Forest Characterization by Fusion of Imaging Spectroscopy and Airborne Laser Scanning

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Hossein Torabzadeh Khorasani

aus dem

Iran

Promotionskomitee

Prof. Dr. Michael E. Schaepman (Vorsitz)
Dr. Felix Morsdorf (Leitung der Dissertation)

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Summary

By covering one third of the world's land area, forests are the dominant terrestrial ecosystems on planet Earth, providing invaluable services for humanity. Carbon sequestration, water purification and nutrient recycling are only a few examples of vital ecosystem services forests provide. However, recent anthropological activities and climate change often cause forest degradation, leading to severe ecological and environmental impact.

Therefore a comprehensive understanding of forests and proper mitigation strategies are required to sustain the services these ecosystems provide. Remote sensing is one of the most helpful, and sometimes the only technique available to quantitatively characterize large forested areas in a rapid and relatively inexpensive manner. Biochemical properties of forests are estimated using spectral information, provided by passive optical sensors, while active remote sensing systems are often exploited for retrieving forest biophysical variables. Nonetheless, limitations of retrieval algorithms and uncertainties of remote sensing data hinder the retrieval of forest properties in heterogeneous forest canopies.

Although two of the most advanced remote sensing systems, imaging spectroscopy (IS) and airborne laser scanning (ALS), provide high quality data, singular datasets currently do not fulfil the requirements for an exhaustive assessment of structurally complex forests. Since IS and ALS data deliver independent, but complementary, information about the forest canopy, fusion of such data ensures a more comprehensive characterization of heterogeneous forests.

For a better understanding of the potential of fusion techniques, current approaches were categorized based on level, method and their final products, in a literature review. Tree species maps were found to have benefited most from complementary ALS and IS data. In addition, tree species composition is one of the most often demanded product for managing and monitoring forested ecosystems. It also serves as a basis for an accurate estimation of other forest properties, e.g. biomass and gross/net primary production.

Consequently, we fused IS and ALS data to more accurately estimate tree species composition, which is one of the main characteristic of mixed forests with complex structure. Two techniques were applied to consolidate the fusion method. First, we inferred the most influential structural and spectral features for species identification. By using a statistical feature selection approach, the most informative spectral bands were found to be in the visible and shortwave infrared region of the spectrum, which strongly enhanced species discriminability. On the other hand, most of the selected structural features were based on leaf-on ALS data, while only a few discriminative features were found in differential structural features, which encapsulate differences between leaf-on and leaf-off ALS datasets. Second, we added spatial information of tree crown outlines to the species classification. This aggregation increased the classification accuracy significantly. Individual tree crown information can be directly derived from ALS data, however, current methods are not accurate enough in complex forests. For this reason, a new method was developed, which iteratively detects trees and delineates their crowns based on the ALS point cloud. In addition to the high accuracy for identifying dominant trees, the proposed algorithm also improves the estimation for the suppressed trees, which is important for analysis of the forest mortality and succession rate. The evaluation of the method in different forest sites, in terms of structural complexity and species composition, confirmed its robustness and transferability to other forest ecosystems.

This dissertation studied the potential of ALS and IS data to improve the characterization of complex forests. By implementing a fusion method based on spatial information of single-tree crowns and using the most discriminative structural and spectral features, we outperformed existing tree species mapping approaches in temperate mixed forests. In addition, the newly

developed three-dimensional segmentation algorithm shows very promising results for single-tree detection and crown delineation in multi-layered forests. Its ability to identify suppressed and understory trees improves biophysical parameters of forests as well as tree species composition maps and reduces estimation bias often found in EO approaches, We conclude that the complementarity of ALS and IS data help to overcome the limitations in characterization of complex, mixed forests, if a proper strategy for data fusion is taken. The method showed the possibility to be extended for fusion of ALS and multi-spectral data in larger areas.

Zusammenfassung

Wälder bedecken rund ein Drittel der Landfläche der Erde und sind damit das vorherrschende Landökosystem. Für den Menschen sind Wälder von unschätzbarem Wert, unter anderem als eine der wichtigsten terrestrischen Kohlenstoffsenken und als eine bedeutende Größe im Wasser- und Nährstoffkreislauf. Dessen ungeachtet gibt es eine stetige Zunahme an anthropogenen Einflüssen in den Wäldern, was in Kombination mit den sich ändernden klimatischen Bedingungen häufig zur Instabilität von Waldökosystemen und damit verbundenen Einschränkungen von Ökosystemdienstleistungen führt.

Dementsprechend sind umfassende Kenntnisse über das Ökosystem Wald notwendig. Nur so könnennachhaltige Nutzungs- und Anpassungsstrategien entwickelt werden, um Ökosystemdienstleistungen zu erhalten. Fernerkundungsdaten und -methoden ermöglichen eine flächendeckende, quantitative Charakterisierung von Waldökosystemen mit einer hohen zeitlichen und räumlichen Auflösung. So können zum Beispiel biochemische Eigenschaften mit passiven, optischen Systemen erfasst oder biophysikalische Variablen mit aktiven Systemen abgeleitet werden. Insbesondere in komplexen Mischwäldern ist aber die Erfassung biochemischer und biophysikalischer Charakteristiken aufgrund von Limitationen in den Auswertealgorithmen und Einschränkungen in den Fernerkundungsdaten häufig nur eingeschränkt möglich gewesen.

Passive, abbildende Spektrometrie (imaging spectroscopy – IS) und aktives, flugzeuggestütztes Laserscanning (airborne laser scanning – ALS) sind fortgeschrittene Verfahren der Fernerkundung, die eine besondere Eignung für die Waldcharakterisierung aufweisen. Aufgrund der technischen Spezifikationen beider Verfahren ist es möglich, mittels Datenfusion eine komplementäre Charakterisierung heterogener Wälder zu erhalten.

In der vorliegenden Dissertation wurden bestehende Fusionsansätze analysiert und kategorisiert; entsprechend ihrer Methodik, der erstellten Produkte und der Fusionsebene (Datenebene vs. Produktebene), wobei insbesondere die Baumartenklassifikation von dem komplementären Informationsgehalt der ALS- und IS-Daten profitierte. Die Baumartenzusammensetzung ist eine der Hauptcharakteristiken von komplexen Mischwäldern und Informationen über die Zusammensetzung der Baumarten sind essentiell für ein Management und das Monitoring dieser Wälder. Darüber hinaus helfen Kenntnisse über die Baumartenverteilung, um eine Abschätzung weiterer Waldeigenschaften, wie zum Beispiel Holzvorrat oder die Brutto/Nettoprimärproduktion, deutlich zu verbessern. Aufbauend auf diesen Ergebnissen wurden für einen komplexen Mischwald eine Fusionsmethodik entwickelt, mit der IS- und ALS-Daten für eine zuverlässige Abschätzung der Baumartenzusammensetzung fusioniert werden konnten. Zuerst wurden dabei strukturelle und spektrale Merkmale hinsichtlich ihrer Bedeutung für eine Baumartenklassifikation untersucht. Basierend auf einer statistischen Methode zur Merkmalsauswahl konnte festgestellt werden, dass neben den strukturellen Informationen aus den ALS-Daten vor allem die Informationen im Bereich des sichtbaren Lichts und des kurzwelligen Infrarots aus den IS-Daten für eine Baumartenklassifikation von Bedeutung sind. In einem weiteren Schritt erfolgte die Baumartenklassifikation unter Zunahme der räumlichen Information der Baumkronen, was die Klassifikationsgenauigkeiten zusätzlich erhöhte.

Die räumlichen Informationen der Baumkronen können zwar direkt anhand von ALS-Daten abgeleitet werden, allerdings haben die bestehenden Methoden deutliche Einschränkungen, wenn sie auf komplexe Mischwälder angewandt werden. Aus diesem Grund wurde eine neue, robuste Methode entwickelt, die sowohl die einzelne Bäume detektiert als auch die zugehörigen Baumkronen in ihren räumlichen Dimensionen beschreibt. Darüber hinaus war es möglich

Bäume zu erfassen, die im Nebenbestand oder im Unterwuchs auftraten und somit nicht zur oberen Kronenschicht gehörten, was insbesondere für Analysen der Waldentwicklung von Bedeutung ist.

In der vorliegenden Dissertation wurde das Potential von ALS und IS für eine verbesserte Charakterisierung von komplexen Wäldern aufgezeigt. Durch die Implementierung einer Fusionsmethode auf dem Level einzelner Baumkronen und durch die automatisierte optimale Auswahl an spektralen und strukturellen Merkmalen konnten neue Massstäbe gesetzt werden im Bereich der Baumartenklassifikation in Mischwäldern der gemässigten Zone. Darüber hinaus wurde ein 3D-Segmentationsalgorithmus entwickelt, der vielversprechende Ergebnisse für die Einzelbaumdetektion und die Baumkronencharakterisierung auch in mehrschichtigen Wäldern zeigt. Damit können die Limitationen bestehender Fernerkundungsansätzen, in Hinblick auf eine umfassende Charakterisierung auch der unteren Waldschichten, zumindest teilweise aufgehoben werden.

Zusammenfassend kann somit festgehalten werden, dass der komplementäre Informationsgehalt von ALS- und IS-Daten zu einer deutlichen Verbesserung der Charakterisierung komplexer Mischwälder führen kann, wenn eine entsprechend angepasste Strategie zur Datenfusion vorliegt.

Table of Content

1

Introduction

1.1 Relevance of forested ecosystems

"Life on earth is inconceivable without trees. Forests create climate, climate influences peoples' character, and so on and so forth. There can be neither civilization nor happiness if forests crash down under the axe, if the climate is harsh and severe, if people are also harsh and severe. ... What a terrible future!"

— Anton P. Chekhov, 1888

Forests roughly cover 30% of the ice-free land surface of the earth (FAO, 2010), but produce three fourths of the total terrestrial net primary productivity (Nabuurs et al., 2007) and accommodate about 90% of the terrestrial biodiversity (Pan et al., 2013). Their vital role in sequestering carbon (Schimel, 2014; Streck and Scholz, 2006), regulating the water quality and quantity (Sweeney and Newbold, 2014), recycling of nutrients (Prescott, 2002) and protecting soil erosion (Hartanto et al., 2003) make forests the most important terrestrial ecosystem. Furthermore, forests have invaluable economical aspects, caused by provisioning services, such as providing timber, paper and pharmaceuticals (Croitoru, 2007; Pearce, 2001).

Changes in forests species composition and distribution, both in space and time influence their function (Wulder et al., 2009). Forest development and succession cause continuous and slow changes, while some human activities and disturbances lead to discontinuous and sudden changes in such ecosystems (Frelich and Reich, 1999; Magnani et al., 2007; Riitters et al., 2002). Considering the invaluable services of forests, any degradation of these ecosystems impact both human health and economy (Myers, 1997).

Fortunately, public demand for conservation and restoration of forests ecosystems is increasing. In order to decelerate climate change, for instance, the Kyoto Protocol allows signatory countries to fulfill part of the emission reduction requirements through the conservation and enhancement of forest ecosystems, which are the main terrestrial carbon sinks (Patenaude et al., 2005; UNFCCC, 1997). In addition, international programs, such as Reducing Emissions from Deforestation and Forest Degradation (REDD+), financially support developing countries to restrain deforestation and rehabilitate degraded lands (Phelps et al., 2010; Thomas et al., 2010).

Therefore, a comprehensive understanding of forest ecosystems and how best to conserve them is important to preserve the essential goods and services that they provide and that we need on planet Earth.

1.2 Remote sensing based forest mapping

Models of ecosystem functioning, which are used to determine inherent forests dynamics, require accurate, reliable and up-to-date information about the forest components. These information are usually described by biophysical and biochemical parameters at different scales (Boyd and Danson, 2005a). Traditional forest mapping approaches directly collect the required data in the field, which is both time consuming and labor intensive over large areas. Besides, monitoring the short-term response of forest ecosystem processes (i.e. at daily to annual frequency) requires very expensive up-to-date in-situ measurements, which are not always possible.

In contrast, remote sensing products, available at increasingly high spatial, spectral and temporal resolutions, allow comprehensive monitoring of terrestrial ecosystems, including forests (Wulder and Franklin, 2003). Remotely sensed data provide wall-to-wall information over large areas in a repetitive, rapid and relatively inexpensive manner (Bodart et al., 2011). In addition to the mapping and monitoring of forest borders, a wide range of parameters are estimated from remotely sensed data in forest ecosystems. The retrieval of biochemical parameters is mostly done through passive optical remote sensing (e.g. Kuusk and Nilson, 2000; Zarco-Tejada et al., 2001; Zhang et al., 2008), while active sensors are often used for estimating biophysical parameters (Karjalainen et al., 2012; Koch, 2010; Neumann et al., 2010). Nevertheless, the complexity of forest canopies, limitations of retrieval algorithm and uncertainties of measurements cause the forest characterization by remote sensing to be underdetermined and then leads to an ill-posed problem (Baret and Buis, 2008; Combal et al., 2003; Koetz et al., 2007a). In this context, two contemporary remote sensing systems, imaging spectroscopy and airborne laser scanning, are promising avenues for providing high quality measurements, resulting in more realistic characterization of forested areas.

1.2.1 Imaging spectroscopy

Imaging Spectroscopy (IS) is the simultaneous acquisition of spatially co-registered images, in many narrow, spectrally contiguous bands (Schaepman et al., 2009). Spectral information contained in IS data over vegetated areas is mainly based on absorption features in the canopy reflectance spectrum related to the biochemistry of the foliage components (Koetz et al., 2007a; Ustin et al., 2004b). IS has been consequently utilized for estimating biochemical parameters of foliage such as pigments concentration (Asner and Martin, 2008a; Jacquemoud et al., 1996; Zarco-Tejada et al., 2004), water

content (Ceccato et al., 2002; Cheng et al., 2011; Clevers et al., 2008) and dry matter content (Martin and Aber, 1997; Serrano et al., 2002). IS data also allows for mapping of plant functional types and species composition at leaf level (Asner and Vitousek, 2005; Schmidtlein, 2005). However their performance is dramatically decreased at canopy level (Féret and Asner, 2011).

A smaller part of spectral variability (mostly in near infrared wavelengths) is induced by scattering processes at the canopy level, and is related to composition, arrangement and biophysical properties of the constituting elements of the canopy (Disney et al., 2006; Kokaly et al., 2009a; Peddle et al., 1999). Leaf Area Index (LAI), canopy cover and aboveground biomass are some examples of the biophysical parameters of canopy that may be estimated from IS data by using vegetation indices calculated from specific wavelengths (De Jong et al., 2003; Gobron et al., 2000; Schlerf and Atzberger, 2006).

The influence of canopy structure on IS data depends on the complexity of the canopy structure, making the estimation of the biochemical parameters uncertain (Asner et al., 2000b; Morsdorf et al., 2009). Applying an empirical regulating factor may provide better estimates in homogeneous canopies, such as agricultural fields and grasslands, by removing the slight influence of the canopy structure (Darvishzadeh et al., 2008; Gitelson et al., 2005). Nevertheless the spectral measurements are more complicated in forest ecosystems, as the objects are trees, consisting of disparate elements (i.e. foliage and branches), which interact with the incoming radiation and may be interfered with background reflectance (Asner, 1998; Myneni et al., 1995). Despite the existing sophisticated methods for forest characterization using IS data (e.g. radiative transfer models), there is an inherent limitation of IS systems to explore the canopy in the vertical dimension. This drives the need for some auxiliary information from independent sources.

1.2.2 Airborne laser scanning

Airborne Laser Scanning (ALS) is an active optical remote sensing system that exploits Light Detection And Ranging (LiDAR) technology. Following the emission of a laser beam through the canopy, a LiDAR instrument records the power and time of the backscattered energy (Baltsavias, 1999). Small footprint ALS systems produce a 3D dataset of discrete points, called point cloud, which represents the geometrical distribution of the returned echoes from constituent elements of the forest canopies. These within-canopy measurements provide more realistic understanding about forest ecosystems at local and regional scales (Hyyppä et al., 2008; Lim et al., 2003b).

Early ALS systems, which recorded first and last returns, were designed for the mapping of terrain topography, while new instruments expose more intermediate values, making them more appropriate for vegetation assessment. Over this, full-waveform instruments digitize the entire backscattered signal with a high frequency, delivering a semi-continuous representation of the return signal. This detailed information results in better estimations of the vegetation properties, particularly in dense and heterogeneous forests (Mallet and Bretar, 2009; Reitberger et al., 2009). Nevertheless the capabilities of the ALS data are affected by other specification of the system, such as footprint size, point density per unit area and laser wavelength (Vosselman and Maas, 2010).

ALS facilitates estimation of various biophysical parameters of forests as well as beneath-canopy topography (Lefsky et al., 2002; Mallet and Bretar, 2009). Canopy height, which is the most requested and relevant parameter in forest inventories, is estimated by using ALS data at stand (Hall et al., 2005; Næsset, 2002), plot (Popescu et al., 2002) and individual tree levels (Popescu et al., 2003; Roberts et al., 2005). Moreover, ALS data provide the unique possibility to explore inside the canopy and determine vertical distribution of foliage and woody elements in the canopy (Næsset and Bjerknes, 2001; Pascual et al., 2008; Zimble et al., 2003). In addition, some biophysical parameters are indirectly estimated using ALS-derived height and allometric models, e.g. Diameter at Breast Height (DBH)(Salas et al., 2010; Vauhkonen et al., 2010), basal area and stem density (Holmgren, 2004). Canopy height along with DBH is the main requirement for estimating forest biomass. Therefore ALS data are used not only to assess the above ground biomass (AGB) but also for evaluating its temporal changes (Næsset and Gobakken, 2008). However the accuracy is lower in dense and multi-layered forests (Lim and Treitz, 2004). Fractional canopy Cover (fCover) and Leaf Area Index (LAI) are two other biophysical metrics that are estimated by analysing first and last echoes (Korhonen and Morsdorf, 2014; Morsdorf et al., 2004) or by inverting physically based models (Koetz et al., 2006a). However, the latter needs more investigation to be considered as a practical approach for LAI estimation.

Nevertheless, ALS data do not provide sufficient information about biochemical properties of a vegetation canopy, due to the single-wavelength measurements by LiDAR systems. Furthermore, accurate interpretation of the ALS data rests on the spectral properties of the canopy. These issues directly influence the capability of the ALS data for mapping of the tree species composition and limit their potential to differentiate only between general groups of species, e.g. conifers and broadleaves (Ørka et al., 2010). New multispectral ALS systems may solve this issue (Morsdorf et al., 2009), however more

ancillary information about the system is required for calibration and must be provided by the factories and surveying companies (Roncat et al., 2014).

The aforementioned products are retrieved either at a certain area (e.g. plot) or at single-tree level, leading to two major forest inventory approaches: area-based and ITC-based. ITC-based techniques provide more accurate estimates of some of the biophysical parameters, such as tree height, crown diameter (Morsdorf et al., 2004), crown-base height (Solberg et al., 2006), basal area and stem volume (Holmgren, 2004). As an active remote sensing system, LiDAR instruments deliver detailed information from inside a tree canopy. This enables single-tree detection and tree crown delineation by using ALS data (Koch et al., 2006a).

1.2.3 Fusion of IS and ALS data

IS data provide information on the foliar biochemical properties at leaf level and, indirectly, on the canopy structure. The estimated biochemical parameters in homogeneous canopies are consistent, though the uncertainties increase in more complex canopies. The direct estimation of leaf biochemical properties then becomes an ill-posed issue when the structural effects are not properly evaluated. Biophysical parameters of the canopy can be estimated from ALS data. However, the laser echoes are also affected by spectral properties of the canopy components and background. In addition, ALS data cannot directly express information on biochemical characteristics of the canopy, be it directly or through modelling. Despite the helpful achievements of IS and ALS systems to determine some forest characteristics, remaining uncertainties in the estimated biophysical and biochemical parameters are propagated through the ecological models, in which they are used, so that forest canopy cannot be accurately characterized by these data alone (Dubayah et al., 2000; Zhang, 2010). In such cases, the ALS-derived canopy structural metrics can be combined with IS-provided spectral information, fulfilling the requirements for comprehensive forest ecological models. Fig. 1.1 shows a general overview of the fusion of ALS and IS data for better understanding of the forest canopy.

Several studies have already illustrated the advantages of the fusion of different remotely sensed data for robust forest ecosystem characterization (Kellndorfer et al., 2010; Treuhaft et al., 2004; Widlowski et al., 2004). Fused IS and ALS data were exploited for assessing the pigments constituents in forest canopy (Blackburn, 2002b; Koetz et al., 2007a; Thomas et al., 2008) as well as biophysical parameters, as for instance basal area (Finley et al., 2013), LAI (Cao et al., 2011) and fCover (Koetz et al., 2007a; Stojanova et al., 2010b).

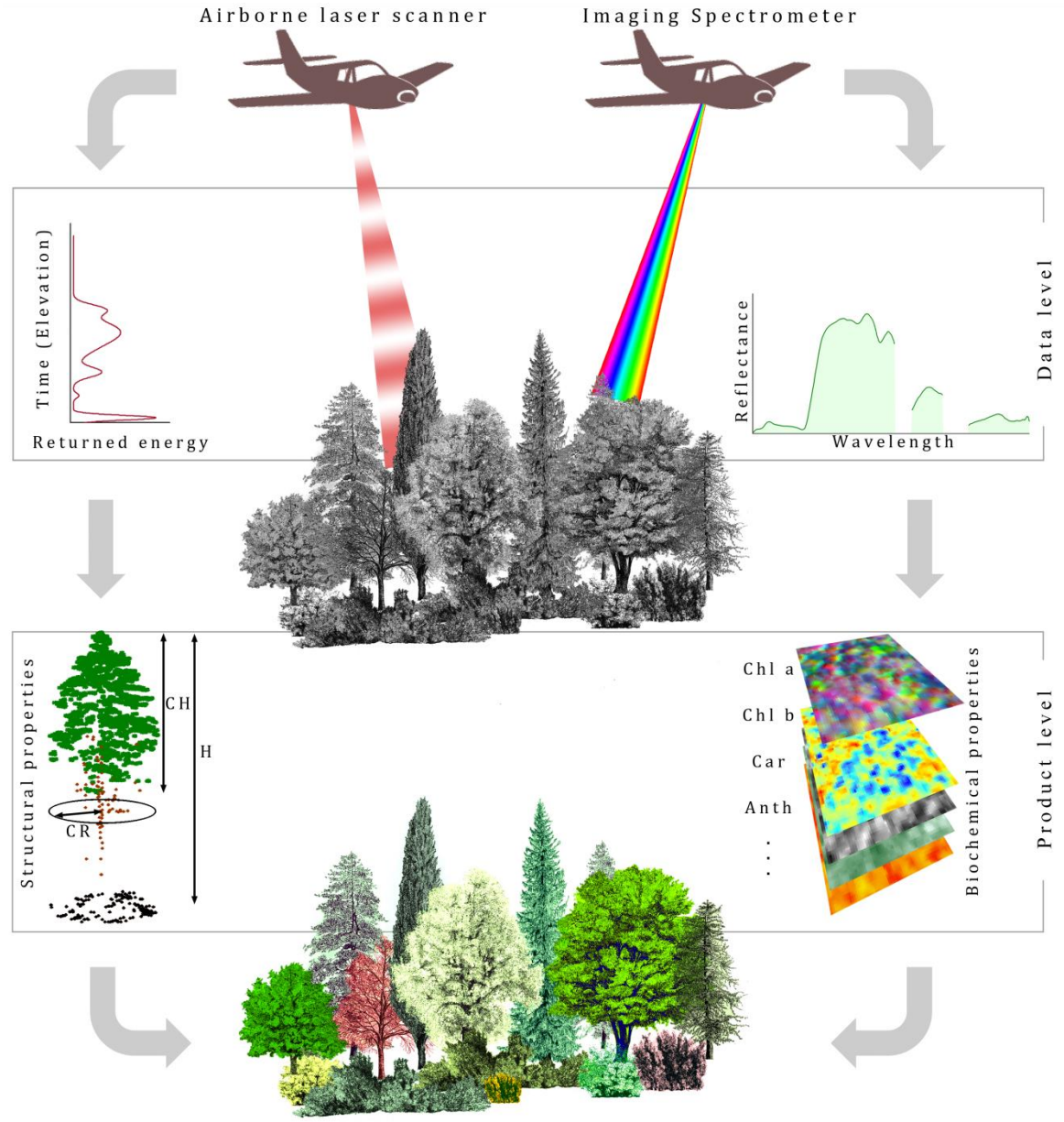

Fig. 1.1. Information flow from airborne remotely sensed data to the forest ecosystem characteristics. CH, H and CR are crown height, tree height and crown radius, respectively. Chl a, Chl b, car and Anth are Chlorophyll a and b, Carotenoids and Anthocyanin, respectively.

The lower uncertainty and higher reliability of combining IS and ALS data relative to single instrument approaches makes fusion method better suited for estimating of higher-level products, where more complicated models are applied (Chasmer et al., 2009a; Cook et al., 2009; Hilker et al., 2008a). For instance, mapping of the spatial abundance of tree species benefits from both spectral and structural discriminators (Buddenbaum et al.,

2013; Heinzel and Koch, 2012; Hill and Thomson, 2005; Jones et al., 2010b). AGB (Breidenbach et al., 2010; Lefsky et al., 2005; Popescu et al., 2004a; Tonolli et al., 2011b) and plant primary production (Asner et al., 2007b; Cook et al., 2009; Hilker et al., 2008a) are other products that can be better derived by fusing IS and ALS data.

Exploiting ALS systems is relatively expensive in comparison with space-borne optical remote sensing systems. Therefore, ALS data may not be available over large areas. Spatial/temporal upscaling is another aspect of data fusion that can address such a problem. Sparse ALS-derived parameters are then extended using either continuous IS data over the landscape or multi-temporal remote sensing observation (Hudak et al., 2002; Lefsky, 2010a). Upscaling of the LiDAR data can even provide forest canopy height at global scale (Lefsky, 2010a).

1.3 Motivation

As explained in the previous sections, imaging spectrometers and laser scanning systems provide independent and complementary data relevant for the assessment of the biochemical and biophysical properties of forested areas. The fusion of such data is a promising approach to improve the potential and accuracy of essential parameters for ecological models, particularly in the case of heterogeneous forest canopies. Several studies have already illustrated the functionality and usefulness of data fusion for robust forest ecosystem characterizations (e.g. Asner et al., 2012b; Chasmer et al., 2009a; Koetz et al., 2008; Swatantran et al., 2011). However, the optimal benefit of data fusion depends on the choice of appropriate method and level. Insufficient attention to practical constraints of the fusion methods may result in inadequate accuracy levels for forest management and ecological models, despite the relatively high costs of ALS and IS datasets. In addition, fused data have different capabilities in facing with different ecological models, resulting in a diverse range of the accuracy and reliability of the derived products. In order to gain a better understanding of the fusion mechanism, a classification of all the potentially extractable products from ALS and IS data fusion is needed.

Forest ecosystem properties are estimated either at a large area (e.g. a sampling plot) or at single-tree level. Although both levels are necessary for forest assessment, forest inventory at single-tree level prepare operational information for precise forest management (Wulder et al., 2008a; Wynne, 2006) and ecological studies at local scale (Chambers et al., 2007; Goetz et al., 2007). Having accurate information about the position of trees and their crown dimensions enhances the estimation of the biophysical and

biochemical parameters as well as tree species composition (Holmgren et al., 2008b). ALS data can be used to assist the detection of single-trees and delineation of their crowns. ALS-provided geometrical inter-relationships between the tree components in 3D format of the point cloud help to virtually reconstruct the trees, in a much more explicit and precise way than is possible with other optical remote sensing data.

