td>269,0</td>
</tr>
<tr>
<td>Mixed</td>
<td>127</td>
<td>9,1</td>
<td>217,1</td>
</tr>
<tr>
<td>No forest type</td>
<td>64</td>
<td>18,1</td>
<td>211,6</td>
</tr>
</tbody>
</table>

The forest variables (canopy height, growing stock, and biomass) were strongly correlated with many of the laser scanning variables, such as the 95th percentile and the mean above ground return height (Figure 8.8). Notably, the observed correlations were less for the broadleaves than for the conifers.
Figure 8.8. Correlation between canopy height and the 95th percentile as well as between growing stock and above-ground biomass and the mean pulse return height above ground.

The model framework provided in Equation 1 converged after 13 iterations of the ITSUR estimation and <5 minutes processing time. All parameters were significant in predicting the four variables (Table 8.3).
Table 8.3. Parameter estimates for the four forest resource models. Suffixes refer to the suffix numbers in Equation 1.

<table>
<thead>
<tr>
<th>Parameter suffix</th>
<th>Canopy height</th>
<th>Growing stock</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std Err</td>
</tr>
<tr>
<td>0</td>
<td>1.06974</td>
<td>0.1677</td>
</tr>
<tr>
<td>1</td>
<td>1.23654</td>
<td>0.0260</td>
</tr>
<tr>
<td>2</td>
<td>-0.09526</td>
<td>0.0315</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The final model system explained more than 90 pct. of the total variation in forest canopy height, but around (72-74%) of the variation in growing stock and forest biomass (Table 8.4). The validation showed a slight reduction in model accuracy for the volume and biomass estimates with a coefficient of determination of 68-69%. The models were unbiased, but the variance was heteroscedastic. As seen from the residual plots (Figure 8.9), deviations from the model mean were in some cases large, exceeding the predicted values, which has implications for model predictions on individual pixels.

Table 8.4. Fit statistics of the four forest resource models for both the estimation and validation data sets.

<table>
<thead>
<tr>
<th>Fit statistic</th>
<th>Estimation (80% of the dataset)</th>
<th>Validation (20% of the dataset)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Canopy height</td>
<td>Growing stock</td>
</tr>
<tr>
<td>AB</td>
<td>0,00</td>
<td>-1,47</td>
</tr>
<tr>
<td>AAB</td>
<td>1,85</td>
<td>68,24</td>
</tr>
<tr>
<td>RMSE</td>
<td>2,57</td>
<td>100,75</td>
</tr>
<tr>
<td>R sq</td>
<td>0,92</td>
<td>0,74</td>
</tr>
</tbody>
</table>
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 8.5).

Table 8.5. Parameter estimates for the four forest resource models estimated for forest types individually. Suffixes refer to the suffix numbers in the equation 1.

<table>
<thead>
<tr>
<th>Parameter suffix</th>
<th>Estimate</th>
<th>Std Err</th>
<th>t Value</th>
<th>Approx Pr &gt;</th>
<th>t</th>
<th></th>
<th>Estimate</th>
<th>Std Err</th>
<th>t Value</th>
<th>Approx Pr &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Canopy height</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Growing stock</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1.36095</td>
<td>0.2991</td>
<td>4.55</td>
<td>&lt;0.0001</td>
<td></td>
<td>5.43796</td>
<td>1.4406</td>
<td>3.77</td>
<td>&lt;0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.27255</td>
<td>0.0381</td>
<td>33.40</td>
<td>&lt;0.0001</td>
<td></td>
<td>0.70818</td>
<td>0.1041</td>
<td>6.81</td>
<td>&lt;0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.16527</td>
<td>0.0457</td>
<td>-3.62</td>
<td>0.0003</td>
<td></td>
<td>0.78236</td>
<td>0.1476</td>
<td>5.30</td>
<td>&lt;0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.37405</td>
<td>0.0924</td>
<td>4.05</td>
<td>&lt;0.0001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 8.9. Residuals of the four forest resource models for predicting forest canopy height, growing stock, above-ground biomass, and total biomass.
The model estimation generally led to unbiased models for the four variables judging from the average bias (AB, Table 8.6). Estimation of the models for individual forest types led to a slight improvement of the overall fit of the four forest resource models in Equation 1 (Table 8.6). However, the estimates also
demonstrated species-specific differences in the model’s ability to predict the different variables. Generally, prediction of conifer forest canopy height, volume and biomass were more accurate than the similar predictions for broadleaved and mixed forests judging from the root mean squared error and the R squared values.

Table 8.6. Fit statistics of the five forest resource models for individual forest types and across all forest types. Note that the fit statistics are calculated for a model estimated on the full dataset, without splitting into an estimation and a validation dataset.

