Towards Automated Forest Mapping

Lars T. Waser, Ruedi Boesch, Zuyuan Wang and Christian Ginzler

Swiss Federal Institute for Forest, Snow and Landscape Research, Zuercherstrasse 111, CH-8903

Birmensdorf, SWITZERLAND

(waser@wsl.ch)

The need for up-to-date and accurate information on forest resources has rapidly increased in recent years. Forest mapping is an important source of information for the assessment of woodland resources and a key issue for any National Forest Inventory (NFI). Nowadays, new perspectives for automated forest mapping are emerging through the latest developments in remote sensing data and techniques.

In this chapter, an overview of current remote sensing data and techniques for mapping woodland and forests, the challenges and requirements for optimization and automation, and the need for validating final products are presented. Special attention is paid to land use - a crucial criterion for forest mapping which, in contrast to land cover, cannot be easily derived from remotely sensed data. Three different approaches for extracting woodland areas (i.e., patches of trees and shrubs) are presented, all of which involve a high degree of automation. Two additional approaches, which are based on NFI forest definitions, are presented. These require the subdivision of woodlands into the classes “used for forestry” and “other use” and implement the criteria “height”, “minimum crown coverage”, “minimum area” and “minimum width”, and land use. Special attention is paid to connecting patches using distance criteria from national forest definitions.

The main points of this chapter are: (1) *forest* needs an exact definition which may differ depending on the country, (2) mapping woodland can be highly automated and is indispensable prior to mapping forests, and (3) forest mapping is now feasible using remote sensing data and techniques, however, it is less automated due to the implementation of a forest definition.

Keywords: remote sensing, 3D point clouds, tree extraction, forest parameters

Glossary:

Airborne Laser Scanning (ALS)

Canopy Height Model (CHM)

Color-Infrared (CIR)

Digital Terrain Model (DTM)

33 Digital Surface Model (DSM),
34 Generalized Linear Model (GLM)
35 Ground Sample Distance (GSD)
36 Individual Tree Crowns (ITC)
37 Interpretation Plot (IP)
38 International Geosphere Biosphere Program (IGBP)
39 K-Nearest Neighbor (k-NN)
40 Light Detection and Ranging (LiDAR)
41 National Forest Inventory (NFI)
42 Normalized Difference Vegetation Index (NDVI)
43 Reducing Emissions from Deforestation and Degradation (REDD)
44 Synthetic Aperture Radar (SAR)
45 Trees Outside Forest (TOF)
46 Vegetation Height Model (VHM)
47 Very High Resolution (VHR)

48

49 **Introduction**

50 This chapter is organized into four main sections: 1) the requirements for automated forest mapping
51 regarding forest definitions, remote sensing data sets and techniques, and existing maps, 2) commonly
52 used data sources and processing techniques, 3) three highly automated approaches for woodland
53 mapping, and 4) two highly automated approaches for forest mapping. The content of each section is
54 briefly summarized.

55 Forest mapping is a critical task because the resulting datasets are fundamental input for a broad
56 range of users and applications, ranging from global environmental change assessment to local forest
57 management planning (see, for example, the **Modelling Wildfire Regimes, and Mapping Insect**
58 **defoliation chapters in this volume**). Precise, up-to-date, and regularly gathered information on the
59 area covered by trees and shrubs is an important basis for assessing woodland resources and
60 understanding the functionality of forests.

61 The need for consistency and the reduction of manual workload are key reasons for automation in
62 forest mapping. Thus, a high degree of automation in the process of assessing woodland is essential for
63 governmental authorities, international reporting (including the Kyoto protocol), activities within the

Reducing Emissions from Deforestation and Degradation (REDD) framework, forest disturbance assessments, and biodiversity and restoration programs. Based on mapped woodland, other forest-related parameters (e.g., forest structure, biomass, and carbon storage) are estimated, which are, in turn, needed for resource management by public and private authorities.

One particular challenge to forest mapping is the fact that the term *forest* is often defined similarly to *woodland* by the remote sensing community. In most studies, a simplified and generalized definition for *forest* is applied, which is mainly based on minimal tree height, minimal tree area, and width and crown coverage, and less on land use according to National Forest Inventories (NFI)s. Thus, besides the availability, processing, and quality of remotely sensed data, in order to map *forest*, an appropriate definition of forest must be applied. The need to clarify the difference between *woodland* and the varying definitions of the term *forest* is highlighted below.

Definitions

The goal of this section is to emphasize the difference between woodland, trees, and forests since a variety of forest-related terms and a wide range of forest definitions exist. Prior to defining the term *forest*, however, a short explanation of the difference between *land cover* and *land use* should be given, since the criteria used to define forests are usually based on their definitions or sometimes a combination of them. Problems arise regarding land use, which, while a key parameter in the NFI definition of forest, is not easily assessable when using remotely sensed data—in contrast to land cover which is assessable.