However, a few challenges still remain. The majority of tree identification methods are raster-based and consist of searching for potential trees within a surface model derived from ALS point heights (Ene et al., 2012; Hyyppa et al., 2001). Because of the partial use of the ALS point cloud, their success in single-layered conifer-dominant forests cannot be transferred into other complex biomes, e.g. mixed temperate or tropical forests (Duncanson et al., 2014; Ferraz et al., 2012). In contrast, benefiting from all the ALS information by point cloud-based methods can enhance the identification of dominated and suppressed trees. These approaches potentially lead to improving single-tree identification, though they are still in their infancy.

Among all the products investigated by synergistically using ALS and IS data, tree species composition mapping has already attracted the most attention. In spite of the importance of tree species maps in forest managements and conservation, this information serves for more accurate estimation of other products, such as timber volume, AGB and Gross Primary Production (GPP) of the forests. IS and ALS data fusion showed considerable potential for improving species composition mapping, despite the strong influence of the number and arrangement of the features derived from ALS or IS data on the overall accuracy of the map and on the discrimination accuracy of each species.

1.4 Research outlines

The present dissertation contributes to the understanding of forest characteristics by exploiting of Imaging Spectroscopy and Airborne Laser Scanning data (IS and ALS, respectively). Available methods and levels of ALS and IS data fusion are compared to explore the benefits of such an approach for forest assessment. The approach taken focuses on combining independent and complementary data to derive tree species composition within a heterogeneous canopy of a mixed forest. A new framework for single-tree identification from ALS data is also proposed, which can properly serve in the context of data fusion. Based on the scientific motivation outlined in the previous section, this dissertation answers the following research questions:

- How different methods and levels of data fusion are influences the estimated forest characteristics?
- Can ALS data help to identify dominated and suppressed trees in a practical framework?
- Together with IS data, what can ALS-derived features contribute to the mapping of tree species composition more accurately in a dense mixed forest?

These research questions are addressed within three peer-reviewed scientific publications contained in the dissertation. More details on the research questions are presented below:

1.4.1 ALS and IS data fusion for forest characterization

The first publication (Torabzadeh et al., 2014) addresses the following research questions:

- Which products profit most from the fusion of IS and ALS data?
- Which methods perform best when applied on the combined ALS and IS data?
- What are the main challenges of combining ALS and IS data?

In this paper, we summarize and classify relevant studies (performed within the last decade) focusing on forest characterization using combined ALS and IS data. This provides an overview of the state of the art in ALS and IS data fusion. All the investigated products were then classified into five categories based on their relevance for assessment of forest ecosystems. We also evaluate the studies based on the obtained accuracy for each product.

1.4.2 Single-tree identification using ALS data in multi-layered forest ecosystem

Considering the critical importance of the forest inventory at single-tree level, we developed a novel approach for detecting individual trees and delineating their crowns simultaneously from ALS point clouds. The iterative nature of this novel method allows exploring the lower layers of the forest canopy to find suppressed and dominated trees as well as larger trees in the upper layer.

The proposed method is described in a second publication (Torabzadeh et al., 2015c) and was validated to address the following research questions:

- To what extent can dominated and suppressed trees in lower strata be detected by this method?

- What are the influences of different canopy conditions, e.g. structural complexity and species composition, on the accuracy of the single-tree detection?

1.4.3 Assessment of tree species composition using a combination of IS and ALS data

In the third publication (Torabzadeh et al., 2015b), we fuse IS data with high point density small-footprint ALS data, acquired in both leaf-on and leaf-off conditions in order to identify tree species within a dense temperate forest in Switzerland. We implemented a statistical feature selection approach to find the best subset of the potential structural and spectral features, causing species classification with higher accuracy.

More specifically, the following research questions are addressed in the third publication:

- What are the most influential spectral bands and ALS-derived structural features for tree species discrimination?
- Which tree species profit most from the fusion approach using the selected features?
- What is the relevance of using single-tree information for the classification of IS, ALS and fused datasets?

1.5 Structure of the thesis

Chapter 1 provides a general background, introduction and problem description in the scientific setting of the dissertation. The potential parameters of forest ecosystems that can be retrieved by IS, ALS and fused data are presented. Furthermore, the main challenges of assessing forest ecosystem by remote sensing techniques are explained, as well as the information gaps that the fusion of the ALS and IS data may fill. Research questions and outline of the dissertation are also addressed and discussed.

Chapter 2 is based on a first-authored peer-reviewed scientific publication (Torabzadeh et al., 2014). It provides an overview of the fusion approaches that have been applied on the IS and ALS data so far. The publication is self-contained in both structure and content.

Chapter 3 consists of a first-authored peer-reviewed scientific publication (Torabzadeh et al., 2015c) introducing a novel single-tree identification method based on ALS point cloud. The performance of the method is investigated in different forest conditions. The publication is self-contained in both structure and content.

Chapter 4 consists of a first-authored peer-reviewed scientific publication (Torabzadeh et al., 2015b). It points to the fusion of ALS and IS data for mapping of the tree species

composition in a dense temperate mixed forest. The publication is self-contained in both structure and content.

Chapter 5 summarizes and discusses the progress and major findings of the single publications presented in chapters 2-4, provides concluding remarks and an outlook.

2

Fusion of imaging spectroscopy and airborne laser scanning data for characterization of forest ecosystems – a review

This chapter is based on:

Torabzadeh, H., Morsdorf, F., & Schaepman, M.E. (2014). Fusion of imaging spectroscopy and airborne laser scanning data for characterization of forest ecosystems – A review. ISPRS Journal of Photogrammetry and Remote Sensing, 97 (0), 25-35

Abstract

Forest ecosystems play an important role in the global carbon cycle and it is largely unknown how this role might be altered by transients imposed by global change and deforestation. Remote sensing can provide information on ecosystem state and functioning and, among others, two remote sensing techniques, Airborne Laser Scanning (ALS) and Imaging Spectroscopy (IS), have been used to characterize forest ecosystems, both independently and combined in fusion approaches. However, the fusion of these datasets should make the best use of the complementarity of both sensors and provide better and more robust vegetation products in forested ecosystems. Similar to other data fusion approaches, satisfying results depend on choosing appropriate fusion levels and methods. In this review paper, we summarize and classify relevant studies that focused on forest characterization using combined ALS and IS data, limited to the last decade. We classified the approaches by fusion level (data or product level) and by choice of methods (physical or empirical methods). Five different categories of products (landcover maps, aboveground biomass, biophysical parameters, gross/net primary productivity and biochemical parameters), have been found as the main aspects of forest ecosystems studied so far. A qualitative accuracy analysis of the products exposed that currently landcover maps are profiting the most from ALS and IS data fusion, while there is room for improvements in respect to the other products, such as biophysical parameters. Only few studies using physical approaches were found, but we expect the use of such approaches will increase with the growing availability of physically based radiative transfer models that can simulate both, ALS and IS data.

2.1 Introduction

Forests cover 31% of the total land surface, yet account for a major fraction of the total terrestrial net primary productivity (FAO, 2010; Nabuurs et al., 2007). Furthermore, as they hold 46% of the total global carbon and about 90% of terrestrial biodiversity, it is mandatory to understand the role of forest ecosystems in the carbon cycle (Kindermann et al., 2008; World Bank, 2003). Models of ecosystem functioning, which are used to determine forests role in e.g. nutrient cycling (with processes such as photosynthesis and evapotranspiration) require accurate information on the forest components, which can be described by biophysical and biochemical parameters on different scales. Particularly, the accurate estimation of these parameters provides the foundation for a robust assessment of greenhouse gases exchange taking place between the atmosphere, vegetation and soil (Boyd and Danson, 2005b; Kokaly et al., 2009b).

Remote sensing has a long tradition in the assessment of forest ecosystems, since it can provide spatially explicit wall-to-wall information over large areas, something which traditional point - or plot-based field measurements cannot.

In addition to other vegetation types, forest ecosystems have been characterized by using passive optical remote sensing systems in a number of studies (Malenovský et al., 2009). These studies mostly built on observing the spectral response of vegetation components (e.g. leaves, shoots and stems), as well as atmosphere and background soil and linked it with biochemical or biophysical parameters of interest (Asner et al., 2003a; Lu, 2006). However, passive optical remote sensing has some limitations when it comes to ecosystem properties that are related to or influenced by forest structure (e.g. leaf area index; Zheng and Moskal, 2009). In general, the structural complexities of forests cause serious challenges for parameter estimation, which traditional methods (field based, passive EO data) of forest assessments cannot overcome to ultimately meet the requirements of scientific models and applications in these types of ecosystems (Antonarakis et al., 2014).

Imaging spectroscopy (IS), is defined as the simultaneous acquisition of spatially coregistered images, in many narrow, spectrally contiguous bands (Schaepman et al., 2009), provides spectral information of an observed surface, which itself is a function of the composition, arrangement and properties of the constituting elements. Consequently IS has been exploited for the estimation of biochemical parameters (Asner et al., 2007a; Schaepman et al., 2009; Ustin et al., 2004a). Still, the data provided by such sensors include

contributions from both the canopy structure and the biochemical properties of canopy elements (Asner et al., 2000a; Morsdorf et al., 2009).

In recent years, light detection and ranging (LiDAR) has emerged, which facilitates estimation of the forest structural parameters (e.g. height, shape and foliage distribution in the vegetation canopy), as well as beneath-canopy topography (Lefsky et al., 2002; Mallet and Bretar, 2009). This makes LiDAR as a promising system for better understanding of variations in forest structure. LiDAR systems are operated from different platform types (i.e. spaceborne, airborne, ground-based) and at different corresponding scales (global, regional and local), however, up to now, most studies concerned with forest ecosystems have exploited airborne laser scanning (ALS) data at local to regional scales (Hyyppä et al., 2008; Lim et al., 2003a).

Despite these different types of remote sensing instruments, no single system currently fulfills the requirements for a comprehensive forest ecosystem characterization. Additionally, more complex forest properties cannot be determined, either directly or with modeling, by one remote sensing system alone (Boyd and Danson, 2005b; Zhang, 2010). For instance, the direct estimation of leaf level properties based on IS alone remains ill-posed, since structural effects and the response due to changes of biochemical parameters are mixed in the recorded signals.

In such cases, fusion of the complementary remote sensing systems IS and ALS appears to be an interesting option to overcome these limitations. Several studies carried out in forest ecosystems have already illustrated the potential of how data fusion (also called data integration or combination) provides robust forest ecosystem characterizations. Yielding less uncertainty and higher reliability than single instrument approaches makes fusion results better suited for application in modelling approaches (Chasmer et al., 2009b; Cook et al., 2009; Hilker et al., 2008b). Since ALS provides a straightforward way to estimate canopy structure metrics, it is expected that errors and uncertainties associated with structural effects can be reduced in the combined approaches, as this information is independent and complementary to the spectral information delivered by IS (Gillespie et al., 2004; Koetz et al., 2007b).

Studies that combined both types of data can be classified either by their products and application domain or by the choice of fusion method. On the product side, recent studies have focused on evaluating landcover maps, aboveground biomass (AGB), bio-physical/chemical parameters and gross/net primary productivity (GPP/NPP) of forests.

Even though data fusion currently attracts much interest of the remote sensing community, some technical and scientific limitations in the applied methods may cause a

less than optimal exploitation of the complementary advantages. Basically, differences between ALS and IS datasets, such as spatial resolution, representation (pixels vs. points) and acquisition time, complicate implementation and validation of fusion methods. To successfully fuse the multi-source datasets provided by the different remote sensing methods, not only the quality of each single data source is relevant, but as well wisely chosen fusion methods and levels at which the data and products are combined. The diversity of combination methods and sometimes-limited attention to practical constraints of the methods lead researchers to achieve results, which have sub-optimal explanatory value, even though they utilize relatively expensive ALS and IS datasets. In other words, imperceptive use of fusion methods (especially empirical methods) for these datasets may solve a given specific problem, but would not improve our knowledge of the complementarity of the datasets for other problems or sites in the future.

Table 2.1

Overview of the references and relevant application domains and products. Some papers appear more than once due to their focus on multiple products.

Products		Reference
Landcover maps	General landcovers	Bork & Su (2007); Geerling et al. (2007); Elaksher (2008); Cook et al. (2009); Verrelst et al. (2009); Arroyo et al. (2010)
	Forest species	Hill & Thomson (2005); Asner et al. (2008); Dalponte et al. (2008); Holmgren et al. (2008a); Lucas et al. (2008a); Jones et al. (2010a); Ke et al. (2010); Nordkvist et al. (2012); Dalponte et al. (2012); Heinzel & Koch (2012); Naidoo et al. (2012); Buddenbaum et al. (2013); Ørka et al. (2013)
	Fuel types	Koetz et al. (2008); Mutlu et al. (2008); Varga & Asner (2008); Erdody & Moskal, (2010); Garcia et al. (2011)
Aboveground biomass (AGB)		Popescu et al. (2004b); Lefsky et al. (2005); Asner et al. (2007a); Anderson et al. (2008); Lucas et al. (2008b); Breidenbach et al. (2010); Clark et al. (2011); Maselli et al. (2011); Swatantran et al. (2011); Tonolli et al. (2011a); Latifi et al. (2012) ; Finley et al. (2013)
Biophysical parameters		Hudak et al. (2002); Popescu et al. (2004b); Hudak et al. (2006); Thomas et al. (2006); Koetz et al. (2007b); Anderson et al. (2008); Erdody & Moskal (2010) ; Stojanova et al. (2010a); Cao et al. (2012); Latifi et al. (2012); Buddenbaum et al. (2013); Finley et al. (2013)
GPP/NPP		Asner et al. (2007a); Cook et al. (2009); Hilker et al. (2008b); Lefsky et al. (2005)
Biochemical parameters		Blackburn (2002a); Koetz et al. (2007b); Thomas et al. (2008)

Although the characterization of forest ecosystems using a combination of ALS and IS data has generally been investigated during the last decades, a comprehensive review of its methods and products is not available yet. A summary of previous studies that have combined ALS and IS data and a discussion of existing issues affecting the results would be valuable contribution to understand the actual capabilities of the combination of these earth observing (EO) systems in forest ecosystems studies.

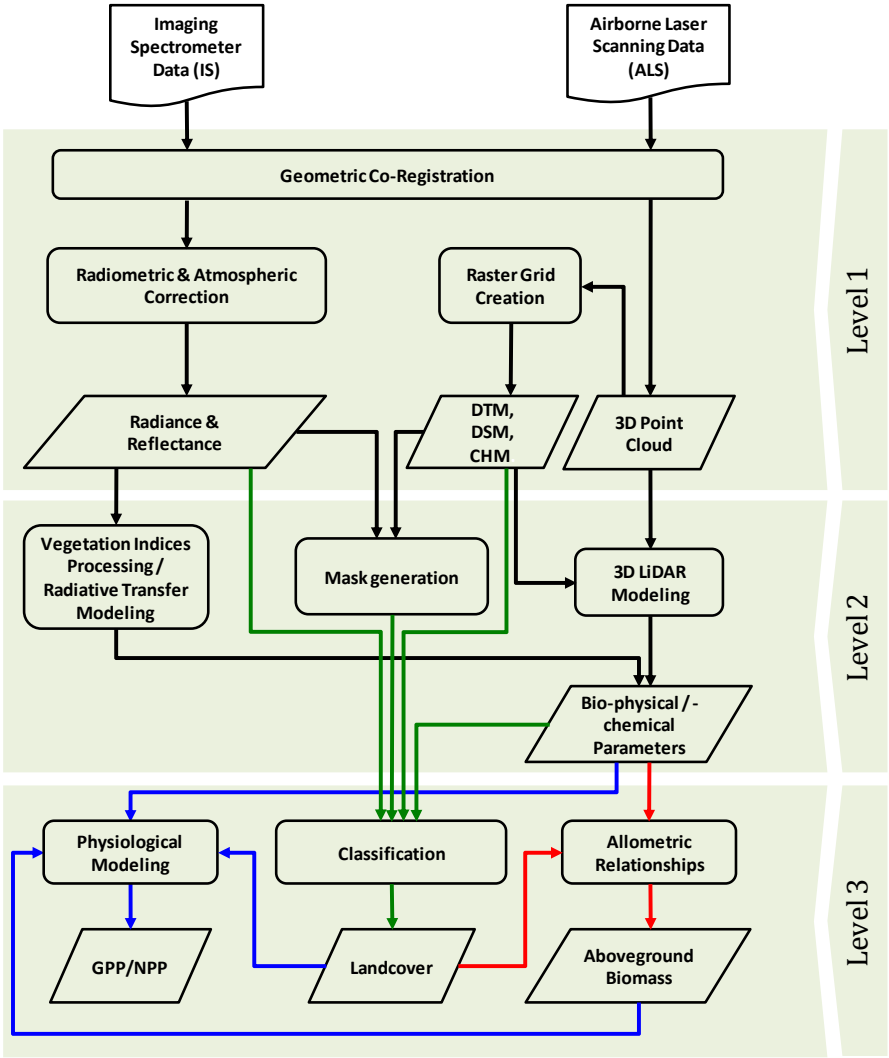

Fig. 2.1. Generalized flowchart of ALS and IS data fusion. The whole workflow can be coarsely separated in three levels, which correspond more or less to the typical processing level definitions of EO data and products. The colorful arrows point to different higher-level products: landcover maps (green), AGB (red) and GPP/NPP (blue). Rounded boxes depict processing steps, while trapezoids depict intermediate and/or final products.

Therefore, this article aims at giving an overview of the state of the art of studies that used a combination of ALS and IS data. More specifically, our objectives are (i) to classify recent researches based on more tangible criteria, (ii) to indicate which products profit most from the fusion and which methods are performing best, and (iii) to point out future directions and main challenges in this subject. For this, we synthesized several published articles concerned with the characterization of forest ecosystems using ALS and IS, which have been classified according to the resulting product(s), as well as the level(s) and method(s) of data fusion. Not all studies provide a quantitative assessment of the obtained accuracies and uncertainties, however, where available we tried to exploit this information for a comparison of their results to highlight better-suited methods or levels for each product.

2.2 Methodology

Out of the numerous studies attempting to combine ALS and IS for forest ecosystem studies, we focused on 48 peer reviewed articles (Table 2.1) which were published in the past 12 years (2002-2013). By using this larger time span, we aim at including the highly cited articles in addition to most newer ones, where the relevance of the work cannot be judged by bibliographic information.

The range of geographical scales covered by these articles varies from regional scale (Ørka et al., 2013) to local scale (Koetz et al., 2008) and from tree level process (Holmgren et al., 2008a) to landscape level process (Swatantran et al., 2011). We tried to include only the articles that deal specifically with the combination of ALS and IS datasets, but the reviewed literature also included a few articles about fusion of ALS data with multi-spectral images. If those approaches were deemed relevant in the general context of this review, we included them as well.

Based on our literature review, Fig. 2.1 shows a generalized flow-chart which most approaches follow when combining ALS and IS datasets. It includes nearly all of the methods and products being used in the considered studies. Similar to other data combination approaches in remote sensing, geometric co-registration of the multiple-source data is the most basic and most important stage. Thus, it is given special consideration and is discussed in section 2.3.3.

2.3 Key characteristics of ALS and IS data

Due to the diverging set of inherent properties of ALS and IS data, different preprocessing steps need to be followed (level 1). On the one hand, the non-contiguous LiDAR data in form of point cloud are usually converted to a raster grid by common spatial interpolation methods, so that the cell size of the ALS grid is generally selected to be equal to the IS dataset cell size. However, different cell sizes have been rarely chosen to ease the computation of further metrics, which may be relevant at different scales (e.g. Popescu et al., 2004b). On the other hand, IS data generally need to be corrected radiometrically and atmospherically. These steps transform the digital numbers to the physical values such as radiance and reflectance of the observed objects. However, in some studies the uncorrected data are directly used in the main processing step (e.g. Erdody and Moskal, 2010).

Although ALS and IS datasets may be combined directly after the preprocessing, including the geo-referencing, they can also be used on their own to generate value- added products (level 2) for fusion at later stages. Vegetation indices are just one example of such products, which are computed by basic algebraic combinations of the reflectance values at different wavelengths. Several empirical studies showed correlation between such indices and vegetation parameters (Viña et al., 2011). Such indices are also used in image classification approaches in order to promote the vegetation species detection (Huete et al., 2002; Peña-Barragán et al., 2011).

Besides, masks generated from ALS or IS data can be used to narrow down the further processing steps and to apply specialized modules for those spatial and/or thematic subsets of the data. Such masks may be applied to separate sunlit and shaded parts of the canopy or to differentiate between areas with photosynthetic vegetation and non-photosynthetic vegetation (Asner et al., 2008).

Such intermediate value-added products as well as the preliminary data can be combined at level 3 to generate even higher-level products, which are more commonly used in forest studies (e.g. landcover maps, AGB and GPP/NPP). These products are introduced in more detail in section 2.5.

2.3.1 ALS data

ALS is an active remote sensing technique that is based on the principle of laser range finding, which sends a laser beam toward an object and measures the time and power of the backscattered energy.

Full waveform LiDAR systems, which deliver a semi-continuous representation of the return signal, can yield better estimates of the vegetation structure (Mallet and Bretar, 2009; Reitberger et al., 2009). However, due to the recent nature of this full-waveform data, most of the fusion approaches reviewed here have used only two returns data (Fig. 2.2(a)).

Most commercially available instruments are small footprint ALS systems utilizing discrete-return LiDAR, which together with their higher sampling rates, provide a better coverage of the surface and better resolution of terrain features. In the fusion approaches reviewed, small-footprint systems are used far more frequently than large footprint systems (Fig. 2.2(b)).

Higher point density data basically increase the probability for a laser pulse to hit the top of the trees, providing better estimates of the tree height (Gaveau and Hill, 2003) and also increase the practical ability of ALS to assess the horizontal distribution of foliage (e.g. fCover; fractional canopy cover). Fig. 2.2(c) shows that most studies use dense LiDAR data (1 to 5 echoes/m^2) for the characterizing of forest canopies, while there are fewer studies using very dense datasets (more than 5 echoes/m^2), either for the sake of avoiding data redundancy or for the sake of lower acquisition costs.

A more complete and general introduction into ALS related technologies, methods and applications can be found in Vosselman & Maas (2010).

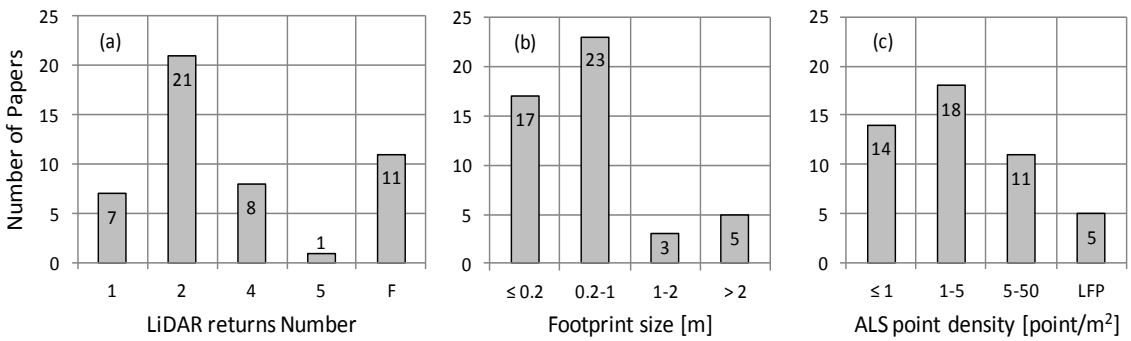

Fig. 2.2. Frequency of reviewed articles based on a) number of echoes per shot; b) footprint diameter (or size); and c) point density; LFP, large footprint.

2.3.2 IS data

The measured signal of IS systems is a result of the interaction of illumination properties, the sensor properties and the geometrical/optical properties of objects. For forest ecosystems, this is more complex, as the objects are trees and their main components (e.g. branches and foliage) interact with the incoming radiation as well as the

background terrain. This complexity also drives the requirement for accurate information about sensor characteristics such as spatial and spectral resolution.

High-resolution optical data, with spatial resolutions in the order of 1 to 5 meters are most commonly combined with ALS data in the reviewed literature (Fig. 2.3(a)).

The high spectral resolution of IS data is a promising feature not only for the discrimination of different vegetation species in forest, but also for assessing of the biochemical and biophysical parameters of such ecosystems. As such, IS data have been found to be more useful than multispectral data for the assessment of the biochemical content at canopy level (Asner and Martin, 2008b) and biophysical parameters such as leaf area index (LAI) (Peng et al., 2003), crown cover (Schlerf and Atzberger, 2006) and AGB (De Jong et al., 2003). Fig. 2.3(b) illustrates the variation in spectral resolution of the optical datasets fused with ALS data in the reviewed articles.

There are other properties of IS data, e.g. temporal and radiometric resolution, but we did not find much information about these aspects in our review. Thus, they are less likely to be relevant in the context of fusion approaches and are not discussed within this study.

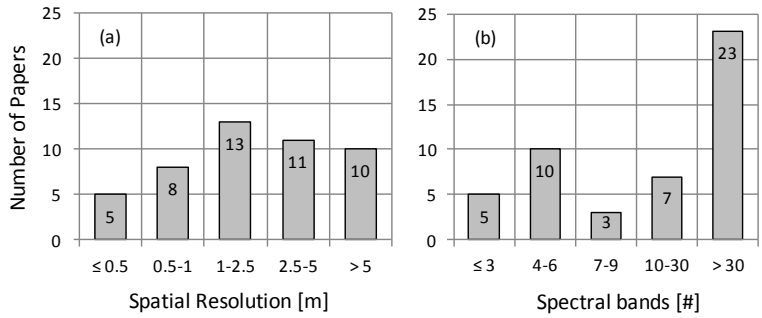

Fig. 2.3. Frequency of reviewed articles based on a) spatial resolution; and b) number of the spectral bands of the IS systems.

2.3.3 Geometric co-registration

As depicted in Fig. 2.1, a prerequisite for all following fusion approaches is the accurate geometric alignment of the two data sources, IS and ALS. While ALS point clouds are generally forward geo-coded with high accuracies (< 0.5 m), the geo-rectification of IS images is of larger concern (McRoberts, 2010). Asner et al. (2012a) showed how a misalignment of ±3 pixels between IS and ALS data reduce the amount of linked information by 30-48% in the combined dataset. Manual co-registration of these datasets using selected tie points may achieve an accuracy of ±1 pixel on these points, but nonlinear propagation of the errors may cause larger misalignments in other areas; the accuracy of

this method depends on the pixel size, the abundance of small uniform objects and spatial distribution of tie points in the data.

One technique which is frequently used to geo-rectify remote sensing imageries is the geometric correction using ground control points (GCPs). This method establishes a geometric transformation between the coordinates of GCPs and their corresponding pixels in the image and then applies it for each pixel, so that coordinate differences on those checkpoints are reduced to the lowest possible level. Although this method can be well applied and is relatively fast in terms of computation time, using only GCPs can still cause that the unknowns in the trajectory of the platforms produce some remarkable residual errors.

To overcome this limitation, a second approach, often called 'back-projecting' works in a different way. It transforms the ALS point cloud to the image coordinate system, which is used for the IS datasets. Direct transformation from ground to image ensures that each laser echo is linked to the actual containing pixel in the image. Afterwards, an identical transformation converts both ALS and IS data to the chosen ground coordinate systems. Although this method is more accurate, it needs the external orientation parameters of the IS system from the time of image acquisition, which makes it slightly more demanding, both in terms of data needs and computation time. Most of the new IS systems that are equipped with GPS/IMU provide this information, however, and these parameters can also be determined using photogrammetric space resection equations. Still, this approach is a viable option for fusion approaches, particularly in combining large ALS and IS datasets (Holmgren et al., 2008a; Valbuena et al., 2011).

