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DIGITAL AERIAL PHOTOGRAFOMETRY FOR ESTIMATING
FOREST INVENTORY ATTRIBUTES: APPLICATIONS FOR
SPATIAL AND TEMPORAL ANALYSIS

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Complete copy of the dissertation approved by the TUM School of Life Sciences Weihenstephan of the Technische Universität München in partial fulfillment of the requirements for the degree of

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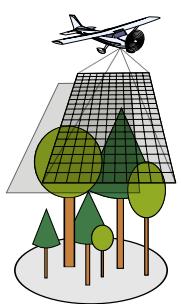
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TEMPORAL ANALYSIS



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The title page shows an artwork displaying the acquisition of overlapping digital aerial images and trees measured on a ground plot (own drawing).

This document was set in L^AT_EX using the `classicthesis` and `arsclassica` packages.

I have found the best way to give advice to your children
is to find out what they want and then advise them to do it.

— *Harry S. Truman*

Dedicated to the loving parents Elisabeth and Ludwig Stepper.

ABSTRACT

Information about canopy height and spatial structure is essential for various tasks in forest planning and management. Retrieving this information from remote sensing data has been focus in research as this technique opens the possibility to assess large forested areas. The work presented in this thesis focussed on utilizing digital aerial imagery from airborne platforms to generate accurate measurements of canopy height by means of image matching algorithms. Together with ground information, necessary for model calibration, different forest inventory attributes can be assessed ...

ZUSAMMENFASSUNG

Informationen über die Bestandeshöhe und die räumliche Verteilung der Bäume in einem Bestand ...

PUBLICATIONS

This dissertation was done in a publication-based manner. The developed methods, the results of the different studies, and the findings were published in the following scientific papers:

List of scientific papers included in this thesis.

- Immitzer, M., Stepper, C., Böck, S., Straub, C. and Atzberger, C. (2016). Use of WorldView-2 stereo imagery and National Forest Inventory data for wall-to-wall mapping of growing stock. *Forest Ecology and Management* **359**, 232–246. doi: [10.1016/j.foreco.2015.10.018](https://doi.org/10.1016/j.foreco.2015.10.018).
- Stepper, C., Straub, C. and Pretzsch, H. (2015a). Assessing height changes in a highly structured forest using regularly acquired aerial image data. *Forestry* **88** (3): 304–316. doi: [10.1093/forestry/cpu050](https://doi.org/10.1093/forestry/cpu050).
- Stepper, C., Straub, C., Immitzer, M. and Pretzsch, H. (submitted). Using canopy heights from digital aerial photogrammetry to enable spatial transfer of forest attribute models: a case study in central Europe. *Scandinavian Journal of Forest Research*.
- Stepper, C., Straub, C. and Pretzsch, H. (2015b). Using semi-global matching point clouds to estimate growing stock at the plot and stand levels: application for a broadleaf-dominated forest in central Europe. *Canadian Journal of Forest Research* **45** (1): 111–123. doi: [10.1139/cjfr-2014-0297](https://doi.org/10.1139/cjfr-2014-0297).
- Straub, C. and Stepper, C. (in press). Using digital aerial photogrammetry and the Random Forests approach to model forest inventory attributes in beech- and spruce-dominated central European forests. *Photogrammetrie, Fernerkundung, Geoinformation (PFG)*.
- White, J. C., Stepper, C., Tompalski, P., Coops, N. C. and Wulder, M. A. (2015). Comparing ALS and Image-Based Point Cloud Metrics and Modelled Forest Inventory Attributes in a Complex Coastal Forest Environment. *Forests* **6** (10): 3704–3732. doi: [10.3390/f6103704](https://doi.org/10.3390/f6103704).

The papers cover different studies completed during the course of my Ph.D. I realised these studies both with my colleagues at the Bavarian State Institute of Forestry as well as in collaboration with scientists from other research institutes.

*In general, the remote sensing problem
can be presented as inferring the order
in the properties and distributions of matter
and energy in the scene from the set
of measurements comprising the image.*

— Strahler et al., 1986

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I would like to take the opportunity to thank all those involved in the work I did in the last years. Without your help and support, I would not have been able to mastering the challenges on my way to this thesis.

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ACRONYMS

ABA	area-based approach
ALS	airborne laser scanning
ACS	angle-count sampling
BaySF	Bayerische Staatsforsten
CHM	canopy height model
DAP	digital aerial photogrammetry
DBH	diameter at breast height
DSM	digital surface model
DTM	digital terrain model
GSD	ground sampling distance
LiDAR	Light Detection and Ranging
ME	mean error
MFI	management forest inventory
NFI	national forest inventory
NVI	Northern Vancouver Island
OLS	ordinary least squares
oob	out-of-bag
PAI	periodic annual increment
RF	random forest
RMSE	root mean squared error
SGM	semi-global matching
WV ₂	WorldView-2

1

Part I

2

3

4

5

DIGITAL AERIAL PHOTOGRAFMETRY FOR ESTIMATING FOREST INVENTORY ATTRIBUTES: APPLICATIONS FOR SPATIAL AND TEMPORAL ANALYSIS

1

INTRODUCTION

1.1 REMOTE SENSING IN FORESTRY

The development of remote sensing is strongly linked with the progress of flight – across different realms from sky to space – with a rather short scientific history. Accordingly, the definition of the term *remote sensing* itself has been evolving over the decades, and even today, scientists do not agree on one universal term. However, as a common basis in the scientific field, a general definition in the broad sense can be the following (Franklin, 2001; Hildebrandt, 1996):

Remote sensing is the acquisition of information about objects or areas from a distance, without making physical contact with them. Further, the processing and analysis of the acquired data as well as the interpretation of the achieved results are essential parts of remote sensing. The predominant aim in remote sensing applications is to achieve quantitative and qualitative information about the occurrence (pattern) of objects, their current state as well as the changes over time.

General definition of remote sensing.

When considering objects on the earth's surface, sensors for acquiring data are typically mounted on aircrafts or satellites. Generally, the sensors collect information by detecting electromagnetic radiation, which is emitted or reflected from the observed objects. Two basic principles of remote sensing data acquisition technologies can be distinguished: (i) passive remote sensing systems, which gather the natural energy that is emitted or reflected by the earth's surface, most commonly the reflected sunlight, and (ii) active remote sensing systems, which themselves emit electromagnetic radiation and measure the reflectance pattern returning from the earth's surface.

Passive and active remote sensing systems.

Examples for passive remote sensing systems include aerial photography or many earth observation satellite systems with multispectral sensors, e.g., Landsat or Sentinel 2. Radar and airborne laser scanning (ALS) are examples of active remote sensing, with both technologies measuring the time delays between emission and return, allowing for the assessment of object location and other properties.

From the advent of these new technologies, remote sensing allowed for the collection of data for vast and difficult-to-access areas. Thus, researchers and practitioners charged with mapping and analysis of natural environments like forests were early adopters to these data sets. Today, due to the fact of a widespread range of applications in forestry, including different scales in space (i.e., from needle to landscape to global) and time (i.e., from seconds to seasons to decades), a large variety of sensors are employed to best meet the research and practical necessities. The following list, which makes no claim to be complete, should facilitate the reader to get a brief overview of important remote sensing systems and their primarily applications.

A large variety of remote sensing systems are used in forestry applications.

EARTH OBSERVATION SATELLITE DATA: Earth observation satellites are purposely designed to acquire data for characterizing environmental sys-

tems on a global scale. As the satellites continuously navigate around the globe, images covering vast areas can be recorded with high temporal repetition rates.

In environmental studies, data from earth observation satellites are typically utilized as information source to create maps of land cover and land use. Many of these satellite systems are designed for long-term global observations, and the image series of these satellites recorded through time make them a primary data source when conducting time series analysis for assessing change pattern, e.g., to quantify forest cover change etc. Technically speaking, most of the applications dealing with satellite imagery can be assigned to the image classification domain.

AERIAL PHOTOGRAPHS: Aerial photographs (airphotos) were pretty much the first largely available remotely sensed data source and have been used manifold in forest research and practice with different fields of applications (see section 1.2). For instance, these data found use in forest management planning or forest inventory in different regions.

AIRBORNE LASER SCANNING: Airborne laser scanning ([ALS](#)), also referred to as airborne Light Detection and Ranging ([LiDAR](#)), has been introduced to forest research in the 1980s and 1990s (Nelson, [2013](#)), and is now widely acknowledged as the primary source to acquire information characterizing the three-dimensional forest vertical structure (Lim et al., [2003](#); Maltamo et al., [2014](#)). [ALS](#) can be used to measure the surface height of objects, e.g., trees, similarly to the photogrammetric measurements from stereo airphotos.

However, the laser pulses emitted from the measuring platform are able to penetrate through small gaps in the canopy, and returns from leaves, branches, or stems additionally allow for the characterization of the vertical canopy structure. Moreover, returns from the ground enable [ALS](#) to even map the terrain underneath forest canopies with high accuracy. This property, the availability to actually measure heights of objects within the canopy and of the ground – which is invisible from optical aerial or satellite images – made [ALS](#) very attractive for forestry applications and stimulated enormous research efforts to fully explore the usability of these data.

1.2 AERIAL PHOTOGRAPHY, AIRBORNE LASER SCANNING AND THE RENAISSANCE OF AERIAL PHOTOGRAMMETRY

1.2.1 Acquisition principles for aerial photographs

Typically, aerial photographs are considered as perspective pictures of the underlying area taken with cameras mounted on aircrafts. In most acquisition cases, vertical photographs are recorded, i.e., the camera is pointing vertically down towards the mapped area. To cover larger areas of interest, aerial image acquisitions are planned and conducted in a block layout: the aircraft is following a series of parallel flight lines, and photographs are taken such that they overlap to a specified amount in both directions along track (*forward*) and across track (*side*; see Figure 1).

Vertical airphotos are perspective pictures of the underlying area with the camera pointing down vertically to the ground.

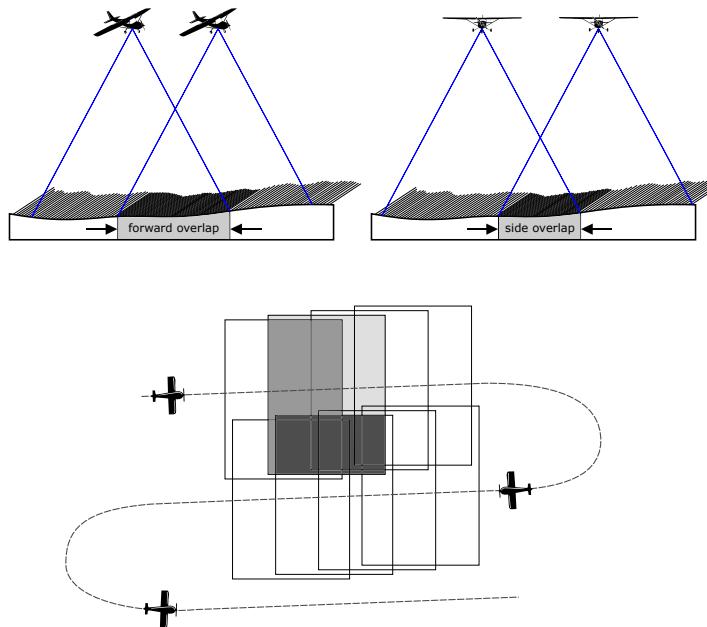


Figure 1: Exemplary setting for aerial photograph acquisitions. The typical overlaps of the images within flight lines (*forward*) and across flight lines (*side*) range between 60–80 % and 20–40 %, respectively (modified after van Laar and Akça, 2007 and Arbeitsgruppe Forstlicher Luftbildinterpretoren, 2012).

In this way, each object within the study area is depicted from at minimum two different positions. The overlapping parts of the images are referred to as the stereoscopic overlap areas, which can be analysed following the stereophotogrammetric measuring principle. This allows for the recovery of exact positions of surface points, i.e., estimating the three-dimensional coordinates of specific points or objects.

Overlapping areas of airphotos allow for photogrammetric analysis.

1.2.2 Early forestry related applications of aerial photography

The use of aerial photography for mapping and monitoring forested landscapes can look back upon a long tradition (Hildebrandt, 1996). Airphotos have been routinely interpreted for several decades by natural resource scientists and managers, most commonly to assist in the mapping of large areas and to inform forest inventory programs (Arbeitsgruppe Forstlicher Luftbildinterpretoren, 2012; Cohen et al., 1996; van Laar and Akça, 2007).

The very first documented trial for utilizing aerial photographs for practical forestry was undertaken as early as 1887, when photos taken from a balloon were used to sketch a map of forest stands close to Berlin in Germany (Hildebrandt, 2010). In subsequent years aerial photographs have been employed for forestry routine tasks throughout the world. This development was especially promoted after the First World War when steerable aircrafts were available and aerial frame cameras were invented.

Typical purposes of application include large scale mapping (e.g., 1:10 000) and forest management planning for intensively managed forests (as common in many European jurisdictions) or in support of region-wide inventory programs with delineations of forest cover maps (like often necessary in North American regions). Further, the aerial imagery has been used for lay-

Airphotos have been used for mapping, for support of forest inventory and management planning, and for monitoring forest vitality.

123 ing out and mapping forest road networks, and, especially with the advent
 124 of the colour-infrared film, for monitoring forest vitality and detecting areas
 125 damaged by, e.g., storms or bark beetle infestations (Hildebrandt, 1996).

126 Whereas until today aerial photographs are used as one of the main
 127 sources of information for the aforementioned areas of application, the full
 128 potential of stereoscopic aerial photo-interpretation has not been unfold un-
 129 til the recent past. From the beginning of aerial photography, analogous
 130 taken pictures were the primary source of information and a lot of manual
 131 processing was necessary prior to analysis. Stereo-interpretation was labour-
 132 intensive and required a high level of training. Due to that, orthophotos
 133 were utilized for analysis in many applications instead of conducting ex-
 134 pensive stereo photo-interpretation. Hildebrandt (1996) emphasized that
 135 even 100 years after the first application of airphotos in forestry, these data
 136 are seldom used for forest mensuration purposes or for forest site assess-
 137 ment.

138 1.2.3 Height assessment via stereophotogrammetry

139 The most valuable technological achievement of stereophotogrammetry is
 140 the ability to actually measure the three-dimensional coordinates of objects,
 141 which can be identified in at least two overlapping images. Having this ste-
 142 reophotogrammetric measuring principle on hand, it seems logical, that tree
 143 height is the most important dendrometric attribute which can be assessed
 144 via stereo aerial photographs (Paine and Kiser, 2012).

Stereophotogrammetry allows for the measurement of 3d coordinates.

145 However, the exact measurement of tree heights is restricted to those trees,
 146 where both the tree top and base is visible in the photos. In dense forest
 147 stands, it actually is impossible to find ground points in the close vicinity
 148 to the trees of interest, in order to get the required elevation of the tree
 149 base. This shortcoming when using aerial photogrammetry as sole remote
 150 sensing information source is one reason which impeded the broad use for
 151 tree height measurements – and for assessing stand heights and related
 152 attributes of interest.