Usually, *land cover* is distinct from *land use*, despite the two terms often being used interchangeably. In short, land cover indicates the physical land type, whereas land use indicates how people are using the land. For example, a temporarily un-stocked area (e.g., after impacts such as fires, storms, or harvesting) will be identified as a non-forest land cover type when using remote sensing data and techniques, but will in fact maintain its status as a forest land use type within the NFI. According to the Food and Agriculture Organization (FAO) (FAO 1997) *land cover* refers to the physical forms of *land cover* observable from airborne and spaceborne remote sensing data, and to their structure. It includes vegetation (e.g. grassland and trees) which may be natural or planted, and non-vegetated areas (e.g. bare ground, asphalt, and water). One of the major land cover issues is that similarly named categories are often defined in different ways (Alford 1993). For example, areas without trees may be classified as forest if the intention is to re-plant (such as in the UK and Ireland), and areas with many trees may not be labeled as forests if the trees are not growing fast enough (such as in Norway and Finland).

Land use refers to the function of land and how it is used by people, that is, the activities undertaken on it to produce goods and services. *Land use* is characterized by the arrangements, activities, and inputs people undertake within a certain *land cover* type to produce, change or maintain the land. Many *land use* classification systems and programs have been developed worldwide. The most commonly used terms in use include *urban, agricultural, forest, water, and wetlands* (FAO/UNEP 1999). A good overview and more details may be found in Fisher et al. (2005).

Forest

Even though a precise and unambiguous definition of *forest* is indispensable when mapping and comparing forest areas, this is frequently neglected by using a simplified term *woodland* (**Fig. 1**). This term can be used to include both trees and shrubs and is one of the most important parameters in forestry. In most NFI, the estimation of forest cover is a crucial parameter and should therefore be easily understood and reproducible. NFI programs are required to produce timely and accurate estimates for a wide range of forest resource variables for a variety of users and applications. They aim to periodically report the current state of and changes in forests by providing quantitative statistical information on area, species composition, volume, and growing stock. Clearly, the definition of *forest* is also crucial to assess areas of deforestation which refer to areas where a forest has formerly been. Using exactly the same unambiguous definitions of forest over time is essential – otherwise, the stated deforestation cannot be properly understood.

The term *forest* always implies a definition (usually the percentage of area covered by trees, with a minimum area and tree height) - although the commonly used terms *stocked area, tree area* or *area covered by trees* are often handled in a similar manner. To classify an area as *forest* or as *non-forest*, different forest definitions are available which should be defined based on exact geometric terms. Unfortunately, current definitions of *forest* are imprecise in most cases. Differing from country to country, a standardized and generally valid definition is non-existent, since the term *forest* can be defined according to different criteria. Moreover, the definition of *forest* varies depending on the context. For example, there may be differences from a silvicultural, ecological, or legal point of view. According to Lund (2016), over 960 forest definitions exist worldwide, while the minimum thresholds for degree of tree cover in these definitions vary between 5% and 80%.

The FAO of the United Nations has defined *forest* as lands which are larger than 0.5 hectares in area, with a tree cover of more than 10% (FAO 2000, 2001, 2010). In most national and global forest

definitions, the key parameters defining *forest* are height, width or area, and crown coverage. According to Tomppo et al. (2010), tree cover thresholds for forest definition in NFIs range from 10% to 50% among different national definitions. For example, this threshold is 10% for France and Scandinavian countries, 20% for Great Britain, Spain and Switzerland, 25% for the United States, rising to 30% for Austria and New Zealand, and 50% in Germany and Hungary. Even on a national level, *forest* is often defined differently by various authoritative bodies within individual countries. Despite the fact that these measurable items describe land cover, land use cannot be easily calculated out of measurable data. Even in the field, the main use of trees is difficult to determine. Deciding whether extensively used fruit trees, olive trees, or Christmas tree plantations close to a forest's edges belong to forestry land or not is highly subjective.

Figure 1. Woodland in the temporal zone of Switzerland consisting of individual trees and shrubs of different ages may belong to a forest or not - depending on the definition of forest used.

Remote sensing for automated mapping of woodland and forest

Remote sensing used in the forestry sector covers a wide variety of techniques and applications for extracting woodland, and while some have been operational for decades, others have only appeared recently and are undergoing fast development (Koch et al. 2008). Providing consistent, reproducible and up-to-date information on various forest parameters proves to be the main advantage of using remote sensing as a tool for monitoring, for example, in the framework of NFIs, and for mapping purposes, for instance, in national map products.

Traditionally, woodland mapping approaches have been the product of visual image interpretations and delineation of aerial imagery in combination with field visits. Thus, their development is time consuming, and restricted to relatively small areas. In addition, shadow effects limit the exact detection of forest borders or small gaps.