<table>
<thead>
<tr>
<th>Fit statistic</th>
<th>Variable</th>
<th>Canopy height</th>
<th>Growing stock</th>
<th>Above-ground biomass</th>
<th>Total biomass</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Full dataset</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>0.00</td>
<td>-1.36</td>
<td>-0.14</td>
<td>-0.19</td>
</tr>
<tr>
<td></td>
<td>AAB</td>
<td>1.81</td>
<td>67.64</td>
<td>36.44</td>
<td>44.60</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>2.50</td>
<td>104.48</td>
<td>56.22</td>
<td>69.48</td>
</tr>
<tr>
<td></td>
<td>R sq</td>
<td>0.93</td>
<td>0.73</td>
<td>0.73</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>Broadleaves</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>-0.01</td>
<td>-1.51</td>
<td>-0.91</td>
<td>-1.11</td>
</tr>
<tr>
<td></td>
<td>AAB</td>
<td>2.01</td>
<td>81.90</td>
<td>44.82</td>
<td>55.29</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>2.75</td>
<td>124.49</td>
<td>68.06</td>
<td>84.67</td>
</tr>
<tr>
<td></td>
<td>R sq</td>
<td>0.91</td>
<td>0.67</td>
<td>0.69</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>Conifers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>-0.00</td>
<td>-0.83</td>
<td>-0.42</td>
<td>-0.52</td>
</tr>
<tr>
<td></td>
<td>AAB</td>
<td>1.39</td>
<td>52.95</td>
<td>27.70</td>
<td>33.29</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>1.88</td>
<td>77.07</td>
<td>38.43</td>
<td>46.25</td>
</tr>
<tr>
<td></td>
<td>R sq</td>
<td>0.94</td>
<td>0.80</td>
<td>0.77</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Mixed forest</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>-0.00</td>
<td>-0.68</td>
<td>-0.30</td>
<td>-0.38</td>
</tr>
<tr>
<td></td>
<td>AAB</td>
<td>1.83</td>
<td>58.65</td>
<td>32.34</td>
<td>40.10</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>2.44</td>
<td>81.83</td>
<td>45.37</td>
<td>56.33</td>
</tr>
<tr>
<td></td>
<td>R sq</td>
<td>0.91</td>
<td>0.77</td>
<td>0.74</td>
<td>0.73</td>
</tr>
</tbody>
</table>

The residuals of the forest type specific estimation of Equation 1 had much the same appearance as those for the general model (Figure 8.10). The residuals are clearly heteroscedastic with a few cases showing large deviation between actual and predicted values. Evidently, the broadleaved forest variables are more difficult for the model to predict.
Discussion of the pixel-based approach to forest resource mapping

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 70% of the variation in volume and biomass. This level of precision is comparable with similar studies in boreal and temperate regions (Næsset, 2004b, a; Næsset et al., 2004; Nord-Larsen and Schumacher, 2012; Nord-Larsen et al., 2017). Large errors were observed for some national inventory sample plots, sometimes exceeding the estimate by more than a hundred percent. In most cases these results are due to the design of the NFI where only the largest trees (dbh > 40 cm) are measured within the full 15 m radius plots. 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.

After estimation the models were applied to a grid of 25 x 25 m pixels to produce the final map (Figure 8.11). The maps clearly show the variation in stocking levels across the landscape even at the relative coarse resolution compared to the other forest resource mapping approaches demonstrated in this report. It may however be discussed if a much finer resolution would be meaningful. As a general rule, the resolution provided in any mapping should not be less than the size of the objects mapped. In case of forest resources, the object is the individual tree. With tree crowns often exceeding a diameter of 15 m, a finer resolution would often not be meaningful as individual pixels predicted to include a certain amount of

Figure 8.10. Residuals of the forest type specific estimation of Equation 1.
biomass would often not contain a single tree despite simply because predictions are made on crown characteristics.

**Figure 8.11. Mapping of forest resources in Frederikshåb Plantation.**

### 8.4 Forest resource mapping discussion and conclusion

In the evaluation of the forest resource mapping, the three different approaches showed similar accuracies. However, owing to differences in resolution and choice of validation/testing datasets, such comparison is difficult. To compare the three different approaches, we estimated total growing stock and biomass for the area scanned with laser scanning in 2020 and compared this to the corresponding estimate from the NFI (Table 8.7). In the evaluation, we clipped the forest resource maps with the forest area within the area scanned in 2020. The forest area used for the analysis was the one obtained with a method corresponding to the forest resource mapping. Specifically, the forest resource map obtained from individual tree delineation was clipped with forest area derived from individual tree crowns; the forest resource map derived from analysis of Planet Scope data was clipped with the forest area obtained from Planet Scope data; the forest resource map obtained from pixel-based regression with point cloud metrics was clipped with the forest area obtained from satellite imagery on Sentinel images.
Table 8.7. Forest resources estimated with the three methods and compared with the NFI estimates for the area included in the 2020 laser scanning of Denmark. Per hectare averages are provided in italics. The forest area used in the analysis was obtained from the corresponding methods of forest area estimation.

<table>
<thead>
<tr>
<th>Method/Data type</th>
<th>Forest area (ha)</th>
<th>Growing stock (1,000 m³)</th>
<th>Above-ground biomass (1,000 tonnes)</th>
<th>Total biomass (1,000 tonnes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial ortho-photos</td>
<td>117,949</td>
<td>7,668</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PlanetScope*</td>
<td>137,311</td>
<td>9,967</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pixel-based mapping from laser scanning**</td>
<td>165,622</td>
<td>18,398</td>
<td>9,548</td>
<td>11,744</td>
</tr>
<tr>
<td>NFI</td>
<td>116,672</td>
<td>15,976</td>
<td>8,486</td>
<td>10,391</td>
</tr>
</tbody>
</table>

* The area provided is the forest area derived from the PlanetScope mapping of forest area. The area estimated from the sum of pixels with biomass estimates is 127,056 ha.