For exact tree height measurements, tree top and base must be visible in the aerial photographs.

153 Soon after the widespread integration of aerial photographs in forestry,
 154 researchers examined their usefulness for forest mensuration tasks, in par-
 155 ticular for determining growing stocks of forest stands. Pioneer work was
 156 done by Hugershoff (1933) and Neumann (1933). They introduced an ap-
 157 proach based on continuous surface measurements and consecutive deriva-
 158 tions of vertical canopy extents, resulting in cross-sectional canopy profiles
 159 of forest stands (Figure 2). In their work, they could demonstrate that the
 160 cross-sectional areas of the canopy profiles were apparently related to the
 161 amount of timber volume at the site of the profile. Spurr (1948) mentioned,
 162 that this method is especially useful when approaching uneven-aged stands,
 163 as variations in tree height and stand density are considered. By construct-
 164 ing multiple parallel cross-sectional profiles of the forest stand of interest,
 165 the *growing space* describing the canopy volume could be constructed and
 166 used as proxy for growing stock.

Cross-sectional canopy profiles can be used to approximate growing stock.

167 However, due to the difficulty to determine these profiles with the ana-
 168 logue instruments available at that time, the method could not gain accept-
 169 ance for widespread use. Meanwhile, researchers seized on that approach
 170 as the development of better instruments facilitated the construction of can-
 171 opy profiles based on stereo aerial photographs. As an example, Maclean
 172 and Martin (1984) measured cross-sectional canopy profile areas from ste-
 173 reoscopic aerial photographs with a stereoplotter, and related these areas

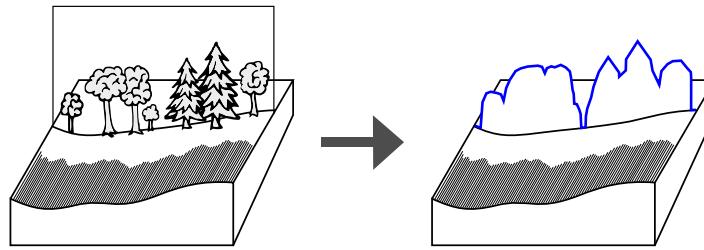


Figure 2: Basic idea of the cross-sectional canopy profile derived from measurements of the three-dimensional forest canopy structure. Detailed measurements of the outer canopy surface are achievable by both the DAP and ALS technology. However, photogrammetric measurements of the ground are restricted to gaps in the canopy. By contrast, active ALS-measurements allow for a detailed description of the terrain even for densely stocked forests. Thus, by combining photogrammetric height measurements of the canopy surface and ALS measurements of the ground, detailed descriptions of actual forest heights become possible (modified after Aldred and Bonnor, 1985, Nelson et al., 1984 and Nilsson, 1996).

174 to timber volume data. They reported the relations to be highly significant,
175 with regression R^2 values ranging from 0.67 to 0.79.

176 Nonetheless, two main aspects remained unsolved until the recent dec-
177 ades and hampered the further integration of these approaches for assessing
178 forest inventory attributes:

- 179 ● Conducting the methods described above with analogous instruments
180 means a high effort in terms of manual work, when height measure-
181 ments for the coverage of larger forest areas is desired.
- 182 ● In dense forests, photogrammetric measurements of ground heights
183 are restricted to irregularly distributed canopy openings. Interpola-
184 tion of these sparse terrain height measurements results in inaccurate
185 descriptions of the forest floor, especially for rough terrains. These er-
186 rors in terrain height are propagated into tree- and stand-height mea-
187 surements.

188 1.2.4 Airborne laser scanning in forestry

189 As mentioned, the three-dimensional characterization of forest canopies by
190 means of remote sensing tools has long been one of the top priority requests.
191 Over the course of the 1980s, a new technology loomed on the horizon. ALS
192 was expected to provide detailed measurements of forest canopies, and in
193 consequence, a lot of research concentrated on exploring the newly opened
194 possibilities. Pioneer work was published, e. g., by Aldred and Bonnor (1985)
195 and Nelson et al. (1984), who primarily focused on the assessment of tree
196 heights and crown closure.

197 Maclean and Krabill (1986) picked up the ideas of Hugershoff (1933), and
198 regressed timber volume against cross-sectional areas of canopy profiles of
199 forests obtained by airborne profiling LiDAR systems. They elaborated on
200 the mensurational significance of the variable *cross-sectional profile area* as
201 a remotely sensed wrapper variable for total tree height, crown diameter
202 and crown closure – three sensitive indicators for timber volume. In their

Drawbacks of
photogrammetric tree
height measurements
impede extensive
application.

ALS was introduced
to forest research in
the 1980s, focusing
on assessing tree
height and crown
closure.

Airborne
LiDAR-based
cross-sectional
profiles were
regressed against
timber volume.

study, Maclean and Krabill (1986) demonstrated that the cross-sectional profile area is a very good indicator for the total amount of timber on a site.

Nelson et al. (1988) tested a number of different laser metrics as predictor variables to develop regression models for timber volume and forest biomass. The set of metrics comprised different measurements of forest height and canopy density. In their analysis, mean canopy height (calculated from the laser pulses and directly proportional to the canopy profile area) proved to be best suited as independent laser variable for predicting timber volume and biomass, respectively.

As stated by Baltsavias (1999), commercial [ALS](#) systems became widely available during the 1990s. These scanning systems were able to record area-covering measurements in contrast to the early profilers, and such provide much greater distributions of height samples. Research studies, in the beginnings conducted especially in the Scandinavian countries, examined the usability of the [ALS](#) systems in forestry applications.

Nilsson (1996) investigated how [ALS](#) data acquisition parameters (laser beam footprint size and sampling density) affect stand height estimation. He further explored the usability of these data for determining stand specific volumes in an even-aged stand dominated by Scots pine in Sweden. He found that the laser mean heights underestimated the ground measured mean tree heights, irrespective of beam divergence. In addition, he could demonstrate, for that study site, that there existed a linear relationship between stand volume and an [ALS](#)-based metric including laser height and pulse density.

Næsset (1997a) used [ALS](#) data to approximate the mean tree height of forest stands in Norway, dominated by either Norway spruce or Scots pine, and reported promising results. For the same stands, he assessed the accuracy of volume estimation by means of multiple regression analysis, utilizing [ALS](#) predictor variables describing mean vegetation heights and canopy cover densities (Næsset, 1997b). He found that mean stand height and mean height of the laser returns (which might be regarded as per area unit of normalized canopy volume) were the most significant predictors for stand volume. The inclusion of the canopy cover metric, however, had a significant impact on the regression.

Consecutive research was conducted, e. g., by Magnussen and Boudewyn (1998) or Means et al. (2000), who reported on successful [ALS](#) applications in British Columbia and Oregon, respectively. The former study primarily focused on the exploration of a large set of possible predictor variables, which can be calculated from the airborne laser scanner measurements, for approximating forest stand heights. The latter demonstrated that [ALS](#) data are capable to produce sound predictions for stand characteristics such as height, basal area and volume. Interestingly, when using the [LiDAR](#) metrics in stepwise regression analysis, height percentile metrics as well as canopy cover metrics were selected for the final models of basal area and volume. Means et al. (2000) further proposed, that [ALS](#) was now a readily available source of information, which can be used to estimate stand characteristics over large areas – and after streamlining the process, maps displaying the spatial distribution of forest inventory attributes can be produced.

Following Means et al. (2000), Næsset and Bjerknes (2001) explored how accurately mean heights of the dominant trees and numbers of stems can be predicted from [ALS](#) metrics over young coniferous forest stands in Norway. In their regression analysis, they applied multiplicative models (in linear form with logarithmically transformed variables) to develop the pre-

dictive models. The final models for dominant height and stem number achieved coefficients of determination (R^2) of 0.83 and 0.42, respectively, with the finally selected predictors being the 90th height percentile plus the laser canopy density for the first and canopy density solely for the second attribute. More important for practical use in forest management, Næsset and Bjerknes (2001) proposed a two-stage procedure for the prediction of mean dominant stand height. To do so, empirical relations between various [ALS](#) metrics and tree heights measured in the field can be built using small georeferenced sample plots. In the second stage, the forest area of interest gets divided into equal-sized cells with the single areas corresponding to the sample plots. The trained models can then be applied to provide estimates of tree heights for the respective cells, and in consequence, for the stands throughout the forests. They evaluated their approach using 29 sample plots for training and 12 test stands, for which they report a mean height difference of 0.23 m between laser-derived and ground-truth stand heights.

In his 2002 paper, Næsset expanded the practical two-stage procedure for the prediction of six forest inventory attributes: mean tree height, dominant height, mean diameter, stem number, basal area, and timber volume (Næsset, 2002a). He tested the procedure for young and mature forest stands following the same statistical methods as described in Næsset and Bjerknes (2001), and concluded that the selected characteristics can be determined at the stand level with fairly high precision except for stem number. In subsequent years, this approach received much attention and was implemented to practical application for large-scale forest inventory and management throughout different forest ecosystems (Hudak et al., 2006; Hyypä et al., 2008; Li et al., 2008; Næsset, 2004; Næsset et al., 2004; Woods et al., 2011).

The great relevance of [ALS](#) in forestry applications, especially for the approximation of forest inventory attributes using the area-based approach was confirmed by White et al. (2013a), who summarized the state-of-the-art approaches, methods, and data. In their best practices guide, they described the entire process for generating forest inventory attributes from [ALS](#) data. Additionally, they discussed the use of different statistical methods for fulfilling the estimation tasks, including machine learning approaches like random forest (RF), which became popular recently. They further pointed to the fact, that there was currently increasing interest to the use of point clouds generated from high resolution digital aerial imagery, particularly for employing these data to generate estimates of forest characteristics in the same way as described above for [ALS](#) data.

1.2.5 Digital images and processing capabilities

During the last decade, aerial photography, and more specifically the photogrammetric evaluation capabilities of stereo airphotos, experienced increased attention in forestry related remote sensing research activities (Holopainen et al., 2015; White, 2016; White et al., 2013b). This development has been instigated by a number of different factors (Haala and Rothermel, 2012; Leberl et al., 2010):

- ongoing improvements in camera technology, especially the introduction and further developments of digital aerial cameras;
- nation-wide availabilities of digitally recorded aerial imagery acquired within routine observation programs run by the surveying authorities;

- 306 • inventions of advanced algorithms for image matching such as the
 307 pixelwise semi-global matching ([SGM](#)) and implementations to popular
 308 remote sensing software packages;
- 309 • rapid progress in hardware capacities enabling for the processing of
 310 large image blocks and the computed [DAP](#) products.

311 The digital acquisition of airborne stereo photography achieved a break-
 312 through in administrative surveying in many jurisdiction, particularly in
 313 central and northern European countries. Due to that, the availability of
 314 good quality photographs with large degrees of overlap has been boosted
 315 in recent years.

316 Moreover, the development of new algorithms for image matching, which
 317 allow for the computation of dense photogrammetric height measurements
 318 from stereo imagery, triggered increasing interest in digital airphotos as
 319 additional data source for retrieving 3d information. Thus, today [DAP](#) is
 320 emerging as an alternate data source to [ALS](#) for the three-dimensional char-
 321 acterization of forest structure.

322 1.3 PREDICTION OF FOREST INVENTORY ATTRIB-

323 UTES

324 As mentioned above, one major field of application for remote sensing in
 325 forestry is forest inventory. Remote sensing data, particularly airphotos,
 326 have been commonly used to assist in inventory tasks, either as auxiliary
 327 data to facilitate inventory design or for other purposes.

328 Nonetheless, with regard to both large-area inventories like national forest
 329 inventories ([NFIs](#)) or inventories purposely conducted for management is-
 330 sues ([MFIs](#)), the primarily used information is still gathered via ground based
 331 measurements at defined field sample plots. Especially with regard to the
 332 intensively managed forest compartments as common in many European
 333 forest enterprises, these inventories are the basis for both forest manage-
 334 ment planning and control.

335 Most often, the ground plots are laid out systematically on a defined grid
 336 (e.g., 200 m x 200 m) throughout the forests, and cover specified areas (e.g.,
 337 500 m²), in order to achieve representative measurements (e.g., Neufanger,
 338 [2011](#)). Those field measurements allow for reliable assessments of the nat-
 339 ural resources when considering the complete forest enterprises or specific
 340 strata. However, these inventories were not purposely designed to allow for
 341 statements at the level of the forest stand, the primary unit of area for forest
 342 management.

343 In contrast to the sample based measurements from terrestrial forest in-
 344 ventories, remote sensing provides data able to cover large areas. By com-
 345 bining both data sources, the ground based measurements of the current
 346 forest state as response variable, and the remotely sensed data providing ex-
 347 planatory information, in a statistical manner, prediction models for forest
 348 inventory attributes by means of remote sensing can be trained and con-
 349 sequently applied to generate area-covering predictions (White et al., [2013a](#)).
 350 Next, these spatially explicit predictions can be used to assist in forest man-
 351 agement, as they can provide information in a high spatial resolution.

352 One common method to accomplish the described necessity for approx-
 353 imating forest inventory attributes and to consecutively predict their numer-
 354 ical values for wall-to-wall mapping is the area-based approach ([ABA](#)). This

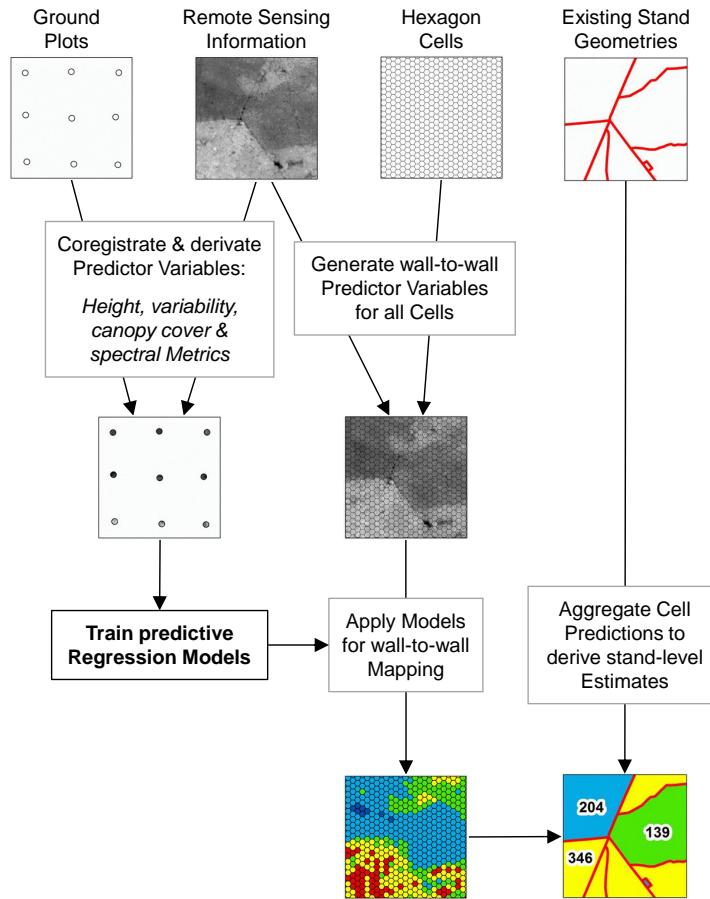


Figure 3: Schematic illustration of the area-based approach for prediction and wall-to-wall mapping of dendrometric forest inventory attributes.

approach, first proposed by Næsset (2002b) for use with [ALS](#) data in large-scale inventory, can be summarized in the processing steps as outlined in Figure 3.