In the two last decades, NFI data has been combined with remote sensing data and techniques (Tomppo et al. 2008, McRoberts et al. 2014) to map *forest* precisely. This has been achieved mostly by extrapolating estimates from field plot samples using the k-nearest neighbor (k-NN) algorithm (Tomppo and Halme 2004). A good overview of remote sensing support for NFIs can be found in McRoberts and Tomppo (2007) and Barrett et al. (2016). While visual image interpretation is quite time consuming and more subjective—which, depending on the experience of the interpreter, may be appropriate for small area applications—mapping *woodland* based on entire satellite images is feasible with high accuracy within short timeframes thanks to highly automated approaches. Existing remote sensing-based forest maps vary in scale (global, continental, pan-European, and national levels), and also in the level of detail (sources of information, forest definition, and target interest groups). While forest stand maps provide very detailed information, forest layers of map products are much more generalized, with scales ranging from a few meters up to 1 km. How accurate and up to date the maps are may vary in both products due to coarse image resolution and a certain time gap between image acquisition and production. Consequently, forest borders, gaps, and areas with close dense forest may not be sufficiently represented to a large degree.

Over the last decade, many at least partly automated forest mapping approaches have been implemented based on remote sensing techniques and data in the framework of research case studies, national forest inventories, and mapping or resource assessment programs. Highly automated mapping approaches that are mostly restricted to relatively small areas have been used in the framework of change detection studies in general (Waser et al. 2008a, Wang et al. 2015), FAO forest definition applications (Magdon et al. 2014), and the assessment of deforestation such as REDD (Gebhardt et al. 2014). Recently, Waser et al. (2015) presented a wall-to-wall forest mapping approach for all of Switzerland incorporating the NFI forest definition.

At the global scale, particularly worth mentioning are the Global Forest Resources Assessment Remote Sensing Survey (FAO 2012) initiated by the Food and Agriculture Organization (FAO), the Global Forest Watch (GFW) (GFW 2016) initiative of the World Resources Institute, the Global Land Cover mapping approach (GLC) (Bartholomé & Belward 2005), the global forest/non-forest mapping initiated by the Japan Aerospace Exploration Agency (JAXA 2016), and the European 2006 Forest cover map (JRC

2016) from the Joint Research Center (JRC). Recently, Hansen et al. (2013) generated a spatially and temporally detailed global forest and forest change map, which provides valuable information for many land use related applications at the regional level. More recently, Schepaschenko et al. (2015) presented a global hybrid forest map approach based on remote sensing data, maps, and FAO statistics, and new global forest/non-forest maps based on ALOS PALSAR data (2007-2010) were developed by Shimada et al. (2014).

Data and Pre-processing

In this section, we review the current state of research and technology required for automated mapping of woodland and forest.

Reference data

Satellite imagery, large mosaics of aerial imagery or a combination of both have become well-accepted sources of landscape information that contribute to the construction of land cover maps. While forest maps are constructed using such images, forest inventory data or derivatives often come from other existing maps. However, these maps are not always sufficiently validated for various reasons. Often, no adequate reference data is available to evaluate maps. The need for reference data and accurate assessment tools for maps that distinguish between the three land cover classes of non-forest, coniferous forest, and deciduous forest is raised in McRoberts (2012). The minimum requirements of reference data sets commonly used for evaluating woodland and forest maps are given in this section. An adequate reference data set can be characterized by the following traits:

- minimal time span between acquisition of reference data and data the mapping is based on
- minimal differences between the reference data and mapping scales
- reproducibility (by different users)
- reliable data source (e.g. from inventory data or field measurements - and not digitized from existing map products)
- representative of the area under investigation (size, dispersion)

The collection of reference data remains time consuming and is the least automated step in the implementation of any mapping approach. In the following sections, examples of practicable and reliable (best practice) reference data sets with pros and cons are presented:

Digitized polygons

In these data sets, acquisition is carried out at the individual tree level and suitable for fine-scale applications and small areas (a few to a few dozen square kilometers), for instance, at stand, local or community levels. In order to be representative of trees within an area of interest, different types of randomly sampled digitized polygons such as tree crowns or crown clusters that belong to entire tree groups anywhere in the woodland—preferably at borders, and in open land as single trees—should be considered. The delineation can be carried out either by digitizing polygons of tree crowns on orthorectified aerial images, or by stereo-interpretation of aerial images. While both methods of collecting reference data can be regarded as very effective—depending on the pre-knowledge and expertise of the interpreter and time availability—the latter depends on the extent of the area to be investigated. **Figure 2** shows examples of these different types of tree and non-tree polygons, which were digitized on true color orthoimages in a study area in Switzerland. While a certain degree of experience is needed on the part of the interpreter, little technical or forest-related knowledge is required. The collected reference data is reliable and reproducible. Depending on the area under investigation, the manual workload can increase rapidly.