** The area provided is the forest area derived from the Sentinel satellite imagery. The area estimated from the sum of pixels with biomass estimates is 132,407 ha.

The three different approaches to forest resource modelling apply quite different approaches, utilize different types of data and returned different products in terms of precision and resolution. Similar to the evaluation of the forest mapping products, this makes the identification of any ‘best’ approach difficult if at all possible. To rank the different approaches, we provided a schematic ranking different aspects related to e.g. accuracy, resolution, update frequency, complexity, and computational cost. Classification ranges from bad/complex/expensive (+) to good/simple/cheap (+++). from poor/bad (+) to high/good (+++) (Table 8.8). In the following, we provide the rationale for the ranking.

**Forest resource mapping from aerial images**

In the forest resource mapping from aerial images, the approach utilized the individual tree crown delineation from the forest mapping previously described. The resolution is consequently high (at the level of individual trees), and the approach enables future assessment of biomass resources and carbon stocks outside the forest, hereby enhancing other parts of the LULUCF emissions accounting. The bi-annual (leaf-off and leaf-on conditions) update of aerial images enables annual update of the forest resource data and also assessment of forest resources back in time as soon as the model is trained. However, the hitherto development in image quality may render long time series impossible to construct – older images simply have too poor a quality. Also, the method employed canopy height maps obtained from LiDAR, which has not been updated at regular intervals previously. The method yielded a high precision and accuracy when tested with independent NFI plot data using beyond state-of-the-art methods but misses understory trees in forests. This may be solved in future versions using improved methods that use the entire plot for training the model instead of individual trees.

The forest resource assessment from aerial images requires expensive hardware and custom-made coding. Similar to the forest area mapping, the produced models may not be readily interpreted and is beyond the
methodology applied elsewhere and hence results are difficult to compare with similar work in other countries. Furthermore, the novelty of the approach implies that the methodology has not been tested with data from several years and its sensitivity to changes in areal image quality and rendering is unknown. As for the mapping of forest area, problems with identifying small tree crowns and understorey trees may cause the method to yield biased results.

*Forest resource mapping from PlanetScope data*

Seemingly, the mapping of forest resources from PlanetScope data represents a compromise between the two other methods. In terms of spatial resolution, the method is in between the two others with a resolution of 3 x 3 m, which can capture larger trees outside forests. Furthermore, the frequent passing of the satellites enables frequent updates of the mapping products. The results produced were consistent across the country and between countries generating comparable results across Europe and over multiple years. Since the method relies on plot-based equations and not on the detection of individual tree crowns, understory trees are included in the estimates.

As the model utilizes the allometry of trees, errors from the cover and height predictions (section 7.2) are propagated and may produce errors. In its present formulation, the method is dependent on LiDAR data for training, but once a model is trained it can be applied on any year without further retraining.

*Pixel based forest resource mapping from LiDAR data*

The pixel-based method uses only freely available LiDAR data and may be processed using standard programmes such as SAS or R. The method is well-established and has been shown to produce reliable results across a wide range of studies conducted in the past three decades (Næsset, 1997, 2004b, a; Næsset et al., 2004; Nord-Larsen and Riis-Nielsen, 2010; Nord-Larsen and Schumacher, 2012; Nord-Larsen et al., 2017; Kangas et al., 2018b).

The pixel-based method produces a coarse representation of forest resources with a resolution of 25 x 25 m. Although a different resolution could be chosen it is of essence to use approximately the same size pixels as the NFI plots on which the model was trained. Moreover, it is a question whether it is meaningful to use a finer resolution than the maximum size of the objects (tree crowns). It is unknown to what extent the map accurately represents the forest resources outside forests albeit the method is certainly able to reflect the occurrence of e.g. shelterbelts (Figure 8.11). Laser scanning data is currently captured for only a fifth of the country every year resulting in a return-time of five years, and it is a question whether this is sufficient for the annual reporting of climate gasses and for applications in general forest management.
Table 8.8. Strength and weaknesses of the proposed methods for forest resource mapping. Classification ranges from bad/complex/expensive (+) to good/simple/cheap (+++).

<table>
<thead>
<tr>
<th>Method</th>
<th>Aerial images (7.1)</th>
<th>PlanetScope (7.2)</th>
<th>LiDAR (7.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>Deep learning model learns from NFI plots to predict biomass from aerial images. Can be converted to tree cover at any resolution.</td>
<td>Forest variables directly derived from tree cover and height maps using allometric equations from NFI data.</td>
<td>Canopy height, growing stock, and biomass estimated for 25x25 m pixels.</td>
</tr>
<tr>
<td>Method</td>
<td>Deep learning</td>
<td>Deep learning</td>
<td>Parametric models</td>
</tr>
<tr>
<td>Accuracy</td>
<td>++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>+++</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Temporal resolution</td>
<td>++</td>
<td>+++</td>
<td>+</td>
</tr>
<tr>
<td>Data costs</td>
<td>+++</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td>Computational costs</td>
<td>+</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>Method complexity</td>
<td>+</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>Continuity</td>
<td>+++</td>
<td>++</td>
<td>++</td>
</tr>
<tr>
<td>Versatility</td>
<td>+++</td>
<td>++</td>
<td>++</td>
</tr>
</tbody>
</table>

The ‘best’ path to future forest resource maps

As for the case of making forest maps, assessing which of the three methods that is best in producing future forest resource maps is not possible without defining what such a map will be used for and consequently what demands it should satisfy. Also in this case, this is no trivial task.