In order to compute the statistical metrics summarizing the remotely sensed measurements of the forest canopy, recorded measurements have to be translated into heights above ground before further use. As mentioned above, one of the most beneficial aspects of [ALS](#) is the possibility to simultaneously acquire height measurements from the vegetation and the underlying terrain. Thus, [ALS](#) data can be directly converted to canopy heights above ground, and used in consecutive analysis. By contrast, photogrammetrically computed heights only describe the outer surface heights – this makes it necessary to employ ground heights from another source (e.g., [ALS](#)), to arrive at the canopy heights above ground.

On a related note, when analysing and further processing these kind of 3d data, one has the option to either stick to the point data, or to translate the irregular measurements to rasterized surface models. Following the first option, no loss in information has to be accepted, but specialized software is necessary for further processing. On the other hand, following option two, which is compelling due to the ease in data storage and the availability of raster processing tools, the operator has to select an appropriate spatial resolution for the computed rasters and has to keep in mind that by the rasterization, some detail information gets lost.

377 **1.4 DIGITAL AERIAL PHOTOGRAHMTRY IN FOREST
378 INVENTORY APPLICATIONS: CURRENT STATE**

379 As mentioned in the previous sections, different technical and methodo-
380 logical developments caused the returning interest of forest scientists and
381 practitioners to aerial photographs, in particular to **DAP**. Therefore, and due
382 to the achievements made with **ALS** data in the meanwhile, it is logical that
383 this stimulated great interest in exploiting the digital imagery to generate
384 **ALS**-like characterizations of vegetation three-dimensional structure, espe-
385 cially as airphotos can be acquired at a fraction of the costs of **LiDAR**.

386 The recent focus of work with **DAP** data in forestry applications was par-
387 ticularly on its use in forest inventory. This development is confirmed by
388 the heavily increased number of published research dealing with these ques-
389 tions in recent years. The following is an attempt to summarize the current
390 developments and research results in this specific field, as the aims and ob-
391 jectives of the work in hand are embedded in this general framework and
392 especially focussed on the use of **DAP** data for forest inventory tasks and to
393 support forest management.

394 At the beginning of this decade, numerous studies focused on the com-
395 parison of **DAP**-based height data and **ALS** data for estimation forest invent-
396 ory attributes following the **ABA**. Initially, studies from Scandinavia were
397 published (Bohlin et al., 2012; Järnstedt et al., 2012; Nurminen et al., 2013;
398 Vastaranta et al., 2013), investigating the predictive capabilities of **DAP**-based
399 height data for a set of attributes. These studies were conducted for man-
400 aged forests in flat terrain – mostly even-aged stands with few species.

401 ERGEBNISSE DER STUDIEN ZUSAMMENFASSEN

402 Later on, research was also conducted for different and more complex
403 forests, e. g., in central Europe (Straub et al., 2013) or the boreal of Ontario,
404 Canada (Pitt et al., 2014). Under these more challenging conditions, the com-
405 parison of model performance for approximating forest inventory attributes
406 approved the results from the formerly conducted studies: the models using
407 **ALS**-based predictor variables achieve somewhat higher accuracies than the
408 models using **DAP**-derived predictor variables.

409 *Zusammenfassung der bisherigen Studien zu ABA and DAP. TABELLE*

410 **1.5 RESEARCH AIMS AND OBJECTIVES**

411 The purpose of the presented work was to scrutinize digital aerial photo-
412 graphs, as regularly acquired by the Surveying Authorities nowadays, for
413 use in forest inventory, forest planning, and forest management. During the
414 course of the project, a range of applications was addressed and examined
415 in different studies. The overarching aims of the presented studies were:

- 416 1. Are digital aerial images acquired within the standardized adminis-
417 trative aerial surveys suitable to compute dense image-based point
418 clouds or digital surface models (**DSMs**) by means of image-matching
419 techniques (e. g., **SGM**), that characterize forest canopy surfaces with a
420 sufficient level of detail?
- 421 2. Can image-based outputs derived from digital airphotos, i.e., point
422 clouds and raster-based surface models, normalized to heights above

*Overall aims of the
studies.*

423 ground using ALS-based digital terrain models ([DTMs](#)), be used to
 424 model key forest inventory attributes, e.g., mean or top height, basal
 425 area, and gross volume?

426 3. Are repeated aerial image acquisitions and the derived image-based
 427 canopy height models ([CHMs](#)) capable to assess canopy height changes
 428 over time?

429 Against this background, more specific research objectives were formulated.
 430 We focused on these objectives in separate studies:

Specific research objectives.

431 Stepper et al. *Can. J. For. Res.* (2015)

- 432 • application of [SGM](#) to generate a very dense 2.5D point cloud that
 433 would provide a detailed characterization of the surface structure of
 434 the forest canopy;
- 435 • examination of several spectral features computed from the orthoim-
 436 agery as additional explanatory variables for estimating gross volume
 437 V , in combination with height and structural variables derived from
 438 the image-based height data;
- 439 • comparative testing of [RF](#) regression models vs. ordinary least squares
 440 ([OLS](#)) linear regression models to estimate V at the plot level, as well
 441 as at the stand level;
- 442 • investigation of the effect of different sampling densities, i.e., system-
 443 atically reduced numbers of terrestrial inventory plots, on the accuracy
 444 and bias of the estimation of V .

445 Straub & Stepper *Photogramm. Fernerkund. Geoinf.* (in press)

- 446 • adoption of the workflow as developed in Stepper et al. (2015b) for
 447 estimating a set of five forest inventory attributes – stem density N ,
 448 basal area G , quadratic mean diameter QMD, volume V , and Lorey's
 449 mean height H_L – using [CHM](#)-based predictor variables and the [RF](#)
 450 approach;
- 451 • evaluation of the impact of the prevailing forest type on the perform-
 452 ance of models used to predict forest attributes. I.e., study areas rep-
 453 resenting common broadleaf- and conifer-dominated forest environ-
 454 ments in German (beech- and spruce-dominated, respectively) were
 455 selected and predictive forest attribute models from both test sites
 456 were compared with respect to accuracy and bias.

457 Stepper et al. *Scand. J. For. Res.* (submitted)

- 458 • investigation of predictive [RF](#) models for the forest attributes d_{100} ,
 459 h_{100} , and V . Specifically, we study feature importance of predictor
 460 variables derived from [SGM](#) point clouds and examine model perform-
 461 ance by means of root mean squared error ([RMSE](#)) and mean error ([ME](#));
- 462 • exploration of the spatial portability of forest attribute models to close-
 463 by forests, i.e., by means of large-area-covering aerial image data. The
 464 spatial transfer is validated at independent ground plots in neighbour-
 465 ing forest areas;

- 466 ● demonstrating the effect of training data coverage on model performance
 467 by systematically eliminating forest inventory plots for model
 468 training.

469 White et al. *Forests* (2015)

- 470 ● characterizing the differences between **ALS**- and image-based point
 471 cloud metrics across a range of environmental conditions, defined by
 472 topographic slope and canopy cover;
- 473 ● generation of area-based predictive models for Lorey's mean height
 474 H_L , basal area G, and gross volume V from both sources of point
 475 cloud data and comparison of model outcomes in the context of the
 476 differences for the **ALS**- and **DAP**-derived metrics and in the context of
 477 different acquisition conditions for the imagery.

478 Immitzer et al. *Forest Ecol. Manag.* (2016)

- 479 ● modelling gross volume V using angle-count sampling (**ACS**) **NFI** field
 480 data and WorldView-2 (**WV2**) stereo satellite imagery by implementing
 481 a multi-circle and multi-metrics approach for prediction at the pixel
 482 level;
- 483 ● evaluating the explanatory power of spectral and height-related met-
 484 rics computed from the multispectral WV-2 imagery and the image-
 485 based **CHM**;
- 486 ● developing a wall-to-wall application method for the predictive mod-
 487 els by using a moving-window approach.

488 Stepper et al. *Forestry* (2015)

- 489 ● application of **SGM** to automatically compute image-based **CHMs** for
 490 two consecutive image data sets acquired as part of the regularly
 491 scheduled aerial image surveys in Bavaria;
- 492 ● derivation and comparison of the periodic annual increment (**PAI**) of
 493 forest height computed from the two **CHMs** and two corresponding
 494 field inventory data sets at georeferenced ground plots;
- 495 ● analysis of the **PAIs** in height for three height classes representing dif-
 496 ferent successional stages – *youth, full vigour* and *old age*.

497 | 2 MATERIALS

498 2.1 STUDY AREAS

499 The research studies, which are compiled in the present work, were con-
500 ducted using remote sensing data and ground based measurements from
501 different test sites (see Figures 4 and 5, and Table 1). The selection of the
502 test sites in *Bavaria*, Germany, was made in order to best meet the following
503 criteria:

- 504 • Field inventory measurements of recent date are available for larger
505 contiguous forested areas.
- 506 • Lapse of time between the acquisition of the airphotos and the ground
507 based measurements is as short as possible.
- 508 • Test sites represent different forest conditions, including topography,
509 climate, tree species, tree species mixture, and forest management
510 practice.

511 The test site on *Northern Vancouver Island* (*NVI*) was selected in order to scrup-
512 ulize the developed methods under largely different conditions, i. e., among
513 other factors, the areal extent of the test site, the prevailing tree species,
514 the applied forest management, and the different strategy for ground data
515 acquisition. Timely coincident data of *ALS* and aerial photography were
516 available for the *NVI* area, which allowed for a comparative analysis of both
517 remote sensing data types for use in forest inventory applications.

Selection criteria for
the study areas in
Bavaria.

A comparative
analysis of *ALS*- and
DAP-based height
data was possible for
the *NVI* test site.

518 **Table 1:** Overview of the different test sites in Bavaria, Germany, and British
Columbia, Canada.

TEST SITE	AREA [km ²]	DOMINANT TREE SPECIES	STUDIES
<i>Spessart</i> (northwestern Bavaria)	446	European beech, sessile oak	Straub and Stepper, 2016
<i>Steigerwald</i> (northwestern Bavaria)	556	European beech, sessile oak	Stepper et al., 2015b; Immitzer et al., 2016; Stepper et al., submitted
<i>Frankenwald</i> (northeastern Bavaria)	396	Norway spruce	Straub and Stepper, 2016; Stepper et al., submitted
<i>Traunstein</i> (southeastern Bavaria)	90	Norway spruce, European beech, white fir	Stepper et al., 2015a
<i>Northern</i> <i>Vancouver Island</i> (British Columbia)	662	Western hemlock, Western red cedar	White et al., 2015

Note: detailed descriptions of the test sites are given in the respective research papers.
Deviating figures for area sizes are due to use of different subsets for the studies.

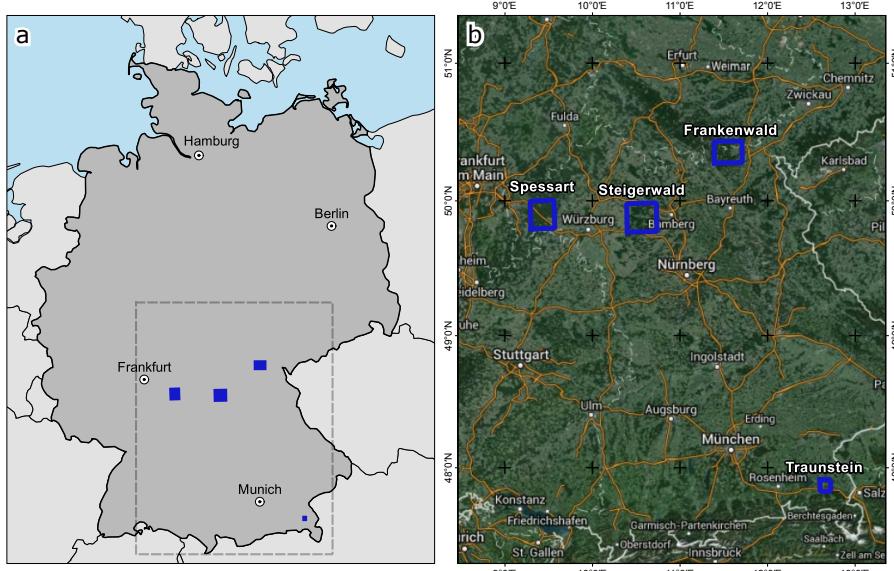


Figure 4: Map of the study areas *Spessart*, *Steigerwald*, *Frankenwald*, and *Traunstein* in Bavaria, Germany. (a) Location in Germany; (b) detailed locations in Bavaria (Images ©Landsat, Mapdata ©GeoBasis-DE/BKG(© 2009), Google).

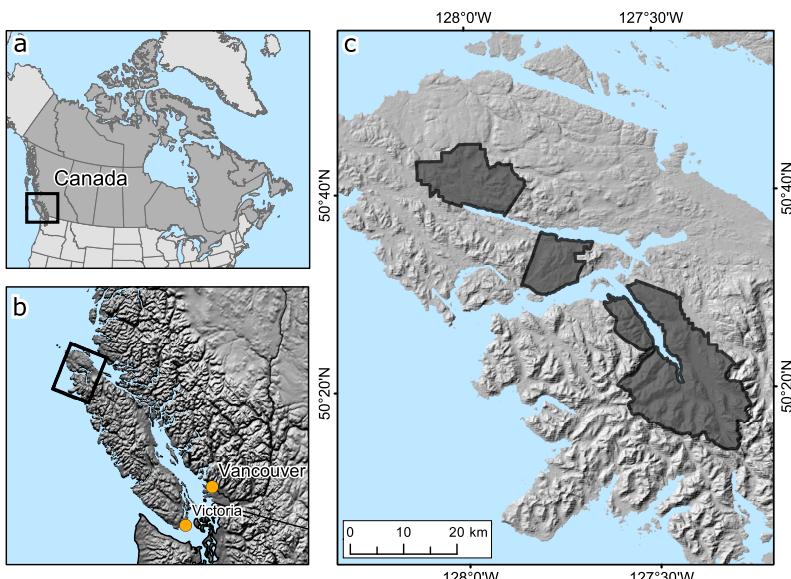


Figure 5: Map of the study area *Northern Vancouver Island* in British Columbia, Canada. (a) Location in British Columbia, Canada; (b) location on Northern Vancouver Island; (c) boundaries of the study area units.