Figure 2. Examples of digitized tree and non-tree polygons based on a true color orthoimage in a mixed temperate forest in Switzerland.

Regular point raster

Tree/non-tree decisions at each grid point in a regular point raster is another very effective method for validating mapped woodland or forest. The regular point raster can either cover the entire area of interest or consist of a limited number of regular points at the edges of a regular grid with a larger mesh size. The optimal mesh size depends on the required level of detail, the area of interest, and the time resources available. If the interpretation is based on stereo-images, the regular grid must be extracted from the digital surface model (DSM)—the same one used for the orthoimage generation. A raster point is assigned as non-tree if the cursor is on the ground or within a shadow on the ground. Problems may occur with areas that have shadows if it is not clear where the exact position of the cursor is set. In these cases, each point must be handled consistently for the entire area of investigation, regardless of the assignment decision. In practice, a 10-50 m mesh size is generally most appropriate for small areas of few square kilometers, and up to 500 m for large areas of several thousand square kilometers. **Figure 3** shows an example of aerial image-interpreted tree/non-tree decisions based on a 10 m regular point grid.

The interpreter's requirements for this approach are similar to that needed for the digitized polygons for which little technical and forest-related knowledge is required. Again, the collected reference data is

248 a reliable and reproducible data source. Depending on the area under investigation, the manual
249 workload can increase rapidly.

251 **Figure 3.** True color aerial image-interpreted point raster for the same area with tree/non-tree decisions. The grid
252 has a spacing of 10 m and shadows on the ground are assigned as non-trees.

253 Another example of the regular point raster approach is the stereo-image interpretation of NFI plots,
254 which usually use a much larger mesh size (see **Figure 4**).

Figure 4: Stereo-interpretation of 25 points of a regular raster for tree/non-tree decisions and the distinction between deciduous (flowers) and coniferous trees (stars) on a false color-infrared aerial image (left). The grid has a spacing of 5 m and is part of the 500 m regular raster for stereo-interpretation in the framework of the Swiss NFI (right).

External data sets

Another method is to use external data sets to validate mapped woodlands or forest, either from existing forest-related data sets such as stand maps and tree cover maps, or from side products, such as layers from any kind of available map (thematic and topographic). The latter are often produced in a context different from forestry. Examples include forest border delineation or the identification of forest areas for layers in topographic maps or for layers in thematic maps, such as land cover/land use vegetation maps or maps from CORINE provided by the European Environmental Agency's International Geosphere Biosphere Program (IGBP - an international research program that studies the phenomenon of global change). The disadvantages of using such data sets are manifold. Issues of concern include data set up-to-dateness (they are often old and rarely updated regularly), and the fact that, as side products, they tend to be less accurate and less detailed than digitized polygons or raster points. An example of delineated forest borders identified as a side product within the framework of a project—which aimed at updating the measurement of agricultural area to match registered cadastral surveying in Switzerland— is illustrated in **Figure 5**.

Figure 5. Forest border delineation (yellow line) based on a LiDAR vegetation height model. Large forest gaps are well represented in the true color aerial image, whereas smaller strips of trees or gaps may not be entirely detected.

Remote sensing systems

Before giving an overview of existing remote sensing systems, we first provide a short explanation of passive/active systems and their history in the context of mapping woodland areas. Passive sensor systems measure energy wavelengths of the electromagnetic spectrum that are reflected or emitted by objects on the earth's surface. Active sensor systems send out energy, in waves or pulses, in the direction of interest and record the energy coming back from the surface. One advantage in favor of active sensors is the ability to obtain measurements at any time, regardless of the season or cloud cover. Passive systems are still more common than active systems.

Historically, the first images taken from airplanes date from the beginning of the 20th Century, followed by the initial development of photogrammetry and applications of aerial photography in the 1920s. In the 1950s, as aerial photography became widely used, tree mapping was done by simple delineation or interpretation based on aerial stereo-images, mostly at regional and national levels (Spurr 1960; Gillis and Leckie 1996). Soon after, spaceborne optical systems proved to be particularly useful for mapping and monitoring forests at the national or even global level. Nowadays, the pace of technical

advancement of sensors and platforms is more rapid than ever before. New developments in sensor technology for airborne (digital aerial cameras, hyperspectral sensors, airborne laser scanning) and spaceborne (multispectral sensors, radar, airborne laser scanning) systems, such as greatly increased geometric, radiometric, and spectral resolution, lead to new perspectives for mapping woodland. In the last decade, great progress has been made in 3D remote sensing, including digital aerial stereo imagery, light detecting and ranging (LiDAR), and synthetic aperture radar (SAR) interferometry. The potential and use of currently implemented sensor systems for mapping woodland in general and individual tree species in particular, both passive and active, are described in more detail below. An overview of commercially available and frequently used sensors is given in **Table 1**. Principally, current digital data from any sensor system enables a high degree of automation in the forest mapping approach. The choice of the most adequate data set depends on several considerations such as temporal availability, costs, continuity, and the technical know-how of the operators. For large-area woodland mapping purposes, 30 m Landsat data might be a good alternative regarding costs and availability, since a huge worldwide archive exists. Archived images can be searched and obtained using the LandsatLook Viewer provided by the U.S. Geological Survey (USGS).