In general, the method of choice should allow high accuracy and a spatial resolution that is equal to or larger than the size of a tree crown. This because it makes little sense to have a resolution less than that of the object being analysed, in this case the individual tree. The exception to the rule is where the analysis is based on individual objects, such as in the estimation of delineated tree crowns from aerial images. In all three cases, we found that the spatial resolution produced was sufficient and in terms of mapping forest, while, to the extent that mapping of trees outside forests is desirable, only the estimates from delineated tree crowns is adequate. The three different methods produced different accuracies and in particular, the bias commonly observed with methods relying on interpretation of image data is concerning. In this respect, the pixel-based, two-stage estimation from LiDAR and NFI data is well proven and implemented elsewhere. Alternatively, recent discoveries in the estimation of biomass from full point clouds using deep regression have shown very high accuracies (Oehmcke et al., 2022) but the methods were not applied in this study.

The frequent and consistent update of the maps is essential for the implementation in private forest management as well as in development of forest analysis procedures such as accuracy assessment of carbon stocks. In general forest growth is slow while the forest growing stocks are small. Even with relatively high certainty in assessing the growing stocks, this creates a risk of an excessively small signal-to-noise ratio if updating forest resource maps at a too small interval. In particular, this will be problematic at small spatial scales and for geographically explicit estimates. For larger areas such as larger forest stands or
entire forests, we find that the five-year update cycle offered by the current set up of airborne laser scanning is sufficient. For geographically explicit estimates (i.e. maps), we encourage the development of post-processing tools aimed at reducing risk of errors in the change estimates.

As for the forest area mapping, the costs in terms of data purchase and computation differ among the three approaches but seem small, considering the effort vested in the overall forest mapping.

As for the forest area mapping, continuity and consistency are pivotal to the choice of method for future forest resource mapping and only methods relying on data sources expected to be available in the medium to long term (15-30 years) should be considered. Specifically for the LiDAR data used by all three approaches, The Danish Agency for Data Supply and Infrastructure expect to continue the current rotation of scanning (i.e., a 5-year cycle), but this should be clarified before any decision is made regarding future forest resource mapping efforts.

In conclusion, the hitherto applied two-stage, area-based method of forest resource mapping may provide a reasonable choice for future forest resource mapping, albeit new methods are currently emerging. Again, as for the forest area mapping, the final choice of method hence depends on further analyses of stakeholder needs.
9 Further perspectives

9.1 Increasing the precision of national forest resource and carbon stock estimates

Auxiliary variables, obtained by remote sensing and correlated with attributes of interest, may not only provide model-based forest resource maps of interest to regional and local forest management and land-use planners, but may also improve the precision of national and regional estimates.

In a study by Magnussen et al. (2018), forest resource maps from an airborne laser scanner (ALS) survey of Denmark (2014–2015, Nord-Larsen et al., 2017) developed in much the same way as described in section 8.3. was used in connection with field observations for analysing potential improvements in the precision of national and regional estimates of volume and total above-ground live tree biomass achievable through a combined use of field data from the NFI plots and a census of LiDAR based predictions of these attributes. In this study, estimates derived exclusively from the field data collected in sample plots (direct estimates or DI for short) were compared to model-assisted (MA) and model-calibrated (MC) results.

Model-assisted estimation is a form of design-based estimation that incorporates both design information (through the inclusion probabilities) and auxiliary information (through a model). The estimator consists of two parts, the mean of the predicted values over the population and the design bias adjustment consisting of inverse probability-weighted “residuals”. The model-calibrated estimator makes an adjustment to the design-based sample weights (the inverse of the sample inclusion probabilities) to achieve equality of the weighted sum of model estimates and the population total.

The results demonstrated that the standard error of the model-assisted and model-calibrated estimates of forest growing stock were 44 and 41% less than the standard error of the direct estimates. The precision gain so obtained corresponds to field sampling of almost three times as many sample plots annually in the national forest inventory.

The result is in line with similar studies (Ekström and Nilsson, 2021) and demonstrates that forest area and resource maps may have large potentials in reducing variation of estimates related to forest resources. This is of particular interest when contemplating the estimation of forest carbon stocks in relation to the climate gas emissions reporting. The reporting is assessing annual differences in carbon stocks to measure emissions from forests. As the annual change in forest carbon pools is small compared to the very large stocks, even small uncertainties in the estimates of the stocks result in large relative uncertainty in the estimate of emissions. Hence reductions of uncertainties in the magnitude observed for model-assisted and model-calibrated estimates would largely improve certainty of emissions reporting. Such gains are however ultimately dependent on regular, accurate, and consistent updating of the forest and forest resource maps such as demonstrated in this report.
9.2 Practical use in forest management

Forest information is collected at many levels and for many purposes. Typically, sampling-based national forest inventories are carried out to provide national- and international-level statistics. These statistics are commonly used to inform national or regional forest programmes, assessment of sustainability, investment calculations for forest industry, strategic-level planning in general, and reporting to international conventions. The inventories are designed to meet these targets with a sufficient precision and at a reasonable price, consequently commonly using sample designs with less than one sample plot per square kilometre.