519 2.2 FIELD DATA

520 2.2.1 Bavarian State Forest Enterprise

521 Main parts of the test sites *Spessart*, *Steigerwald*, and *Frankenwald* are state-
 522 owned land, mostly managed forests with a great variety of stand develop-
 523 ment stages. The areas are managed by the Bayerische Staatsforsten ([BaySF](#)),

and field data are recorded frequently according to their forest management guidelines (Neufanger, 2011).

For the respective forests, recurring terrestrial sample-based forest inventory systems are installed, and comprehensive measurements are carried out on a 10-year frequency basis. The permanent ground plots where the data are collected are laid out in a regular grid pattern of 200 m x 200 m. The plot centres are permanently marked in the field, and during the inventories, each particular plot location is georeferenced using a GPS device.

The forest management inventories in the state forests of Bavaria make use of the sampling concept with three concentric measurement circles at the respective ground plots. A general introduction to this concept can be found in van Laar and Akça (2007). Here, the trees are recorded with all relevant attributes in dependency of their diameter at breast height (DBH; measured at 1.3 m above ground) and their distance to the plot centre. For the forest inventories conducted by BaySF, the radii and DBH thresholds for the concentric circles assembling a circular inventory plot typically are set as summarized in Table 2.

Table 2: Radii and DBH thresholds for the concentric sampling circles assembling a ground plot in typical BaySF management inventories.

CIRCLE NO.	RADIUS [m]	AREA [m ²]	DBH [cm]
1	2.82	25	< 12
2	6.31	125	12–29.9
3	12.62	500	≥ 30

Based on the individual tree measurements, a set of forest inventory attributes is computed. These compiled data sets include, *inter alia*, mean tree height, basal area per hectare, and gross volume per hectare. In the course of the research project, other attributes, e. g., stand top height, came into focus, and procedures were applied to compute the attributes from the individual tree measurements.

The field data for the BaySF test sites included in this work, namely *Spessart*, *Steigerwald*, and *Frankenwald*, were recorded in 2011, 2010, and 2014, respectively. For more detailed descriptions of the field data acquisitions as well as the derivation of forest inventory attributes, refer to the respective sections in the articles.

2.2.2 National forest inventory data

Field data from the German NFI were selected as reference data for model training in the study of Immitzer et al. (2016). Contrary to the concentric sampling circles used within the management forest inventories of BaySF, the German NFI is based on angle-count sampling (ACS) as basic sampling principle. Here, the probability of a tree for inclusion to the measurements is proportional to its basal area at a defined height. Each tree trunk is focused from the sample plot centre and is selected if the DBH exceeds a prescribed angle width (defined by the so called basal area factor). For more information regarding the German NFI and the ACS method, refer to the corresponding section in the paper (Immitzer et al., 2016) or to Polley et al. (2010).

Ground plots for terrestrial inventory measurements are permanently marked in the Bavarian state forests.

Tree measurements at the plots are made according to concentric sampling circles.

A set of forest inventory attributes is computed based on the individual tree measurements.

Field data in the test sites Spessart, Steigerwald, and Frankenwald were acquired in 2011, 2010, and 2014.

ACS is used as basic sampling principle in the German NFI.

Our study was conducted in the *Steigerwald* test site, and a total of 92 sample plots from the most recent NFI were used for modelling. The field measurements were conducted in 2011 and 2012, and field-based estimates of growing stock, separately for conifers and broadleaves, were made available to us.

NFI field data were recorded in 2011 and 2012.

2.2.3 Municipal Forest of Traunstein

The forest area, which was chosen as test site for the study of Stepper et al. (2015a), is part of the municipal forest which belongs to the city of Traunstein. The forest stands are actively managed to support an uneven-aged mixed-species forest and comprise a great variety of successional stages, i.e., heterogeneous species composition, many different age classes, and multi-layered stands.

Similarly to the field sampling design described above for the BaySF inventories (subsection 2.2.1), the permanently marked field plots within the *Traunstein* study area – 228, in total – are distributed in a regular grid pattern of 100 m x 100 m. At the plots, measurements are carried out using concentric sampling circles, based on the following radii and corresponding DBH thresholds: 3.15 m ($DBH < 10$ cm), 6.31 m ($10 \leq DBH < 30$ cm) and 12.62 m ($DBH \geq 30$ cm).

The *Traunstein* forest test site was selected for our experiment of assessing forest height changes by means of DAP-based CHMs, as field measurements from two terrestrial inventories carried out in 2008 and 2013 were available. Using the ground plot measurements, field-based top heights were calculated for each inventory plot, and in consequence, field-based periodic annual increment (PAI) could be derived as reference for our investigation. Details regarding the ground measurements and the subsequent calculations are given in the respective sections of the paper (Stepper et al., 2015a).

Field measurements collected in 2008 and 2013 were available for the *Traunstein* test site.

2.2.4 Northern Vancouver Island

To select the ground plot locations in the NVI study area, a stratified random sampling design was used. The ground plots were allocated to five different strata, defined by species information, biogeographic data, and elevation data. The sample locations within the strata were selected by a systematic partition, informed by the 3d ALS-derived feature space.

Stratified random sampling was used to select the ground plot locations at NVI.

In total, 140 ground plots were established within the NVI test site (which corresponds to a much greater area representativeness of the individual plots compared to the ones described in subsections 2.2.1 and 2.2.3). In the field, the plot centres were established using a GPS device, and all live standing trees with $DBH \geq 12.0$ cm were measured within a radius of 14 m (615.75m^2). The individual tree measurements included DBH, stem height, age and other mensurational data, and estimates for different forest inventory attributes, including Lorey's mean height, basal area, and gross volume, were calculated for each plot (White et al., 2015).

2.3 REMOTE SENSING DATA

This work was purposely designed to investigate digital aerial photographs as remote sensing data for use in forest inventory and management ap-

609 plications. Thus, airphotos were the primary remotely sensed data used
 610 for analysis in this study. Besides aerial photography, we examined stereo
 611 WorldView-2 ([WV2](#)) satellite data for generating 3d height measurements of
 612 forest canopies, and the consequent use for a wall-to-wall mapping applica-
 613 tion of forest inventory data. [ALS](#) data were used twofold: (i) as indispens-
 614 able source of information providing detailed elevation models, i. e., ground
 615 heights of the terrain; (ii) as reference remote sensing data used in the [ABA](#)
 616 modelling of forest inventory attributes, i. e., to judge the achieved results
 617 when using [DAP](#) derived height information.

618 2.3.1 Digital Aerial Photographs

619 The digital aerial photographs used for the studies conducted in the Bav-
 620 arian test sites (see Table 1) were provided by the Bavarian Administration
 621 for Surveying. Currently, the aerial photographs are updated every three
 622 years in Bavaria. General specifications for these official aerial photographs
 623 are provided in LDBV ([2015b](#)).

Digital airphotos are acquired routinely by the Bavarian Administration for Surveying.

624 All images used in our studies were acquired during leaf-on conditions
 625 with digital aerial frame cameras, and both panchromatic (PAN) and PAN-
 626 sharpened multispectral images (blue, green, red, and near infrared) of the
 627 same radiometric resolution (12 bit) were available. The aerial photographs
 628 were acquired such that a ground sampling distance ([GSD](#)) of 0.20 m could
 629 be ensured for all images.

630 The overlaps of the stereo images varied between different years of data
 631 acquisition and different test sites, but, in general, overlaps in forward and
 632 side direction of 65–75 % and 25–40 % were achieved. For details regarding
 633 the used camera type, the individual image overlaps, and the flight dates
 634 of the aerial surveys, the reader is referred to the respective sections of the
 635 research articles.

The typical overlaps of the stereo images in Bavaria were 65–75 % in forward and 25–40 % in side direction.

636 With regard to the study conducted on [NVI](#), digital aerial imagery was
 637 acquired by the tree farm licensee Western Forest Products Inc. being re-
 638 sponsible for the management of the forests within the study area. For
 639 complete coverage of the area, imagery was acquired during four different
 640 flights from August to October 2012. The photographs were acquired with
 641 a minimum of 60 % along-track (forward) and 20 % across-track (side) over-
 642 lap. The airphotos were provided as 4-band (blue, green, red, near infrared)
 643 multispectral images with a 0.30 m [GSD](#) and 8 bit radiometric resolution.

644 2.3.2 World-View 2 Data

645 In the study of Immitzer et al. ([2016](#)) we explored the usability of high-
 646 resolution optical satellite imagery recorded in stereoscopic collection mode
 647 for the image-based generation of 3d height data and further application.
 648 Therefore, [WV2](#) stereo satellite image data were used. [WV2](#) records panchro-
 649 matic images plus multispectral images comprising eight spectral bands
 650 (coastal, blue, green, yellow, red, red edge, near infrared 1, near infrared 2;
 651 Digital Globe, [2013](#)).

652 For the test site *Steigerwald* complete coverage was achieved through two
 653 stereo-image pairs, i. e., four [WV2](#) images, which were recorded under leaf-
 654 on conditions in August 2013. The spectral data were atmospherically cor-
 655 rected and thus, top-of-canopy spectral reflectance was available for further
 656 analysis. The [WV2](#) data were provided as panchromatic images with 0.50 m

657 spatial resolution, and as 8-band multispectral images resampled to 1.0 m
658 pixel size.

659 2.3.3 Airborne Laser Scanning Data

660 As mentioned above, one essential benefit of [ALS](#) data sets is that measurements
661 describing the canopy structure and the ground surface can be
662 acquired simultaneously. This allows for the computation of vegetation
663 heights using inherent ground measurements. For the [DAP](#)-based reconstruc-
664 tion of vegetation height, additional bare earth information is necessary.

665 The Bavarian Administration for Surveying routinely runs [ALS](#) mapping
666 surveys in order to achieve accurate measurements of the terrain (however,
667 with no distinct repeat cycle). Based on these [ALS](#) data, digital terrain mod-
668 els ([DTMs](#)) with 1 m ground resolution are available for the entire area of the
669 country (LDBV, 2015a). In the course of the research project, the [ALS](#)-based
670 [DTMs](#) were used for the height normalization of the [DAP](#)-based surface mea-
671 surements. Canopy heights were consequently calculated as difference of the
672 image-based surface heights and the [ALS](#)-based terrain heights.

*DTMs with 1 m
ground resolution are
available for the
entire area of
Bavaria.*

673 In the [NVI](#) study area [ALS](#) point clouds were acquired at the same time as
674 the digital airphotos, i. e., in August and September 2012. The data had an
675 average return point density of 11.6 points·m². Based on the ground returns
676 from that data, a [DTM](#) with a spatial resolution of 1 m was created. The [DTM](#)
677 was used to normalize the [ALS](#) point cloud heights to heights above ground
678 level. In addition, the image-based points from the [NVI](#) study area were
679 transformed to heights above ground using the same [ALS](#)-based [DTM](#).

680 3 | METHODS

681 3.1 DIGITAL AERIAL PHOTOGRAHMTRY

682 3.1.1 General Considerations on Image Matching

683 Photogrammetry is a measurement technique to derive 3d coordinates of
684 object points, which are depicted on images taken from different positions
685 (Lemmens, 2011). By utilizing the stereophotogrammetric measuring prin-
686 ciple (see subsection 1.2.3) and with known orientation parameters of the
687 images¹, the coordinates of the objects of interest can be retrieved via trian-
688 gulation. According to Schenk (1999, p. 231),

689 "[o]ne of the most fundamental processes in photogrammetry
690 is to identify and to measure conjugate points in two or more
691 overlapping photographs. Stereo photogrammetry relies entirely
692 on conjugate points. In analogue and analytical photogrammetry
693 the identification of conjugate points is performed by a human
694 operator; in digital photogrammetry one attempts to solve the
695 problem automatically – a process known as image matching."

3d coordinates of
objects can be derived
from stereo images
via photogrammetry.

Identification and
measurement of
conjugate points in
overlapping images
is fundamental in
photogrammetry.

696 The introduction of stereo-image matching techniques in photogrammetry
697 allowed for automation in different processing steps, particularly in the cre-
698 ation of dense height measurements, and is the fundamental basis for DAP.
699 Generally speaking, the aim of image matching is to identify corresponding
700 pattern in the stereo-image pairs, i. e., the base and the match image. The
701 problem in finding these correspondences is to trace and locate the pattern
702 in the match image as the conjugate of a pattern in the base image (Lem-
703 mens, 2011).

704 Traditionally, the image-matching methods may be assigned to two cat-
705 egories depending on how the image – an array of pixels storing digital
706 numbers – is approached (ERDAS, 2010; Gruen, 2012). The first category
707 can be classified as *feature-based matching* approaches. These focus on the
708 evaluation of similarities of extracted features in both base and match image,
709 which may be depictions of prominent features like corners of buildings,
710 road crossings, or solitaire trees in case of aerial photographs. The second
711 group of algorithms can be categorized as *area-based matching* approaches.
712 Here, correspondence between the stereo images is sought using the grey
713 level values in regularly shaped patches, e. g., 9x9 pixel windows. A refer-
714 ence window, remaining at a constant location in the base image, is defined
715 as source for calculating correlation to candidate windows on the match
716 image. Many different search windows in the match image are evaluated
717 until the location for correspondence is determined by the highest value for
718 the correlation coefficient. Consequently, the centre pixels of the reference
719 and search window are selected as corresponding points. Most commonly,
720 normalized cross-correlation (NCC) is used for calculating correlation and
721 acceptance of the match depends on whether the similarity value exceeds

Established image
matching categories:
feature-based and
area-based
matching.

¹ *interior orientation:* focal length, principal point (X, Y), pixel size; *exterior orientation:* position coordinates of the projection centre (X, Y, Z), plus angular parameters (ω, ϕ, κ).

722 a predefined threshold (Lemmens, 2011). A trade-off is associated with the
 723 definition of the correlation threshold: whereas choosing too small values al-
 724 lows for many mismatches, i. e., wrong correspondences of pixels, too high
 725 values impede many matches and in consequence, the density of matches
 726 found for a stereo-image pair decreases.

727 3.1.2 Semi-global Matching

728 Problems with finding correspondences are especially connected to object
 729 boundaries, fine structures, low and repetitive textures, and recording and
 730 illumination differences in the images. In order to overcome these draw-
 731 backs, effort was put into developing new image-matching methods. One
 732 approach which have gained considerable attention in recent years, is the
 733 so-called semi-global matching ([SGM](#)) technique introduced by Hirschmüller
 734 (2005, 2008). [SGM](#) is based on the idea of pixelwise matching and approxim-
 735 ating a global 2d smoothness constraint by combining many 1d constraints.
 736 The basic steps of [SGM](#) are:

- 737 • Generation of epipolar images by projectively warp the base and match
 738 images with known geometries such that the epipolar lines are hori-
 739 zontal.
- 740 • Calculation of possible disparities for each pixel along the epipolar
 741 search lines in the base image and computation of matching costs for
 742 each candidate disparity by a similarity measure (e. g., Mutual Inform-
 743 ation, Census) comparing the pixel grey values.
- 744 • Aggregation of costs by pathwise accumulation of minimal costs along
 745 a certain number of 1d path directions through the base image. Here,
 746 additional smoothness constraints are introduced by penalizing dis-
 747 parity changes.
- 748 • Determination of final disparities for each pixel in the base image by
 749 selecting the candidate pixel in the match image that corresponds to
 750 the minimum cost.
- 751 • Intersection of viewing rays in the stereo images according to the final
 752 disparity image to achieve dense 3d point clouds in object space.