To guarantee a homogenous and integral woodland or forest cover map several factors need to be eliminated or at least minimized. First, the time span between the acquisition of data the mapping is based on and that for validation purposes should be minimized. This is an essential point because forest cover usually changes within a few years. Second, external factors (e.g., atmospheric influence, clouds, shadows, dust, and illumination factors such as sun angle and topography) should be reduced. While clouds and shadows might cover the area of interest, dust or illumination effects affect the reflectance of the forest canopy. Both result in a decrease in the accuracy of the mapped areas. Third, the optimal time of data acquisition is during the vegetation period. Thus, phenology is crucial, as certain differences in woodland can be distinguished by remote sensing techniques only within a restricted period, for example, under leaves-on conditions.

Passive systems

Over the past decade, airborne photogrammetric film cameras used to extract individual tree crowns (e.g., Brandtberg 2002) or to extract shrub and tree cover (e.g., Waser et al. 2008b) have been replaced by high resolution digital airborne sensors (Petrie and Walker 2007), which provide higher spectral and radiometric resolution, and are regularly updated and available in almost all countries. Different studies have successfully used digital aerial imagery to extract individual tree crowns (Hirschmugl et al. 2007,

and Chubey et al. 2009), trees and shrubs (Waser et al. 2010), and to generate a countrywide wall-to-wall forest cover map (Waser et al. 2015). Other studies (e.g., Darvishsefat et al. 2002 and APEX 2011) underscore the advantages of using hyperspectral imagery with a spectrum range from 400–2,500 nm and between 100–300 image bands for tree species classifications and fewer for mapping forest.

Over the past 30 years, spaceborne systems have also been successfully used for mapping woodland or forest, resulting in many mapping products (see *Mapping Woodland and Forest on page xy*). There is a broad range of spaceborne systems, including low spatial resolution (GSD 0.5–1 km) satellite systems such as NOAA AVHRR (e.g. Kennedy and Bertolo 2002) and SPOT4-VEGETATION (e.g. Stibig et al. 2004) for global applications, medium-resolution satellites (GSD 10–30 m) such as Landsat TM, ETM+ for national and continental applications (e.g. Keil et al. 1990; Pekkarinen et al. (2009), and ASTER (e.g. Stoffels et al. 2012).

Since the launch of IKONOS at the end of 1999, different series of very high resolution (VHR) satellite images exist (e.g., KOMPSAT-2, ORBVVIEW-3, QUICKBIRD-2, RAPIDEYE, and WORLDVIEW-2) for mapping forest and forest type (e.g. Förster and Kleinschmit 2008, Immitzer et al. 2012, and Waser et al. 2014). With the exception of RAPIDEYE (only multispectral bands with GSD 6.5 m), they provide all spatial resolutions for panchromatic images between 0.5 and 1 m, and for multispectral images between 1.8 m and 6.5 m. New perspectives for woodland and forest mapping regarding temporal and spatial resolution are provided by a group of upcoming new satellite sensors (e.g. WORLDVIEW-3 and Sentinel-2 which carries an innovative wide swath high-resolution multispectral imager at 13 spectral bands). In addition to currently operational programs, there is continuous development of novel observation techniques, methodologies, and technology related to land use and land cover applications at a more scientific level.

Active systems

Approximately fifteen years ago, airborne laser scanning (ALS) generated considerable interest in the forestry sector. Providing 3D information to assess forest conditions has improved from the average forest stand scale to the individual tree scale. In the last decade, ALS has revolutionized the process of automated mapping of forest/non forest and has been frequently implemented (e.g., Næsset 2007; Straub et al. 2008; Eysn et al. 2015). Recently, full-waveform light detecting and ranging (LiDAR) systems have opened new perspectives by providing representations of both canopy profiles and surface topography. ALS campaigns have become more feasible at the countrywide scale, and new technologies have facilitated a more precise mapping of forest (Næsset and Gobakken 2005; Koch et al. 2009;

Lindberg and Hollaus 2012; Straub et al. 2013). A good overview of individual tree cover and extraction using ALS data can be found in Kaartinen et al. (2012). Promising results for the extraction of woodland areas are obtained by combining LiDAR with multispectral images (Wang et al. 2007, Waser et al. 2015) or hyperspectral images (Dalponte et al. 2014).