At the forest holding level, spatially explicit forest data are needed to support forest owners in their strategic planning as well as for short term decision-making and planning of forest management. Forest management inventories have traditionally been carried out using both visual assessment of, for example, species distribution and forest cover as well as various types of sample plot measurements. Typically, such inventories are supported by aerial images for the division of the forest into manageable units called “stands” and to identify other useful elements for the mapping of the forest, such as forest roads, terrain, wet areas, ditches etc. The sample design used in the forest management inventories is commonly more detailed than the national forest inventories and is commonly focused on the mature and therefore valuable forest stands of importance to the forest owner.

Historically, national forest inventories and forest management inventories have been two separate activities carried out by different actors in the forest sector. Large-scale remote sensing information such as the different types of data presented in this pilot study (section 6) may change the roles and interplay of national forest inventories and forest management inventories, from completely independent processes to processes with possible synergies. Specifically, the interlinking of national forest inventory plots with remotely sensed data to produce wall-to-wall forest and forest resource maps readily used by forest owners and managers for forest management and planning bridges the gap between the inventory methods.

The mapping products produced in relation to this pilot study may readily be implemented in forest management inventories (Figure 9.1). In this way they may support future sustainable management of the forest resource, providing detailed and multifaceted information on for example forest resources, forest development, carbon stocks, and habitat quality. As such, the information provided can play an important role in the sustainable procurement of resources for the transition to a future carbon neutral society.

The bridging of national and forest management inventories for future sustainable forest management has been demonstrated among the Nordic countries including Denmark (Nord-Larsen and Schumacher, 2012; Nord-Larsen et al., 2017), Finland (Maltamo et al., 2014), Norway (Næsset, 2007), and Sweden (Nilsson et al., 2017). However, the costs associated with the implementation and use of the information provided in forest management programmes and routines requires that forest owners and managers may expect that such information will be available in foreseeable future. Consequently, the gain of producing remotely
sensed and detailed forest information for local and sustainable forest management is dependent on the frequent, reliable, and consistent updating of the forest resource maps.

Figure 9.1. Stand level estimates of forest canopy height (left) and growing stock (right) from Frederikshåb Plantation.

9.3 Use of forest maps in relation to biodiversity mapping

Forests play an important role in ecosystems, providing structure, shelter, and resources that support unique and diverse species communities. The importance of forests for biodiversity can be especially significant in areas that have a long history of deforestation and degradation, as they act as a last refuge for specially adapted forest organisms (Hanski, 1998; Gaublomme et al., 2014). In Denmark, as in much of Northern Europe, a long history of human activities has reduced forest cover to far below its natural state (Biodiversitetsrådet, 2022). Nearly two thirds of the land surface in Denmark is dedicated to crop production, while even the small amount of remaining forest is mostly managed for timber extraction (Levin, 2019; Nord-Larsen et al., 2021). Despite the increase in national forest cover in the last decades, the conservation status of all ten forest types protected by the EU Habitats Directive is classified as “strongly unfavourable” for supporting biodiversity – resulting mainly from the poor structural and functional condition of these forests (Fredshavn et al., 2019).

In light of the ongoing global biodiversity crisis (Barnosky et al., 2011; IPBES, 2019), understanding current and future biodiversity patterns is more important than ever. For understanding and mapping biodiversity
patterns, knowledge of the distribution and quality of habitat is invaluable. Knowledge of the relationship between species’ occurrences and their environment can help us predict their distribution in unsampled areas, which can help to overcome the logistical limitations of in situ sampling and can serve to predict changes under future scenarios of climate and/or management change. National scale citizen science programs – if well-designed to cover sufficient temporal and spatial resolutions – can be a cost-effective tool for supporting the monitoring of the state and change in local biodiversity (Geldmann et al., 2016). However, even for high quality citizen science data, their use in scientific research is often limited by the lack of linked environmental data as well as the risk of erroneous data owing to lack of expertise by volunteers. Remote sensing offers a promising opportunity to supplement in situ biological observations with meaningful data on the state of the local environment (Chandler et al., 2017).

With this pilot project we aim to provide an example of the biodiversity-related outputs that can be produced based on the Forest Map initiative products; a predictive map of forest bird species richness across Denmark using existing and newly developed maps of forest cover, type, and structure. This process will highlight the potential of the Forest Map initiative for use in management and conservation planning. We also provide examples of potential future uses for the proposed forest maps of interest for biodiversity research and monitoring.

Materials and methods for mapping bird diversity

We used point count data from the Common Bird Monitoring programme organised by Birdlife Denmark (1975-present, for more information see Eskildsen et al., 2021). Surveys were conducted along different length routes consisting of at least 10, but mostly 20 points – at which all birds seen or heard within a 5-minute period were recorded. Repeat observations of routes were made at the same time of year (± 7 days) and time of day (± 30 mins), and under good weather conditions. To match the timing of environmental data, we subset the years used to ensure a reasonable overlap. We therefore only used observations between 2014 and 2016, which we pooled to calculate mean species richness per point count. For our analysis, we considered volunteer bird observations from the summer breeding season (1st May – 15th June) for point counts on routes that began before midday. In total there were 3,568 point counts retained (Figure 9.2). We cleaned the observations to remove records of species that are not confirmed as breeding in Denmark (Vikstrøm and Moshøj, 2020), are uncertain identifications, or are hybrid species. Lastly, we aggregated sub-species to the species level and focused our analysis on species that have forests as their habitat (i.e., they occupy forest habitats during their breeding season; Cramp, 2006; Storchová and Hořák, 2018).