Another geometric issue in combining ALS and IS datasets relates to the intrinsic discontinuity of the ALS data. The raw product of ALS surveys is the point cloud, whereas for IS it is a pixel map. Using typical systems, several of these ALS points may fall within one IS pixel and clever interpolation and/or weighting schemes will have to be applied to produce a raster image from the ALS data, which has the same spatial characteristics as the IS data (García et al., 2011). However, a thorough investigation of such interpolation routines and how pixel-based IS properties (e.g. IFOV) might affect the combination has not been carried out yet, but should be addressed in the future.

2.4 ALS and IS data Fusion

Fusion methods have been widely used in optical remote sensing for image interpretation, classification and change detection (Ehlers et al., 2010; Roy et al., 2008).

Some of these kinds of data fusion, for instance the so-called pan sharpening, have been developed for similar data types; exploiting those for such different datasets as ALS and IS might not provide best results. Fusion of data that come from an active sensor with data from a passive one is even more complicated due to the large differences in the measured physical quantities, geometry of data acquisition and sources of illumination.

Similar to most other data analysis approaches in remote sensing, current combination approaches of ALS and IS for estimating of the forest biophysical and biochemical parameters include both empirical (section 2.4.1) and physical approaches (section 2.4.2). Both type of approaches have been used extensively for the estimation of forest parameters using ALS and IS alone, however, because of their straightforwardness, empirical methods have been employed far more for fusion than the more sophisticated physical approaches (Fig. 2.4(a)).

2.4.1 Empirical methods

The most straightforward approach of data fusion are the empirical methods (also called statistical approach), which is based on image classification and regression models. In such methods, statistical techniques are used to establish a relation between the remote sensing data (e.g. reflectance or height values) and in-situ measurements of the desired environmental properties.

When speaking of continuous variable responses, image classification techniques are the most widely used empirical methods to generate landcover maps, which are often used in data combination as well. In order to combine multi-source data, non-parametric classifiers show better performance in the context of multi-weighted data, e.g. nearest neighbor techniques (Tomppo et al., 2008), and handle high-dimensional data easier, e.g. support vector machines (SVMs; Waske and Benediktsson, 2007b). Since the major application of these classification methods is the generation of landcover products, they are further presented in section 2.5.1.

The second group of empirical approaches with a broad base of applications in data fusion is called regression-based methods, which are usually used for assessing continuous fields of biophysical and biochemical parameters, opposed to the discrete representation found in landcover products.

Despite the straightforward approach, the need of field and/or training data for establishing the models or classification scheme leads to a lack of generalization and transferability of such approaches, making them sensor specific and dependent on time and space. Especially for data fusion, which deals with multisource datasets, calibration of

empirical models needs a large amount of different in-situ measurements, which severely increase expenses and time associated with such approaches.

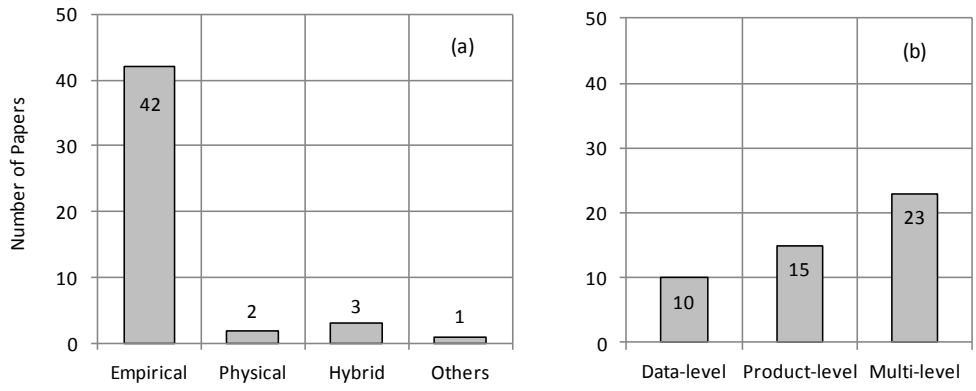

Fig. 2.4. Statistics of the reviewed literature considering a) fusion methods; and b) fusion levels.

2.4.2 Physically based methods

The second large group of methods for characterizing forests includes physical approaches, which employ physical laws to interpret the interaction between electromagnetic wave and components of the observed objects. The simulation of the radiative transfer using geometric optical representations of the vegetation are among the most frequent physical approaches being widely used for IS data in both forward and inverse modes.

Up to now, such approaches are not directly applied to fuse ALS and IS data, but they are used at the product-level (Cao et al., 2012). For instance, the inversion of radiative transfer models (RTMs), which are used widely for forest characterization by IS data alone, has been applied to estimate pigments, nitrogen and water content (Asner et al., 2007a). These products are then used further in the combination process, when other independently generated structural products from ALS point cloud are also included. However, physical models for LiDAR data are only a quite recent development, in particular for small footprint ALS data. For large footprint LiDAR, there have been the developments of a few geometric optical models (Ni-Meister et al., 2001; Sun and Ranson, 2000). Still, small-footprint ALS data can be used in conjunction with these models by aggregating small footprint data to larger footprint (e.g. Koetz et al., 2007b), but losing many of the inherent advantages of the small-footprint information.

Although physical approaches can effectively remove the need for empirical calibration and thus reduce the confinement of approaches to a particular site and time, the inherent complexity of the associated methods and tools cause a steep learning curve. In addition,

issues with selecting the best solution in inversion approaches and the sensitivity to initial model parameterization resulted in less use of such models by researchers than its potential might suggest. Applying 3D RTMs, which use the same parameterization of vegetation and processes for ALS and IS data alike, may facilitate physically based fusion of these data. However, until now, the absence of proper physical models has led to physically based fusion approaches being used only at the product level, but not yet at the raw data level.

2.4.3 Fusion level

Remotely sensed data may generally be combined at different levels in order to get the best solution for ecosystem characterization. The levels are often linked to the processing chain of the EO data, e.g. prevalent fusion methods in optical remote sensing can be classified into being at the pixel, feature or decision level (Zhang, 2010). This kind of classification may suit well if the data sources are in form of images, but since ALS originally delivers non-imagery datasets, we propose to use different naming of the fusion levels.

Carvalho et al. (2003) categorized fusion approaches into data level and variable level, which appears to be more comprehensive for the combination of fundamentally different data sources such as ALS and IS. By considering previous classifications and because there is no definition for ALS and IS fusion levels so far, we propose to categorize ALS and IS data fusion levels into data, product and multi-level (i.e. combined use of data and product level).

Following the mandatory preprocessing steps of ALS and IS datasets, they can be directly combined together at the data level. At this level, ALS data is usually used in a grid format, where the pixel values are some statistical representative of the height distribution of the contained raw laser returns. Additionally, the digital surface model (DSM), digital terrain model (DTM) and canopy height model (CHM), which is the subtraction of the DTM from the DSM, are other commonly used raster representations of ALS data for fusion at the data-level (Asner et al., 2008; Breidenbach et al., 2010).

On the other hand, the combination at the product-level is carried out after remote sensing signals have been converted to ecosystem parameters by going through separate processing chains for ALS and IS data. A wide range of evaluated parameters from ALS data may be used for data fusion at this level. Simple statistics such as mean, median and standard deviation of terrain corrected echo heights (Clark et al., 2011; Dalponte et al., 2012; Erdody and Moskal, 2010), height percentiles (Nordkvist et al., 2012) and the

vertical profiles of canopy height and volume (Jones et al., 2010a; Lefsky et al., 2005) are some of these ALS-derived products. However, more complex biophysical parameters such as position of trees and dimension of the crowns (Colgan et al., 2012; Kobayashi et al., 2012), canopy gap fraction (Clark et al., 2011; Hilker et al., 2008b) and LAI (Cook et al., 2009) can also be generated before the fusion, albeit with a slightly larger procedural effort, and additional field-based calibration measurements are often needed.

Regarding the estimated parameters from IS data, vegetation indices (Tonolli et al., 2011a), principle component analysis (PCA), minimum noise fraction (MNF) and spectral angle mapper are employed to reduce the commonly found IS data redundancy (Latifi et al., 2012; Mutlu et al., 2008; Naidoo et al., 2012).

In some cases, ALS or IS data are combined at both levels, which we call multi-level fusion. For instance, some studies use an ALS-derived DSM or DTM for the geo-correction of the IS data and at a later stage, ALS-derived metrics to help with IS based estimation of additional parameters. When we consider the reviewed studies, multi-level combination has attracted the most attention; in these cases, ALS products and raw data are used alike in the fusion process with IS data (Fig. 2.4(b)).

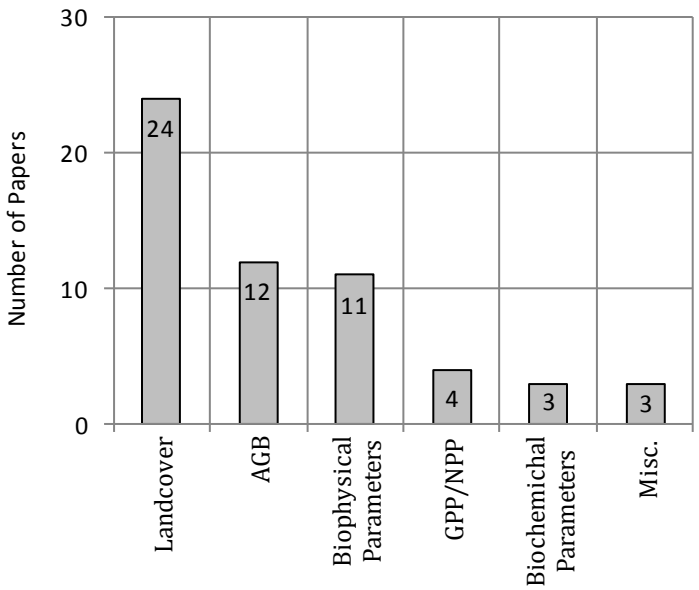

Fig. 2.5. Distribution of fused ALS and IS products organized in six categories (these products are described in 48 peer reviewed articles).

2.5 Estimating forest ecosystem properties

Relevant forest ecosystem properties do not only serve as general indicators of the ecosystem state, but also serve as input into ecosystem models, which may as well be nested components in global carbon cycle and climate models.

While forest ecology includes an extensive list of parameters, the ones that can be assessed by remote sensing can be generally classified into biophysical and biochemical parameters. Some of the most relevant biochemical parameters include water content and pigment concentration in forest constituent parts, which can be estimated by IS (Asner and Martin, 2008b). Biophysical parameters, which can be defined at different scales (e.g. canopy, plot and stand), describe the canopy structure in the form of parameters such as height, LAI, fCover and so on. Recently, estimating such parameters by fusion of the multi-sensor data has received increased attention (Koch, 2010).

In addition, according to the reviewed literature, three higher-level products have been subject to a number of studies as well, those are landcover maps, AGB and GPP/NPP. Thus, we classify the products in these five classes, which are presented in Fig. 2.5, along with the number of studies attributed to each class. Apparently, the most active application domains of fusion are production of landcover maps, AGB and biophysical parameters. We therefore exclude detailed description of the estimating approaches of GPP/NPP and biochemical parameters due to low number of researches.

To quantitatively evaluate the performance of the different fusion approaches, we consider the provided accuracies in literature. Because of the variation in product type, different parameters have been used to report accuracy (e.g. overall accuracy, kappa coefficient, R, R^2 and RMSE). However, we tried to make all accuracy estimators compatible in order to facilitate a direct comparison. All provided accuracies were therefore transformed to overall accuracy (for classification approaches) or the coefficient of determination (R^2, for all other approaches), which ranges from zero to one. Fig. 2.6 shows the respective averaged accuracies for the retrieved products using ALS, IS and combined datasets. In addition, the presented standard deviations in this figure can be interpreted as the robustness of the retrieval of a particular product. Due to a lack of studies in some categories such as GPP/NPP and biochemical parameters, a statistical comparison of the provided accuracies is not possible.

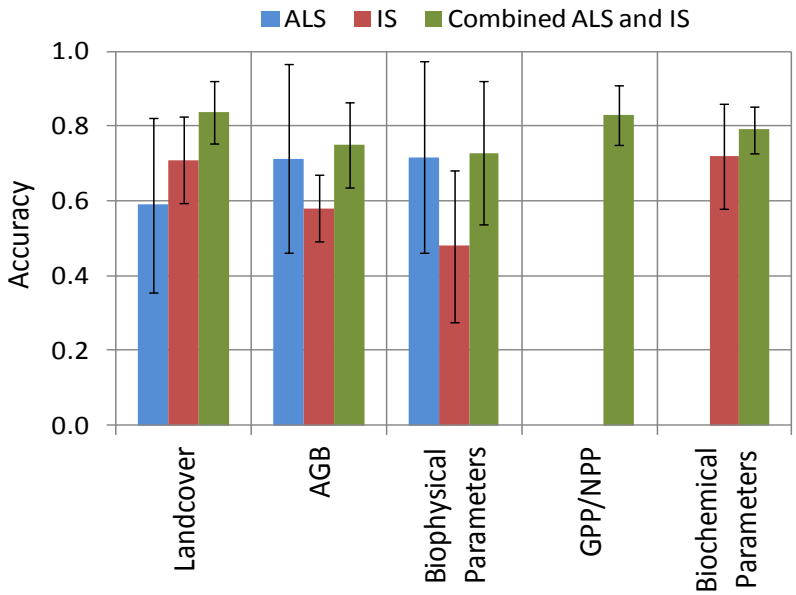

Fig. 2.6. Comparison of the accuracy level between different products evaluated individually by ALS, IS, as well as using combined datasets.

2.5.1 Landcover map

Although traditional landcover maps, generated solely by IS (or multi-spectral) data, are sufficient for many applications, the obtainable accuracies, however, are limited (Nordkvist et al., 2012). Besides the important role of the landcover maps for the management of forested areas, they also have a notable function in assessment of AGB and GPP/NPP of heterogeneous forest regions by using different species-specific relationships.

To serve forest ecosystems studies, three different types of landcover maps are produced by using combined ALS and IS data; these are general landcover maps, species maps and fuel type maps. General landcover maps are aimed at providing the spatial abundance of all landcover types in a study area (including forests and surrounding regions), generally for a better forest management planning. In case where there are tangible disparities in the canopy height of different landcovers, ALS data provide reliable height information for the classification, in addition to the spectral information from IS data.

Forest species maps, which illustrate distribution of different vegetation species in the study area, provide essential indices for forest inventory and management. Using vertical characteristics of forest canopies (e.g. height distributions) being estimated from ALS data helps classification approaches to distinguish vegetation species more precisely (Dalponte et al., 2012; Hill and Thomson, 2005). In addition to generating prevalent forest species maps , combined data are also used for invasive species detection (Asner et al., 2008).

Forest fuel types depend very much on the vegetation structure in both horizontal and vertical direction as well as flammability of the vegetation elements. While ALS data provide the structural details of forest canopies, the ignitability of the foliage components, can be determined by IS data, making the fusion approach an ideal match for this multi-dimensional problem (Koetz et al., 2008). Due to the large influence of the structural parameters in fuel type classification, some studies have as well combined ALS data with multispectral (Mutlu et al., 2008).

Landcover maps are mostly generated with image classification methods. While image classification methods for optical remotely sensed data are well matured, ALS data are generally used in the form of auxiliary information to improve the classification accuracy. Since such methods apply only to images, the discrete LiDAR points must be converted; in this processing step, some uncertainties may contaminate the ALS data (section 2.3.3).

Almost all possible image classification approaches (e.g. pixel or object based, hard or soft classifiers and parametric or non-parametric classifiers) have been utilized for fused datasets. Although simple parametric classification methods can successfully deal with multispectral datasets, advanced forms (e.g. SMA; spectral mixture analysis) are required in order to handle the high dimensional IS data cubes. Best suited would be however non-parametric classifiers, such as SVMs, which can deal better with high dimensional data, no matter if it was generated by one or multiple sensors (Waske et al., 2010).

Despite of the diversity of the classification methods, they provide the appropriate tools to integrate different types of information regardless of its inherent properties. Lower level ALS products (such as DTM, DSM and CHM) have extensively contributed to landcover map generation when raw IS data (reflectance or radiance) are being used on the other hand (Ke et al., 2010). The statistics calculated from the ALS point cloud, e.g. maximum, median and average height of points in each image pixel, have also been fused to the image data (Geerling et al., 2007; Verrelst et al., 2009). For sufficiently high point densities, the use of statistical dispersion factors, e.g. standard deviation or height percentiles, which provide an assessment of the vertical echo distribution within each pixel are also helpful (Dalponte et al., 2012; García et al., 2011; Mutlu et al., 2008). In object-based classification algorithms, ALS-derived dimension and position of the tree crowns are used for initial definition of the segment boundaries (Colgan et al., 2012; Holmgren et al., 2008a; Ørka et al., 2013).

On the other hand, IS data also provide a wide range of information supporting landcover mapping. The basic data used come typically in form of reflectance or radiance images; however, statistical means of data reduction such as PCA (Hill and Thomson,

2005), MNF (Mutlu et al., 2008) and SMA (Naidoo et al., 2012) are used to select the most informative subset of the spectral bands.

2.5.2 Aboveground biomass (AGB)

The amount of forest biomass and its temporal changes are a consequence of the reaction of forest ecosystems to the environmental conditions and are linked with the alteration of the carbon sequestration. Monitoring AGB changes in forests also provides information on deforestation and regrowth.

Recent researches confirm that ALS estimated forest AGB has a better accuracy than other remote sensing approaches (Koch, 2010). However, adding IS data still slightly helps to improve the estimation of biomass, especially if IS data are used to provide information on species, stress and biochemical details (Swatantran et al., 2011).

Generally, two major approaches have been tested in the combination of ALS and IS data for AGB assessment so far. The first approach, which is called species-specific regression, specifies a unique regression model for each vegetation species that is present in the study area. The equations are generally established using the height of the trees (or bushes), being calculated from ALS data. If required, additional parameters, e.g. diameter at breast height, can be determined by allometric relationships, which are compiled for each species from extensive field measurements. Since ALS data cannot generate accurate species map in general, IS data help to fill this gap and provide the discrimination of different species to be used in conjunction with the ALS-derived features. Although this approach should generally increase the accuracy of AGB estimation, uncertainties in the species map may lead to large errors in the final results.

The second approach establishes a multiple regression model so that biomass is estimated directly from IS and ALS-derived parameters. This approach is more complicated, since selecting the best type of model as well as finding the proper regression coefficients needs a massive computational effort (Finley et al., 2013). Present ALS-derived metrics do usually relate to canopy height and canopy cover, including the vertical variation of such. Unlike ALS data, which are often used in the form of estimated biophysical parameters for regression analysis, IS data are normally used in two forms, raw image data (including band ratios) and evaluated products. Despite the large number of methods to estimate the parameters and their associated uncertainties, an equally important challenge is how to choose an independent set of variables that are most sensitive to AGB. Some statistical methods such as iterative jackknife technique (Lucas et al., 2008b) and genetic algorithms (Latifi et al., 2012) are applied to provide best results.

Comparing the above approaches shows that the species-specific fusion provides more accurate results than the multiple regression analysis of IS and ALS-derived metrics (Swatantran et al., 2011). Implementing a hybrid method that applies multiple regression models for each species may achieve even better performance, however no such study has yet been carried out.

2.5.3 Biophysical parameters

A set of correctly estimated biophysical parameters can notably contribute to a comprehensive understanding of the forest ecosystem. Even though AGB falls into this category as well, we have opted to discuss it separately due to the large number of respective studies found in the literature. The remaining biophysical parameters being subject of estimation by fusion approaches are mostly related to the structure of the forest canopy, except for fraction of absorbed photosynthetically active radiation (fAPAR). The investigated parameters and range of their estimation uncertainties are shown in Table 2.2.

Height is the main parameter that can be directly estimated from ALS data, however, appropriate field measurements may be required for its calibration and refinement, in case the acquisition settings or site conditions were suboptimal. Height can be estimated at different scales (i.e. tree, stand, plot, etc.) and quantized in the vertical direction (e.g. height percentiles). These estimations form the main basis for further estimation of forest biophysical parameters.

One of the major disadvantages of ALS systems is that acquisition costs over large areas are still much higher compared to most optical remote sensing methods. In consequence, upscaling of ALS-derived metrics with larger-extent IS data, is another possible fusion approach. ALS-derived canopy height have been scaled up to a larger area with satellite remotely sensed data, e.g. Landsat ETM+, by using linear regression analysis, kriging and co-kriging (Hudak et al., 2002) and machine learning techniques (Stojanova et al., 2010a). Similar approach was exploited for estimating forest canopy height in global scale using combined spaceborne IS and LiDAR data (Lefsky, 2010b).

Basal area is another parameter that has been indirectly estimated along with stem/tree diameter and density by using regression analysis of the ALS-derived features (e.g. canopy height) and IS reflectance data, MNFs and landcover classes (Anderson et al., 2008; Erdody and Moskal, 2010; Finley et al., 2013; Hudak et al., 2006; Popescu et al., 2004b).

Table 2.2

Biophysical parameters estimated by combined data and their uncertainty ranges.

biophysical parameter	Reference	Uncertainty range (R^2)
Canopy height (Upscaling)	Hudak et al. (2002); Stojanova et al. (2010)	0.67-0.89
Basal area	Popescu et al. (2004); Hudak et al. (2006); Anderson et al. (2008); Finley et al. (2013)	0.25-0.92
Canopy base height	Buddenbaum et al. (2013); Erdody & Moskal (2010)	0.80-0.82
fAPAR*	Thomas et al. (2006)	0.82-0.90
LAI	Koetz et al. (2007); Cao et al. (2012)	0.52-0.75
fCover	Koetz et al. (2007); Stojanova et al. (2010)	0.78-0.84
Stem/tree density	Hudak et al. (2006); Erdody & Moskal (2010); Latifi et al. (2012); Finley et al. (2013)	0.75-0.88
Stem/tree diameter	Popescu et al. (2004); Anderson et al. (2008); Finley et al. (2013)	0.32-0.90

* not a purely structural parameter.

Using physical method, Koetz et al. (2007b) coupled two canopy radiative transfer models (one for ALS, one for IS), which both use LAI and fCover as parameter. The chosen approach strongly decreased the uncertainty of fCover, however, the estimated LAI resulted in a decrease in accuracy, possibly hinting at different parameterizations within the two models.

2.6 Discussion

Considering only the specifications of the ALS and IS datasets (e.g. footprint size, spatial resolution) used in combination we cannot observe a significant relationship. The data used are often chosen based on their availability and not much effort has gone into studying the potential deficiencies that originate from the acquisition settings of the data sources. Only few systems exist that combine ALS and IS instruments in one platform (Asner et al., 2012a; Cook et al., 2013; Kampe et al., 2010), and only few of the previous approaches were using either ALS or IS data that were collected specifically for vegetation characterization. Traditionally, small footprint ALS systems with relative low point density and two returns were most often used in combination approaches (Fig. 2.2). But recently provided capabilities of modern ALS systems, e.g. full waveform (Heinzel and Koch, 2012) and very high point density (Holmgren et al., 2008a), will play a dominating role in the near future.

Since all the fusion approaches fundamentally require the co-registration of datasets, any uncertainty at this stage destructively influences the accuracy of the final products, regardless of fusion method and level. It is expected that combined sensors with one INS/GPS estimated trajectory, which enables the back-projecting approach will reach the acceptable geometric accuracy for data fusion and produce highly compatible datasets (St-Onge et al., 2008).

Considering the choice of fusion methods, physical approaches have seldom been employed so far and their performance is still not optimal for some parameters, e.g. biochemical parameters. Nevertheless, ALS data have shown their potential to overcome the ill-posed problem of solely IS based physical model approaches (Koetz et al., 2007b). The current lack of suitable physical models for small footprint ALS data has caused the use of less-than-optimal models (originally designed for large footprint data) or even discourages researchers from using physical approaches at all. The recent development or enhancements of specialized 3D RTM to model ALS data may fill this gap in the future.

Our analysis suggests that adding ALS data to models that are specially designed for IS data, e.g. image classification, will make better use of the complementary advantages of both datasets than adding IS data to existing methods used for ALS-data analysis, e.g. regression analysis. This shows the need for the modification of the present models or the examination of different data fusion approaches, e.g. data assimilation. In addition, the intrinsic properties of these datasets render them difficult to compare on a one-to-one basis: ALS data can be converted to regular grids similar to IS data, while IS datasets cannot generally be converted to irregular point clouds.

Comparing the accuracy of the products, Fig. 2.6 shows that current fusion approaches and the utilized datasets are very well suited for landcover map generation and partially for AGB, while their performance for other biophysical parameters is less than optimal.

Landcover map generation approaches are usually successful in spite of their simplicity. It shows that by using both datasets together not only the accuracies increase, but also the reliability of the product improves. This likely shows that current approaches for landcover product generation are efficiently making use of the complementary properties of ALS and IS data. In fact, image classification approaches provide a suitable means for data fusion, however, a potential mismatch of information mainly from the top of the canopy (IS) and structural information within the canopy (ALS) is still remain unsolved.

In addition, some features of the backscattered LiDAR wave (e.g. amplitude and width) are often not distributed uniformly in vertical direction. Aggregating the ALS point-cloud

into a single image (e.g. CHM or intensity) therefore causes some uncertainties and reduces both data and information, which influences the fusion capabilities. Producing a number of raster images from ALS data at different vertical layers can overcome this limitation to some extent and provides additional and easily exploited information to the image classification process. ALS-derived height percentiles (Mutlu et al., 2008; Nordkvist et al., 2012) or basic local statistics of the point cloud (Verrelst et al., 2009) are some examples.

Considering the achieved accuracies in the literature (Fig. 2.6) reveals that combined data obtain higher accuracies rather than IS or ALS data only. The reliability of the evaluated AGB with combined data has been also improved over using ALS data only, nevertheless there is no additional value compared to IS data. Since the accuracy of species-specific relationships for AGB estimation is higher, opposed to using a single allometric equation in heterogeneous forests (Henry et al., 2011), species information provided by IS data actually improves AGB estimation.

In term of accuracy, the worst performance can be observed for the estimation of biophysical parameters, when ALS data alone sometimes deliver better accuracy than combined data (Fig. 2.6). The primary reason for this relates to different measurement principles; while ALS estimates mostly structural information of the canopies, IS determines physical/chemical properties of vegetation that influence reflection/absorption of EM energy, including structure. The direct measuring of the geometry of the canopy makes the connection of LiDAR data to biophysical parameters more straightforward, e.g. by simple regression approaches (Lefsky et al., 1999), whereas the indirect link between spectrometric measurements and biophysical parameters of forest needs more complicated models, e.g. such of the radiative regime. Purely empirical approaches are therefore not ideally suited for multi-source data fusion. Consequently, physically based models for forward simulation and inversion of IS data improves biophysical parameters assessment (Schlerf and Atzberger, 2006) and ALS-derived metrics may enhance the model parameterization.

The large range of the achieved accuracy for the forest biophysical parameters (Table 2.2) indicates that general improvement in data fusion is strongly related to the choice of fusion method and level as well as vegetation species. Due to error propagation from the basic product estimation into the combination phase, product-level combination may cause an increase of the uncertainties associated with single-sensor products, especially for some of the biophysical parameters such as basal area and stem diameter (Anderson et al., 2008; Popescu et al., 2004b). Additionally, many approaches for the

assessment of a number of biophysical parameters (e.g. LAI and vertical crown extension) are still in development stages or have not reached full maturity yet.