Radar systems with synthetic aperture radar (SAR) sensors, such as ERS-1, ERS-2, ENVISAT and RADARSAT, have increased rapidly over the last few years, and have been used particularly in tropical regions for the detection of forest gaps or for delineation of forest boundaries (Fransson et al. 2007, Hajnsek et al. 2009). Since this method is unaffected by cloud cover and sun illumination, frequent updates of forest conditions of entire regions are possible (Rosenquist et al. 2007). SAR sensors have frequently been used to detect fragmentation (Dong et al. 2014), deforestation, and entire forest areas (e.g., Wagner et al. 2003, Thiel et al. 2006, Rahman and Sumantyo 2010).

Processing of input data sets

Prior to mapping woodland and forest, input data has to be prepared. The degree of automation possible and the number of steps required for this preparation will vary depending on the input data used and on the chosen mapping approach. The most common steps are briefly described below. From a methodological point of view, improved methods in image processing, automatic generation of DSM using new image matching methods, and image classification based on objects, have been developed in recent years. Meanwhile, computer systems and software packages are fast and typically easy to set up so that application can be made to large areas, for instance, when providing wall-to-wall products.

Pre-processing of image data

Data pre-processing incorporates atmospheric & radiometric corrections of images, stereo-image matching, and the derivation of image features required for forest mapping. Atmospheric and radiometric corrections were originally developed for satellite images, and are frequently and necessarily applied to optimize image quality. The objective of atmospheric correction is to retrieve the surface reflectance (that characterizes surface properties) from image data by removing atmospheric effects that cause absorption and scattering of solar radiation. Radiometric correction is applied to remove radiometric errors or distortions (correction for sun angle and topography). Recently, new software packages also enable radiometric corrections for airborne sensors. For multi-scene applications and for image strips, it is strongly suggested to analyze radiometric corrections at least within—but preferably between as well—image strips from the same acquisition date.

Image based point clouds

Image-based point clouds from stereo-images of airborne sensors are frequently used to calculate a Digital Surface Model (DSM) in the context of forest mapping. In cases where both a digital surface model (DSM) and a digital terrain model (DTM) (e.g. obtained from LiDAR) are available, the mapping can be based on calculating a potential canopy cover by subtracting the DTM from the DSM (see **Figures 6 & 7**). While DSM and DTM on open ground can be derived from both ALS and from stereo-images, DTM generation of forests is restricted to ALS. Point cloud data from images or ALS data have been used operationally to map forest via automated delineation of forest/non forest vegetation (Straub et al. 2008; Koch et al. 2009; Waser et al. 2011, Waser et al. 2015). Enhanced image matching algorithms, such as semi-global image matching (for example in Hirschmüller 2008) or similar multi-image matching methods (Wagner 2011) permit the extraction of woodland with high accuracy and degree of detail (e.g., forest borders and small openings between trees).

To separate non-vegetation objects (e.g. buildings) from high vegetation (tall shrubs or trees), spectral information from aerial images (preferably from the near infrared band) or other types of information extracted from them are used. For example, Ginzler and Hobi (2015) used the normalized difference vegetation index (NDVI) to separate vegetation from non-vegetation areas and produced a wall-to-wall vegetation height model (VHM) for Switzerland in its entirety. Since the near-infrared is crucial for the detection of vegetation, separation problems arise if only true-color images are available. In this case, a canopy height model (CHM) can be used - if stereo-images are available. If only a 3D point cloud from an airborne laser scanning campaign is available, methods of echo-ratio are used to separate vegetation from artificial objects (Eysn et al. 2012).

To summarize, image matching provides essential information—such as height information as shown in Figure 7—about the surface of vegetation. Since it can be done using commercial software packages and carried out semi-automatically, it requires relatively little expert knowledge. More expertise may be necessary to fully understand the algorithms employed.

Figure 6. Example of airborne true-color orthoimage (left) with the corresponding hillshade of the potential canopy cover for a study area in Switzerland (right).

Figure 7. Hillshade of four different height classes obtained from a normalized DSM.

Image segmentation

The extraction of individual trees or groups of tree clusters is needed in the workflow of many highly automated mapping approaches and is often based on image segmentation. In this step, homogeneous image parts are subdivided into smaller patches or partitions. Nowadays, commercially available software packages are widely used making it possible to obtain optimal (according to the requirements of the mapping approach) image segments by iteratively adapting parameters such as the degree of homogeneity and the shape of image objects (Baatz and Schäpe 2000). Successful segmentation is

430 followed by adjusting the size of objects to the scale of the assessment. For example, tree crowns and
431 tree clusters must be adjusted differently when the mapping is set to the individual tree level or to the
432 forest stand level. While image segmentation is carried out with a high degree of automation and is
433 relatively simple using most software packages, problems occur when the area of interest increases.
434 Depending on the level of detail and the spatial resolution of the images, these problems may already
435 arise for areas of a few square kilometers. In such cases, subdividing the area into smaller parts can
436 resolve the issue, but this will increase the required effort in terms of time and handling and
437 consequently result in a loss of automation.