To model bird species richness, we obtained environmental data on forest type, cover, and distribution, alongside detailed three-dimensional (3D) structure from LiDAR, land cover composition, and climate conditions. To combine these disparate data sources, we resampled all layers to the same 300 x 300 m grid, which facilitated data extraction and was an appropriate scale for predicting observed bird richness. As the completed Forest Map of Denmark was not complete at the time of writing, we used remotely sensed layers that form part of the forest map pipeline (Figure 9.2). From the satellite-based estimation of forests in Denmark, we used a map of total forest cover and two maps delineating forest types (deciduous and
For measuring three-dimensional habitat structure, we used compiled data from the national LiDAR aerial survey program. We used the EcoDes-DK15 data set, which describes a broad range of ecological descriptors across Denmark (Assmann et al., 2022) and was assembled from the freely available LiDAR data from the Danish Agency for Efficiency and Data Supply (SDFI). The original LiDAR scans were predominantly carried out during leaf off and have a point density of 4-5 per m² (for details see Assmann et al., 2022). All ecological descriptors are stored as rasters at a resolution of 10 m x 10 m. From the LiDAR we included several descriptors of vegetation structure and amount: canopy, canopy openness, vegetation returns at various heights, and foliage height diversity. Foliage height diversity represents vertical structural complexity of vegetation and is calculated as the Shannon diversity index of vegetation stratified into five vertical layers (0–2 m, 2–5 m, 5–10 m, 10–15 m, and >15 m; (MacArthur and MacArthur, 1961; Clawges et al., 2008). These are also the layers we included to measure the raw amount of vegetation returns in each layer. From the LiDAR data we also included the derived topographic wetness index, which uses the terrain profile to indicate the relative wetness of the ground by determining natural drainage patterns. For all LiDAR variables we calculated their mean value and standard deviation in the final 300 m cells, resulting in 18 variables total.

We extracted land cover data from a pan-European land cover map for the year 2015 (30 x 30 m; Pflugmacher et al., 2019). For each of the 9 land cover classes present at our sites we calculated the percent cover of each cell at the scale of our final analysis (300 m). To describe land cover heterogeneity, we calculated ‘habitat diversity’, using the reciprocal Simpson index of land cover classes (Simpson, 1949). This metric represents compositional heterogeneity by calculating the probability that two randomly selected points are in different classes. The metric increases with the number and/or evenness of habitat types. In total there were 10 land cover variables. To account for the influence of climate on biodiversity patterns, we included four bioclimatic variables developed as part of the CHELSA data set (30 arc sec, ~1km global downsampled climate data; Karger et al., 2017, 2021). We selected mean annual air temperature, temperature seasonality, annual precipitation amount, and precipitation seasonality. We extracted the value of the climate variables for each 300 m cell. All climate variables were based on the years 1981 to 2010. Our models also included latitude and longitude of each cell to account for site differences related to location that were not captured by our environmental variables.

Analysis of bird observations

The analysis workflow consisted of 1) extracting the environmental and response data, 2) implementing a random forest model to explain the response (Breiman, 2001), and 3) projecting the model across all of
Denmark. As a precursor, we calculated the mean species richness for all 300 m cells which contained more than one point count (6%). In total there were 3,315 cells (0.67%) containing bird observations. Following this, we extracted the environmental data from each of the 40 variables for every grid cell which also contained bird observations. We split the data into three segments: 60% for training and optimising the model, 20% for testing the different candidate models to find the best, and the last 20% of the data was exclusively used to validate the final model’s accuracy. The data was split amongst these segments randomly following division into spatial blocks (25 x 25 km) to properly capture the model’s predictive ability outside of previously seen areas.

Model hyperparameters that we tuned during the training phase were node depth and the number of random variables tried at each split (mtry). Variables at each split were divided into 20 parts to find the variable and split point that minimised the mean squared error of the response. We used 300 trees for each training run, which was shown to be sufficient for model error convergence. The best performing model in the training phase (assessed by lowest root mean squared error to the testing data) had a terminal node size of 100 data points and tried 15 variables at each split. We fit our final model with 2000 decision trees and 80% of the data (60% from training and 20% from testing). We used permutation based variable importance to assess the role of each variable in the final model. We assessed our final model performance using the validation data set and projected the model to the whole of Denmark using the environmental data layers.