753 More details regarding the performed steps in [SGM](#) and the implemented
 754 algorithms are provided in, e. g., Hirschmüller (2008, 2011) and Gehrke et al.
 755 (2010).

756 We applied the [SGM](#) approach for image matching and consecutive deriva-
 757 tion of image-based surface heights throughout the studies presented in this
 758 work². For the processing, we used the [SGM](#) implementation within the Re-
 759 mote Sensing Software Package Graz (RSG). The cost function used in RSG
 760 follows the Census disparity measure, and the matching procedure is hier-
 761 archically structured as coarse to fine matching, with consequent disparity
 762 calculations on four image pyramid levels.

763 We selected the panchromatic band of the stereo images for matching in
 764 all Bavarian test sites. Due to the low across-track overlaps of the images,
 765 we used only stereo-image pairs from the along-track overlap for calculation.
 766 For the [NVI](#) test site, the airphotos were only available as multispectral images
 767 ([RGBI](#)). Here, the green band was selected for matching.

*Panchromatic images
 were used for
 matching of
 along-track
 stereo-image pairs
 covering the
 Bavarian test sites.*

2 except for Immitzer et al. (2016): here, the area-based normalized cross-correlation method implemented in LPS eATE (ERDAS IMAGINE 2014) was used.

As outputs from dense stereo matching in RSG, we opted for using the raw dense 3d point clouds from the respective stereo pairs and used additional utility software for further processing. In the work concerned with the assessment of height changes (Stepper et al., 2015a), we used DSMs as outputs from the RSG streamline for further analysis.

The products from DAP, i. e., the dense image-based point clouds or the DSMs, were further processed to calculate the object heights above ground by using the ALS-based elevation heights for subtraction. Subsequently, different data processing steps (clipping to inventory point geometries, etc.) were performed in order to prepare appropriate data sets for consequent use in statistical modelling. Details regarding the particular processing steps are given in the respective paper sections.

3.2 STATISTICAL MODELLING

As introduced in sections 1.2 and 1.3, the area-based approach (ABA) gained strong interest for integrating remote sensing data sets, in particular ALS and DAP-based products, for use in forest inventory and mapping applications.

In this context, i. e., for the combination of ground based measurements and the remotely sensed data, statistical models which can produce unbiased and accurate estimates of the forest attribute of interest by means of remote sensing predictor variables play a key role. In the ABA workflow (see Figure 3), the statistical models are trained with known samples, namely the ground-based inventory measurements and the descriptive statistics (*metrics*) calculated from the remote sensing data clipped to the areas of the georeferenced inventory plots – and consequently, these models are applied to predict estimates over entire forest areas.

Therefore it is crucial, that the chosen model type is able to accurately map the statistical dependency between the remote sensing predictor variables and the response variables derived from the ground measurements (e. g., mean stand height or volume). In the literature, different regression approaches (parametric and non-parametric) were applied to fulfil this task. Besides linear regression modelling, the decision-tree based approach random forest (RF) was most widely used for predictive modelling of forest inventory attributes through the course of the presented studies. Therefore, and without judging other approaches for their appropriateness, the main characteristics of RF and its actual application are described.

The statistical model describes the dependency between the remote sensing predictors and the ground-based response.

3.2.1 Random Forest for Regression

RF can be assigned to the domain of non-parametric modelling approaches. Thus, no *a priori* assumptions about relationships between predictor and response variables are made (White et al., 2013a). Due to that, and to the fact that very little tuning is required during model building, RF has become a popular method in predictive modelling.

RF requires no a priori assumption about the relationship of predictors and response variables.

RF, developed by Breiman (2001), is an ensemble regression tree algorithm (see Algorithm 1) based on a large collection of *de-correlated* decision trees (Hastie et al., 2009). RF can be seen as further development of bagging (*bootstrap aggregation*), as the individual trees that constitute the forest are fitted to bootstrap-sampled versions of the training data, and averaged to get the final result (for a schematic of *bootstrap sampling*, see Figure 6).

An ensemble of de-correlated decision trees forms a RF model.

Algorithm 1: Random Forest for Regression (modified after Hastie et al., 2009 and Kuhn and Johnson, 2013).

```

1 Select the number of trees to build,  $B$ :
2 for  $b = 1$  to  $B$ : do
3   (1) Draw a bootstrap sample  $Z^*$  of size  $N$  from the training data.
4   (2) Train a tree model  $T_b$  to the bootstrapped data, by recursively repeating
      the following steps for each terminal node of the tree, until the minimum
      node size  $n_{\min}$  is reached.
5     for each split: do
6       (a) Select  $m$  variables at random from the  $p$  predictor variables ( $m \leq p$ ).
7       (b) Pick the best variable/split-point among the  $m$ .
8       (c) Split the node into two data nodes.
9     end
10   end
11 Output the ensemble of trees  $\{T_b\}_1^B$ .
12 To make a prediction at a new point  $x$ :
13  $\hat{f}_{rf}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x)$ 

```

815 In **RF**, a second randomization is introduced to the tree-building process,
 816 in order to additionally reduce the correlation between the trees: the al-
 817 gorithm randomly selects a subset of predictor variables as candidates for
 818 splitting at each decision node. **RF** has two potential parameters for adjust-
 819 ment: (a) the number of randomly selected predictors m , from which to
 820 choose at each split (commonly referred to as m_{try}). For use in regression,
 821 the algorithm inventor Breiman recommended $p/3$ as default value, i. e., one
 822 third of the number of predictors (Breiman, 2001); (b) the number of trees
 823 in the forest (commonly referred to as n_{tree}). As **RF** is not prone to over-
 824 fitting, large numbers of trees do not adversely affect the model accuracy.
 825 However, the computational expense increases. Kuhn and Johnson (2013)
 826 suggest 1 000 trees as starting point, and adjustment in dependence of the
 827 achieved model performance. Important advances and features of **RF** are:

828 **DISTRIBUTION INDEPENDENCE** The variables (x, y) used as predictors and
 829 response in modelling do not have to follow a predefined distribution.

830 **DIMENSIONALITY** In **RF**, high-dimensional and highly correlated data sets
 831 can be processed without suffering a loss in performance.

832 **OUT-OF-BAG (oob)** For each observation $z_i = (x_i, y_i)$, its random forest pre-
 833 dictor can be computed by averaging only those trees corresponding
 834 to bootstrap samples in which z_i is not included (see Figure 6). Doing
 835 so, an **oob** error estimate is almost identical to that obtained by N-fold
 836 cross-validation (cf. Hastie et al., 2009). Thus, performance measures
 837 can be computed along the way during **RF** model training.

838 **VARIABLE IMPORTANCE** Information on the importance of each predictor
 839 variable used in model building can be computed twofold: (a) as meas-
 840 ure of the total decrease in node impurities from splitting on each
 841 variable, averaged over all trees; (b) as mean decrease of prediction
 842 accuracy, when permuting the values of the predictor variables in the
 843 **oob** samples, again averaged over all trees.

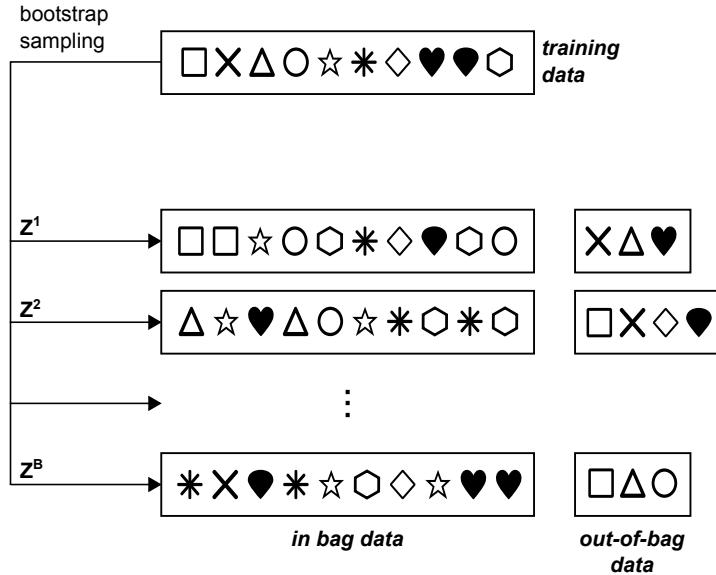


Figure 6: Schematic of bootstrap resampling as used in [RF](#) for drawing the training samples for the individual regression trees. The training sample data are depicted as symbols and are allocated to B subsets, each taken as random sample *with replacement*. The subsets are of the same size as the original training data and can contain multiple instances of the same data point. Samples not selected by the bootstrap are the *out-of-bag* data and can be used to estimate model performance (modified after Kuhn and Johnson, 2013).

3.2.2 Model Implementation for predicting Forest Inventory Attributes

We used functionalities and add-on packages of the open-source statistical software R to accomplish all statistical tasks. For model development (using the data gathered at the forest inventory plots) and prediction to unknown samples by means of [RF](#), the functionalities provided in the packages [caret](#) (Kuhn, 2015) and [randomForest](#) (Liaw and Wiener, 2002) were principally used.

With regard to the tuning parameters of [RF](#), we followed the recommendation of Kuhn and Johnson (2013): The number of regression trees in the respective forests was set to $n_{tree} = 1000$, and the number of variables randomly selected at each split was set to $m_{try} = p/3$.

In all studies, the root mean squared error ([RMSE](#)) and mean error ([ME](#)) measures were selected to evaluate model performance, i. e., model accuracy and bias. In the studies of Stepper et al. (2015b), Straub and Stepper (2016) and White et al. (2015), we applied a 10-fold cross-validation repeated five times to assess model performance and in the studies of Immitzter et al. (2016) and Stepper et al. (submitted) the [oob](#)-estimates were used for model evaluation.

Additionally, the model performance at the stand level, i. e., after wall-to-wall prediction mapping and aggregating to forest stands, was examined in the studies of Immitzter et al. (2016) and Stepper et al. (2015b). Independent inventory data from nearby forests were utilized to assess model transferability in the study of Stepper et al. (submitted), again by means of [RMSE](#) and [ME](#). For more details regarding model training and evaluation, the reader is referred to the respective articles.

3.3 HEIGHT CHANGE ASSESSMENT

Elaborating on the aim to test the utility of digital stereo images from repeat surveys for forest height change assessment, we developed a workflow as illustrated in Figure 7.

We followed the SGM approach (see section 3.1) to accomplish image matching of the stereo airphotos. In our study (Stepper et al., 2015a), we chose the RSG software utilities for image matching and used the implemented functionality to output DSMs with 1 m resolution for both dates of image acquisition. Finally, CHMs were derived by subtracting the elevation values of the bare earth DTM from the z-values of the two DSMs.

Terrestrial inventory measurements, acquired for circular 500 m² plots, were used as reference for the assessment of forest canopy height and height changes. H100 was calculated from the field measurements as height metric approximating top heights of forest stands. In our study, H100 was defined as the average height of the 100 stems per hectare with the largest DBHs (see Algorithm 1 in the article for the explicit computation rule set).

To link the CHM-heights with the field-based H100 top heights, various height percentiles (25th, 50th, 75th, 90th, 95th, and maximum) were calculated from the CHM-values for the areas within each of the 500 m² circular

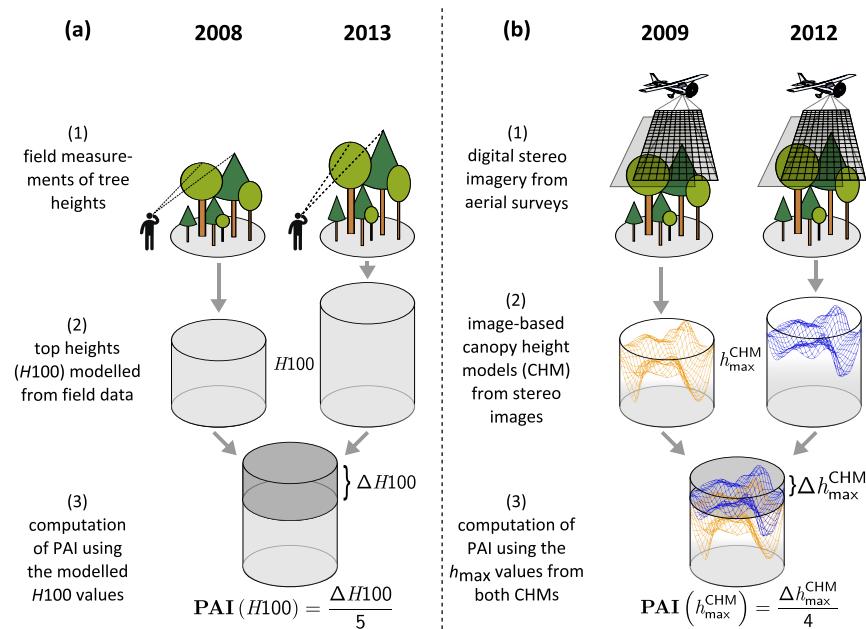


Figure 7: Methodological workflow for height change assessment using terrestrial measurements and CHMs based on stereo airphotos from repeat aerial image surveys. **(a)** Terrestrial assessment: (1) tree crown heights are measured for representative samples at the respective inventory plots, (2) top heights (H_{100}) are modelled using the height measurements of trees from the overstory and emergent tree layers, (3) PAI is calculated as the difference between the modelled H_{100} values for the two inventories. **(b)** Aerial image assessment: (1) digital stereo images are acquired in regularly scheduled aerial surveys, (2) CHMs are created by subtracting LiDAR-derived terrain heights from image-based surface models, (3) PAI is computed as the difference between the maximum height values (h_{\max}) from the two CHMs divided by the time lapse between the two image dates.

plots. The percentiles were correlated to the field-based top heights and the maximum height of the CHM (h_{max}) turned out to achieve highest correlation values. Thus, this variable was selected for the height change assessment.

Height differences between the two points in time from the terrestrial and the aerial image acquisitions were used to calculate periodic annual increments (PAIs) as standardized increment measures per unit of time (see Figure 7). The PAIs, both from the field measurements and the image-based height data, were regressed against the H100 top height values based on the initial field data (from $t_{1,field}$) to analyse the relationship between initial forest height and height growth. Finally, differences between increments for initial height classes representing various forest successional stages were examined.

4 | RESULTS

The results of the conducted research studies were presented to scholars in different scientific papers published in peer-reviewed journals (see list of publications on page vi). In the following, the main findings of the respective papers are summarized (section 4.1). Afterwards, the results of each paper are given in detail and my personal contribution to each paper is highlighted (section 4.2).