438 Thus, from a practical point of view, operational use on larger areas must be a compromise between
439 the size of the area to be investigated and the level of detail. For example, it may be necessary to
440 proceed at the stand-level scale rather than at the individual tree level. **Figures 8 & 9** illustrate aerial
441 image segmentation at the individual tree level for mixed temperate stands.

443 Figure 8. *True color aerial image of different forest stands in a mixed temperate forest in Switzerland.*

Figure 9. *The same area with the corresponding image objects (different shades of green) after segmentation at the individual tree crown level.*

Image classification

There are several other methods—with varying degrees of automation—of classifying images that are appropriate for mapping woodland areas and forest. Since image classification is crucial to the mapping process, important principles and background information are briefly outlined below.

Over the past decade, a number of significant developments in object-based image analysis—such as multi-resolution image segmentation and the identification of object relationships—have become available for classification purposes. According to Jensen (2005), the general objective of image classification is the automatic allocation of all pixels to land cover classes or specific themes. The most appropriate classification strategy depends on the biophysical characteristics of the research area. These include the topography or heterogeneity of the land cover, the homogeneity of the remote sensing data, the illumination level, the date of acquisition, the training data, the representative samples, and *a priori* knowledge.

Broadly, classification techniques can be categorized as follows:

- supervised: imposing our perceptions on the spectral data. Pixels or image objects are assigned to classes by matching them with spectral properties found in training data sets. Examples include minimum distance algorithms, maximum likelihood, more advanced techniques such as neural networks, fuzzy logic (see **Chapter 6 – Fuzzy Classification of Vegetation for Ecosystem Mapping**), support vector machine and regression techniques.
- unsupervised: spectral data imposes constraints on our interpretation and involves grouping data into categories based on some measure of inherent similarity. Separability of image clusters must be maximized. Class names are assigned to image clusters after classification (for example, k-means).
- parametric: based on probability density functions and the assumption that the data has come from a type of probability distribution (for example, discriminant analysis)
- non-parametric: based on probability density functions and no assumptions regarding the distribution of the data (for example, nearest neighbor)

Mapping woodland and forest is either carried out on entire forest patches or at the individual tree level (Leckie et al. 2003, Chubey et al. 2009). Several studies highlight the advantages of combining

multi-resolution segmentation with object-based classification (Laliberte et al. 2004, Lamonaca et al. 2008, Waser et al. 2012).

In some studies, simple regression techniques were used to extract tree areas (Naesset and Gobbaken 2005) or generalized linear models to assess tree and shrub probability (Waser et al. 2008a and 2008b, 2011), since it is well known that a deterministic representation expressed in terms of a limited number of land cover categories (e.g. trees, non-trees) leads to a loss of information. Still other studies are based on local maxima algorithms (Koch et al. 2009, Dalponte et al. 2014, Eysn et al. 2015) or in combination with a maximum likelihood classifier (Leckie et al. 2003). Examples of other techniques include the use of fuzzy algorithms at the individual tree level (Brandtberg 2002), nearest neighbor techniques (Laliberte et al. 2004), k-means clustering (Reitberger et al. 2006), and region merging techniques (Wang et al. 2007).

An overview of studies that have successfully used remotely sensed data with the methods applied for mapping woodland or forest is provided in **Table 1**.

Table 1. Overview of studies utilizing airborne and spaceborne remote sensing data for mapping forest and woodland. The table provides author references, location, data source, and method used.

Study	Country	Data source	Method*
Brandtberg (2002)	Sweden	Aerial images	FA
Leckie et al. (2003)	Canada	Aerial images	LM /ML
Laliberte et al. (2004)	US-New Mexico	Aerial images	NN
Leckie et al. (2005)	Canada	Aerial images	LM / ML
Naesset and Gobbaken (2005)	Norway	LiDAR	REG
Reitberger et al. (2006)	Germany	LiDAR	KM
Straub et al. (2008)	Germany	LiDAR	REG
Hirschmugl et al. (2007)	Austria	aerial images	RM
Wang et al. (2007)	Switzerland	LiDAR, aerial images	RM
Straub et al. (2008)	Germany	LiDAR	REG
Waser et al. (2008 a& b)	Switzerland	aerial images	REG
Koch et al. (2009)	Germany	LiDAR	LM
Waser et al. (2010)	Germany	aerial images	REG
Waser et al. (2011)	Switzerland	aerial images	REG