Although the use of fused approaches has improved the estimation of biochemical parameters at the canopy level (Niemann et al., 2012), we cannot make a quantitative analysis on the improvement for these kinds of products (incl. GPP/NPP) based on the current literature.

2.7 Conclusions

In this paper, we collected and classified contributions of the last decade focusing on forest characterization using combined ALS and IS data. We chose contributions using standard database searches that appeared in the peer reviewed literature in the last 12 years (2002–2013). The main objective was to classify the identified fusion methods based on methodology, level of fusion and their final products. We defined five different categories of products (landcover maps, AGB, biophysical parameters, GPP/NPP and biochemical parameters) which cover most of the published products. Furthermore we analyzed the accuracy of the products and deduced that landcover maps are profiting the most from ALS and IS data fusion, while current models/levels of combination do not yet meet the expectations for a few of biophysical parameters (e.g. basal area and stem diameter). The large range of obtained accuracies suggests that black-box fusion approach of such datasets cannot yet provide robust results and that using specific models for each product is a critical design choice. Consequently, we have observed that employing a suitable model and level of fusion, which matches the desired products, substantially improves forest parameter estimation and better exploits the complementarity of ALS and IS datasets.

Nowadays, benefits of the fused ALS and IS sensors have triggered some attempts to design multispectral LiDAR systems that use LiDAR at different wavelengths. Simulation of such systems and even ground-based test runs have been done (Garrigues et al., 2006; Gaulton et al., 2013; Morsdorf et al., 2009), but vegetation targeted airborne or spaceborne systems are yet to come. Currently the closest integration of ALS and IS data collection is provided by systems such as the Carnegie Airborne Observatory (CAO; Asner et al., 2012a), which combines the instruments on the same platform and thus achieves very similar data acquisition geometries for both datasets, although the proper synchronization of these systems remains an issue.

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3

3D iterative tree crown delineation in a multi–layered forest using airborne laser scanning

This chapter is based on:

Torabzadeh, H., Leiterer, R., Tuia, D., Schaepman, M.E., & Morsdorf, F. (2015c). 3D iterative tree crown delineation in a multi–layered forest using airborne laser scanning. Remote Sensing of Environment, submitted.

Abstract

A tree is the smallest unit considered in forest management. Identification of single trees from airborne laser scanning (ALS) data facilitates accurate estimation of biophysical and structural properties in a forest canopy. Although a large number of methods have been developed for tree identification, most of them are not able to detect trees located in lower strata of multi-layered forests. This results in large uncertainties when aiming at an unbiased estimation of forest inventory parameters from ALS-derived single-tree information. We present an iterative framework for simultaneous detection of single trees and delineation of their crowns. The algorithm combines two segmentation approaches in horizontal and vertical dimensions, facilitating the extraction of understorey trees. We validate our method using forest inventory data at four different sites showing different structural complexity and species composition. Our method correctly identifies 80% and 78% of the trees in the two complex structured sites, while these rates increase to 85% and 81%, respectively in simpler canopies. However, the total number of detected trees decreases in the lower layers; 87%, 79% and 72% of the trees are identified in the upper, intermediate and lower layers. This decrease is smaller than for previous studies and the higher amount of detected supressed trees demonstrates superior performance in complex, multi-layered canopies.

3.1 Introduction

Field-based collection of accurate, reliable and comprehensive forest inventory data is often limited by technical or economic issues, especially in dense forests and difficult terrains (Hyyppä et al., 2000; McRoberts and Tomppo, 2007). Among existing remote sensing approaches, airborne laser scanning (ALS) data has become an important approach for forest inventory mapping. Small-footprint ALS systems provide dense and accurately georeferenced 3D locations of reflecting objects, the so-called point cloud, from which a vast variety of relevant information on forest structure can be derived (Goetz and Dubayah, 2011; Wulder et al., 2012). The synergistic use of ALS data with imaging spectrometry additionally provides accurate maps of tree species composition and distribution in different forest ecosystems (Dalponte et al., 2014; Jones et al., 2010b; Torabzadeh et al., 2014). Area-based methods (Næsset, 2007) use aggregated height metrics that are related to biophysical properties of the vegetation canopy at a given spatial unit (i.e. sample plots, stands or raster cells). However, linking the estimated biophysical parameters to single tree properties using these approaches is difficult. Furthermore, a single tree is the natural scale for the derivation of important inventory parameters, such as tree height, crown dimensions (Reitberger et al., 2009) and tree species (Torabzadeh et al., 2015b). But to retrieve such parameters, accurate extraction of the individual tree crowns (ITCs) must be performed beforehand.

Despite a large variety of methods using ALS data for single tree identification, they typically fall into two major categories (Koch et al., 2014): raster-based or point cloud based methods. In the first group, local maxima derived from a canopy height model (CHM) are often used as an approximation for the top of the tree (e.g. Ene et al., 2012; Hyyppa et al., 2001; Persson et al., 2002; Solberg et al., 2006). Following the tree detection step, a crown delineation approach is carried out in order to estimate ITC parameters (Vauhkonen et al., 2013). Based on the CHM, the different approaches are mainly region growing (Hyyppa et al., 2001; Solberg et al., 2006), watershed segmentation (Koch et al., 2006b; Pouliot et al., 2005; Yu et al., 2011), or template matching (Holmgren et al., 2012).

Although accurate to extract tree crowns for the upper story, using CHM in raster-based methods decreases their ability to detect dominated trees. CHM is an overgeneralized representation of the heterogeneous canopy and cannot properly provide information on the vertical structure of trees (Valbuena et al., 2014; Yu et al., 2004). Suppressed trees and the understory layer are very likely to be absent in CHMs, particularly in forests with dense canopies. This is while that accurate identification of the

suppressed trees helps for better understanding of the forest dynamics, such as the mortality and succession rates (Falkowski et al., 2009; Keane et al., 2001). In addition, the CHM quality depends on the interpolation method, grid size and type of the smoothing method (Gupta et al., 2010; Hyyppa et al., 2001), restricting the capability of the raster-based methods for tree detection and crown delineation (Jing et al., 2012b).

The second group directly uses the point cloud for single tree identification. In contrast to using CHMs, direct delineation of tree crowns based on the ALS point cloud provides more details and helps to solve ambiguities. For instance, one of the first point-cloud based ITC methods (Morsdorf et al., 2004) was the only method able to produce estimates of crown base height without bias in an international comparison study (Kaartinen et al., 2012). Nowadays, point cloud based methods are supported by new ALS systems (e.g., full-waveform systems), which lead to very dense point clouds of forest canopies with a better vertical dispersion (Reitberger et al., 2008b). This possibility of better assessing the vertical stratification of the forest canopy, motivated researchers to develop new methods based on ALS point clouds (Li et al., 2012).

Point cloud-based methods find tree positions by a direct analysis of spatial/statistical relations between the points. In addition to identifying the trees in the upper layer only, these approaches potentially address all strata in multi-layered forests, due to naturally working in 3D space.

Rahman and Gorte (2009) analysed the density of high points to detect single trees. They show superior detection of the flat-top tree crowns (i.e. deciduous trees) rather than raster-based approaches. However, the tree crown segments still need to be processed to improve the accuracy of tree detection and tree crown delineation.

Li et al. (2012) considered the relative spacing between trees to find seed points, which are estimates for tree positions. The highest point within a limited searching area defines the tree position, followed by a downward region growing to shape the tree crown. Although 86% of detection rate in a conifer-dominant forest were reported by using this method, it examined the upper layer only and did not detect the suppressed and understory trees. The reported detection rates in a boreal forest ranged from 40% to 95%, 5% to 45% and less than 20% for dominant, co-dominant and intermediate/suppressed trees (Kaartinen et al., 2012). Ferraz et al. (2012) introduced an iterative clustering method based on mean-shift segmentation, which does not use CHM information. Besides the improvement for the trees in the intermediate layer, the suppressed broadleaf trees were hardly detected.

The advantages of using ALS point clouds for crown delineation initiated some hybrid approaches: Single trees are detected by raster-based methods and their crowns are delineated in the 3D space of the point cloud by e.g. applying k-mean clustering approaches using CHM-derived seed points (Gupta et al., 2010; Morsdorf et al., 2004).

In order to improve the tree detection rate in multi-layered forests, Reitberger et al. (2009) exert normalized cut segmentation on groups of trees derived from a watershed segmented CHM. Despite the better performance compared to raster-based methods, many trees in the lower and intermediate layers remained still undetected.

The vertical distribution of the ALS returns can be interpreted as a representation of the canopy volume profile (Coops et al., 2007; Lefsky et al., 2002; MacArthur and Horn, 1969), and its analysis can reveal vertical gaps between different strata (Lefsky et al., 1999). Considering this concept, Duncanson et al. (2014) implemented a vertical stratification of CHM-derived watershed segments. They separated the understory strata by finding a potential trough in the vertical point distribution. About 30% of the suppressed trees were detected correctly. However, inherent uncertainties of the CHM hindered better results. Thus, replacing CHM-derived segments with the results of a point cloud based approach may lead to even better results.

In summary, point cloud-based and hybrid approaches show superior performance for single tree identification, especially in heterogeneous forest canopies. It is very important though to include a proper vertical stratification model, which should provide better tree detection in different strata.

In this paper, we propose an iterative approach for detecting individual trees in ALS point clouds and simultaneously delineating their crowns. The main objectives of the present paper are (i) to propose a method for the efficient use of ALS point clouds for single tree extraction, (ii) to investigate the results for different forest canopy conditions, i.e. in terms of canopy structure and species composition, and (iii) to evaluate the performance for different strata, with emphasis on suppressed trees.

3.2 Data collection

3.2.1 Study area

We validated our proposed algorithm in Leskova Dolina, located in the Dinaric Alps in south-west Slovenia (45, 39 N, 14, 28 E). Forest covers more than 97% of the area with high karst geology at the average altitude of 870m above sea level (Vilhar et al., 2010). We

selected four different plots, differing in terms of forest management regime, species diversity and structural complexity. The plots A and B consist of single-layered canopies with medium crown coverage. These plots are mainly dominated by conifer trees, such as Silver fir (*Abies alba*) and Norway spruce (*Picea abies*), together with European beech (*Fagus sylvatica*). Plot C and D are managed by a close-to-nature strategy, resulting into dense forests dominated by broadleaf trees with multi-layered canopies. In addition to the aforementioned tree species, in these plots Sycamore maple (*Acer pseudoplatanus*) and Wych elm (*Ulmus glabra*) are present.

Table 3.1

Forest inventory statistics and characteristics of sample plots (modified after Eysn et al., 2015).

Plot Name	Stem density (/ha)	Average DBH (cm)	Deciduous (%)	Basal area (m^2/ha)	Species	Structural complexity
A	265	34	24	29	Silver fir, Norway spruce and European beech	Single-layered
B	185	22	22	28	Silver fir, Norway spruce and European beech	Single-layered
C	585	26	53	38	Silver fir, Norway spruce, European beech, Sycamore maple and Wych elm	Multi-layered
D	460	33	47	54	Silver fir, European beech and Sycamore maple	Multi-layered

3.2.2 Field data

The forest inventory data was collected in the framework of the project NEWFOR (www.newfor.net). The data are freely available for academic research along with ALS data of the sites. Field data were collected in November 2008 for each plot with a size of 2000 m2. The plot centres were located by global navigation satellite system (GNSS) measurements. However, relative stem positions were measured using compass bearing and distances. Tree heights were measured using a hypsometer (Haglöf Vertex IV; www.haglofcg.com). The reported positioning accuracies are ±1.0 m for both horizontal and vertical distances (Eysn et al., 2015). Tree number, species and diameter at breast height (DBH) were collected for all trees (DBH > 10 cm) in each plot. Table 3.1 shows the details of the collected attributes. In addition, the trees were split into three layers with respect to their height. These layers were used as proxy for the social position of the trees,

containing trees higher than 25 m height (upper layer), between 15 m and 25 m (intermediate layer) and lower than 15 m height (lower layer).

3.2.3 ALS data

In October 9, 2009 a full waveform ALS dataset was acquired using RIEGL LMS-Q560 (www.riegle.com). The wavelength of the laser was 1550 nm. The scanner was mounted on a helicopter (Eurocopter EC120B), with a flight altitude of 400–600 m altitude above ground. The ALS was operated with a 180 kHz scan rate and a laser beam divergence of 0.5 mrad. Considering the flight specifications and the LiDAR system setting, an average echo density of 30 points/m2 and an approximated footprint diameter of 0.30 m were achieved. The ALS data were registered by the data provider in the Gauss-Krüger D48 coordinate system, corresponding to the forest inventory data (Eysn et al., 2014).

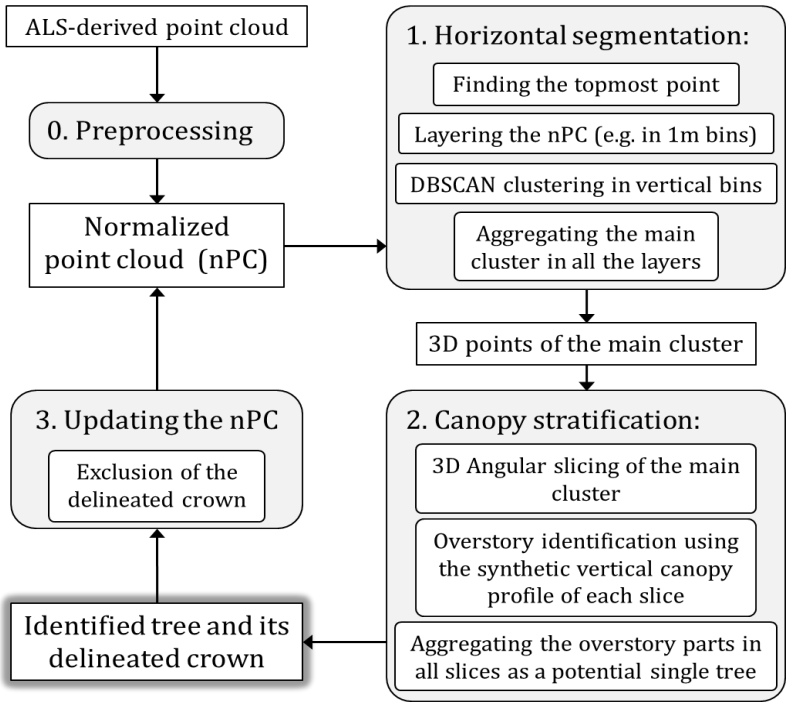

Fig. 3.1. Workflow diagram. First, the horizontal segmentation is applied to the preprocessed normalized point cloud (nPC). Second, the resulting sub-canopy is stratified using the position of the troughs in the synthetic vertical canopy profiles. Third, the resulted crowns are sequentially excluded from the nPC. These steps are iterated until nPC becomes an empty point cloud. The rectangles depict input data or generated information, while the rounded rectangles represent processing modules.

3.3 Methodology

The proposed method consists of three parts, which are sequentially and iteratively applied on the ALS point cloud (Fig. 3.1). In the preprocessing step, a digital terrain model (DTM) is generated by spatial filtering of the last and single returns. These points are identified as ground and subsequently interpolated and smoothed. Note that the standard DTM derived by the LiDAR data provider may just as well be used (Eysn et al., 2015). The corresponding DTM value for each point is then subtracted from the absolute height, resulting in a topographically normalized point cloud. In the following we detail the three steps in our proposed algorithm:

3.3.1 Horizontal segmentation

The first segmentation module in our method is called horizontal segmentation, which discriminate the points belonging to a candidate tree, from those belonging to other trees in the neighbourhood. Applying the subroutines shown in Fig. 3.1.1 results in a subset of the point cloud, containing at least one crown candidate and probably includes parts of other tree crowns underneath.

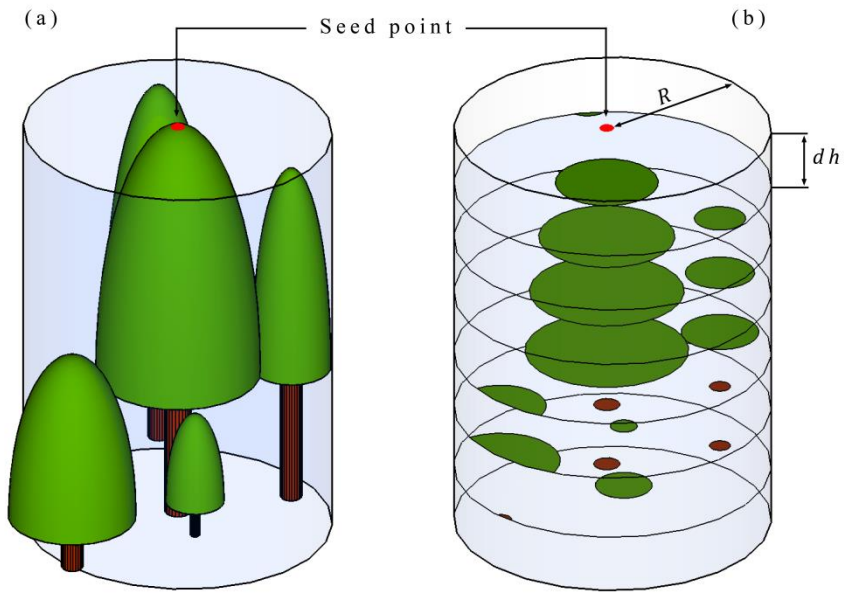

Fig. 3.2. Schematic presentation of the horizontal segmentation, where a cylindrical subset delimits the search region around the seed point with radius *R* (a), and the subset is stratified into the vertical bins with height differences of *dh* (b).

The topmost point in the normalized point cloud (nPC; Wang et al., 2008) generally belongs to the tallest tree in the plot. Considering this assumption, we use the highest

point (or global maxima), as seed point, and a subset of the point cloud corresponding to a circular area around the seed point. Although a smaller subset would speed up the further processing, the subset has to be large enough to include all the potential points that are part of the desired tree. The search radius (*R*) should be set to a greater value than the size of the largest crown in the plot area and is derived from the forest inventory data. All the points in the 3D cylinder within the selected radius are considered (Fig. 3.2a).

The resulting subset is stratified into vertical bins (Fig. 3.2 b). The bin size is controlled by the parameter *dh* and is constant within the canopy profile. All the points falling into a vertical bin are projected on a horizontal plane, reducing the point cloud to a 2D point distribution for each bin. Then the algorithm proceeds from the top to the bottom in the vertical direction.

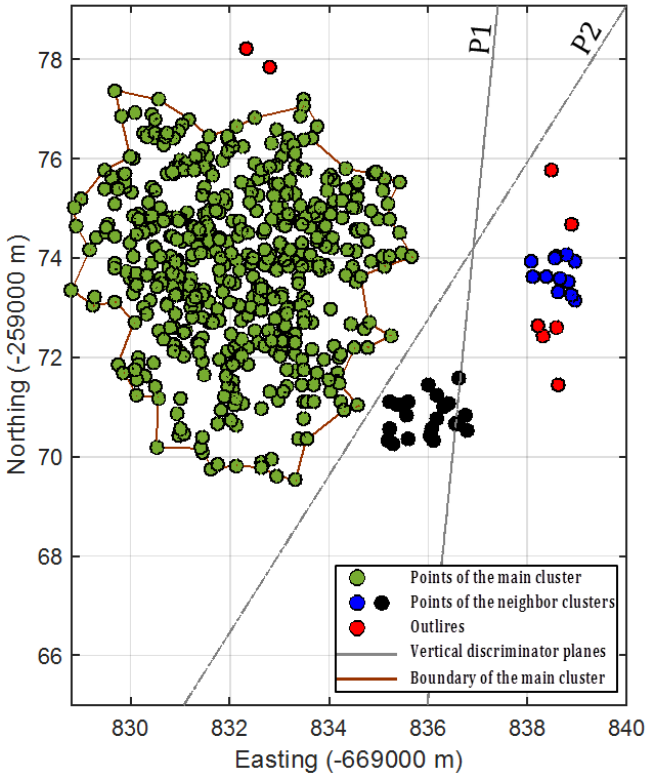

Fig. 3.3. Performance of DBSCAN for a selected vertical bin with the parameters of ε=0.50 m and *minPts*=3. P1 and P2 point to the discriminative planes.

First, all the points in the top bin are clustered by using a density-based clustering algorithm. In density-based clustering, clusters are defined as regions of higher density than the rest of the dataset. In other words, the spatially distributed points are grouped together on the basis of their distance between them (Kriegel et al., 2011). Due to the

lesser complexity of these slices and no need of a pre-specified number of clusters, DBSCAN (Ester et al., 1996) is selected as the main core of segmentation in this step. DBSCAN connects the points located within a certain distance threshold (ε) and satisfying a density criterion (Sriperumbudur and Steinwart, 2012). The latter is defined by the minimum number of points required to form a dense area (*minPts*). Applying DBSCAN yields the main cluster, which contains the seed point, neighbour clusters and potential outliers not satisfying the criteria (Fig. 3.3).

Then if there is any other cluster formed in the neighbourhood of the main cluster, a vertical discriminative plane is defined between them, followed by removing all points beyond it.

Finally, all the points belonging to the main clusters in the current bin are projected into the next bin, densifying the main cluster when the bins are traversing toward the ground. Since inside of a tree contains fewer points, this projection helps the clustering to be more consistent in all the bins. Therefore, the last bin includes all the points that accumulated around the seed points and are segmented to be members of the main cluster (Fig. 3.4a). The selected points are then converted back to the 3D space to shape the potential tree and likely some branches and foliage of lower strata trees as well (Fig. 3.4b).

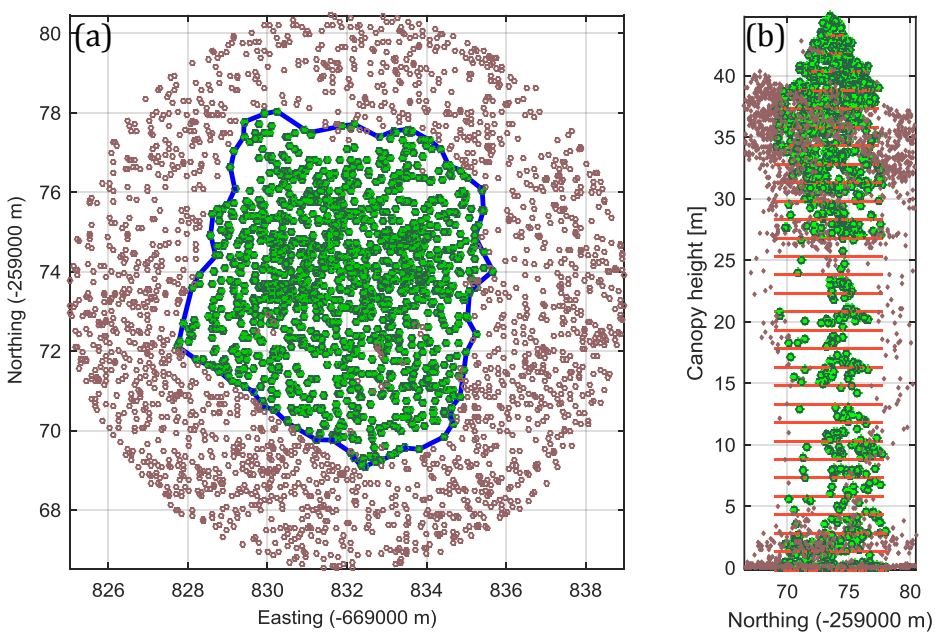

Fig. 3.4. An example of the horizontal segmentation (R=7 m; dh=1.5 m); top view of the last bin, in which all potential points are accumulated (a), and front view of the vertical layering (b).

3.3.2 Canopy stratification

The preliminary results of the previous step represent a single crown in the top canopy layer and may also include other trees in the lower strata. Possible different vertical strata are the outcomes of this step (Fig. 3.1.2). A one-dimensional analysis of the vertical distribution of the ALS points may fail to detect a gap between the strata, since the asymmetric shape of the trees may only be separated by a 3D discriminant surface and not by a simple, one dimensional height threshold. To overcome this issue, the segmented points are divided into equally sized 3D radial sectors (hereafter called pie-slices) using a cylindrical coordinate system, where the seed point is taken as the origin (Fig. 3.5a). This semi-dynamic threshold helps to consider small suppressed trees in different directions beneath the candidate dominant tree. The number of pie-slices is a tuneable parameter and should be set according to the echo density of the ALS dataset. However, we kept this parameter constant in this study for simplification.

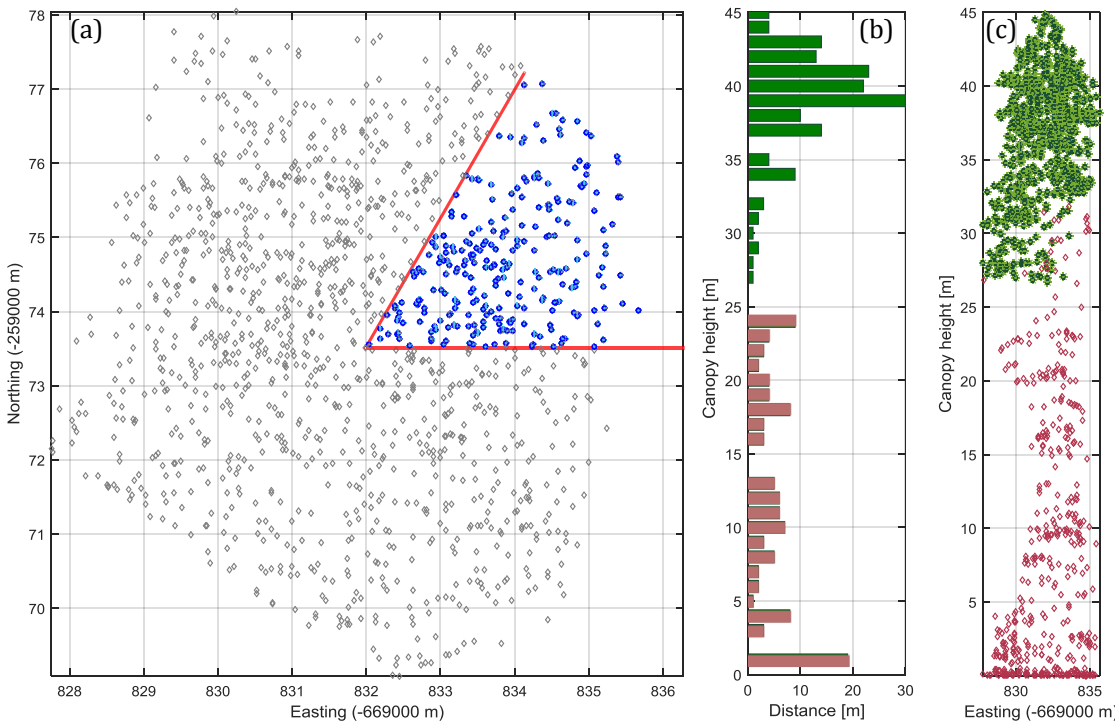

Fig. 3.5. Canopy stratification of a tree. The point cloud is equally divided into pie-sliced regions of 60 degrees each (a). Using vertical gap length stratification (2 m), in which less than 1% of points per bin exist, allowed to detect an overstory layer above 27 m (b). Aggregating all the overstory layer points shaped the topmost stratum, represented by the green points in (c).

For each pie-slice, the height histogram is examined to identify gaps of a given size, called *gap length* (Fig. 3.5b). This parameter can be measured directly in the forest (i.e. similarly to tree height measuring) or can be inferred from expert knowledge. All the points that are situated above the identified gap are assigned to the overstory layer, thus shaping the crown of a single tree (Fig. 3.5c).