Results on bird diversity mapping

Our final model was built using a sample size of 2,724 cases and achieved a percent variation explained (pseudo-$R^2$) of 36% on the in sample data and 24% on the out of sample validation data. The validation data (591 cases) had a mean observed richness of 3.14 species per point count and the mean absolute error (MAE) of the model predictions was 0.95 species. Projecting this model to the whole of Denmark we get an estimate of how many forest bird species will likely be seen during a 5-minute point count in each 300 m grid cell (Fig. 1c). Mapped richness of forest bird species correlated strongly and positively with areas of high forest cover, as expected. However, our model also identified metrics of vegetation structure as important variables – for example, the mean and standard deviation of canopy height. The density of individual tree crowns, a layer developed from orthophotos as part of the forest map project, was ranked as the third most important environmental variable in our final model.
Figure 9.2. Modelling forest bird species richness. a) The distribution of volunteer point counts between 2014 and 2016 (3,568 points) organised by Bird Life Denmark (Dansk Ornitologisk Forening). b) An example of tree crown data that forms part of the digital forest map and was used in the modelling procedure. c) Example projection of modelled forest species richness – units are the expected number of forest bird species that would be seen during a five-minute point count (resolution 300 m).

Mapping forests for biodiversity assessment

Large scale, cost effective, and accurate mapping of forests is now possible thanks to advances in remote sensing technology and machine learning. The development of these new methods has begun to change the way we conduct forest inventories – and has seen rapid uptake in the Nordic countries (see Kangas et al., 2018a for a review). Remote sensing has also been successfully applied to the task of mapping and understanding biodiversity, with research increasingly including three-dimensional structure, for example, from national LiDAR data sets (Simonson et al., 2014; Moudrý et al., 2022).

Mapping the distribution of forests and their quality is an important step towards understanding and predicting the composition of biological communities in space and time. For this pilot study we used an array of remotely sensed environmental data to model the richness of forest bird species across Denmark. We show that new forest-related variables created as part of the forest map project provided biologically relevant information that helped explain biodiversity patterns. Projecting these relationships into space, we were able to build a predictive map of forest bird richness at an unprecedented high resolution (300 m) across all of Denmark. This first map, showing good concordance with areas of high forest cover, paves the
road for similar mapping for other organism groups as well as further research into the relative importance of individual variables for driving the distribution of richness and individual species.

The composition and complexity of forests, which tends to be higher in more natural forests, is positively correlated with the richness of animals and plants, as the structure that trees provide create habitats for many species (DeGraaf et al., 1998; Michel and Winter, 2009). More detailed information on the structure and biomass of forest areas as provided by remote sensing will therefore be key to better understanding the relationship between species to their environment, and ultimately for predicting and mapping richness patterns. Birds are a good case study in this regard, as they move and operate in three-dimensional space. Research on birds has long shown that the vertical complexity of forest structure, measured as foliage height diversity, often correlates positively with bird diversity (MacArthur and MacArthur, 1961; Goetz et al., 2007). The positive relationship between foliage height diversity and forest bird richness found in this pilot analysis points towards the potential utility of temporally repeated forest structure maps. These maps could serve to monitor, for example, the effects of long-term changes in forest structure on biodiversity in newly protected areas or of changed forest management practices. Measurement of vertical foliage complexity have also been shown to correlate strongly with total vegetation biomass (Verner and Larson, 1989; Clawges et al., 2008). Therefore, maps of Danish forest biomass will be a useful product in this, and other fields of biodiversity research.

The map produced in this pilot study makes ecological sense, i.e., there are more forest birds in highly forested areas, in particular in forests of high structural complexity, as reflected by the positive relationship found between richness and variation in canopy height. Yet, there is still a relatively large amount of unexplained variation in predicted richness (78%) that the input forest maps were unable to capture in our model. This finding suggests that there are unaccounted for variables that would help explain the observed biodiversity patterns and/or random variation. Key missing variables may include more detailed local climate data and information on the form and intensity of land management practices. There is also the complex web of biotic interactions with other organisms in their ecosystem – e.g., through competition and predation– which is known to influence biodiversity patterns at this scale (Gotelli et al., 2010). Individual species distribution models (e.g., Deneu et al., 2022) may better capture species habitat requirements and provide more accurate and informative maps of species composition at landscape scales. However, more comprehensive knowledge of forest cover, structure, and resources would undoubtedly enhance the accuracy of biodiversity models. Further, the predictive performance of similar models could potentially be higher for sedentary organism groups that may respond more strongly to local habitat requirements than birds, e.g. fungi and understorey plants (Moeslund et al., 2019). While our results indicate that on-the-ground biodiversity surveys are still needed, and that we cannot yet predict fine-scale bird richness from remotely sensed forest maps alone, our pilot map is a first for providing a detailed representation of spatial gradients in bird richness across Denmark that can form the basis for future fine-tuning and research.

In this pilot study, we have shown that not only do we expect the final forest map to be useful in biodiversity research, but that its constituent products can be valuable as well. Forest bird species richness was positively influenced by tree density in our model, and we expect that even more information at the
individual tree level will be extremely valuable. For example, the remote sensing process used to develop the forest map permits the identification of particularly large individual trees, both inside and outside forests. These trees often host diverse ecological communities, and are likely to occur in older, less managed forest areas that may have high biodiversity value for bird species and other organism groups. The identification of dominant tree species or functional groups from remote sensing is an additional product that could be implemented in the future of the forest map initiative, as is done for the Norwegian forest resource map (Breidenbach et al., 2021). This type of product could help us to better understand and predict the level and distribution of biodiversity.