4.1 OVERALL RESULTS OF THE PRESENTED WORK

In Table 3, a very general overview of the achieved results according to the overall aims of this work (see section 1.5) is given. The first aim, i. e., the examination of image-based height measurements derived from stereo remote sensing data sets for the description of forest canopy surfaces, was pursued in all studies.

Table 3: Overview of research aims and achieved results covered by the respective studies.

STUDIES	AIM 1: Are digital aerial images and DAP suitable to compute image-based outputs to characterize forest canopy surfaces?	AIM 2: Can image-based point clouds or raster-based surface models be used to model forest inventory attributes?	AIM 3: Are CHMs derived from repeated airphoto acquisitions capable to assess canopy height changes over time?
Stepper et al. <i>Can. J. For. Res.</i> (2015)	✓	✓	
Straub & Stepper <i>Photogramm. Fernerkund. Geoinf.</i> (in press)	✓	✓	
Stepper et al. <i>Scand. J. For. Res.</i> (submitted)	✓	✓	
White et al. <i>Forests</i> (2015)	✓	✓	
Immitzler et al. <i>Forest Ecol. Manag.</i> (2016)	✓ ^a	✓ ^b	
Stepper et al. <i>Forestry</i> (2015)	✓		✓

^a Stereo satellite image data were used in this study for image matching and consecutive computation of canopy surface heights.

^b In contrast to the other studies, ACS-based field data from NFI measurements were used for model training in this study.

915 **4.2 DETAILED DESCRIPTION OF THE RESULTS PER**
 916 **ARTICLE**

917 **4.2.1 Stepper et al. *Can. J. For. Res.* (2015)**

918 **TITLE** Using semi-global matching point clouds to estimate growing stock
 919 at the plot and stand levels: application for a broadleaf-dominated
 920 forest in central Europe

921 **AUTHORS** Christoph Stepper, Christoph Straub, and Hans Pretzsch

922 **JOURNAL** Canadian Journal of Forest Research (Publisher: National Research
 923 Council Canada, NRC Research Press, ISSN: 0045-5067, Journal Impact
 924 Factor, 2014: 1.683)

925 **ABSTRACT** Dense image-based point clouds have great potential to accurately
 926 assess forest attributes such as growing stock. The objective of this study was to combine height and spectral information obtained
 927 from UltraCamXp stereo images to model the growing stock in a highly structured broadleaf-dominated forest (77.5 km^2) in southern
 928 Germany. We used semi-global matching (SGM) to generate a dense point cloud and subtracted elevation values obtained from airborne
 929 laser scanner (ALS) data to compute canopy height. Sixty-seven explanatory variables were derived from the point cloud and an orthoimage for use in the model. Two different approaches — the linear regression model (lm) and the random forests model (rf) — were tested. We investigated the impact that varying amounts of training data had on model performance. Plot data from a previously acquired set of 1875 inventory plots was systematically eliminated to form three progressively less dense subsets of 937, 461, and 226 inventory plots. Model evaluation at the plot level (size: 500 m^2) yielded relative root mean squared errors (RMSEs) ranging from 31.27% to 35.61% for lm and from 30.92% to 36.02% for rf. At the stand level (mean stand size: 32 ha), RMSEs from 14.76% to 15.73% for lm and from 13.87% to 14.99% for rf were achieved. Therefore, similar results were obtained from both modeling approaches. The reduction in the number of inventory plots did not considerably affect the precision. Our findings underline the potential for aerial stereo imagery in combination with ALS-based terrain heights to support forest inventory and management.

950 **CONTRIBUTION** Christoph Stepper and Christoph Straub developed the concept for the study and Christoph Stepper designed the experimental setting. Hans Pretzsch gave helpful comments on the study structure and the relevance of the research.

954 Christoph Stepper processed all ground inventory and remote sensing data. He performed the photogrammetric working steps to gain the image-based canopy height information and the orthoimage for the complete test site. In this study, we scrutinized both height and spectral variables as predictor variables for modelling gross volume. Christoph Stepper computed the point-cloud variables and Christoph Straub computed the variables extracted from the gridded CHM and the orthoimage. Christoph Stepper performed the area-based modelling workflow testing both regression approaches and applied the

models for wall-to-wall mapping. He conducted the model evaluation at the stand level and compiled all results. Christoph Stepper and Christoph Straub interpreted the model outcomes and formulated the findings of this research.

Christoph Stepper prepared the manuscript including all figures and tables in close collaboration with Christoph Straub. Hans Pretzsch gave valuable advice for the interpretation of the results, for the discussion of the findings and the composition of the manuscript. All authors contributed to the critical revisions of the article.

4.2.2 Straub & Stepper *Photogramm. Fernerkund. Geoinf.* (in press)

TITLE Using digital aerial photogrammetry and the Random Forest approach to model forest inventory attributes in beech- and spruce-dominated central European forests

AUTHORS Christoph Straub and *Christoph Stepper*

JOURNAL Photogrammetrie–Fernerkundung–Geoinformation, PFG
(Publisher: Schweizerbart Science Publishers, ISSN: 1432-8364, Journal Impact Factor, 2014: 0.733)

ABSTRACT Surface models generated using dense image matching of aerial photographs have potential for use in the area-based prediction of forest inventory attributes. Few studies have examined the impact of forest type on the performance of models used to predict forest attributes. Moreover, with regard to central European forests, little is known about how accurately attributes other than volume and basal area can be estimated using image-based surface models. Thus, in this study, we assessed the accuracy of such estimates for five forest attributes — stem density N, basal area G, quadratic mean diameter QMD, volume V, and Lorey's mean height H_L — for a beech- and a spruce-dominated forest in northern Bavaria, Germany. These estimates were made using a workflow combining data from aerial photographs obtained from regularly scheduled surveys and field plot measurements from periodic forest inventories conducted in Bavarian state forests. Semi-Global Matching was used to derive surface models from the air photos which were normalized with terrain models from airborne laserscanning to derive canopy height models (CHM). Based on the CHM values at the respective field plots, a set of 14 predictor variables characterizing the height distribution was computed. For the prediction, individual Random Forests models were trained and cross validated separately for both test sites. With respect to relative RMSEs, i.e. divided by the observation means, most distinct differences were observed for the prediction of QMD with a slightly higher level of accuracy for the spruce-dominated forest. Best results were achieved for H_L , while poorest model performances were obtained for N. The relative plot-level RMSEs for N, G, QMD, V, and H_L were: 70.3%, 36.0%, 32.3%, 37.8%, and 12.4% for the beech-dominated and 74.9%, 35.2%, 24.9%, 33.3%, and 12.4% for the spruce-dominated forest. Thus, with the exception of QMD, forest type did not considerably influence the model accuracies.

1010 **CONTRIBUTION** The idea for this comparative analysis of models for a set
 1011 of forest inventory attributes across two different forest types was de-
 1012 veloped together by both authors.

1013 For the implementation, Christoph Stepper processed the aerial im-
 1014 agery and the **SGM** data to generate the **CHMs** for both test sites. He also
 1015 computed the not readily available forest inventory attributes based
 1016 on the tree list data from the ground plot measurements. Christoph
 1017 Straub calculated the set of predictor variables from the **CHM** height
 1018 values at the inventory plots and built the predictive **RF** models based
 1019 on existing code developed in Stepper et al. (2015b).

1020 Both authors conducted the analysis and interpretation of the modell-
 1021 ing results and wrote the manuscript.

1022 4.2.3 Stepper et al. *Scand. J. For. Res.* (submitted)

1023 **TITLE** Using canopy heights from digital aerial photogrammetry to enable
 1024 spatial transfer of forest attribute models: a case study in central
 1025 Europe

1026 **AUTHORS** Christoph Stepper, Christoph Straub, Markus Immitzer, and Hans
 1027 Pretzsch

1028 **JOURNAL** Scandinavian Journal of Forest Research (Publisher: Nordic Forest
 1029 Research Cooperation Committee, Taylor & Francis, ISSN: 0282-7581,
 1030 Journal Impact Factor, 2014: 1.537)

1031 **ABSTRACT** This paper describes a workflow utilizing detailed canopy height
 1032 information derived from digital airphotos combined with ground in-
 1033 ventory information gathered in state-owned forests and regression
 1034 modelling techniques to quantify forest growing stocks in private wood-
 1035 lands, for which little information is generally available. Random
 1036 forest models were trained to predict three different variables at the
 1037 plot level: quadratic mean diameter of the 100 largest trees (d_{100}),
 1038 basal area weighted mean height of the 100 largest trees (h_{100}), and
 1039 gross volume ((V)). Two separate models were created – one for a
 1040 spruce- and one for a beech-dominated test site. We examined the spa-
 1041 tial portability of the models by using them to predict the aforemen-
 1042 tioned variables at actual inventory plots in nearby forests, in which
 1043 simultaneous ground sampling took place. When data from the full
 1044 set of available plots were used for training, the predictions for d_{100} ,
 1045 h_{100} , and V achieved out-of-bag model accuracies (scaled RMSEs) of
 1046 15.1%, 10.1% and 35.3% for the spruce- and 15.9%, 9.7%, and 32.1%
 1047 for the beech-dominated forest, respectively. The corresponding inde-
 1048 pendent RMSEs for the nearby forests were 15.2%, 10.5%, and 33.6%
 1049 for the spruce- and 15.5%, 8.9%, and 33.7% for the beech-dominated
 1050 test site, respectively.

1051 **CONTRIBUTION** Christoph Stepper developed the idea for this study and
 1052 the other authors contributed to the experimental layout.

1053 Christoph Stepper conducted the analysis. He processed the image
 1054 data and prepared the inventory data for subsequent use in modelling.
 1055 He wrote the R code following previous work (Stepper et al., 2015b)
 1056 and performed all modelling steps. Christoph Stepper discussed the
 1057 results, considering helpful comments of the co-authors.

1058 Christoph Stepper wrote the manuscript and compiled the figures,
 1059 with comments and advise from all other authors.

1060 4.2.4 White et al. *Forests* (2015)

1061 **TITLE** Comparing ALS and image-based point cloud metrics and modelled
 1062 forest inventory attributes in a complex coastal forest environment

1063 **AUTHORS** Joanne C. White, *Christoph Stepper*, Piotr Tompalski, Nicholas C.
 1064 Coops, and Michael A. Wulder

1065 **JOURNAL** *Forests* (Publisher: MDPI, ISSN: 1999-4907, Journal Impact Factor,
 1066 2014: 1.449)

1067 **ABSTRACT** Digital aerial photogrammetry (DAP) is emerging as an alternate
 1068 data source to airborne laser scanning (ALS) data for three-dimensional
 1069 characterization of forest structure. In this study we compare point
 1070 cloud metrics and plot-level model estimates derived from ALS data
 1071 and an image-based point cloud generated using semi-global match-
 1072 ing (SGM) for a complex, coastal forest in western Canada. Plot-level
 1073 estimates of Lorey's mean height (H), basal area (G), and gross volume
 1074 (V) were modelled using an area-based approach. Metrics and model
 1075 outcomes were evaluated across a series of strata defined by slope and
 1076 canopy cover, as well as by image acquisition date. We found stat-
 1077 istically significant differences between ALS and SGM metrics for all
 1078 strata for five of the eight metrics we used for model development.
 1079 We also found that the similarity between metrics from the two data
 1080 sources generally increased with increasing canopy cover, particularly
 1081 for upper canopy metrics, whereas trends across slope classes were
 1082 less consistent. Model outcomes from ALS and SGM were compar-
 1083 able. We found the greatest difference in model outcomes was for H
 1084 ($\Delta RMSE = 5.04\%$). By comparison, $\Delta RMSE$ was 2.33% for G and
 1085 3.63% for V. We did not discern any corresponding trends in model
 1086 outcomes across slope and canopy cover strata, or associated with dif-
 1087 ferent image acquisition dates.

1088 **CONTRIBUTION** This research was made possible by international collab-
 1089 oration of the Bavarian State Institute of Forestry, the Department
 1090 of Forest Research at University of British Columbia, and the Cana-
 1091 dian Forest Service. The contact was made by Christoph Stepper and
 1092 Joanne White.

1093 Joanne White and Christoph Stepper set up the design of the study,
 1094 with conceptual advice of all other authors. Joanne White coordi-
 1095 nated the progress of the study, including the contacts with external
 1096 partners for acquisition of all field inventory and remote sensing data
 1097 used. Christoph Stepper conducted all photogrammetry work for ob-
 1098 taining image-based canopy height information. Piotr Tompalski and
 1099 Christoph Stepper processed the [ALS](#) and [DAP](#) data for further ana-
 1100 lysis. Joanne White lead investigations on the comparison of point
 1101 cloud metrics across a series of strata defined by slope and canopy
 1102 cover and Christoph Stepper was responsible for modelling and ana-
 1103 lysing plot level predictions for Lorey's mean height, basal area, and
 1104 gross volume. All authors discussed the results and implications and
 1105 contributed in formulating the findings of that research.

1106 Joanne White and Christoph Stepper wrote the manuscript. Christoph
 1107 Stepper, Joanne White, and Piotr Tompalski prepared the figures and
 1108 assembled the artwork. All authors commented on the manuscript
 1109 and participated in revising the manuscript.

1110 4.2.5 Immitzer et al. *Forest Ecol. Manag.* (2016)

1111 **TITLE** Use of WorldView-2 stereo imagery and National Forest Inventory
 1112 data for wall-to-wall mapping of growing stock

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 1114 Straub, and Clement Atzberger

1115 **JOURNAL** Forest Ecology and Management (Publisher: Elsevier, ISSN: 0378-
 1116 1127, Journal Impact Factor, 2014: 2.660)

1117 **ABSTRACT** Angle-count sampling (ACS) is an established method in forest
 1118 mensuration and is implemented in different National Forest Inventories (NFI). However, due to the lack of fixed reference areas of the
 1119 inventory plots, these ACS-based field data are seldom used as training
 1120 data for wall-to-wall mapping applications at forest enterprise level. In
 1121 this paper, we demonstrate an approach to overcome this shortcoming.
 1122 For a study area in northern Bavaria, Germany, we used ACS-based
 1123 NFI data for model training to generate wall-to-wall maps of growing
 1124 stock for broadleaf, conifer and mixed forest stands. Both spectral and
 1125 height information from the very high resolution WorldView-2 (WV2)
 1126 satellite were used as auxiliary information and the non-parametric
 1127 Random Forests (RF) algorithm was chosen as modeling approach.
 1128 The growing stock predictions were validated using out-of-bag (OOB)
 1129 samples and further verified at the plot and stand level using addi-
 1130 tional data. For validation, field plots from a Management Forest In-
 1131 ventory (MFI) and delineated forest stands were used. Compared to
 1132 stand-level aggregations based on field plots from the MFI, our ap-
 1133 proach explained 56% of the variability in the growing stock (R^2) with
 1134 a relative RMSE of 15% at the stand level ($n = 252$). As expected,
 1135 the scatter was higher at the plot-level ($n = 3973$). Nonetheless, the
 1136 models still achieved acceptable performance measures ($R^2 = 0.44$;
 1137 RMSE = 34%).