3.3.3 Updating the point cloud

All points belonging to the identified tree are then removed from the point cloud (Fig. 3.1.3). The updated nPC is returned to the processing chain for delineation of the next tree crown (regarding to the tree height) and the whole procedure is repeated until all the points of the point cloud are assigned to a specific tree or the remaining points are not sufficient to shape a tree crown based on the parameter *treePts*. The iterative nature of the method will identify and remove all the trees from the tallest to the shortest. In other words, the understory and suppressed trees have high chance to be detected in the last iterations, when the masking trees on the top have been removed. Some parts of the tall trees (e.g. trunks) may remain in the lower strata, however they do not satisfy the criteria in the horizontal segmentation step to shape a crown and are therefore disregarded. In addition to other parameters, introducing a minimum number of points to form a tree (*treePts*) leads the method to remove these residuals from the point cloud.

In the following, the required tree variables (i.e. stem position, tree height, crown base height, crown area and canopy volume) are extracted for all of the identified trees. The planimetric position of the top point of a tree is considered as the stem position, while the crown base height is the height of the lowest point in the crown. The crown volume is computed with a convex hull including the points of the delineated crown.

3.3.4 Parameterization

The proposed algorithm involves six pre-defined parameters: the search radius (R), the vertical layering bin size (dh), two parameters for DBSCAN (ε, *minPts*), the minimum gap size (*gap length*) and the minimum number of points per tree crown (*treePts*). These parameters can be categorized into two classes, based on the estimation approach considered. First, R and *gap length*, can be directly inferred from the forest inventory data. The second category includes dh, ε, *minPts* and *treePts*, which are mostly driven by the ALS data characteristics.

R can be directly assigned using the largest crown dimension from the single tree inventory. Gap length must be determined from other measurements, such as the average tree height in each stratum in conjunction with the information of the crown base height. The best case would be to measure the tree height and crown base height of trees that are close to each other. In the absence of such measures, expert knowledge may be used to set gap length correctly.

The second class of parameters were defined based on the ALS data specification (e.g. point density and number of returns). The best combination of the remaining parameters was estimated from a set of trees (training dataset) by minimizing a cost function. The geometric information of a few trees (N), e.g. tree height and crown diameter in a few different directions, should be collected during the field measurement campaign and serves as training dataset. In the absence of field measurements, these parameters may be provided from expert interpretation of aerial photographs or by visual inspection of the ALS point cloud. In this study, we used the latter approach to define training data because of the lack of other data sources.

The corresponding ALS data for each tree were then subjected to our algorithm using a range of values for the tuneable parameters. The best parameter set should provide the lowest number of false negative and false positive echoes. Pouliot et al. (2002) proposed an accuracy index (AI) for a pixel-based crown delineation, which can be applied for vector-based data as well. With some modifications, we calculated an uncertainty factor ($\overline{U}$), serving as the cost function:

$$\overline{U} = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{f_n}{n} + \frac{f_p}{\hat{n}}\right)_i\right| \tag{1}$$

where for the *ith* training tree, n is the total number of points belong to it, $\hat{n}$ is the number of the assigned points to the tree, f_n indicates the omitted points (false negative) and f_p represents the incorrectly labelled points (false positive). This cost function is an average of the uncertainties involved with each training tree, and its minimization eventually provides an optimum set of parameters. The quality of the estimated parameters directly depends on the quantity of the training trees as well as their quality. Avoiding the use of too complex trees in this step, therefore, should provide more reasonable parameters.

3.3.5 Algorithm evaluation

The proposed algorithm is evaluated with a validation approach at the individual tree level. Based on the objectives of this study, the accuracy is analysed in different height classes and for the entire forest canopy.

The in-situ measured trees are compared to the delineated trees through an updated version of a spatial matching procedure, first described in (Morsdorf et al., 2004). For each reference tree, the 5 m neighbourhood is searched to find the closest tree from all detected trees. In addition, the height of the candidate tree for matching needs to be in a ±2 m range to the height of the reference tree. If more than one tree meets these criteria, only the closest tree is kept. The assigned trees are subsequently removed from the dataset of detected trees, preventing multiple assignments to a reference tree. The reference trees that could not be linked to any of the detected trees are considered in the omission error. On the contrary, the number of the detected trees that could not be linked to a reference tree is considered as the commission error. Following (Reitberger et al., 2009), we compute two values that indicate the model performance. First, the number of correctly detected trees divided by the total number of reference data, i.e. detection rate (DT), which represents the performance of the model. Second, the ratio of unmatched trees (false positives) to the total number of the detected trees (FP), representing the over/under estimation of the model.

Two spatial accuracy components are also estimated using the root mean square error in the horizontal and vertical dimensions, representing the uncertainty of the derived stem position (Δxy) and tree height (Δh). However, these values are strongly affected by the accuracy of the field measurements as well.

Table 3.2

Estimated values of the control parameters, when a minimum of the cost function ($\overline{U}$; Eq. 1) was reached. *dh* and ε were varied from 0.5 to 1.5 meters in 0.25 m steps. In addition, *minPts* was changed from 1 to 5, while *treePts* was changed from 80 to 150 in 5 points steps.

Plot name	Number of training trees (N)	*dh* (m)	ε (m)	*minPts*	*treePts*	$\overline{U}$
A	6	1.25	1	2	110	0.1620
B	4	1	1	2	125	0.1450
C	8	0.5	1	3	85	0.1902
D	7	0.75	1	2	90	0.1701

3.4 Results

The group of parameters that are based on the field measurements or expert knowledge were kept constant for all plots, at 5 m and 1.5 m for R and gap length, respectively. Considering the total number of reference trees per plot, we used 6, 4, 8 and 7 training trees to parameterize the models for plots A to D, respectively.

Both *dh* and ε were changed from 0.5 m to 1.5 m using 0.25 m steps, however the value of ε was found best at 1m for all plots. The *minPts* was varied from 1 to 5 points, and ultimately fixed at 2 points (except for plot C with 3 points). The *treePts* parameter was varied between 80 and 150 points with steps of 5 points. Table 3.2 provides more details of the iterative parameterization approach for the test plots. The minimum values of the cost function approximately declined to 0.16, 0.14, 0.19 and 0.17 for plots A to D, respectively.

Table 3.3

Accuracies matrix for each plot. DT is the ratio of the correctly detected trees in comparison to the reference trees, and FP is the ratio of the unmatched trees to the total number of the detected trees. Δh and Δxy show the accuracies for the tree height and tree position estimations, respectively.

Plot name	DT per height layer (%)				FP (%)	Δh (m)	Δxy (m)
	5-15m	15-25m	> 25m	all			
A	69	100	87	85	21	0.38	1.64
B	67	83	90	81	21	0.48	1.74
C	81	79	85	80	30	0.87	1.53
D	67	73	86	78	31	0.42	1.55
Total	**72**	**79**	**87**	**81**	**28**	**0.60**	**1.58**

The model was then applied to the entire area of each plot, using the estimated parameters. The overall tree detection rates are of 85, 81, 80 and 78 % for plots A to D, respectively. These values are the outcomes of the minor statistics in the different strata. Table 3.3 shows DT values accompanying the total number of falsely identified trees, which are 21, 21, 30 and 31 %. The accuracy of the estimated tree height varies from 0.38 m to 0.87 m. The stem positions were estimated with 1.55 m to 1.74 m accuracy.

The accuracy components were also calculated for all the trees in the four plots, representing the overall performance of the method. For all plots, 81% of the trees were

correctly detected together with 28% of FP. In addition, 72%, 79% and 87% of the trees were properly identified in the lower, intermediate and upper layer, respectively.

The detailed results are presented in Fig. 3.6 using a bar graph for each plot. In addition to the tree detection rates, errors of omission and commissions are displayed for each height layer. The geometric (height and location) accuracies derived using the matched trees are presented in Fig. 3.7.

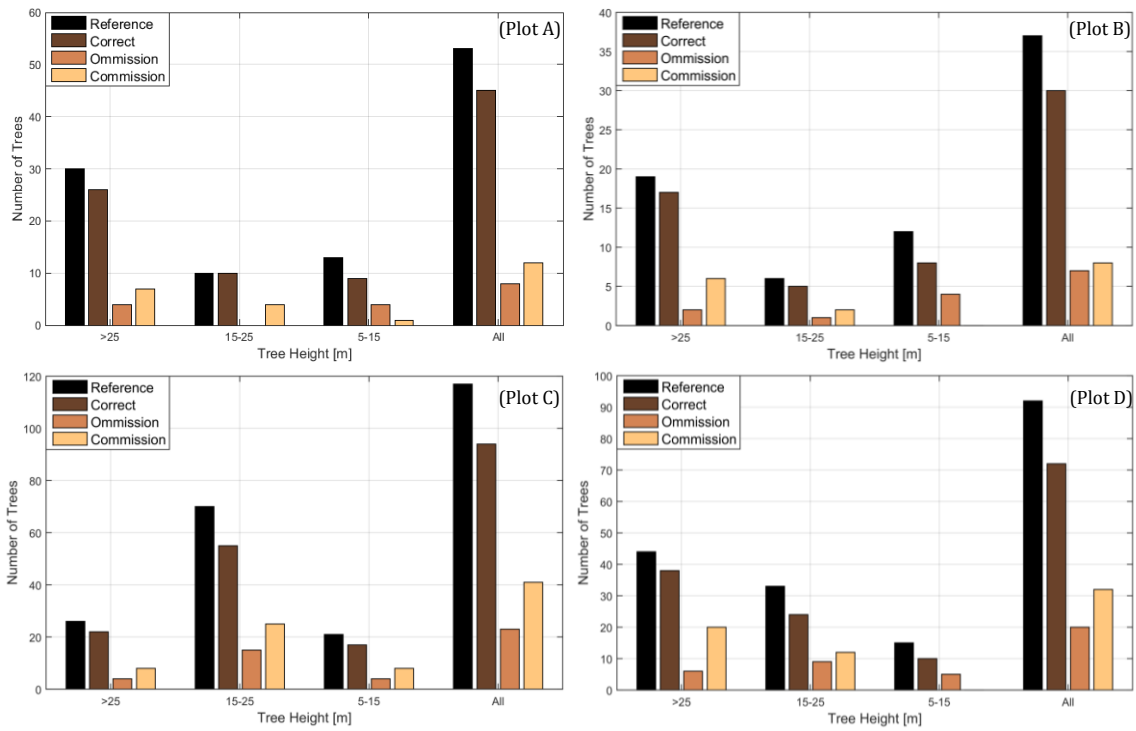

Fig. 3.6. Accuracies at individual tree level, showing the number of reference trees and the correctly detected, omitted and committed trees for each sample plot.

3.5 Discussion

The reported statistics for forest structural diversity (Houston Durrant et al., 2011)show that almost two thirds of the European forests are single-layered, and more than 60% have basal area greater than 20 m2/ha. However, no more than five tree species can be found in 95% of these forests. By comparing with the characteristics of our study sites (Table 3.1), we believe they properly cover the structural complexity and species composition of the European forests.

For the discussion of the results, we divided our study sites into two parts. One is formed by plots A and B, the conifer dominated plots with lower stem densities and single-

layer canopies (denoted as simple sites). The other is formed by the broadleaved tree dominated plots C and D, with higher stem densities and multi-layered canopies (denoted as complex sites).

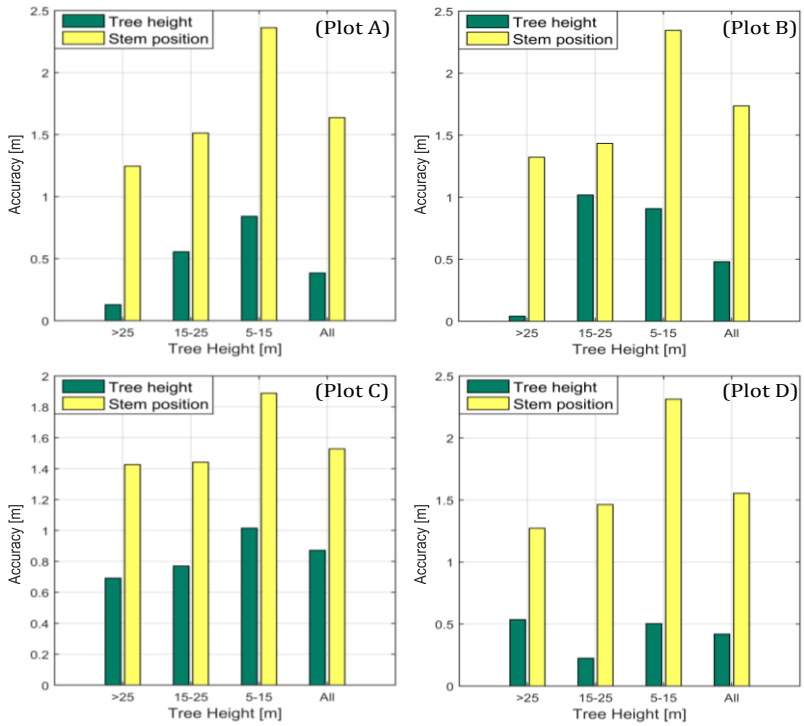

Fig. 3.7. Spatial accuracy assessment of tree height and tree position estimations for each site.

3.5.1 Parametrization

In addition to *R* and *gap length*, which were kept constant for all the plots, the results of the model parametrization (Table 3.2) show the relation between the control parameters of the model and the forest characteristics of the study sites (Table 3.1). The derived values for *dh* were larger in the simple sites, showing the need for a more precise layering of the canopy for complex sites with a smaller value of dh. The other parameter (*treePts*) showed a similar behaviour. Since the LiDAR data settings were the same for all plots, trees in the simple sites (plots A and B) were basically more exposed to the laser pulses than the trees in the more complex sites (plots C and D).

The two parameters of DBSCAN clustering stayed constant in the parameterization step. The ε, which is tightly linked to the laser point density, was estimated as one meter for all the plots. However, the evaluated value for *minPts* was two points for all the sites, except for plot C with three points. These results indicate that the DBSCAN parameters are

independent from the canopy conditions. In other words, if the laser scanning data specifications are constant, the estimated values for ε and *minPts* for one plot can be used for the full site.

3.5.2 Evaluation

The quantitative comparison with previously published ITC methods is difficult, as they are based on different datasets and are subject to changing conditions of the test sites. Nevertheless, the comparison of the resulting accuracies with other individual tree detection methods (which were also tested in conifer-dominated and mixed forests) indicates some strengths and weaknesses of the proposed approach. The detection rates in conifer-dominated plots (83% in average for plots A and B) are higher than those provided by raster-based methods for similar forest conditions (e.g., 71% by Persson et al. (2002) and 66% by Solberg et al. (2006)) and comparable to the reported accuracy by Li et al. (2012), who achieved ~86% by applying a point cloud based method.

The provided overall DT for plots C and D was 79% in average. Among the point cloud based approaches applied for mixed forest, the percentage of correctly detected trees ranges from ~66% (Reitberger et al., 2009) to ~73% (Ferraz et al., 2012; Wang et al., 2008). However, raster-based methods provide similar values, ranging from ~62% (Koch et al., 2006b) to ~73% (Jing et al., 2012b).

Considering the number of trees correctly detected at different vertical strata from previous studies, there is a tendency towards smaller detection rates in the lower layers, while upper layer trees have very high detection rates (Persson et al., 2002). In a deciduous forest, Duncanson et al. (2014) were able to identify 70%, 58%, 35%, 21% of the trees in the dominant, co-dominant, intermediate and suppressed layers, respectively. In conifer forests, these values are generally higher for the upper layer, but not for the other, lower strata. For example, Solberg et al. (2006) reported a detection rate of 93% for dominant trees, but only 19% for trees in the suppressed strata. Reitberger et al. (2009) showed that 88% of trees in the upper layer were correctly identified in a mixed forest, but these values fall to 35% and 24% for the intermediate and lower layer, respectively.

As could be expected, the accuracy for the upper layer (87%) is in good agreement with similar studies in mixed forests (Reitberger et al., 2009; Yao et al., 2012); it is higher than the accuracies found in deciduous forest (Duncanson et al., 2014) and less than the accuracies reported for conifer dominated forest (Solberg et al., 2006). The little variation between these accuracies can be explained by the common approach used by the above-

mentioned studies (including the present study), which all make use of a local or global maximum detection for finding the treetops in the upper layer.

For the trees in the intermediate strata, the algorithm performs very well with a DT value of 79%. Although the definitions of intermediate strata are different in the literature, the best reported accuracy of the different methods is 65% by (Ferraz et al., 2012). The other methods, which search for the local maxima, typically have lower detection rates in the intermediate layer (~35%).

Detection of suppressed trees is a particular strength of the suggested approach. The provided 72% DT for the lower layer is by far higher than all previously published single tree identification approaches. Regardless of the forest type, the best rate of the suppressed tree detection was achieved by Reitberger et al. (2009), which was 24%. Although the lower ability of ALS data to characterize suppressed trees causes a lower accuracy for this stratum, the iterative updating of the point cloud after identification of each tree provides a higher chance for them to be identified. In addition, using a semi-dynamic threshold to differentiate between upper and lower layers provides assistance for the detection of small trees, which are situated beneath a larger one.

Comparing the average DTs for all strata (Table 3.3) shows some variation. Due to the relatively high detection rates in all layers, the overall performance of the model is high, regardless of the vertical complexity of forest (single- or multi-layered). This explains why the overall accuracy of plot B, which is the simplest plot, is close to the accuracy of the most complex plot in this study (plot C). This shows, that despite the different conditions of the plots, the total detection rates are similar, and indicates a low sensitivity of the algorithm to forest conditions (in terms of density, structure and species composition).

The percentage of the false positives was about 30% for both complex sites, showing that the method was oversegmenting. In such complex forests, isolated groups of branches are likely identified as an individual tree by our approach. This effect is less present in the simpler plots, with only 21% of false positives, due to the lower presence of deciduous trees there. This finding is in line with other studies (e.g. Vauhkonen et al., 2011). Generally, in conifer-dominated forests, with a prevalent conical crown shape, the algorithm is more successful. The resulted number of false positives is higher than the values of 11% and 9% reported by Reitberger et al. (2009) and Ferraz et al. (2012), respectively, but less than the values of 26% by Solberg et al. (2006) or 60% by Duncanson et al. (2014). Obviously, the reported values for false positives (or error of commission) are very diverse in the literature, leading to inaccurate comparisons between

the current and the previous studies. Generally, the point cloud based approaches yield more false positives than raster-based methods.

Regarding the spatial accuracy (Table 3.3, Fig. 3.7), our approach resulted in an average accuracy of 0.6 m and 1.58 m for tree heights and stem positions, respectively. Considering the measurement approach of reference data, which reported ±1 m accuracy for the geometric measurements, the results are reasonably acceptable. The worst results were observed in the lower layer. This may be related to the lacking of training trees in the lower stratum or less accurate reference data.

3.5.3 Requirements of the method

The proposed method can be applied to any type of point cloud, such as point clouds based on discrete and full-waveform LiDAR systems. However, there are some inherent data requirements for using it as its best.

The availability of ALS data with high point densities (greater than 5 m-2) is the first requirement of the proposed method. Although this is likely no issue for recent ALS surveys using modern FW systems, the applicability on previously acquired ALS data with a lower point density could be limited.

The proposed method has likely some limitations in very steep terrain, due to the use of a topographically corrected point cloud. This can reshape the tree crowns situated in areas with high slopes (Li et al., 2012; Vega et al., 2014) and consequently negatively impact the accuracy of the horizontal segmentation (Khosravipour et al., 2015). Thus, the sensitivity of the method to the terrain slope should be investigated in the future.

Since the core clustering part of the method (DBSCAN) uses only one parameter as distance criterion, the point cloud spacing in X and Y direction should be roughly similar. Data by older ALS systems with different sampling rate along track and across track (e.g. systems that use a fibre-optic for beam deflection, such as the Toposys Falcon series) cannot be directly exploited. In such a case, one solution would be to apply a scale factor on the data to make the data uniformly distributed. The identified trees must then be transformed back at by the use of an inverse scaling factor.

Providing enough and accurate training trees for the parametrization of the method may pose a serious challenge in multi-layered canopies. Although the training trees in the upper layer are easily identified and introduced to the method, the discrimination of trees in the lower layers needs more effort. Especially so, if the training method is planned based on optical remote sensing data (e.g. orthophotos), recognising smaller and suppressed trees is nearly impossible. We recommend planning the in situ measurements

accordingly during the forest inventory to overcome this issue, i.e. by measuring the crown dimensions of a few suppressed trees in the field.

3.6 Conclusions

This study presents a method to identify single trees in different strata by exploiting spatial relations within the ALS point cloud. Unlike other approaches, the proposed method iteratively applies two steps of segmentation within the ALS point cloud, in both horizontal and vertical dimensions, and thus improves the detection of suppressed trees. The sequential implementation of the horizontal segmentation and canopy stratification leads to a clear improvement in the detection rate, particularly for the trees present in intermediate and lower layers.

Superior identification of the dominated trees not only improves the overall performance of the single tree detection, which is requested for precise forest management, but also helps for better understanding of the forest dynamics (Wehrli et al., 2005). For instance, more accurate estimation of the number of suppressed trees is very relevant for forest mortality and succession models (Falkowski et al., 2009; Keane et al., 2001).

Our study sites contain the major range of the structural diversity in European forests (Houston et al., 2011). Therefore, by testing the method in these sample plots, our method shows some promise for transferability to other forest compositions. The method detects dominant trees robustly, regardless of the structural complexity of the forest. The advantage of using publicly available ALS and inventory data is that benchmarking of the methods will be much easier. We are looking forward to other approaches challenging the performance of our method on the NewFor sites.

However, in the future we recommend a simpler parameterization of our method. This may be achieved by either applying new technologies for in-situ measurements of sample plots, e.g. by terrestrial laser scanning, or by integration of other sources of remote sensing data, such as UAV-provided aerial photographs.

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4

Tree species classification in temperate mixed forests using a combination of imaging spectroscopy and airborne laser scanning

This chapter is based on:

Torabzadeh, H., Leiterer, R., Hueni, A., Schaepman, M.E., & Morsdorf, F. (2015b). Tree species classification in temperate mixed forests using a combination of imaging spectroscopy and airborne laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing, in review.

Abstract

Knowledge of the spatial distribution of tree species is important for efficiently managing and monitoring forested ecosystems, especially in mixed forests of the temperate zone. In this study, we fused imaging spectroscopy (IS) data with high point density small-footprint airborne laser scanning (ALS) data, acquired in both, leaf-on and leaf-off conditions, for tree species identification in a dense temperate forest in Switzerland. In addition to the spectral reflectance of the sunlit part of the tree crowns, structural features computed based on the height, intensity and point density distribution of ALS data in both the vertical and horizontal dimensions are used as features. Features were extracted using a pixel-based (1 m by 1 m) and an individual tree crown approach. In addition, we tested a floating forward selection of features along with standard data reduction methods such as principal components analysis (PCA). Results of the feature selection method revealed that the ALS-derived features provided relevant structural information for species identification, while IS-derived features added complementary biochemical information.

Multiclass support vector machines (SVMs) were used for classification of the high dimensional feature space. When comparing the accuracies of three different combinations of ALS and IS data, the highest classification accuracy (kappa=90.3%) was obtained by fusing a selected set of features at individual tree crowns (ITC), while the best kappa accuracies resulting from IS or ALS data only were 75.5% and 75.8%, respectively. Inclusion of the ITC information improved the classification results for all datasets, however, this improvement is significantly higher for ALS derived datasets (+33%). McNemar's test was used to statistically verify the significance of the changes in kappa accuracy among the ITC-based datasets ($p<0.0001$). Our results show that accurate ITC information drastically improves classification accuracy of tree species in dense forests and that multi-seasonal ALS structural attributes play a major part in species discrimination.

4.1 Introduction

Tree species composition and their spatial distribution strongly influence the quality of the forest habitats, forest biodiversity (Puumalainen et al., 2003), and forest management strategies (Ørka et al., 2013). In addition, spatially explicit information on the tree species composition improves the estimation of forest biomass and productivity by using species-specific models (Swatantran et al., 2011). Different passive remote sensing systems provide multi-scale and frequent measurements, which facilitate identification of the tree species composition in different forest ecosystems (Clark and Roberts, 2012; Stoffels et al., 2015; Wulder et al., 2008b). Among all, imaging spectroscopy (IS) can provide maps of tree species distribution with higher accuracies (Cochrane, 2000; Feret and Asner, 2013; Martin et al., 1998). IS sensors measure solar electromagnetic energy reflected from the Earth's surface in a large number of spectrally contiguous bands simultaneously (Goetz et al., 1985; Schaepman et al., 2009). Such systems obtain spectral information of vegetation, which itself is a function of both the biochemical properties of foliage as well as the biophysical characteristics of the canopy (Asner and Martin, 2008a), given that the atmospheric influence has been properly corrected for. Although species identification using IS data works very well at the leaf level (Zhang et al., 2006), their spectral discriminability decreases in heterogeneous canopies due to the increasing effect of vegetation structure (Leckie et al., 2005). This leads to lower classification accuracies at the canopy level than those observed at the leaf level (Clark et al., 2005).

The mixing of spectral features increases when the diversity of species is high (e.g. in tropical forests) or the canopies structure is more complex in both vertical and horizontal dimensions (Asner et al., 2014). The latter is often a problem in dense temperate mixed forests, which may contain multiple vertical layers and complex canopy compositions. Consequently, relying on the spectral information alone intensifies the difficulties of successful tree species discrimination in such optically thick and complex biomes.

On the other hand, airborne laser scanning (ALS) systems, equipped with light detection and ranging (LiDAR) devices, can provide a three dimensional characterization of the vegetation canopy. ALS data have been frequently used for accurate estimation of canopy structural parameters, such as tree height (Andersen et al., 2006; Morsdorf et al., 2004; Tesfamichael et al., 2010), tree crown diameter (Falkowski et al., 2006; Popescu et al., 2003), fractional canopy cover (Hopkinson and Chasmer, 2009; Korhonen et al., 2011), leaf area index (LAI) (Morsdorf et al., 2006; Tang et al., 2014), and biomass (Næsset and Gobakken, 2008; Zhao et al., 2009). In addition, waveform-based metrics (e.g. amplitude

and echo width) have been increasingly used for forest characterization (Hovi and Korpela, 2014; Reitberger et al., 2008a; Wagner, 2010). The proper use of both, height and waveform metrics, results in an adequate accuracy level, although only a few species can be discriminated (Holmgren and Persson, 2004; Ørka et al., 2009). Additionally, changes of ALS-derived features in different conditions (i.e. leaf-on vs. leaf-off) have been found to be significantly linked to tree species (Ørka et al., 2010). Therefore, surveying ALS data in leaf-on and leaf-off conditions for tree species identification has recently attracted some attention (Brandtberg, 2007; Kim et al., 2009; Yao et al., 2012). Nevertheless, due to deficiencies of ALS systems to provide information on the biochemical characteristics of vegetation, identifying tree species from ALS data only might not yet meet the requirements of the application domains (McRoberts et al., 2010).

Consequently, fusing the information derived from ALS and IS data is a promising technique and a couple of studies have successfully applied fusion of ALS and IS data for tree species classification in different types of forest ecosystems (Clark et al., 2005; Dalponte et al., 2012). Most of the studies were focused on savanna biomes , where the ALS-derived tree height was reported to be an important feature for the tree species classification (Naidoo et al., 2012).

The mix of coniferous and deciduous species and stand age are some factors that increase the structural diversity in temperate forest and lead to higher complexity (McElhinny et al., 2005). Likely, the complexity of temperate mixed forests causes a scarcity of studies for this forest type and for an effective use of combined use of IS and ALS data, more innovative and sophisticated ALS-derived features are needed. For instance, canopy volume profiles, LiDAR waveform metrics and the use of canopy texture variables produce a higher efficiency for tree species classification than using only the tree height (Dalponte et al., 2012; Heinzel and Koch, 2012; Jones et al., 2010b). However, the potential accuracy improvement depends on the level and methods of the fusion, making sure that the complementarity of ALS and IS data are exploited to their fullest potential.