A major strength of the proposed forest map project will be the sustained implementation of the mapping process each year. The pipelines developed to map forest attributes based on orthophotos could further be applicable to reconstruct past developments in forest structures using historical orthophotos, which in turn will enable unique research into changes in biodiversity in response to long-term forest dynamics. Temporal changes are an important yet understudied feature of ecological systems. Therefore, being able to relate changes in forest cover, structure, and biomass to changes in biodiversity will aid our understanding of dynamic ecological processes, as well as providing an indicator of the current and likely future health of biodiversity in Denmark.

In conclusion, the proposal to create an annually updated forest map of Denmark will have numerous benefits for our understanding of biodiversity dynamics across space and time. Our small pilot analysis of forest bird richness patterns demonstrated the usefulness of the forest map’s constituent parts – in particular, we found a strong influence of tree density estimated from remotely sensed tree crowns. Although our results were limited to forest bird species, the coordination of the forest map project will undoubtedly contribute to our understanding of diversity patterns for many other taxonomic groups and will be a valuable resource for biodiversity research in Denmark.
10 References


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Riis-Nielsen, T., 2016. Tabel- og feltbeskrivelse for DKSkov - den danske NFI (National Forest Inventory). In, Frederiksber, Denmark.


Vizzari, M., 2022. PlanetScope, Sentinel-2, and Sentinel-1 Data Integration for Object-Based Land Cover Classification in Google Earth Engine. 14, 2628.


Figure 11.1. NFI database structure. Description of the individual tables may be found in Riis-Nielsen (2016).
11.2 Forest map cookbook

Workflows for creating a consistent, updated forest map.
Work-flow of tree crown mapping from aerial ortho-photos

Figure 11.2. Work flow for the delineation of tree crowns from aerial ortho-photos.
Table 11.1. Basics for the modelling of individual tree crowns from the aerial data. A flow-diagram of the process may be found in Figure 11.2.

<table>
<thead>
<tr>
<th>Coding language</th>
<th>Python</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main environmental dependencies</td>
<td>Tensorflow, Keras, gdal</td>
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<tr>
<td>Software for labeling</td>
<td>QGIS</td>
</tr>
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<td>Labeling time</td>
<td>Approx. 3 weeks</td>
</tr>
<tr>
<td>Number of training epochs with default settings</td>
<td>1000~1500</td>
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<tr>
<td>Training time</td>
<td>Approx. 35 hours with 1 GPU (GeForce RTX 3090)</td>
</tr>
<tr>
<td>Prediction speed</td>
<td>Approx. 25 seconds per 1km*1km grid (batch size = 32)</td>
</tr>
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</table>
Figure 11.3. Work-flow for the delineation of tree canopies using PlanetScope data.
Work-flow of forest area mapping with sentinel data

Figure 11.4. Processing diagram on forest classification from Sentinel 1 and 2 data using NFI labelled data. Red shapes done in google earth engine and blue shapes done in Rstudio.
Figure 11.5. Processing diagram of the steps in the forest delineation of tree or canopy polygons into a forest map in accordance with international definitions.
Table 11.2. Agriculture codes with possible forest cover. Some codes are unlikely to have forest cover (specifically grassland), but the selection has been made as wide as possible to avoid excess preclusion of potential forest lands.

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
<th>Code</th>
<th>Description</th>
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<tbody>
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<td>247</td>
<td>Miljøgræs MVJ-tilsagn</td>
<td>576</td>
<td>Skovrejsning (statslig) - forbedring af vandmiljø og grundvandsbeskyttelse</td>
</tr>
<tr>
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<td>577</td>
<td>Skov med biodiversitetsformål</td>
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<td>578</td>
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<td>Anden skovdrift</td>
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<td>Skovdrift med fjernelse af ved</td>
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<td>Pyntegrønt, økologisk jordbrug</td>
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<td>Juletærer og pyntegrønt</td>
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<td>Skovrejsning i projektområde, som ikke er omfattet af tilsagn</td>
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<td>Bæredygtig skovdrift i Natura 2000-område</td>
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<td>MVJ, ej udtagning, ej landbrugsareal</td>
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<td>El</td>
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<td>MFO-brak, udtagning, ej landbrugsareal</td>
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<td>MFO - Lavskov</td>
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<td>Skovrejsning (privat) – kulstofbinding og grundvandsbeskyttelse</td>
<td>907</td>
<td>Naturarealer, økologisk jordbrug</td>
</tr>
</tbody>
</table>
11.3 Forest resource map cookbook
Work-flow of forest resource mapping from individual tree crowns

Figure 11.6. Work-flow of forest resource mapping from delineation of individual tree crowns.

- Individual tree crowns
  - + canopy height map → Height per tree (H)
  - + forest type map → Forest type per tree
  - geometry → Tree crown diameter (CD)
  - Global allometric equations: $AGB^{allo} = function (CD, H, forest type)$
    - $AGB^{allo}$ per tree → Sum entire NFI plot
    - $AGB^{NFI}$ per plot → Locally calibrated AGB per plot
Figure 11.7. Work-flow for the mapping of forest resources from PlanetScope images.
Work-flow of pixel-based mapping of forest resources from laser scanning data

Figure 11.8. Work-flow diagram of the mapping of forest resources from laser scanning data. The two-stage procedure is shown by red (first stage) and blue (second stage) arrows.