1138 **CONTRIBUTION** Markus Immitzer and Clement Atzberger initiated the study.
 1139 Markus Immitzer, Clement Atzberger, and Christoph Stepper contrib-
 1140 uted to the initial experimental design and developed the new ap-
 1141 proach for using ACS-based NFI plot data as training data for wall-to-
 1142 wall mapping applications. The novelty of the approach, i. e., the sim-
 1143 ultaneous use of multiple concentric circles around the NFI plot centres
 1144 for calculating explanatory variables based on remote sensing inform-
 1145 ation, was developed by Markus Immitzer and Clement Atzberger in
 1146 close collaboration with Christoph Stepper.

1147 Markus Immitzer processed the remote sensing data and conducted
 1148 the main parts of the analysis, including programming of the proce-
 1149 dures and compiling the results in tables and figures. Christoph Straub
 1150 computed the vegetation mask based on the WV2 data. Christoph Step-
 1151 per prepared the inventory data used for model training (NFI) and
 1152 model evaluation (MFI). Sebastian Böck helped in programming and
 1153 analysis.

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Markus Immitzer and Christoph Stepper prepared all figures and flow-charts for the article and wrote the initial draft of the manuscript together with Clement Atzberger. All authors contributed to the final manuscript and participated in revising the manuscript for publication.

1160 4.2.6 Stepper et al. *Forestry* (2015)

1161 **TITLE** Assessing height changes in a highly structured forest using regularly
 1162 acquired aerial image data

1163 **AUTHORS** *Christoph Stepper, Christoph Straub, and Hans Pretzsch*

1164 **JOURNAL** *Forestry* (Publisher: Institute of Chartered Foresters, Oxford Uni-
 1165 versity Press, ISSN: 0015-752X, Journal Impact Factor, 2014: 2.093)

1166 **ABSTRACT** In this paper, we demonstrate the effectiveness of digital stereo
 1167 images and canopy height models (CHMs) derived from them for
 1168 forest height change assessment. Top heights were derived for 199 ter-
 1169 restrial inventory plots from forest inventories conducted in 2008 and
 1170 2013 in a forest near Traunstein, Germany. Semi-Global Matching was
 1171 applied to two sets of aerial stereo images, acquired in 2009 and 2012,
 1172 respectively, to compute CHMs. Subsequently, several height percent-
 1173 tiles were calculated from the areas in the CHMs that lay within the
 1174 inventory plot locations. The maximum CHM value (h_{\max}) had the
 1175 highest correlation with the field-based canopy top heights and was
 1176 selected for use in all further analysis. Periodic annual increments
 1177 (PAIs) of forest height were calculated from both the remote sensing
 1178 and the field data at the inventory plot locations. Scatterplots of the
 1179 PAIs over top height revealed similar patterns in the results derived
 1180 from the two data sets. The inventory plots were assigned to three
 1181 height classes representing various forest successional stages — *youth*,
 1182 *full vigour* and *old age*. The PAI distributions within the three height
 1183 classes were significantly different from one another. Our findings
 1184 suggest that CHMs derived from repeat aerial image surveys can be
 1185 a viable tool to measure canopy heights and to assess forest height
 1186 changes over time, even for a highly structured, mixed forest in cen-
 1187 tral Europe.

1188 **CONTRIBUTION** All authors contributed to the idea of the work and jointly
 1189 conceived the experiment.

1190 Christoph Stepper made all data ready for analysis, including the pro-
 1191 cessing of the aerial imagery and the ground inventory data. He con-
 1192 ducted the main parts of the statistical analysis, i. e., selecting the ap-
 1193 propriate methods, writing the code and carrying out the experiments.
 1194 Christoph Stepper and Christoph Straub examined and discussed the
 1195 results. Hans Pretzsch contributed in result interpretation and in pla-
 1196 cing the findings into a broader context in the forest research disci-
 1197 pline.

1198 Christoph Stepper wrote the first draft of the manuscript and pre-
 1199 pared all figures and artwork, with valuable contributions of Chris-
 1200 topf Straub. Hans Pretzsch added helpful edits to the manuscript and
 1201 gave advice on the content.

1202 5 | DISCUSSION

1203 Different aspects of utilizing digital airphotos and height measurements de-
1204 rived thereof by means of DAP for forest inventory and forest management
1205 were considered in the studies presented in this thesis. Overall, the results
1206 confirm that image-based point clouds and CHMs are a viable source of in-
1207 formation to characterize the three-dimensional structure of forest canopies,
1208 at least for the forest types examined in the different studies (see Table 1).

1209 The primary motivations for initiating this work were:

- 1210 • the need for spatially explicit information on the current state of forest
1211 stands in order to facilitate forest management practice;
- 1212 • the unexploited potential of using digital aerial photographs for the
1213 three-dimensional characterization of forest canopies;
- 1214 • the recently launched algorithms to process stereo airphotos to gener-
1215 ate image-based height measurements covering large areas;
- 1216 • the possibility to test the DAP-based height measurement as surrogate
1217 for ALS-based data when spatially predicting forest inventory attrib-
1218 utes.

1219 As mentioned in the introduction, large parts of the theoretical frame-
1220 work on using 3d information in forest inventory were developed based on
1221 ALS data (e.g., Næsset, 2002b). Meanwhile, airborne imaging technologies
1222 (e.g., digital cameras) and image processing algorithms and software (e.g.,
1223 SGM) have emerged that enable workflows possible to generate image-based
1224 point clouds and DSMs covering large areas (White, 2016). Those 3d mea-
1225 surements achieve similar degrees of detail for forest canopy surfaces as the
1226 airborne LiDAR-based measurements, and with the large-scale availability
1227 of ALS-based DTMs, canopy heights above ground can be derived from the
1228 photogrammetric data with little additional effort.

- 1229 • Schwerpunkt der Studien: Mitteleuropäische Waldverhältnisse -> Ergeb-
1230 nisse für Schätzung wichtiger Forstlicher Kennzahlen ok
- 1231 • Vergleich mit LiDAR in Canada -> DAP Daten sind ein sinnvolle Er-
1232 gänzung zu Laser Scanning Daten -> ermöglichen neue Inventurforts-
1233 chreibungsverfahren -> viel billiger als Lidar
1234 -> regelmäßige Befliegung
1235 -> zusätzliche Verfügbarkeit der Spektralen Information
- 1236 • Wie genau lassen sich die verschiedenen forstlichen Parameter mit der
1237 gewählten Methode abschätzen?
- 1238 • auf die unterschiedlichen Kennzahlen eingehen.
- 1239 • Holzvolumen -> nächste Schritte: Einzelbaum-Verfahren / Durchmesserver-
1240 teilung approximieren

- 1241 ● stärkere Integration der spektralen Kennwerte in die Modellierung
1242 (evtl. auch Verwendung von hochaufgelösten Satellitendaten (Phäno-
1243 logie), um Tree species unterscheidbar zu machen)
- 1244 ● was waren die wichtigsten Prädiktoren für die unterschiedlichen forst-
1245 lichen Parameter -> Vergleich der Studien -> allgemeingültige Aus-
1246 sage möglich? Tendenzen? Vergleich mit Lidar?
- 1247 ● untersucht: Wie verhalten sich die Modelle in nadel- bzw. laubdomin-
1248 ierten Wäldern! Frankenwald vs. Spessart/Steigerwald // Mischwald
1249 (Wald der Zukunft) -> Traunstein?
- 1250 ● ungelöste Aufgaben: Aussagen über die Baumarten-spezifischen An-
1251 gaben (z.b. Holzvorrat Nadelbäume vs. Holzvorrat Laubbäume)

6 | CONCLUSION

1253 The presented methods and achieved results from the different studies ap-
1254 proved the high potential of **DAP** for use in forest inventory and monitoring
1255 tasks. In the studies, image-based height data were employed in combina-
1256 tion with different field-measured information sources (management forest
1257 inventories, national forest inventory) on a range of spatial scales. Addition-
1258 ally, due to the lower acquisition costs compared to **ALS**, and the high recur-
1259 rence frequency of the administrative aerial surveys, airphotos and derived
1260 **DAP** products can provide an important bridge between the operational, tac-
1261 tical, and strategic forest management levels.

1262 The studies confirmed that **DAP**-based height information can be used in
1263 conjunction with ground-based measurements to establish predictive mod-
1264 els for a set of forest inventory attributes (see Stepper et al., **submitted**,
1265 **2015b**; Straub and Stepper, **2016**; White et al., **2015**). Similar to **ALS**, the most
1266 predictive canopy metrics derived from the **DAP**-based measurements were
1267 height metrics, which are most appropriate to describe the canopy *growing*
1268 *space*. It could be demonstrated, that the intra-metric correlation is higher
1269 for the image-based data compared to the **ALS** data (see White et al., **2015**),
1270 indicating that it is sufficient for modelling to work with a subset of the
1271 computed metrics. In Stepper et al. (**2015b**) we could show, that ...

- 1272 ● Baumartenklassifikation ?!?
- 1273 ● UAV?

Part II
APPENDIX

BIBLIOGRAPHY

- Aldred, A. H. and Bonnor, G. M. (1985). *Applications of airborne lasers to forest surveys*. Vol. 51. Information report / Petawawa National Forestry Institute. Chalk River, Ont.: Petawawa National Forestry Institute, Canadian Forestry Service, Agriculture Canada. ISBN: 9780662138655 (cit. on p. 6).
- Arbeitsgruppe Forstlicher Luftbildinterpretationen, ed. (2012). *Das digitale Luftbild: Ein Praxisleitfaden für Anwender im Forst- und Umweltbereich*. Vol. 7. Beiträge aus der Nordwestdeutschen Forstlichen Versuchsanstalt. Göttingen: Univ.-Verl. Göttingen. ISBN: 9783863950552 (cit. on p. 4).
- Baltsavias, E. P. (1999). Airborne laser scanning: Existing systems and firms and other resources. *ISPRS Journal of Photogrammetry and Remote Sensing* **54** (2-3): 164–198. DOI: [10.1016/S0924-2716\(99\)00016-7](https://doi.org/10.1016/S0924-2716(99)00016-7) (cit. on p. 7).
- Bohlin, J., Wallerman, J. and Fransson, J. E. (2012). Forest variable estimation using photogrammetric matching of digital aerial images in combination with a high-resolution DEM. *Scandinavian Journal of Forest Research* **27** (7): 692–699. DOI: [10.1080/02827581.2012.686625](https://doi.org/10.1080/02827581.2012.686625) (cit. on p. 11).
- Breiman, L. (2001). Random forests. *Machine learning* **45** (1): 5–32 (cit. on pp. 22, 23).
- Cohen, W. B., Kushla, J. D., Ripple, W. J. and Garman, S. L. (1996). An introduction to digital methods in remote sensing of forested ecosystems: Focus on the Pacific Northwest, USA. *Environmental Management* **20** (3): 421–435. DOI: [10.1007/BF01203849](https://doi.org/10.1007/BF01203849) (cit. on p. 4).
- Digital Globe (2013). *WorldView-2: Data Sheet*. URL: http://global.digitalglobe.com/sites/default/files/DG_WorldView2_DS_PROD.pdf (cit. on p. 18).
- ERDAS, ed. (2010). *ERDAS Field Guide* (cit. on p. 20).
- Franklin, S. E. (2001). *Remote sensing for sustainable forest management*. Boca Raton, Fla.: Lewis Pub. ISBN: 9781420032857 (cit. on p. 2).
- Gehrke, S., Morin, K., Downey, M., Boehrer, N. and Fuchs, T. (2010). Semi-global matching: An alternative to LIDAR for DSM generation. In: *Proceedings of the 2010 Canadian Geomatics Conference and Symposium of Commission I* (cit. on p. 21).
- Gruen, A. (2012). Development and Status of Image Matching in Photogrammetry. *The Photogrammetric Record* **27** (137): 36–57. DOI: [10.1111/j.1477-9730.2011.00671.x](https://doi.org/10.1111/j.1477-9730.2011.00671.x) (cit. on p. 20).
- Haala, N. and Rothermel, M. (2012). Dense Multi-Stereo Matching for High Quality Digital Elevation Models. *Photogrammetrie, Fernerkundung, Geoinformation (PFG)* **2012** (4): 331–343. DOI: [10.1127/1432-8364/2012/0121](https://doi.org/10.1127/1432-8364/2012/0121) (cit. on p. 8).
- Hastie, T., Tibshirani, R. and Friedman, J. H. (2009). *The elements of statistical learning: Data mining, inference, and prediction*. 2nd ed. Springer series in statistics. New York: Springer. ISBN: 9780387848570 (cit. on pp. 22, 23).
- Hildebrandt, G. (1996). *Fernerkundung und Luftbildmessung: für Forstwirtschaft, Vegetationskartierung und Landschaftsökologie*. 1. Aufl. Heidelberg: Wichmann. ISBN: 3879072388 (cit. on pp. 2, 4, 5).
- Hildebrandt, G. (2010). The Beginnings of Aerial Photogrammetry and Interpretation in German Forestry after 1945. *Photogrammetrie - Fernerkundung - Geoinformation* **2010** (4): 235–242. DOI: [10.1127/1432-8364/2010/0051](https://doi.org/10.1127/1432-8364/2010/0051) (cit. on p. 4).