In contrast with the common categories of fusion levels in remote sensing (i.e. pixel-, feature- and decision-level (Pohl and Van Genderen, 1998), which best suits image data), data-, product- and multi-level approaches are more consistent for fusion of ALS and IS data (Torabzadeh et al., 2014). Up to now, multi-level fusion, in which raw data and retrieved products are combined, is the most established method to discriminate tree species, e.g. by fusing IS-measured reflectance with ALS-derived metrics (Cho et al., 2012; Dalponte et al., 2012; Jones et al., 2010b). Principal component analysis (Ørka et al., 2013; Sarrazin et al., 2012) and vegetation indices (Naidoo et al., 2012) have been also fused

with ALS-derived features. However, these simplified forms of IS data may not be a sufficient indicator for the spectral response of different species. In the same way, extracting only a few structural features (mainly canopy/tree height) from ALS data and subsequent fusion with IS information may improve the tree species identification, but additional useful information of ALS data are partly disregarded (Ghosh et al., 2014b). In other words, focusing on the main spectral and structural metrics only may deprive some species from a more accurate characterization. Therefore, assessing all derivable IS and ALS features seems to be necessary, particularly for dense temperate mixed forest. Using of a large number of features in the classification causes high-dimensionality problems (Hughes, 1968) and decreases the species identification accuracy. This can be tackled by using data reduction techniques such as principal component analysis (Harsanyi and Chein, 1994) and wavelet transform (Bruce et al., 2002), though the results may not be interpretable in terms of biophysical/biochemical properties. Consequently, iterative feature selection approaches were applied to find the most effective features for classification of different vegetation types using remotely sensed data (Alonzo et al., 2014; Dalponte et al., 2012). Ørka et al. (2010) discriminated coniferous and deciduous trees by using ALS data in different canopy conditions, but to the best of our knowledge no studies have yet investigated the potential of fusing ALS-derived structural features in both leaf-on and leaf-off conditions with IS data.

The superiority of tree species classification using optical remote sensing data (including IS) at individual tree crowns (ITC) over pixel level has been reported in several studies (e.g. Clark et al., 2005; Gougeon, 1995; Lucas et al., 2008a), however species classification at ITC is still challenging, particularly in dense forest (Feret and Asner, 2013). In respect to ALS data, classification at ITC level can be directly translated to ITC-based forest inventory approaches (Hyyppä et al., 2008; Vauhkonen et al., 2014), but more effort is needed to link the results of a pixel-based classification to forest inventory. The fusion of IS and ALS data provides opportunity of using ALS-derived crown boundaries (i.e. polygons) for the classification of the tree species. Dalponte et al. (2014) aggregated a pixel level tree species map by using ITCs based crown polygons, resulting in an improvement of the classification accuracy. However, we are not aware of any study that compared the classified ALS, IS and fused datasets at ITC level.

The overall aim of the study is to explore the fusion of ALS data (in leaf- on/off conditions) with spectral data provided by the Airborne Prism EXperiment (APEX; Schaepman et al., 2015) spectrometer in order to discriminate common tree species in dense temperate mixed forests. More specifically, we will identify the most influential

spectral bands and ALS-derived features for tree species discrimination. Additionally, we will assess which tree species profit most from the fusion approach using the selected features. In a final step, we will test for the relevance of using an individual tree crown (ITC) approach for the classification of IS, ALS and fused datasets in comparison to a standard pixel-based approach.

4.2 Data collection

4.2.1 Study area

This study was conducted in a semi-natural, temperate forest (47°28'N, 8°21'E), located on the southern slope of the Laegeren northwest of Zurich. The mixed forest consists of European beech (*Fagus sylvatica*), European ash (*Fraxinus excelsior*), European silver fir (*Abies alba*), Norway spruce (*Picea abies*), Sycamore maple (*Acer pseudoplatanus*), Wych elm (*Ulmus glabra*) and Norway maple (*Acer platanoides*), in order of abundance. In addition, it includes some dead trees, with only a few of them still standing.

The area of exhaustive single-tree inventory is 330 m × 260 m in size and its elevation ranges from 620 to 810 m above sea level (a.s.l.). The high diversity in respect to species type, age (up to 185 years) and diameter distribution results in a very heterogeneous forest canopy, both horizontally and vertically. Despite the small size of the area, it contains all the tree species present in the larger Laegeren area and includes very dense deciduous-dominated canopy in the north, and less dense conifer-dominated stands in the south (Fig. 4.1). Therefore, this area can be considered as a good representative for the forested area around. More information about the environmental conditions of the study area can be found in Eugster et al. (2007).

4.2.2 ALS data

Two independent full-waveform small-footprint ALS datasets were acquired under leaf-off (April 10th, 2010) and leaf-on (August 1st, 2010) canopy conditions using a RIEGL LMS-Q560 and a LMS-Q680i, respectively. The average flying altitude of 500 m above the ground along with 0.5 mrad divergence laser beam yielded a footprint diameter of approximately 0.25 m. The overlapping flight strips and a pulse repetition frequency of 200 KHz led to a mean echo density of 20 m^{-2} and 40 m^{-2} in the leaf-off and leaf-on datasets, respectively (Fig. 4.1 (b)).

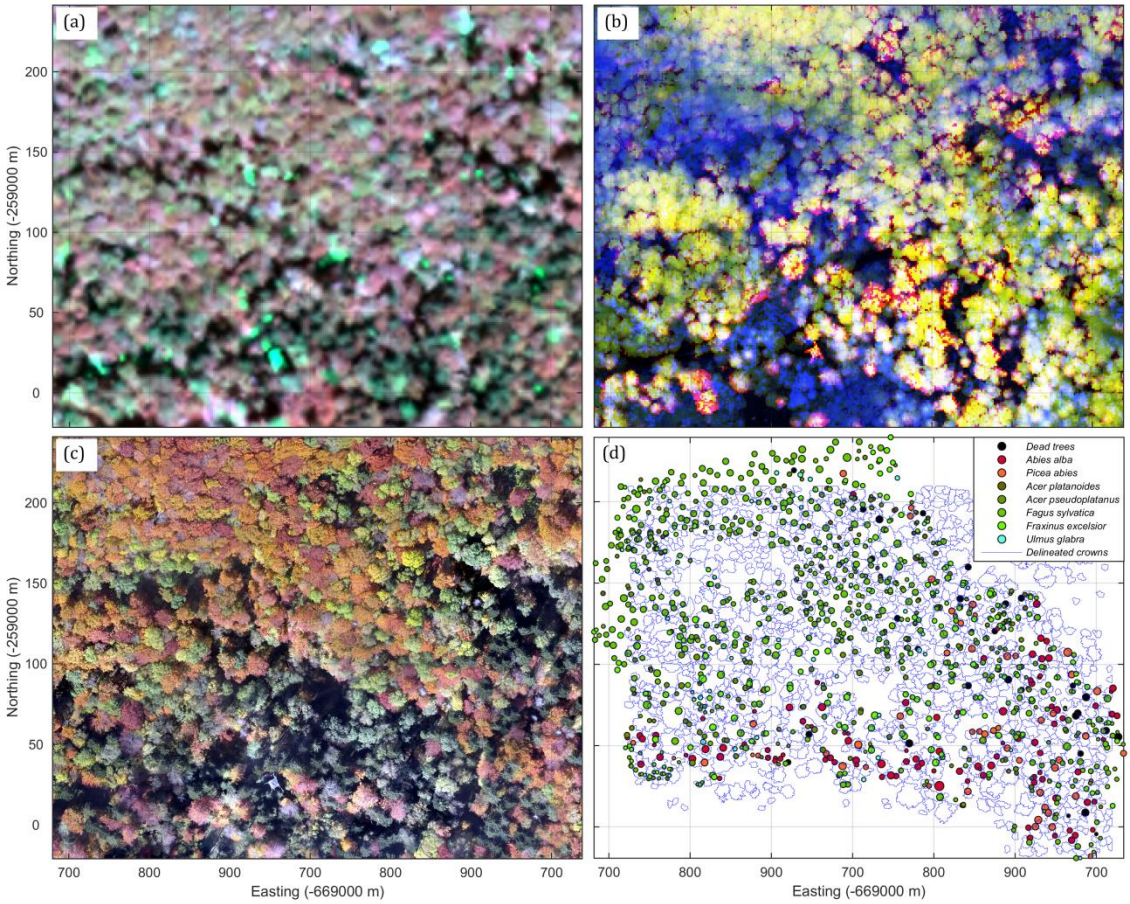

Fig. 4.1. An overview of the remote sensing and in-situ data of the study area; (a) false color composite (R: 860, G: 650 and B: 552 nm) of the APEX dataset at 2m ground pixel size; (b) color composite of different ALS-derived height percentiles (R: HP_{99}, G: HP_{50} and B: HP_{10}) at 1m ground pixel size; (c) true color composite (R: 640, G: 550 and B: 470 nm) of the UAV-derived ortho-mosaic at 0.08 m ground pixel size; (d) the delineated crowns from UAV data superimposed with the in-situ forest inventory. The size of the circles represents the DBH of each tree (0.2m to 1.42m).

Following radiometric calibration of the ALS echoes (Höfle and Pfeifer, 2007), a point cloud was generated using the trajectory data provided by the global positioning system (GPS) and inertial measurement unit (IMU). Geometric validation of the point cloud using six ground control points confirmed 0.5 m in horizontal and 0.15 m in vertical accuracy. ALS waveforms were decomposed using Gaussian pulse estimation to obtain the waveform attributes (e.g. range, amplitude and width) of each echo with Riegl's software RiANALYZE 3.0.8 (Wagner et al., 2006). The digital surface model (DSM) and the digital terrain model (DTM) were produced using spatial filtering along with waveform attributes of the points, for details see Leiterer et al. (2012). The canopy height model (CHM) was then generated by subtracting the DTM from the DSM.

4.2.3 APEX imaging spectrometer data

APEX data were acquired on September 3, 2013, around 11:04 A.M. local time, with solar zenith and azimuth angles of 40.7° and 166.3°, respectively. The study area was entirely covered by a single flight line, acquired at 4590 m a.s.l., resulting in approximately 2m x 2 m ground pixel size. APEX samples upwelling radiance between 376 to 2502 nm in 299 spectral bands with a spectral resolution (full width half maximum) between 3.4 nm and 14.5 nm, depending on the specific band. More detailed information about the APEX specifications can be found in Schaepman et al. (2015).

The data were radiometrically calibrated to achieve at-sensor radiances (Hueni et al., 2013), and then atmospherically corrected using the ATCOR-4 standard approach (Richter and Schläpfer, 2002) to obtain top of canopy reflectance values (Fig. 4.1(a)). Bands in atmospheric water absorption regions (1335-1489 nm and 1784-1985 nm) were removed (van Aardt and Wynne, 2001). In addition, due to low signal to noise ratios, wavelengths within 376-399nm and 2424-2502nm were removed, reducing the APEX dataset to 241 bands. These bands are distributed in visible (VIS; 399-700nm), near infrared (NIR; 700-1326nm) and two shortwave infrared (SWIR1; 1495-1776nm and SWIR2; 1990-2422nm) spectral regions.

The geometric rectification was performed using PARGE (Schläpfer and Richter, 2002) and the ALS-derived DSM in the nearest neighbour resampling mode. Using ALS-derived control points, the root mean square error (RMSE) was evaluated to be less than half APEX pixel (<1 m), which confirms reasonable geometric adaptation of IS and ALS data. In order to retain a maximum of the ALS information, the IS reflectance cube was ultimately resampled to 1x1 m pixel size.

4.2.4 UAV data

The automatic delineation of individual tree crowns (ITCs) from remote sensing data generally brings substantial amount of uncertainties into the tree species classification process (Dalponte et al., 2014). Since ITC delineation in our study was not providing high accuracies with neither ALS nor IS data, we decided to use very high-resolution aerial photographs, captured by a commercial non-metric RGB camera. The platform was an ultra-light drone, called eBee (SenseFly), which was flown on October 21, 2013, at 270 m above ground. The time is coincident with leaves senescence in autumn and we hypothesized that differences in leaf-colors caused by leaf pigments variations would facilitate the ITC delineation. Following the geometric rectification of 174 images, the

resulting 0.08 m x 0.08 m spatial resolution ortho-mosaic was geometrically co-registered to the ALS and IS datasets (Fig. 4.1(c)).

Using a semi-automatic segmentation approach (Haara and Haarala, 2002), possible ITCs were detected from combined UAV-derived ortho-mosaic and ALS-derived CHM. The extracted tree crown shapes were visually checked to avoid any conflict or mixed crowns. Crown polygons that appeared to contain more than a single, top-layer tree crown were consequently removed from the final datasets (Fig. 4.1(d)).

4.2.5 Ground reference data

Collecting tree species data at the single-tree level was part of a comprehensive in-situ forest inventory in April 2013. Each tree with a diameter at breast height (DBH) greater than 0.2 m was accurately located (<1m) using land surveying instruments. In addition to tree species, other tree variables were measured as well (e.g. DBH, social status, horizontal crown displacement, number of canopy layers, vitality, approximated crown size, and crown projection area). The total number of observed trees was 1203 (Fig. 4.1(d)). Table 4.1 contains more details about the measured trees and their characteristics.

Table 4.1

Common (co-dominant) tree species present in the study area, with attribute data.

Species group	Class No.	Species name	Scientific name	Observed frequency	Average DBH (cm)
Standing dead trees	1			30	64
Conifer	2	European silver fir	*Abies alba*	108	55
	3	Norway spruce	*Picea abies*	51	66
Broadleaf	4	Norway maple	*Acer platanoides*	40	31
	5	Sycamore maple	*Acer pseudoplatanus*	168	35
	6	European beech	*Fagus sylvatica*	515	46
	7	European ash	*Fraxinus excelsior*	248	43
	8	Wych elm	*Ulmus glabra*	43	28
Total				1203	

The in-situ observed trees were linked to the UAV-delineated ITCs using geometrical (coordinates and crown size) and attributive (vertical layer) constraints. As a result, 244 well-matched trees, in which the crowns contain at least four pixels of the IS dataset, were considered as reference data. The trees were chosen so that the distribution of the species resembles that of the overall reference data. However, the shade-tolerant species (e.g. Sycamore maple) might not be sufficiently represented in the aerial photographs. For each

species, 70 percent of the ITCs were randomly selected as training set, with the remaining ITCs used for validation (Table 4.2).

Table 4.2

Per-species training and validation data sets of reference ITCs and quantity of sunlit pixels comprising them after excluding shadow regions (in brackets).

Class No.	Species name	Reference ITCs	
		Training	Validation
1	Dead tree	8 (121)	3 (41)
2	European silver fir	31 (967)	13 (452)
3	Norway spruce	22 (830)	9 (246)
4	Norway maple	7 (159)	3 (105)
5	Sycamore maple	14 (467)	6 (187)
6	European beech	42 (2900)	18 (1225)
7	European ash	37 (1703)	16 (594)
8	Wych elm	11 (252)	4 (66)
Total		172 (7399)	72 (2916)

4.3 Methods

4.3.1 Remote sensing features

Spectral and structural features were generated from the IS and the ALS datasets by using two different methods. First, we use a pixel-based approach (PBA), in which the ALS data are aggregated on a predefined grid with one square meter size (coincident to a quarter of an IS pixel). The IS dataset was resampled to the finer pixel size. Although this grid size has likely no benefit for IS-derived features, it ensures that the approach can profit most from the high density of the ALS point cloud. The second approach is an ITC-based method (Breidenbach et al., 2010), where data are convened inside the crown of each single tree cluster. With the help of the UAV-derived ITCs, all the features were extracted and aggregated within the corresponding tree crown polygon.

4.3.1.1 Retrieving structural features from ALS data

We estimated a set of commonly used height metrics (e.g. height percentiles) from the terrain corrected ALS point cloud in both leaf-on and leaf-off conditions (Latifi et al., 2012). In addition, we derived structural features based on histograms of the vertical echo distribution (percentage of echoes per vertical bin) and histograms of the full-waveform features (e.g. summarized intensity per vertical bin) within each spatial unit, either the 1 m pixel or the tree crown polygon. These histograms can be considered as synthetic waveforms reflecting canopy structure features, where the shape of the waveform is, inter

alia, affected by the specific canopy structure (Blair and Hofton, 1999; Koetz et al., 2006b; Leiterer et al., 2015).

We calculated the histograms with a bin size of one meter and retained only the histogram bins with values >1 % for the computation of the structural features. To define canopy related structural features, we applied a height threshold of three meters (according to the Swiss national forest inventory threshold for determining trees) in order to distinguish between the canopy and the ground. To separate individual canopy layers, we assumed that vertical gaps in the canopy needed to be greater than 3 m; this threshold was defined based on expert knowledge of foresters used in the labelling of the produced maps. Subsequently, we labelled the canopy layer with the largest vertical extent as the dominant main layer.

Following the calculation of 10th to 90th and 99th height percentiles, the canopy intensities were further summarized using the height percentiles, named i^{th} intensity percentile (Donoghue et al., 2007). By discretizing each column into 10 equal vertical bins, we calculated the number of echoes per bin (termed PD_i). Moreover, the differences between the corresponding features extracted from leaf-off data and leaf-on data were calculated, providing 78 ALS-derived structural features in total. We call the latter ones differential features, and label them with a prefix of Δ. An overview and a description of the calculated structural features are provided in Table 4.3. These features were calculated inside the one-meter pixels and ITCs.

4.3.1.2 Extracting spectral features from IS data

Since shaded and sunlit parts of canopy have very different apparent spectra in IS data, and since shadowed parts suffer from a low signal-to-noise ratio, exploiting only sunlit pixels is strongly advised (Clark et al., 2005; Leckie et al., 2005). Therefore, we used the ALS-derived DSM in combination with the solar azimuth and zenith angles of the APEX data acquisition, to identify and exclude shaded pixels from the dataset. Furthermore, by applying a 3 m height threshold on the CHM values, all the corresponding IS pixels were removed from the dataset to ensure that only canopy >3 m is considered in the further analysis. In addition to the reflectance values inside each pixel, the average of all pixel values within an ITC was computed as the ITC-based spectral features.

Table 4.3

39 structural features derived from ALS data in leaf-on condition. 39 similar features were calculated for leaf-off data and the conjugate differences between leaf-on and -off data were used, resulting in total 78 ALS-derived features.

Feature No.	Feature name	Description
1	*veg_height*	Maximum echo height above ground
2	*veg_length*	Amount of histogram bins (bin size = 1m) with a percentage proportion of echoes > 1%
3	*veg_ratio*	Ratio of vegetation length to the maximum vegetation height (*veg_length*/*veg_height*)
4	*canopy_extent_ratio*	Ratio of the height of the lowest canopy stratum to the maximum vegetation height
5	*layer_no*	Amount of distinguishable canopy layer
6	*dom_layer_pos*	Relative position of the canopy layer with the largest vertical extent (top, middle, bottom)
7	*int_1*	Cumulative intensity > 1 m above ground
8	*int_3*	Cumulative intensity > 3m above ground
9	*int_top*	Cumulative intensity for the top part of the canopy (maximum vegetation height – 3 m)
10-19	HP_{10}-HP_{90} and HP_{99}	10th to 90th and 99th height percentiles
20-29	IP_{10}-IP_{100}	10th to 100th intensity percentiles
30-39	PD_1-PD_{10}	Point density in each vertical bins

4.3.2 Feature selection

Using supervised techniques for remote sensing data classification usually faces some limiting factors. In particular, the Hughes's phenomenon (or curse of dimensionality) occurs when high-dimensional data are classified with a small number of training samples (Hughes, 1968). High correlation between contiguous spectral measurements may also lead to a decrease of the classifier performance (Féret and Asner, 2011). In addition, processing of a large number of features results in a massive computational cost. A common solution is to extract the intrinsic dimensionality of the data (Chein and Qian, 2004) and decrease the number of actual features used accordingly, e.g. by a feature selection approach. In such an approach, only the most discriminant and informative subset of original data is preserved.

Various feature selection algorithms have been used for this purpose (e.g. Jain and Zongker, 1997; Kudo and Sklansky, 2000; Pal and Foody, 2010; Serpico and Bruzzone, 2001). We chose to apply an extended version of the forward feature selection, called sequential forward floating selection (SFFS) to identify the optimal features in both ALS and IS datasets. The SFFS involves a backward procedure that reconsiders the previously selected features, decreasing the sensitivity to the initial conditions (Pudil et al., 1994). The recursive updating provides a sub-optimal set of features at every step, however, it

may increase the computational cost (Yang et al., 2012). Along with the SFFS searching strategy, we used transformed divergence (*TD*), which is a saturated version of the divergence (Forestier et al., 2012), as a separability criterion. For two classes *i* and *j*, it is written as follows:

$$D_{ij} = \frac{1}{2} tr\left[\left(C_i - C_j\right)\left(C_i^{-1} - C_j^{-1}\right)\right] + \frac{1}{2} tr\left[\left(C_i^{-1} - C_j^{-1}\right)\left(\mu_i - \mu_j\right)\left(\mu_i - \mu_j\right)^T\right] \quad (1)$$

$$TD_{ij} = 2\left(1 - exp\left(-\frac{1}{8}\, D_{ij}\right)\right) \quad (2)$$

where between classes divergence (D_{ij}) is computed from mean vectors (μ) and covariance matrices (C) of each class. To extend *TD* to allow for multiclass evaluation, we average the computed *TD* values for all pairs of classes, resulting in a single parameter that should be maximized.

On the other hand, principal component analysis (PCA), which exploits the eigenvalues distribution, was used to reveal the intrinsic dimensionality of each dataset. The rank of the first eigenvalue that is responsible for less than 0.01% of the data indicates the intrinsic dimensionality. The percentage of occurrences of a feature in all SFFS iterations (1276 times) indicates the rank of it. The top-ranked features were then chosen, so that the quantity of the selected features is equal to the intrinsic dimensionality. The feature selection was first applied on the IS data and then on the stacked IS and ALS data. The comparison of these results reveals what types of features are more relevant in species differentiation.

4.3.3 Classification

Conventional parametric classifiers have only limited use when applied to multi-sensor, high dimensional remotely sensed data (Waske and Benediktsson, 2007a). In the past few decades, the intrinsic peculiarity of multi-source data has led to the introduction of numerous advanced non-parametric supervised classifiers such as artificial neural networks (Benediktsson et al., 1990) or more recently support vector machines (SVMs) (Huang et al., 2002). Insensitivity to high-dimensional data, stability, convexity of the cost function and robustness regarding scant training samples make SVM highly efficient in tree species classification, and consequently its results outperform conventional approaches (Dalponte et al., 2012; Koetz et al., 2008; Melgani and Bruzzone, 2004).

SVM tries to separate two classes by fitting an optimal hyperplane to the training samples in the feature space. The distance between closest training samples and the hyperplane, called margin, defines the cost function. Minimizing both cost function and the error of the inseparable training samples indicate the optimal hyperplane (Bruzzone and Carlin, 2006). A penalty parameter C controls the amount of the misclassification for non-separable samples. This is the only parameter to tune in linear SVM, however, for linearly inseparable cases, a kernel function transforms the original data into a higher dimensional space. A Gaussian radial basis function (RBF), in which the width of Gaussian function is controlled by the parameter γ, is widely used as a kernel in remote sensing applications of SVM. With a proper parameterization of the kernel it provides the best separating hyperplane (Koetz et al., 2008).

In this study, we used a multiclass SVM classifier with a RBF kernel. Although SVM was originally developed as a binary classifier (Vapnik, 1998), it was extended to classification of multiple classes using either "one against all" (OAA) or "one against one" (OAO) strategies (Foody and Mathur, 2004). The OAA approach employs a set of binary classifiers to separate each class from the rest. The winning class is the one that receives the highest discriminant function values. In contrast, the OAO strategy involves all possible pair-wise SVMs, in which two classes were compared against each other. Therefore n(n-1)/2 SVMs are produced for each vector, resulting in 28 SVMs in our study, having 8 classes in total. The summation of the SVMs for each vector (or pixel) then indicates its final class to assign (Melgani and Bruzzone, 2004). Although in comparison with other classifiers the SVM is less sensitive to the class imbalance problem (Japkowicz and Stephen, 2002), the OAO provides a good opportunity to balance the number of training data during the classification (Sun et al., 2007). Since the reference data in our study does not follow a uniform distribution, we used the OAO approach to avoid the class imbalance problem. Applying a five-fold cross validation during training, optimum pairs of (C, γ) were determined. For this, γ was tuned between 0.25 and 2.5, when C ranged from one to 100. The datasets were classified using the MATLAB-implemented interface of the LIBSVM package (Chang and Lin, 2011).

4.3.4 Accuracy assessment

A cross-tabulation of the classification results against the validation dataset provides the confusion matrices. Due to differing size of the reference ITCs, neglecting the area of the crowns distorts the validation results. Therefore, we decided to cross-compare the classification results and the reference crowns in a pixel-by-pixel approach, resulting in

more accurate confusion matrices. The matrix-derived metrics kappa coefficient in form of percentage (K), producer's (PA) and user's accuracies (UA) were used for the accuracy assessment. This factor takes into account the entire confusion matrix instead of simply the diagonal elements, making it more suitable for comparison of different classification results (Pignatti et al., 2009). PA and UA were then analyzed to find those species that benefit most from the combined datasets.

A McNemar's statistical test was used to evaluate the significance of differences between SVM classification results (Jones et al., 2010b). This non-parametric test is based on comparing the calculated standardized value against tabulated values (Foody, 2004). The calculated p-values then were compared with a significance level of 5% for all possible pairs of the classification results.

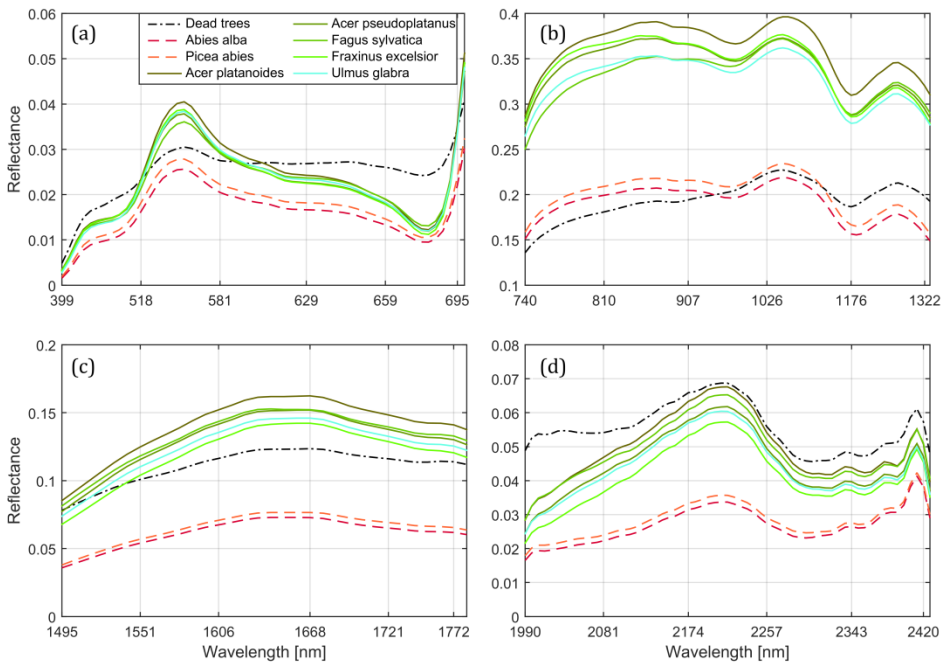

Fig. 4.2. Average spectral signature of each species based on the validation set in the visible (a), near infrared (b) and shortwave infrared (c, d) ranges.