- Hirschmüller, H. (2005). Accurate and Efficient Stereo Processing by Semi-Global Matching and Mutual Information. In: *CVPR 2005*. Ed. by Schmid, C., Soatto, S. and Tomasi, C. Vol. 2. Los Alamitos, CA, USA: IEEE Computer Society, 807–814. doi: [10.1109/CVPR.2005.56](https://doi.org/10.1109/CVPR.2005.56) (cit. on p. 21).
- Hirschmüller, H. (2008). Stereo Processing by Semiglobal Matching and Mutual Information. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **30** (2): 328–341. doi: [10.1109/TPAMI.2007.1166](https://doi.org/10.1109/TPAMI.2007.1166) (cit. on p. 21).
- Hirschmüller, H. (2011). Semi-Global Matching - Motivation, Developments and Applications. In: *Proceedings of the 53rd Photogrammetric Week*. Ed. by Fritsch, D., 5–11 (cit. on p. 21).
- Holopainen, M., Vastaranta, M., Karjalainen, M., Karila, K., Kaasalainen, S., Honkavaara, E. and Hyyppä, J. (2015). Forest Inventory Attribute Estimation using Airborne Laser Scanning, Aerial Stereo Imagery, Radargrammetry and Interferometry - Finnish Experiences of the 3d Techniques. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences* **II-3/W4**, 63–69. doi: [10.5194/isprsaannals-II-3-W4-63-2015](https://doi.org/10.5194/isprsaannals-II-3-W4-63-2015) (cit. on p. 8).
- Hudak, A. T., Crookston, N. L., Evans, J. S., Falkowski, M. J., Smith, A. M., Gessler, P. E. and Morgan, P. (2006). Regression modeling and mapping of coniferous forest basal area and tree density from discrete-return lidar and multispectral satellite data. *Canadian Journal of Remote Sensing* **32** (2): 126–138. doi: [10.5589/m06-007](https://doi.org/10.5589/m06-007) (cit. on p. 8).
- Hugershoff, R. (1933). Die photogrammetrische Vorratsermittlung. *Tharandter Forstliches Jahrbuch* **84**, 159–166 (cit. on pp. 5, 6).
- Hyyppä, J., Hyyppä, H., Leckie, D., Gougeon, F., Yu, X. and Maltamo, M. (2008). Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *International Journal of Remote Sensing* **29** (5): 1339–1366. doi: [10.1080/01431160701736489](https://doi.org/10.1080/01431160701736489) (cit. on p. 8).
- Immitzer, M., Stepper, C., Böck, S., Straub, C. and Atzberger, C. (2016). Use of WorldView-2 stereo imagery and National Forest Inventory data for wall-to-wall mapping of growing stock. *Forest Ecology and Management* **359**, 232–246. doi: [10.1016/j.foreco.2015.10.018](https://doi.org/10.1016/j.foreco.2015.10.018) (cit. on pp. 14, 16, 18, 21, 24).
- Järnstedt, J., Pekkarinen, A., Tuominen, S., Ginzler, C., Holopainen, M. and Vitala, R. (2012). Forest variable estimation using a high-resolution digital surface model. *ISPRS Journal of Photogrammetry and Remote Sensing* **74**, 78–84. doi: [10.1016/j.isprsjprs.2012.08.006](https://doi.org/10.1016/j.isprsjprs.2012.08.006) (cit. on p. 11).
- Kuhn, M. (2015). *caret: Classification and Regression Training*. URL: <http://CRAN.R-project.org/package=caret> (cit. on p. 24).
- Kuhn, M. and Johnson, K. (2013). *Applied Predictive Modeling*. New York: Springer. ISBN: 9781461468486. doi: [10.1007/978-1-4614-6849-3](https://doi.org/10.1007/978-1-4614-6849-3) (cit. on pp. 23, 24).
- LDBV (2015a). *Digitale Geländemodelle (DGM): Product information leaflet*. Ed. by Landesamt für Digitalisierung, Breitband und Vermessung Bayern. München. URL: http://vermessung.bayern.de/file/pdf/1614/download_faltblatt-dgm09.pdf (cit. on p. 19).
- LDBV (2015b). *Luftbildprodukte: Product information leaflet*. Ed. by Landesamt für Digitalisierung, Breitband und Vermessung Bayern. München. URL: http://vermessung.bayern.de/file/pdf/1039/download_faltblatt-luftbilder08.pdf (cit. on p. 18).

- Leberl, F., Irschara, A., Pock, T., Meixner, P., Gruber, M., Scholz, S. and Wiechert, A. (2010). Point Clouds: Lidar versus 3D Vision. *Photogrammetric engineering and remote sensing* **76** (10): 1123–1134 (cit. on p. 8).
- Lemmens, M. (2011). Photogrammetry: Geometric Data from Imagery. In: *Geo-information*. Ed. by Lemmens, M. Dordrecht: Springer Netherlands, 123–151. ISBN: 9789400716667. DOI: [10.1007/978-94-007-1667-4_7](https://doi.org/10.1007/978-94-007-1667-4_7) (cit. on pp. 20, 21).
- Li, Y., Andersen, H.-E. and McGaughey, R. (2008). A comparison of statistical methods for estimating forest biomass from light detection and ranging data. *Western journal of applied forestry* **23** (4): 223–231 (cit. on p. 8).
- Liaw, A. and Wiener, M. (2002). Classification and Regression by randomForest. *R news* **2** (3): 18–22 (cit. on p. 24).
- Lim, K., Treitz, P., Wulder, M., St-Onge, B. and Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography* **27** (1): 88–106. DOI: [10.1191/030913303pp360ra](https://doi.org/10.1191/030913303pp360ra) (cit. on p. 3).
- Maclean, G. A. and Krabill, W. (1986). Gross-Merchantable Timber Volume Estimation Using an Airborne Lidar System. *Canadian Journal of Remote Sensing* **12** (1): 7–18. DOI: [10.1080/07038992.1986.10855092](https://doi.org/10.1080/07038992.1986.10855092) (cit. on pp. 6, 7).
- Maclean, G. A. and Martin, G. L. (1984). Merchantable timber volume estimation using cross-sectional photogrammetric and densitometric methods. *Canadian Journal of Forest Research* **14** (6): 803–810. DOI: [10.1139/x84-142](https://doi.org/10.1139/x84-142) (cit. on p. 5).
- Magnussen, S. and Boudewyn, P. (1998). Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. *Canadian Journal of Forest Research* **28** (7): 1016–1031 (cit. on p. 7).
- Maltamo, M., Næsset, E. and Vauhkonen, J., eds. (2014). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies*. Vol. 27. Managing forest ecosystems. Dordrecht: Springer Netherlands. ISBN: 9789401786621. DOI: [10.1007/978-94-017-8663-8](https://doi.org/10.1007/978-94-017-8663-8) (cit. on p. 3).
- Means, J. E., Acker, S. A., Fitt, B. J., Renslow, M., Emerson, L. and Hendrix, C.J. (2000). Predicting forest stand characteristics with airborne scanning lidar. *Photogrammetric engineering and remote sensing* **66** (11): 1367–1372 (cit. on p. 7).
- Næsset, E. (1997a). Determination of mean tree height of forest stands using airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing* **52** (2): 49–56 (cit. on p. 7).
- Næsset, E. (1997b). Estimating timber volume of forest stands using airborne laser scanner data. *Remote Sensing of Environment* **61** (2): 246–253 (cit. on p. 7).
- Næsset, E. (2002a). Determination of mean tree height of forest stands by digital photogrammetry. *Scandinavian Journal of Forest Research* **17** (5): 446–459 (cit. on p. 8).
- Næsset, E. (2002b). Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment* **80** (1): 88–99 (cit. on pp. 10, 34).
- Næsset, E. (2004). Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. *Scandinavian Journal of Forest Research* **19** (2): 164–179. DOI: [10.1080/02827580310019257](https://doi.org/10.1080/02827580310019257) (cit. on p. 8).
- Næsset, E. and Bjerknes, K.-O. (2001). Estimating tree heights and number of stems in young forest stands using airborne laser scanner data. *Remote Sensing of Environment* **78** (3): 328–340. DOI: [10.1016/S0034-4257\(01\)00228-0](https://doi.org/10.1016/S0034-4257(01)00228-0) (cit. on pp. 7, 8).

- Næsset, E., Gobakken, T., Holmgren, J., Hyppä, H., Hyppä, J., Maltamo, M., Nilsson, M., Olsson, H., Persson, Å. and Söderman, U. (2004). Laser scanning of forest resources: the nordic experience. *Scandinavian Journal of Forest Research* **19** (6): 482–499. doi: [10.1080/02827580410019553](https://doi.org/10.1080/02827580410019553) (cit. on p. 8).
- Nelson, R. (2013). How did we get here? An early history of forestry lidar. *Canadian Journal of Remote Sensing* **39** (S1): S6–S17. doi: [10.5589/m13-011](https://doi.org/10.5589/m13-011) (cit. on p. 3).
- Nelson, R., Krabill, W. and Maclean, G. A. (1984). Determining forest canopy characteristics using airborne laser data. *Remote Sensing of Environment* **15** (3): 201–212 (cit. on p. 6).
- Nelson, R., Krabill, W. and Tonelli, J. (1988). Estimating forest biomass and volume using airborne laser data. *Remote Sensing of Environment* **24** (2): 247–267. doi: [10.1016/0034-4257\(88\)90028-4](https://doi.org/10.1016/0034-4257(88)90028-4) (cit. on p. 7).
- Neufanger, M. (2011). *Richtlinie für die mittel- und langfristige Forstbetriebsplanung in den Bayerischen Staatsforsten: Forsteinrichtungsrichtlinie – FER 2011*. Ed. by Bayerische Staatsforsten. Regensburg (cit. on pp. 9, 16).
- Neumann, C. (1933). Beitrag zur Vorratsermittlung aus Luftmessbildern. Dissertation. Dresden: Sächsische Technische Hochschule (cit. on p. 5).
- Nilsson, M. (1996). Estimation of tree heights and stand volume using an airborne lidar system. *Remote Sensing of Environment* **56** (1): 1–7. doi: [10.1016/0034-4257\(95\)00224-3](https://doi.org/10.1016/0034-4257(95)00224-3) (cit. on pp. 6, 7).
- Nurminen, K., Karjalainen, M., Yu, X., Hyppä, J. and Honkavaara, E. (2013). Performance of dense digital surface models based on image matching in the estimation of plot-level forest variables. *ISPRS Journal of Photogrammetry and Remote Sensing* **83**, 104–115. doi: [10.1016/j.isprsjprs.2013.06.005](https://doi.org/10.1016/j.isprsjprs.2013.06.005) (cit. on p. 11).
- Paine, D. P. and Kiser, J. D. (2012). *Aerial photography and image interpretation*. 3rd ed. Hoboken: Wiley. ISBN: 1118112644 (cit. on p. 5).
- Pitt, D. G., Woods, M. and Penner, M. (2014). A Comparison of Point Clouds Derived from Stereo Imagery and Airborne Laser Scanning for the Area-Based Estimation of Forest Inventory Attributes in Boreal Ontario. *Canadian Journal of Remote Sensing* **40** (3): 214–232. doi: [10.1080/07038992.2014.958420](https://doi.org/10.1080/07038992.2014.958420) (cit. on p. 11).
- Polley, H., Schmitz, F., Hennig, P. and Kroher, F. (2010). Germany: Chapter 13. In: *National Forest Inventories*. Ed. by Tomppo, E., Gschwantner, T., Lawrence, M. and McRoberts, R. E. Dordrecht: Springer Netherlands, 223–243. ISBN: 9789048132324 (cit. on p. 16).
- Schenk, T. (1999). *Digital photogrammetry: Vol. I: Background, fundamentals, automatic orientation produceres*. Laurelville, OH: TerraScience (cit. on p. 20).
- Spurr, S. H. (1948). *Aerial photographs in forestry: Deutsche Übersetzung*. New York: The Ronald Press Company (cit. on p. 5).
- Stepper, C., Straub, C., Immitzer, M. and Pretzsch, H. (submitted). Using canopy heights from digital aerial photogrammetry to enable spatial transfer of forest attribute models: a case study in central Europe. *Scandinavian Journal of Forest Research* (cit. on pp. 14, 24, 36).
- Stepper, C., Straub, C. and Pretzsch, H. (2015a). Assessing height changes in a highly structured forest using regularly acquired aerial image data. *Forestry* **88** (3): 304–316. doi: [10.1093/forestry/cpu050](https://doi.org/10.1093/forestry/cpu050) (cit. on pp. 14, 17, 22, 25).
- Stepper, C., Straub, C. and Pretzsch, H. (2015b). Using semi-global matching point clouds to estimate growing stock at the plot and stand levels: ap-

- plication for a broadleaf-dominated forest in central Europe. *Canadian Journal of Forest Research* **45** (1): 111–123. doi: [10.1139/cjfr-2014-0297](https://doi.org/10.1139/cjfr-2014-0297) (cit. on pp. 12, 14, 24, 30, 36).
- Strahler, A. H., Woodcock, C. E. and Smith, J. A. (1986). On the nature of models in remote sensing. *Remote Sensing of Environment* **20** (2): 121–139 (cit. on p. vii).
- Straub, C. and Stepper, C. (2016). Using Digital Aerial Photogrammetry and the Random Forest Approach to Model Forest Inventory Attributes in Beech- and Spruce-dominated Central European Forests. *Photogrammetrie, Fernerkundung, Geoinformation (PFG)*. doi: [10.1127/pfg/2016/0292](https://doi.org/10.1127/pfg/2016/0292) (cit. on pp. 14, 24, 36).
- Straub, C., Stepper, C., Seitz, R. and Waser, L. T. (2013). Potential of UltraCamX stereo images for estimating timber volume and basal area at the plot level in mixed European forests. *Canadian Journal of Forest Research* **43** (8): 731–741. doi: [10.1139/cjfr-2013-0125](https://doi.org/10.1139/cjfr-2013-0125) (cit. on p. 11).
- van Laar, A. and Akça, A. (2007). *Forest mensuration*. [2nd ed]. Vol. v. 13. Managing forest ecosystems. Dordrecht: Springer. ISBN: 9789048174973 (cit. on pp. 4, 16).
- Vastaranta, M., Wulder, M. A., White, J. C., Pekkarinen, A., Tuominen, S., Ginzler, C., Kankare, V., Holopainen, M., Hyppä, J. and Hyppä, H. (2013). Airborne laser scanning and digital stereo imagery measures of forest structure: comparative results and implications to forest mapping and inventory update. *Canadian Journal of Remote Sensing* **39** (5): 382–395. doi: [10.5589/m13-046](https://doi.org/10.5589/m13-046) (cit. on p. 11).
- White, J. C. (2016). Characterizing Three-Dimensional Forest Structure From Digital Aerial Photogrammetry: A Competing or Complementary Technology to Airborne LiDAR? *BC Forest Professional* (March - April 2016): 12–13 (cit. on pp. 8, 34).
- White, J. C., Stepper, C., Tompalski, P., Coops, N. C. and Wulder, M. A. (2015). Comparing ALS and Image-Based Point Cloud Metrics and Modelled Forest Inventory Attributes in a Complex Coastal Forest Environment. *Forests* **6** (10): 3704–3732. doi: [10.3390/f6103704](https://doi.org/10.3390/f6103704) (cit. on pp. 14, 17, 24, 36).
- White, J. C., Wulder, M. A., Varhola, A., Vastaranta, M., Coops, N. C., Cook, B. D., Pitt, D. and Woods, M. (2013a). *A best practices guide for generating forest inventory attributes from airborne laser scanning data using the area-based approach*. Vol. FI-X-010. Information report. Victoria, BC, Canada. ISBN: 9781100223858 (cit. on pp. 8, 9, 22).
- White, J. C., Wulder, M. A., Vastaranta, M., Coops, N. C., Pitt, D. and Woods, M. (2013b). The Utility of Image-Based Point Clouds for Forest Inventory: A Comparison with Airborne Laser Scanning. *Forests* **4** (3): 518–536. doi: [10.3390/f4030518](https://doi.org/10.3390/f4030518) (cit. on p. 8).
- Woods, M., Pitt, D., Penner, M., Lim, K., Nesbitt, D., Etheridge, D. and Treitz, P. (2011). Operational implementation of a LiDAR inventory in Boreal Ontario. *The Forestry Chronicle* **87** (4): 512–528 (cit. on p. 8).

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SYMBOLS

- 3d, *see* three-dimensional
- A
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 - accuracy, 24
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