4.4 Results

Fig. 4.2 shows the average spectral signature in the four parts of the spectrum, i.e. VIS, NIR, SWIR1 and SWIR2, for the different tree species present in our study area. Although two groups of the broadleaf and conifer species seem separable from each other, similarities are very high among all the broadleaf species as well as among the two conifer species. The ALS-derived structural features also exhibit a condensed pattern; however, in

some features (e.g. *int_top*, ΔIP_{10} and ΔIP_{60}) the species seem to be apart from each other (Fig. 4.3).

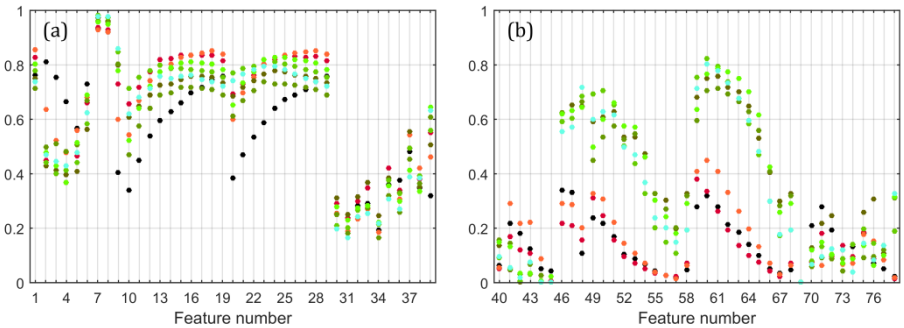

Fig. 4.3. Average ALS-derived structural features for each species from leaf-on (a) and leaf-off (b) datasets. Feature numbers are explained in Table 3 .Color schemes follow those of Fig 4.1.

4.4.1 Selected features

The result of the PCA indicates that the intrinsic dimensionality of the IS and ALS data is 24 and 58, respectively. These values were chosen as upper limits for the number of features in the feature selection process. Fig. 4.4 presents the results of the feature selection, as applied to the IS data only. The 24 selected top-ranked features are accumulated in the NIR plateau (740-940nm), apart from one single band in the SWIR region. The highest rank (81%) was achieved with the band at 775 nm.

When combining all structural and spectral features in the feature selection process, a total number of 78 features were selected, in sets of 58 and 24 features from the top-ranked ALS-derived features and IS-derived features, respectively. Fig. 4.5 shows the location of the selected features in the spectrum alongside the number of the structural features. The top-ranked spectral features are now better distributed across the spectrum, with some hotspots in the shorter wavelengths of the VIS (413-500 nm) and SWIR2 (1990-2132 nm) parts. However, the highest rank (71%) is still placed at 775 nm.

Regarding the ALS data, almost all of the leaf-on features were selected (33 from 39), and only 50% of the intensity percentiles (IP_{30}, IP_{40}, IP_{50}, IP_{90} and IP_{100}) and one of the point densities features (PD_2) were not included. Differential features were chosen less (only 25 from 39), in particular *Δveg_length* and *Δveg_ratio* were not included as well as two point densities features (ΔPD_2, ΔPD_9). In addition, the half of both height percentiles (ΔHP_{10}, ΔHP_{30}, ΔHP_{40}, ΔHP_{60} and ΔHP_{70}) and intensity percentiles (ΔIP_{20}, ΔIP_{30}, ΔIP_{40}, ΔIP_{90} and

ΔIP$_{100}$) were rejected. *veg_length, int_1* and *layer_no* reached highest ranks regarding the leaf-on features, while *ΔIP*$_{10}$, *ΔIP*$_{60}$ and *Δint_1* are the top-ranked ones from the differential structural features.

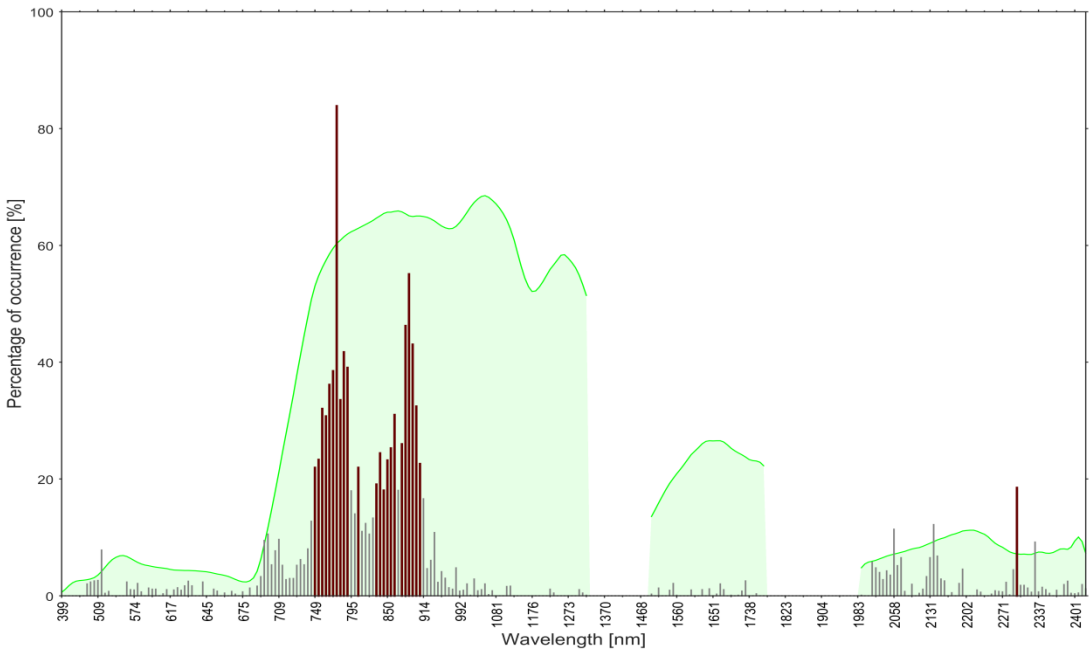

Fig. 4.4. Occurrence of the selected bands from IS data, superimposed with an average spectrum of a beech tree. The rank of feature (%) refers to the frequency of selected bands in all SFFS iterations. Gray columns show the rank of all contributing feature, whereas brown color indicates 24 top-ranked bands.

4.4.2 SVM classification

Using the entire 241 spectral bands of the IS data along with the 78 ALS-derived features increases the computation time by a large amount. Besides, the PCA results show that the 24 first principal components (PCs) of the IS data contain 99.9% of the original information. Therefore, we decided to use the 24 primary PCs, termed ISPC, instead of all the APEX spectral bands. Considering this point, we ended up with seven datasets as described in Table 4.4. The selected spectral features using the PBA and ITC approaches resulted in ISPC$_{(PBA)}$ and ISPC$_{(ITC)}$ sets, with 24 features in each. Applying the same approach for the structural features also provided two 78-feature datasets, ALS$_{(PBA)}$ and ALS$_{(ITC)}$. Stacking the two datasets together, resulted in two combined datasets each containing 102 features (ISPC+ALS$_{(PBA)}$ and ISPC+ALS$_{(ITC)}$). Lastly, IS+ALS$_{(ITC\text{-}SFFS)}$ is the dataset which includes the best of the selected features from both spectral and structural sets (see section 4.5.1), containing 82 features.

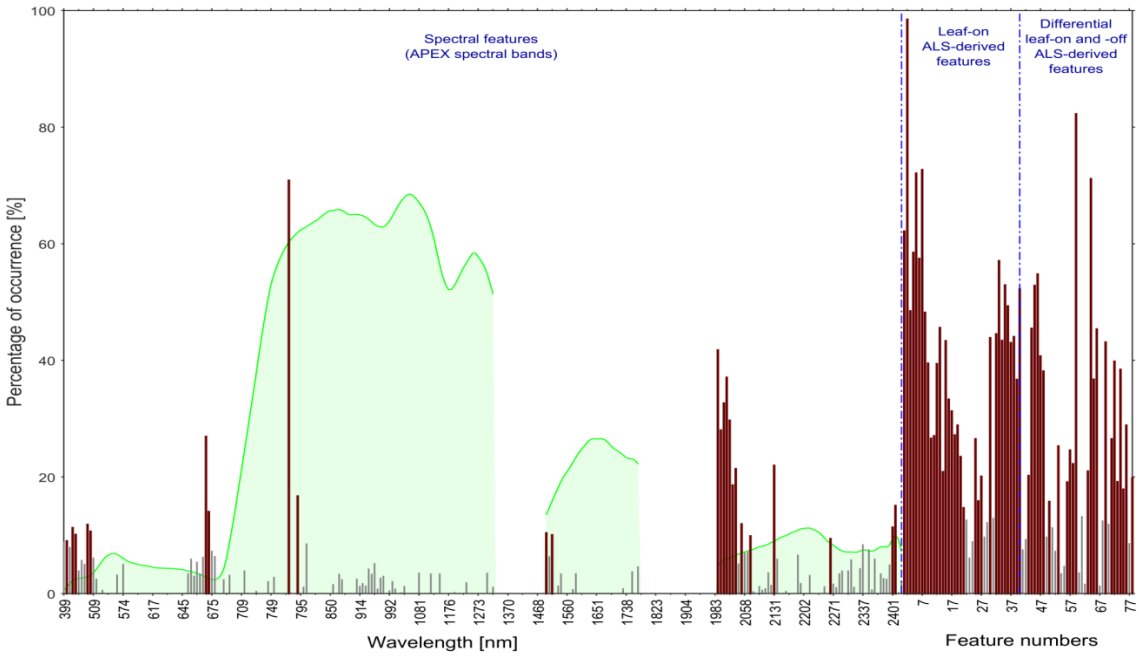

Fig. 4.5. 82 Top-ranked spectral and structural features (brown columns), selected from the combination of IS and ALS data. Gray columns show the rank of each contributing feature. Feature numbers (ALS, left) are detailed in Table 4.3.

Table 4.5 provides the accuracies of the SVM classification results. Using the IS data with the pixel-based spectral features ($ISPC_{(PBA)}$) resulted in a kappa accuracy of 64.4%, while aggregating to ITC level ($ISPC_{(ITC)}$) yielded in +11.1% accuracy improvement. Considering only ALS-derived features, $ALS_{(PBA)}$ achieved the lowest accuracy (K=42.8%), however, applying the ITC-based approach on the structural features ($ALS_{(ITC)}$) resulted in an increase of 33% of kappa (to 75.8%).

Table 4.4

Classification datasets comprising different combinations of spectral and structural features.

Dataset name	IS-derived features	ALS-derived features	Description
$ISPC_{(PBA)}$	24		Area-based extracted spectral features from the first PCs of the IS data.
$ISPC_{(ITC)}$	24		ITC-based extracted spectral features from the first PCs of the IS data.
$ALS_{(PBA)}$		78	Area-based structural features derived from ALS point cloud.
$ALS_{(ITC)}$		78	ITC-based structural features derived from ALS point cloud.
$ISPC+ALS_{(PBA)}$	24	78	Combination of $ISPC_{(PBA)}$ and $ALS_{(PBA)}$
$ISPC+ALS_{(ITC)}$	24	78	Combination of $ISPC_{(ITC)}$ and $ALS_{(ITC)}$
$IS+ALS_{(ITC\text{-}SFFS)}$	24	58	Combination of the selected features from ITC-based aggregated spectral bands of APEX (241 bands) and structural features derived from ALS point cloud.

In the case of combined IS and ALS datasets, the map from the pixel-based approach $ISPC+ALS_{(PBA)}$ was less accurate (K=68.1%) than the ITC approach (K=84.8%).

Nevertheless, the IS+ALS$_{(ITC\text{-}SFFS)}$ provided results with a kappa accuracy of 90.3%, which is the highest among all the datasets. When comparing using the ITC approach with the PBA for all datasets, the increase in kappa accuracy over ISPC+ALS$_{(PBA)}$ were found to be +16.7 and +22.2 for ISPC+ALS$_{(ITC)}$ and IS+ALS$_{(ITC\text{-}SFFS)}$, respectively.

Table 4.5

Class-specific comparison of classification accuracies (Producer's and User's accuracies) as well as overall performance (Kappa accuracy).

Class No.	Species name	Accuracy	ISPC (PBA)	ISPC (ITC)	ALS (PBA)	ALS (ITC)	ISPC+ALS (PBA)	ISPC+ALS (ITC)	IS+ALS (ITC-SFFS)
1	Dead tree	Producer's	82.6	92.7	52.1	25.0	92.3	100.0	100.0
		User's	95.0	95.0	62.5	85.0	90.0	100.0	97.5
2	European silver Fir	Producer's	69.5	83.7	64.2	85.2	68.5	93.7	91.0
		User's	56.9	78.0	58.7	63.0	64.6	81.1	90.9
3	Norway spruce	Producer's	64.2	70.4	56.7	70.0	60.7	76.5	90.7
		User's	62.8	74.6	42.3	74.4	55.9	99.8	87.5
4	Norway maple	Producer's	30.6	48.9	0.0	64.6	66.7	80.0	60.0
		User's	13.1	26.2	0.0	60.7	23.8	66.7	100.0
5	Sycamore maple	Producer's	47.5	54.5	68.3	86.5	59.1	72.9	89.4
		User's	44.3	52.7	20.5	70.7	64.5	88.6	92.7
6	European beech	Producer's	81.5	90.4	62.9	89.1	85.2	95.3	100.0
		User's	91.2	93.8	88.4	95.3	93.1	96.8	99.7
7	European ash	Producer's	79.8	84.9	56.5	85.4	80.9	94.9	98.5
		User's	75.1	82.2	42.7	83.5	74.7	78.9	85.0
8	Wych elm	Producer's	25.9	37.1	0.0	27.8	32.9	28.0	30.9
		User's	25.9	44.4	0.0	12.3	32.1	34.6	63.0
		Kappa	**64.4**	**75.5**	**42.8**	**75.8**	**68.1**	**84.8**	**90.3**

4.4.3 Significance test

The pairwise comparison of classification results with the McNemar's test shows, that the differences between all the results are highly significant ($p<0.0001$), except the differences between ISPC$_{(PBA)}$ and the results from two of the fused datasets (Table 4.6). The difference observed between ISPC$_{(PBA)}$ and ISPC+ALS$_{(PBA)}$ is still significant (though very low; $p<0.05$), whereas the difference between ISPC$_{(PBA)}$ and ISPC+ALS$_{(ITC)}$ is not significant ($p<0.1$).

4.4.4 Among species comparison

Based on the results of the significance test and because the pixel-based extraction of spectral and structural features showed lower accuracies compared to the ITC-based counterparts, we neglected them for the accuracy analysis among different species. In addition, the number of samples is very different for PBA and ITC approaches, potentially making a comparison for species differences biased. Hence, changes in both PA and UA were computed for each species based on the results of the ALS$_{(ITC)}$, ISPC+ALS$_{(ITC)}$ and

IS+ALS$_{(ITC-SFFS)}$, and the accuracies achieved using the ITC-based spectral features (ISPC$_{(ITC)}$) were used as the reference (Fig. 4.6).

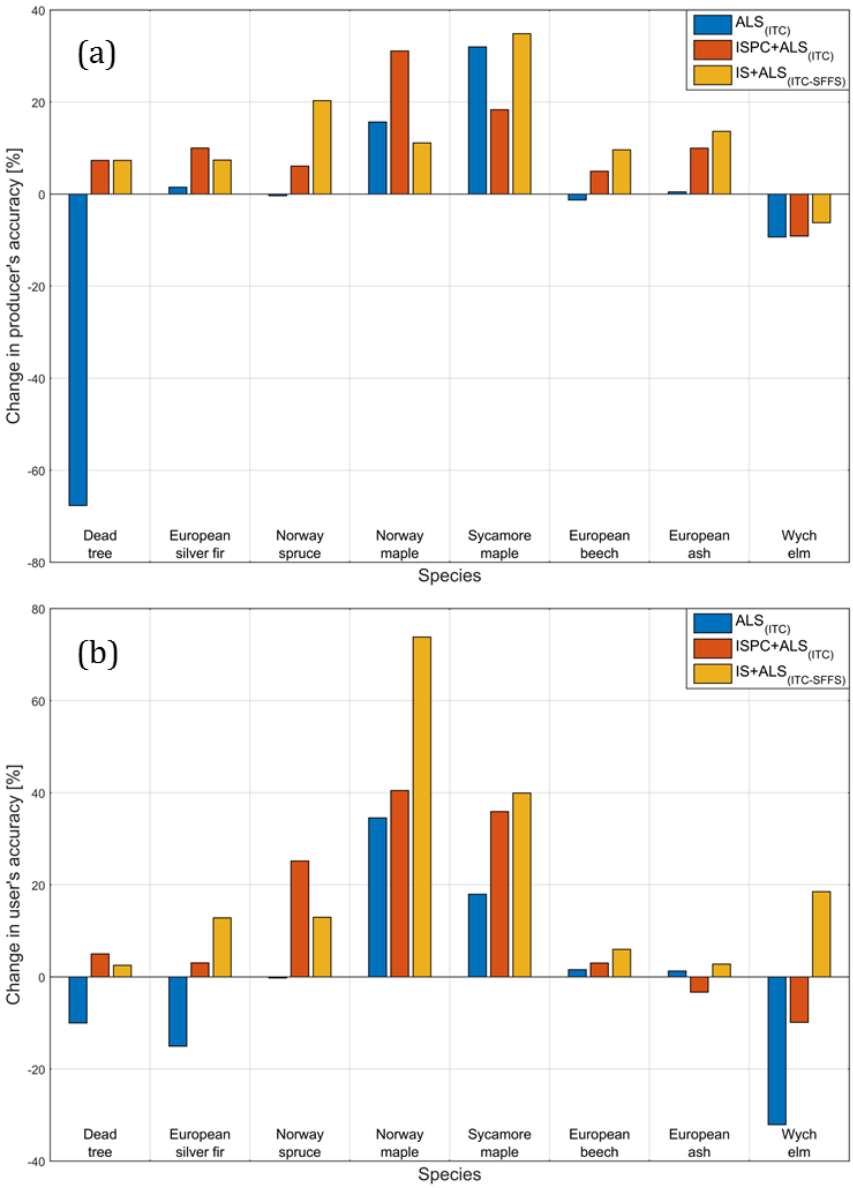

Fig. 4.6. Relative differences in producer (a) and user (b) accuracies of ITC-based datasets, based on ITC spectral features forming the baseline.

Classifying the species using ALS$_{(ITC)}$ dataset resulted in a decrease of both PA and UA for dead trees (PA=-67.7%; UA=-10%) and Wych elm (PA=-9.3%; UA=-32.1%). Contrary, we found an increase of these accuracies for Norway maples (PA=+15.7%; UA=+34.5%) and Sycamore maple (PA=+32%; UA=+18%). Minor changes were observed for European beech (PA=-1.3%; UA=+1.5%) and ash (PA=+0.5%; UA=+1.3%), which are likely too small to be of significance.

Adding structural features to the ITC-based spectral features increased the PA for almost all classes, except Wych elm (PA=-9.1%). A decrease of UA was observed for European ash (UA=-3.3%) and Wych elm (UA=-9.9%).

The fusion of the selected spectral and structural features ($IS+ALS_{(ITC\text{-}SFFS)}$) resulted in an improvement of PA for all species and an increase of UA was observed for all classes, but Wych elm (PA=-6.2%).

Table 4.6

McNemar's test results (|z| values and p-values) for all pairs of the datasets. If not indicated otherwise, the P-values are <0.0001.

	$ISPC_{(ITC)}$	$ALS_{(PBA)}$	$ALS_{(ITC)}$	$ISPC+ALS_{(PBA)}$	$ISPC+ALS_{(ITC)}$	$IS+ALS_{(ITC\text{-}SFFS)}$
$ISPC_{(PBA)}$	5.586	5.754	1.812	1.101 (p<0.05)	1.179 (p<0.1)	3.619
$ISPC_{(ITC)}$		7.236	5.167	5.116	5.370	3.040
$ALS_{(PBA)}$			5.347	6.117	5.761	7.108
$ALS_{(ITC)}$				2.595	2.243	4.494
$ISPC+ALS_{(PBA)}$					1.577	3.936
$ISPC+ALS_{(ITC)}$						3.936

4.5 Discussion

Our results show that using IS data only, a discrimination of classes is only achieved at the species group level (e.g. conifer and broadleaf), but not at the level of single species in our study area. On the other hand, the not very distinct patterns of the leaf-on ALS-derived features explains the low performance of ALS data for discrimination of the tree species, however, differential (leaf-on - leaf-off) features show a clear separation between two groups of broadleaf and conifer trees (Heinzel and Koch, 2011; Kim et al., 2009). Therefore, the synergistically use of ALS and IS information is necessary for a superior classifying of the trees at the species level, particularly in a mixed dense temperate forest.

Comparing the kappa accuracies of the different datasets (Table 4.5) shows that aggregating the source data to ITC level not only improves the species classification for ALS and IS data separately, but also for their combination. This improvement, was expected for IS data (Clark et al., 2005) and fused datasets (Dalponte et al., 2014). However, the significant improvement of the kappa accuracy for ALS data when working at ITC level (33%) is considerable. Even though the classification accuracy of the IS data is much higher than the ALS data in the pixel-based approach, switching to ITC based

aggregation closes the gap between the two methods. It appears as if adding the spatial information of the tree crowns to the ALS features compensates for lacking the discriminative power of the spectral information. In this study, we used UAV-derived ITCs for the aggregation within datasets, due to large errors originating from automatic segmentation of the crowns based on both ALS and IS data. While for the latter the low spatial resolution of the image data will likely remain to be a problem, recent advances of the ALS based ITC segmentation should provide promising levels of accuracy for ITC delineation (Hu et al., 2014; Jing et al., 2012a), even for complex ecosystem as the temperate mixed forest used in this study. In case such methods can provide accurate crown outlines, it will result in a superior species classification in dense forests using ALS data alone.

The highest kappa accuracy observed in this study was a result of the fusion of selected IS and ALS features in an ITC approach. Although this dataset used less features than ISPC+ALS$_{(ITC)}$ without feature selection, its higher performance shows that the neglected features did not contribute to an improved classification, but merely deteriorated the overall accuracy. Comparing the three combined datasets indicates that both the methodology (ITC vs. PBA) and a wise selection of contributing features (e.g. selected bands vs. PCs) are critical to get the most out of the ALS and IS data fusion in terms of tree species classification.

Regarding the results of the feature selection applied on the IS bands (Fig. 4.4), the spectral bands with the most discriminative power were accumulated in the NIR plateau, which is known as the most sensitive region to leaf and canopy structure (Kokaly et al., 2009a). Specifically in dense forests, this part of the spectrum is controlled by some of the major structural variables of the canopy (i.e. LAI and leaf angle distribution (Asner, 1998; Thenkabail et al., 2004)). This could indicate that among species structural differences have a larger impact on the spectral signature than biochemical properties in our study site. In the IS based feature selection process, only one band was outside the NIR region, being within the SWIR2 region. Because of the scarcity of the information provided by one single band only, linking this single band to bio- physical/chemical properties of the canopy needs more investigation.

Adding the ALS-derived features to the feature selection entirely changes the selected spectral bands (Fig. 4.5). Now, the selected bands are much more distributed along the entire spectrum. Except for two bands, no previously chosen NIR bands were selected, showing superiority of the ALS-derived structural features over those structure related spectral bands. There is some agreement between these results and the findings of

other researchers, who looked at the most discriminative bands for tree species classification only based on IS data species (Dalponte et al., 2009; Datt, 2000; Fassnacht et al., 2014; Naidoo et al., 2012). However, a quantitative comparison of the results is not possible due to the differences in data, methods and biomes between the studies.

The two selected NIR bands in 775 nm and 790 nm were also chosen, as ALS features were not included. Literature provides little information about these specific spectral bands; they are typically grouped with other NIR wavelengths that are more sensitive to structure, e.g. as done in the studies mentioned above. This indicates that the information provided by these two bands is not only relevant for tree species discrimination, but that they are also independent from ALS-derived structural features.

The 775 nm band at the leading edge of NIR plateau gained the highest score among all IS bands with and without combination with ALS features, thus being of most relevance for species separation. This finding is similar to the results of Schmidt and Skidmore (2003), where 771 nm was found to be the most relevant spectral feature to discriminate different vegetation types.

In the visible part of the spectrum, a few of the selected bands are situated in the blue and red regions, which are well-known to be related to photosynthetic absorption by chlorophyll and carotenoid (Ustin et al., 2009). The selected bands correspond to leaf pigment absorption peaks, located around 433nm and 664 nm (Inada, 1980). Other statistical methods that looked into selection of features from IS data (e.g. stepwise discriminant analysis (Sarrazin et al., 2012) and angle-based band selection (Cho et al., 2010)) have also found that the observed reflectance within the blue and red regions is highly relevant for tree species discrimination in forest ecosystems.

In the shortwave infrared part of the spectrum, more than half of the selected bands are located. Non-pigment leaf constituents, specifically water, nitrogen, cellulose and lignin, generally dominate this region (Clark and Roberts, 2012). These bands often contain dry matter absorption (Jacquemoud et al., 1995) as well as non-photosynthetic vegetation (NPV; Roberts et al., 2004). The selected SWIR bands are clearly corresponding to the absorption features of cellulose, nitrogen and protein content of leaves (Curran, 1989; Kokaly et al., 2009a). These results are well in line with those of Datt (2000) and Fassnacht et al. (2014), where they showed that SWIR bands are good discriminators for tree species classification.

Although other studies (Alonzo et al., 2014; Dalponte et al., 2009; Fassnacht et al., 2014) have found contribution of bands in the green (~500 nm to 600 nm) part of the VIS region, which is known for its chlorophyll-related high relative reflectivity peak (Gitelson

et al., 1996), these bands were not selected in our approach. Chlorophyll concentration has a simple and significant relationship to canopy structural properties of the plants, especially tree height (Kenzo et al., 2006; Rijkers et al., 2000). Since we are using a direct estimation of structural parameters based on ALS data, the bands located in the green region might be outperformed by these features. In addition, according to the resource compensation response of trees, an increase of the chlorophyll content is restricted by hydraulic limitation of tree height (Hubbard et al., 1999). Therefore, in an area with the same ecological conditions and availability of resources, chlorophyll content at the top of canopy may not be a good parameter for tree species discrimination, though this needs more investigation.

Regarding the selected subset of ALS features, it shows that the majority of the excluded features of the leaf-on ALS feature are intensity percentiles. It is well known that ALS intensity in vegetation suffers from an ill-posedness regarding contributions from the size and reflectance of the scatterers within a laser footprint (Morsdorf et al., 2010). This will only be resolved by using true multi-spectral LiDAR designs (Morsdorf et al., 2009; Woodhouse et al., 2011). Thus, with current instrument designs it appears as if IS sensors can make better use of canopy spectral properties compared to ALS systems.

One particular reason for rejecting a large number of variables from the differential structural features is their low absolute value. Variables that do not change between leaf-on and leaf-off conditions (e.g. *Δveg_length*) tend towards zero, and are consequently rejected.

In view of the number and kind of the selected features, every selected spectral band seems to contain some characteristics of the tree species that ALS-derived features cannot provide. In other words, fusion of these selected features makes sure that the approach benefits most from the complementarities of the ALS and IS data.

More detailed study of the PA and UA values reveals some imbalance in the identification of different species (Fig. 4.6). Using only ALS data provided the worst PA and UA, meaning ALS do not provide enough relevant features to detect the tree species, particularly the standing dead trees. Due to the absence of the leaves on these trees for all year, their structure is similar in both leaf-on and leaf-off datasets, rendering the differential ALS-derived features less discriminative. The most informative ALS-derived features for the identification of this class are linked to the vertical dimension of the crown (i.e. *veg_length, veg_ratio* and crown ratio) and to the intensity of the top layer. On the other hand, IS data were successful for the differentiation of photosynthetic and non-photosynthetic parts of vegetation (Asner et al., 2003b; Guerschman et al., 2009).

However, due to the intensive competition for light in dense forests, such as the studied one, shade-tolerant species and understory bushes rapidly occupy the space beneath dead trees. Consequently, the spectral signature of a dead tree is likely to be a mix of the wooden part and the living vegetation in the lower layers of the canopy. Despite the low discriminative power of ALS data for this class, ALS can provide good characterizations of the understory (Hill and Broughton, 2009; Leiterer et al., 2013), resulting in very high classification accuracies when synergistically using ALS and IS data.

With respect to single species, European silver fir and Norway spruce were classified quite accurately with either ALS or IS data alone, but combining the features resulted in a significant further increase of the accuracy. Although these two conifer species are spectrally similar, adding specific ALS-derived features (e.g. *veg_length*) increases the PA accuracy to more than 90%.

Similar to other temperate mixed forests in Europe, both Norway and Sycamore maple occur mostly as scattered understory trees and rarely are dominant. However, Norway maple is less shade-tolerated than Sycamore maple (Nowak and Rowntree, 1990; Wyckoff and Webb, 1996). Consequently, these two species seldom appear in the top layers of the canopy, and thus are less well captured using passive optical sensors (including IS). In addition, we can also infer this by comparing between the number of the ITCs found for maples (particularly Sycamore maple) using aerial photo interpretation and the forest inventory records, which show much more maple trees than our remote sensing based inventory. Therefore, IS data are not able to provide information on these co-dominant species, but the ALS-derived vertical information helps to achieve a comparatively accurate detection. These capabilities of the ALS data are also imparted to the combined data, and consequently, the highest accuracies for the maple species are achieved by fusion of the ALS and IS features.

Although the increase of user- and producer accuracies for the major dominant species (i.e. European beech and ash) using the fused data is not very large, we note a large positive effect on the overall accuracy.

The classification results for Wych elm are very poor and somewhat unexpected. This species is subject to the Dutch elm disease all over Europe, causing an increase of its extinction rate (Coleman, 2009; Röhrig, 1996). The time difference between ALS data acquisition and the forest inventory (3 years) might well be enough for this fungous to convert an alive elm tree to a dead standing tree. Confusion of the Wych elm and dead trees based on ALS features (and logically in the fused feature set) could thus be due to this issue, but further investigation is required.

4.6 Conclusions

This study evaluated the synergistic use of imaging spectroscopy and laser scanning data to improve tree species mapping in temperate mixed forest. We used SVM classification at the product level, where ALS-derived structural variables complemented spectral information of IS in order to classify eight different tree species in addition to standing dead trees.

The most influential spectral and structural features on tree species identification were found using a sequential feature selection method. The results confirmed that ALS-derived structural features outperform the structure related spectral bands (mainly in the NIR region), causing more contribution of the IS bands that are sensitive to major photosynthetic pigments (VIS region) and non-pigment constituents (SWIR regions) in the fused approach. These results show that ALS data provide the required structural information for species differentiation, while IS data provide complimentary biochemical information. Upcoming multi-spectral laser scanners could be optimized towards tree species discrimination based on our arranging of the spectral features, so that the current instruments using NIR wavelengths should be best-complemented additional ones in the blue and red regions of the spectrum.

We studied the performance of tree species classification based on IS-derived spectral features and ALS-derived structural features using both pixel-based and ITC-based approaches. Using an ITC-based aggregation of features improved the capability of the ALS, IS and combined datasets for species classification, however, the accuracy increase for ALS features was the largest. Interestingly, our results suggest that high point density small footprint LiDAR in both leaf-on and leaf-off condition can provide a similar accuracy as hyperspectral data, if accurate ITC polygons are available. Although the current ITC delineation approaches from ALS data provide accurate results in scattered or simple forest ecosystems (e.g. savannas or pure coniferous stands), they do not yet perform as well in dense and complex forests. Recent improvements (Duncanson et al., 2014; Ferraz et al., 2012) of these methods, however, are promising and may allow for using only ALS data for tree species classification in the future.

When comparing the accuracies of three different combinations of ALS and IS data, the highest classification accuracies were achieved by the fused datasets using ITC-based aggregation. The fusion of the features found in the feature selection provided the highest accuracy even with a lower number of contributing features. In addition to overall performance of the classification, which showed the superiority of the fusion approach, we

evaluated as well the users and producers accuracies to find the tree species that benefit the most from the combination of IS and ALS data. Although all species except Wych elm benefited from the fusion, the scattered understory species (i.e. Norway and Sycamore maples) had the highest accuracies improvement.

Future work extending this study could include acquiring additional IS data in leaf-off condition to see whether multi-temporal spectral features can also improve the species differentiation. Furthermore, the methods to delineate ITCs from ALS data itself need to be improved for better performance in complex environments and better applicability in operational (i.e. large-scale) approaches.

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5

Synthesis

5.1 Main achievements

The main achievements of this dissertation are structured according to the publications (chapter 2-4) and their respective research questions detailed in section 1.5.

5.1.1 State of the art of forest characterization using fusion of ALS and IS data

- Which products profit most from the fusion of IS and ALS data?

Among the numerous studies attempting to synergistically use ALS and IS for forest ecosystem studies, we considered 48 peer reviewed articles, which were published in a period of 12 years leading up to 2013. We selected highly cited articles published in this larger time span in addition to most of the newer ones, where their significance could not be judged by bibliographic information.

By classification of all products, have been already estimated by fusing ALS and IS data, five main categories were defined. Landcover maps, AGB, biophysical parameters, GPP/NPP and biochemical parameters are the products that cover most of the published products.

Analysis of the accuracy of the products revealed that landcover maps are profiting the most from ALS and IS data fusion. The pattern of the accuracies clearly shows the achievement of the fusion methods for this product, where either ALS or IS data alone produced lower accuracies (Torabzadeh et al., 2014). This indicates that present approaches for landcover mapping are efficiently making use of the complementary properties of IS and ALS data.

In contrast, current data fusion methods cannot substantially improve the estimation of the biophysical parameters and AGB, in comparison with the same estimations based on ALS data only. ALS systems provide direct measurements of the geometry of the canopy, establishing a more straightforward connection of LiDAR echoes to biophysical parameters (Lefsky et al., 1999). These can be handled by empirical methods, though the indirect link between such parameters and IS signal requires more complicated models. Moreover, signal to noise ratio (SNR) of the IS systems are generally higher in NIR region of the spectrum (Guanter et al., 2015), which is influenced by leaf and canopy structure (Kokaly et al., 2009a).

- Which methods perform best when applied on the combined ALS and IS data?

Similar to many other remote sensing techniques, the methods for fusion of the ALS and IS data can be classified into two main groups: empirical and physically based

methods (Atkinson and Lewis, 2000; Petropoulos et al., 2009). The latter have seldom been implemented so far and their performance is still not optimal for some estimates at canopy level, such as plant area index (le Maire et al., 2008). However involving ALS data overcomes the ill-posed problem of using physical models based on only IS data (Koetz et al., 2007a).

Considering different types of the empirical methods, our analysis illustrates that specially-designed models for IS data, e.g. image classification for species composition mapping, truly adopt ALS data. On the contrary, adding IS data to the existing methods used for ALS data analysis, e.g. regression analysis for AGB estimation, cannot properly use the complementary advantages of both datasets (Torabzadeh et al., 2014). This highlights the essential requirements for product-oriented development of the present models.

Due to the inherent differences between ALS and IS data, traditional classification of data fusion levels (Pohl and Van Genderen, 1998) does not fit here. Therefore, three different levels of data fusion were defined: data-level, product-level and multi-level. Since the ALS point cloud is a vector dataset, they need to be converted to a raster grid to be properly combined with remote sensing images. Accordingly, there is a high tendency by researchers to combine IS and ALS data at multi-level, where potential ALS-derived products are fused with raw IS data.

- What are the main challenges of combining ALS and IS data?

Besides the uncertain co-registration of the datasets, which is a critical issue for using multi-source data in general (McRoberts et al., 2010), IS data represent the information mainly from the top of the canopy, while ALS data replicate structural information within the canopy. This inherent difference between ALS and IS data must be considered in the fusion methods.

Fusion at product-level and multi-level suit for forest assessment, however, the methods for retrieving the products may not fulfil the requests of the fusion methods (Torabzadeh et al., 2014). For instance, 3D radiative transfer models need to be parametrize with detail geometrical information of individual trees. Nevertheless, the approaches for single-tree extraction from nor IS neither ALS data do provide enough accuracy, particularly in mixed forests. The availability of ALS data with high point density, in the last decade, initiated another type of single-tree identification approach based on the ALS point cloud (Koch et al., 2014). They successfully identify dominant trees, however identification methods still need to be developed in order to detect suppressed and understory trees in multi-layered forests. In addition, improving the biophysical and

biochemical retrieval approaches is necessary in order to benefit from the advantages of fusion.

5.1.2 Multi-layered forest exploration at single-tree level

- To what extent can dominated and suppressed trees in lower strata be detected?

Dominated trees in multi-layered forest are barely extracted by traditional methods from ALS data. The raster-based approaches, which use CHM, may accurately identify the dominant trees, but they are not able to retrieve enough information about the dominated trees (Koch et al., 2014). Although using point cloud based methods may detect some of those, the lesser number of laser echoes in the lower layers decreases the detectability of the suppressed trees. To overcome this issue, methods should be adopted for exploiting the full potential of high point density ALS data, which are provided by new LiDAR systems in last few years.

We developed an iterative 3D algorithm that directly uses the ALS point cloud. It sequentially identifies the trees from the uppermost layer downwards, providing a better chance for the dominated trees to be detected. We validated the proposed method in four datasets at individual tree level. In addition to the comparable performance of the method for dominant trees, it identified the suppressed trees by far higher than all previously published single tree detection methods. The method correctly identified 72% of the trees in the lower strata, resulting in an overall detection rate of 81% (Torabzadeh et al., 2015c). It shows that the iterative extracting of the trees facilitates to identify the single trees, likely regardless of the layers they are situated in.

- What are the influences of different canopy conditions on accuracy of the single-tree detection?

The canopy condition is the most important object property that influences the distribution of the LiDAR echoes in an ALS point cloud. Species composition and structural complexity of a forest are the main indicators of the canopy conditions. Accordingly, we tested our method in four different sites, having different ratios of needle- and broad-leaf species as well as different number of strata. Regarding to the structural complexity, two of the sites have simpler vertical structure, i.e. single-layered, while the other sites are multi-layered. In addition, large ranges of stem density and DBH values confirm the high structural diversity of the selected sample sites.

Our findings show that the performance of the method most likely stays constant in terms of the detection rate in different canopy conditions (Torabzadeh et al., 2015c). This

is because of the capability of the algorithm for correctly identifying the suppressed trees, which are the main source of the uncertainty in complex forests in other methods. In other words, the high performance of the proposed method to detect the dominated trees provides stable results, regardless of the variety of the canopy structure and species composition.

5.1.3 Assessment of tree species composition using a combination of IS and ALS data

- What are the most influential spectral bands and structural features for tree species discrimination?

In contrast to combining optical remote sensing data together, it is not possible to fuse ALS and IS data at raw-data level, due to the inherent dissimilarity (pixels vs. points) between the datasets. Further, generating a set of relevant features from ALS (and perhaps IS data) establishes the fusion at product-level. Since each feature is a simplified form of the original data, a proper feature selection method is needed to guarantee to profit the most of the fusion (Dalponte et al., 2012; Ghosh et al., 2014a).

Along with the spectral bands, which are the reflectance values in different wavelengths, we extracted different structural features from both leaf-on and leaf-off ALS datasets. Starting with 319 spectral and structural features, the most influential structural and spectral features for tree species discrimination were found using a sequential forward floating selection method. The results showed that the structural features entirely change the arrangement of the contributing spectral bands. The selected spectral bands are much more distributed along the entire spectrum by adding ALS-derived structural features (Torabzadeh et al., 2015b).

In the visible part of the spectrum, the selected spectral bands are located in the blue and red regions. These regions are known to be sensitive to photosynthetic absorption mainly by chlorophyll a and carotenoids (Gitelson et al., 2005; Ustin et al., 2009). The SWIR part of the spectrum contains more than half of the selected bands. The non-pigment leaf constituents, such as nitrogen, cellulose, lignin and water generally dominate this region (Clark and Roberts, 2012; Kokaly et al., 2009a). Altogether, ALS-derived structural features outperform the structure-related spectral bands (concentrated in the NIR region), leading to a larger relevance for the IS bands that are affected by major photosynthetic pigments (VIS region) and non-pigment constituents (SWIR regions) in the fused approach.

On the other hand, most of the structural features derived from leaf-on ALS data were selected except for a few of intensity percentiles. However, a large number of the differential structural features were excluded, likely because some of the features remain stable between leaf-on and leaf-off conditions. Unlike the selected spectral features, which can be easily interpreted, the reasons for selection of the structural features are unfortunately not so explicit (Torabzadeh et al., 2015a). This asks for more research in the future.

Considering the number and type, every selected spectral band seems to indicate some characteristics of the tree species that ALS-derived features cannot provide. In other words, fusion of these selected features makes sure that our approach benefits most from the complementarities of the ALS and IS data.

- Which tree species profit most from the fusion approach using the selected features?

The resulting high overall accuracy shows the advantages of the method for tree species classification in a mixed temperate forest. However, based on the biophysical and biochemical properties of each species, the increase of the identification rate by using fused data may vary. In light of the detailed improvements for each species a more obvious picture of the fusion method becomes available (Jones et al., 2010b). We consequently evaluated users and producers accuracies to find the tree species that benefit the most from the fusion of IS and ALS data.

Although all the tree species in this study were superiorly discriminated by using fused ALS and IS data, an imbalance in the identification of different species is observed. For instance, we found that the main dominant species, i.e. European beech and ash, were more accurately identified by using the fusion of the selected features rather than ALS or IS data alone. This provided a large positive effect on the overall accuracy. Both conifer species, i.e. European silver fir and Norway spruce, were classified quite accurately with either ALS or IS data alone, but combining the features resulted in a significant further increase of the accuracy (Torabzadeh et al., 2015b).

The results show that ALS data alone does not provide enough relevant features to tree species information in all cases, especially for the standing dead trees and Wych elm. In contrast, ALS-derived features showed to be discriminative for shade-tolerant tree species, i.e. Norway maple and Sycamore maple, while IS data are not able to provide information, because they are likely not associated with surface pixels. Therefore, such scattered understory species had the highest accuracy improvement and consequently profit most from the fusion approach.

- What is the relevance of using single-tree information for tree species classification using IS, ALS and fused datasets?

Tree species can be classified using remotely sensed data by two main approaches: pixel-based and ITC-based (Yu et al., 2006). Despite of the simplicity of the pixel-based approaches (Blaschke, 2010), there is not a natural link between the IS data units, i.e. pixels, and natural components of the forests, i.e. trees. Alternatively, classification of the tree species at the single-tree level can directly be translated to ITC-based forest inventory data (Hyyppä et al., 2008; Vauhkonen et al., 2014). However, ITC-based species identification needs more effort to identify the tree crowns before the classification. Since most of the structural parameters are defined at the ITC level, e.g. height and crown dimensions, extracting the feature form ALS data at this level is more reasonable than pixel-level.

We extracted the structural and spectral features at both pixel and ITC levels to enable the comparison of these particular scales. Comparing the overall accuracies shows that including the ITC information not only advances the species classification for ALS and IS data alone, but also for their combination (Torabzadeh et al., 2015b). Although the improvement was expected for IS data, the significant increase in the kappa accuracy for ALS data when working at ITC level is considerable. It shows that switching to ITC-based methods enhances the relevance of the ALS data for tree species classification. It seems that lack of the spectral information in ALS data can be compensated by adding the spatial information of tree crowns to the ALS-derived structural features.

The highest overall accuracy achieved in our study was provided by using fused ALS and IS data in the ITC-based approach. While, the accuracy of the pixel-based fusion was lower than the one observed for the IS data in ITC-based method (Torabzadeh et al., 2015b). This shows that using pixel-based methods are not the best choice for fusing ALS and IS data in dense forests. Besides, including the spatial information of tree crowns increases the discriminative power of the ALS data, resulting in a significant improvement of the capability of the fused data for tree species identification. Therefore we recommend to use ITC-based classifications for fused IS and ALS data.

5.2 Conclusions

Remote sensing is becoming the most important source to provide information for the quantitative understanding of forest ecosystems at different scales (Kerr and Ostrovsky, 2003; Wulder et al., 2012). This research was motivated by the increasing requests for using two contemporary systems of remote sensing, i.e. ALS and IS, for forest characterization (Asner et al., 2004; Dubayah and Drake, 2000). On the one hand, detailed information on the spectral characteristics of the forest provided by IS data helps to estimate biochemical properties of a forest canopy (Kokaly et al., 2009a; Schlerf et al., 2010). On the other hand, ALS data provide direct three-dimensional measurements of the forest components, improving our knowledge about their biophysical properties (Hyyppä et al., 2008; Morsdorf et al., 2006). Accurate estimation of biochemical and biophysical parameters are an essential need for forest management and ecological models (Johnsen et al., 2001; Nightingale et al., 2004). This leads to a better understanding of the current situation of forested ecosystems (Lefsky et al., 2002) and a better prediction of their responses to boundary factors, such as climate change (Bonan, 2008; Hamann and Wang, 2006), anthropological degradation (Koh et al., 2011) and invasive species (Asner et al., 2008).

Although both IS and ALS data may show great capabilities for assessing simple structured forests, such as sparse and single-layered forests, exploiting them in complex forests, with heterogeneities in species composition, age and structure, they did not succeed on their own (Clark et al., 2005; Leckie et al., 2005). In this thesis, we fused the complementary IS and ALS data to overcome these limitations, particular for complex forests.

Given the large variety of approaches for data fusion, we categorized them based on level, method and their final products. Analysis of the literature reveals that forest species maps are profiting the most from data fusion, where the ALS and IS data are mainly combined in multi-level fashion. In addition to the relevance for forest management (Hall et al., 2003; Ørka et al., 2013), tree species composition is one of the most important indicators for biological diversity in forest ecosystems (Lindenmayer et al., 2000; Puumalainen et al., 2003). Moreover, tree species mapping is one of the main requirements for estimation of other important forest characteristics, such as AGB (Swatantran et al., 2011) and GPP (Schull et al., 2015). Nevertheless, considering the reported accuracies of the species maps shows that a black-box fusion approach does not provide robust results.

Therefore we focused on two techniques that can consolidate the fusion of ALS and IS data for tree species mapping in heterogeneous forests. First, we searched for the influential features, derived from ALS and IS data, that can enhance the complementarity of the data most. Second, we used the spatial information of tree crowns in an ITC-based species classification method, empowering the species discriminability by using the fused data.

Although fusing ALS and IS data can be carried out at raw data level, it will cause losing a lot of information on the inside of canopy that can be delivered by ALS data. Due to retaining all the informative features, multi-level fusion is a better match for these datasets.

In addition, to get rid of the curse of dimensionality (Hughes, 1968) and save computation time and costs, we showed that using a sequential feature selection before fusion of the ALS and IS data, properly selects the most discriminative spectral and structural features for tree species classification. It also prevents data redundancy. In contrast with other statistical approaches, e.g. PCA, it also preserves the original features unchanged during the processing, which is necessary for later interpretation and finding the relations between the selected features and the biochemical/biophysical properties of the vegetation.

In the absence of the ALS data, the most discriminative spectral bands are concentrated in the NIR region of the spectrum, which is known to be influenced by leaf and canopy structures (Kokaly et al., 2009a). Adding the ALS data causes a shift of the selected spectral features to VIS and SWIR regions, which are sensitive to photosynthetic pigments and non-pigment constituents (Curran, 1989; Ustin et al., 2009). This shows that ALS-derived features outperform the structurally related spectral bands and facilitate that other important bands are used. Classification results confirmed the capabilities of the selected subset of the features. Thus we suggest fusing the spectral bands that are sensitive to the biochemical properties of the foliage with the ALS-derived structural features, resulting in higher species classification accuracy.

Trees are the most natural unit in a forest, while pixels are the basic measuring units in optical remote sensing. Using a pixel-based method for forest inventory may succeed in a homogeneous canopy, but it cannot deliver an accurate species map in complex forests (Warren and Collins, 2007). Increasing the structural heterogeneity in forests causes a sharp increase in the amount of mixed pixels (Koetz et al., 2008), in which the recorded signals are composed by different species tree components, shadows and background

(Jiang et al., 2006). In this case, species identification is more applicable at single-tree level, in which all the IS pixels, belonging to a tree, are aggregated to have similar values.

By applying an ITC-based approach for tree species classification in a temperate mixed forest, we found improvements in the capability of the ALS and IS data as well as the fused dataset. Whereas the pixel-based approach could not properly add the complementary ALS features to IS data, resulting in no significant improvement in species identification by using the fused dataset than IS dataset. Nevertheless, for ITC-based species classification, accurate extraction of the single-tree crowns must be performed beforehand.

In addition to tree species classification, estimation of the forest properties at individual tree level is requested for precise forest management and ecosystem studies at local scale (Chen et al., 2012; Duncanson et al., 2015). Small footprint ALS systems, with high point density, provide 3D information of individual trees components (Wulder et al., 2012), suited for single-tree identification (Koch et al., 2014). Spatial distribution of the laser echoes is directly connected to the geometrical properties of trees (Ørka et al., 2009). However, an applicable method must be employed to fully benefit from the data.

Despite the existence of a large number of methods for single-tree extraction from ALS data, the detection rates are still low in heterogeneous mixed forests. The dominated trees are not identified properly in such multi-layered forest canopy, resulting in a biased estimation of forest inventory parameters. Quantitative information about the trees that are situated in lower strata is needed for a better understanding of the forest dynamics (Keane et al., 2001). For instance, assessment of the suppressed and understory trees helps for better modelling of forest fire (Staver et al., 2009) or estimation of succession rate (Falkowski et al., 2006).

We found the solution in applying a 3D iterative approach, in which both tree detection and delineation of the related crowns are simultaneously carried out. This development provides a higher chance for the suppressed and understory trees to be identified.

The superiority of the proposed algorithm in detection of the trees in lower layers not only improves our estimates on the small suppressed trees, which is important for forest growth analysis (Binkley et al., 2010), but also increases the overall performance of the ITC identification. The high accuracies achieved in four different forest sites show the robustness and transferability of the method to other forest ecosystems, because the characteristics of our study sites include a large part of the structural diversity range in European forests (Houston et al., 2011).

This dissertation has shown the benefits and feasibility of fusing ALS and IS data for tree species mapping in dense forests. Together with the spectral bands, the large number

of structural features, derived from ALS data in leaf-on and leaf-off conditions, provides the detailed information on the spectral and structural variability between different species. The feature selection method also allows for obtaining the best subset of the features. Finally, the ITC-based method ensures a spatial aggregation, which is mandatory to fully exploit the complementarity of the ALS and IS data. We conclude that the potential of ALS and IS data can improve our understanding about characteristics of complex forests. By implementing a proper fusion method, we efficiently employed the complementarity of such datasets to map tree species composition. In addition, the new developed three-dimensional algorithm presented promising results on single-tree detection and crown delineation in multi-layered forests, enhancing the biophysical parameters of forests and supporting the fusion method. The presented techniques in this dissertation highlight the way that how ALS and IS data fusion can help to overcome the limitations in characterization of the complex, mixed forests.

5.3 Outlook

For both single-tree identification and tree species classification cases, limited in-situ measurements were available, restricting our studies to relatively small areas. Since the results indicate the transferability of the methods for larger extents, they can be applied at larger scales with more support from cantonal/federal forest organizations in the future.

The requirements of the tree crown delineation algorithm limit its applicability in very steep terrain, particularly in broadleaf-dominated forests. The shape of the crowns is changed during the transformation from DSM to CHM. Therefore, replacing the fixed vertical direction with flexible search directions, based on topography of the forest floor, can make the model more operational in such forests. In addition, including other characteristics of the laser echoes, e.g. intensity, may help to improve the crown delineation. With the increasing use of full-waveform ALS systems and development of multi-spectral laser scanners, additional useful features are expected to be available in the near future.

Beside this, the proposed technique for parametrization fulfils the requirements of the tree identification algorithm, but it may cause some difficulties in more complex forests. Therefore, we recommend a simpler parameterization in the future. For instance, exploiting new technologies for forest inventory, such as terrestrial laser scanning, or integration of other sources of remote sensing data, such as UAV-provided aerial photographs, can resolve the issue of the parametrization.

Although high species classification accuracy was achieved by using multi-level fusion, product level fusion may provide an additional increase, where biochemical parameters of the tree canopies are primarily estimated from IS data and are then fused to the ALS-derived structural features. However, the uncertainties of the IS-derived biochemical properties at canopy level are not as accurate as leaf level, but using 3D physical models promises to fill the gap in the future.

The fused ALS and IS data provided high accuracies for tree species mapping, however unavailability of the IS data in leaf-off canopy condition causes an imbalance between the datasets. Therefore, we recommend to test an additional IS dataset in leaf-off condition to investigate if multi-temporal spectral features can also improve the species classification accuracy.

Last but not least, accurate mapping of tree species composition is one of the essential needs to estimate other high level products of forests, such as GPP and AGB. Fusion of the ALS and IS data at ITC-level provides a unique opportunity for a more precise estimation of these products. However, analysis of the uncertainty propagation is needed to find the best scale of the species information to be efficiently included in the GPP or AGM estimation models.

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Curriculum Vitae

Academic education

2010—2015 **Ph.D.** University of Zurich, Department of Geography, Remote Sensing Laboratories (RSL), Zurich, Switzerland. Thesis: *Forest Characterization by Fusion of Imaging Spectroscopy and Airborne Laser Scanning*.

1999—2001 **MSc** Civil Engineering - Photogrammetry, K.N.Toosi University of Technology, Tehran, Iran. Thesis: *Integration of Optical and Radar Imageries for Precise Land-Cover Mapping*.

1995—1999 **BSc** Civil Engineering - Surveying, University of Isfahan, Isfahan, Iran. Project: *Geodetic Network for Measuring Reservoirs Temporal Displacements – Optimum Design.*

1990—1994 **High School Diploma** Physics and Mathematics, Ebne Sina High School, Hamedan, Iran.

Professional experience

2010—2015 **Research assistant**, University of Zurich, Department of Geography, Remote Sensing Laboratories (RSL), Zurich, Switzerland.

2001—2010 **Lecturer**, Geo-science courses for civil engineering graduate students and Bachelor courses, Bu-Ali Sina University, Engineering Faculty, Hamedan, Iran.

2000—2002 **Staff scientist**, Iranian Space Agency (ISA), Department of Remote Sensing, Tehran, Iran.

Graduate courses and professional training

- Graduate Seminar I & II
- Retreat seminar I & II
- Scientific writing
- Project management
- Principles and theories in geography
- Specialization in Remote Sensing
- Time and self management
- Voice training and presentation I & II

Oral contributions

- ISPRS International Conference on "Sensors and Models in Photogrammetry and Remote Sensing (SMPR)", 2013, Tehran, Iran

- Swiss Geoscience meeting, 2013, Lausanne, Switzerland
- IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2014, Quebec City, Canada.
- IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2015, Milan, Italy.

Publications

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