Eysn et al. (2012)	Austria	LiDAR	LM
Kaartinen et al. (2012)	Finland	LiDAR	LM, RM, KM
Waser (2012)	Switzerland	aerial images	REG
Dalponte et al. (2014)	Norway	LiDAR, aerial images	LM
Eysn et al. (2015)	Central Europe	LIDAR	LM
Waser et al. (2015)	Switzerland	Aerial images	TH
Dees et al. (1998)	Germany	Landsat	REG
Kennedy and Bertolo (2002)	Europe	AVHRR	REG
Stibig et al. (2004)	SE Asia	SPOT-4	KM
Laliberte et al. (2004)	US-New Mexico	Quickbird	NN
Förster et al. (2005)	Germany	ASTER, SPOT-5	FA
Förster and Kleinschmit (2008)	Germany	Quickbird-2	FA
Pekkarinen et al. (2009)	Europe	Landsat ETM	NN
Hansen et al. (2013)	Global	Landsat TM, ETM	REG

**Methods: Fuzzy algorithms (FA), k-means clustering (KM), k-nearest neighbor (kNN), Linear discriminant analysis (LDA), Local minima / maxima (LM), Maximum likelihood (ML), Nearest neighbor (NN), Regression techniques (REG), Region growing or merging (RM), Quadratic discriminant analysis (QDA), unsupervised (US), thresholds (TH).*

Mapping woodland

This section illustrates three highly automated approaches to mapping woodland in different biogeographical regions in Switzerland. For each approach, the basics of each method, data, results (tables, but especially figures and illustrations), and a discussion of pros and cons are given.

A hierarchical segmentation approach for mapping woodland

The principles of image segmentation are given in the section *Image segmentation*. Mean-shift—a non-parametric statistical method—is a special form of segmentation which was originally presented by Fukunaga and Hostetler (1975) and generalized by Cheng (1995) 20 years later. It is a robust and highly automated algorithm, and is based on a simple iterative procedure that shifts each data point in the feature space (n-dimensions where the imagery variables or canopy height are) to the average of data points in its neighborhood. The algorithm is frequently applied to color images because most of the generated regions can be delineated semantically. The algorithm starts by converting the image data

into a feature space. For each data point, the mean-shift algorithm defines a window around it and computes the mean of the data point. The algorithm associates each data point with the nearby peak as identified by the dataset's probability function. The center of the window then shifts to the mean. The algorithm is repeated until it converges. Finally, each pixel is grouped together based on all corresponding convergence points. Figure 10 shows an example of the resulting segmentation of one false color-infrared (CIR) aerial image with the segmented region borders indicated with yellow lines.

Figure 10. False color infrared aerial image of woodland (left) and the segmented crowns obtained by mean-shift segmentation (right).

This relatively simple technique for most pixel-based tree canopy mapping creates thresholds for either single bands of the image or derived data such as NDVI. Similarly, there are two important thresholds, one of which is the NDVI value and the other is the CHM value. In general, the rule is set whereby a segment is identified as woodland if the mean values of NDVI and CHM of all pixels within one segment are higher than the predefined thresholds. Segments containing shadows, for example, along the boundaries of a woodland, may also include groups of trees. Since these segments can be extracted as woodland, a slight overestimation of woodland is thus obtained. Consequently, a hierarchical segmentation approach is implemented because of the advantages of color-infrared and NDVI images. **Figure 11** shows a hierarchical segmentation method flow chart. The two thresholds ψ are applied to NDVI and λ to CHM data. The segment is classified as wooded-area if its mean values of NDVI and CHM are higher than the pre-defined thresholds. Woodland is then classified using the segments as obtained in *woody1* and *woody2*.

The results produced provide the basis for various forest applications, including the calculation of canopy cover, forest area delineation using explicit definitions and the extraction of gaps in forest

531 masks. Due to the highly automated processing chain, further extended study areas would need to be
 532 investigated in order to verify the different threshold combinations.

535 **Figure 11.** Flow chart of the hierarchical segmentation method implemented to map woodland based on NDVI
 536 and CHM thresholds.
 537
 538

The resulting mapped woodland is illustrated for close forest, open forest, and a mixture of the two in
Figure 12.

Figure 12. Examples of CIR images with different woodland and different types of mapped forests.

Individual tree and tree crown detection

Tree height and crown geometry are two basic woodland features from a remote sensing perspective and complement spectral information with rigid geometry. Numerous highly automated approaches based on ALS or image matching have been proposed to detect individual trees (ITD) and individual tree crowns (ITC). Most of these focus on the reconstruction of the DSM or CHM, which provides a representation of the outer geometry of tree canopies. DSMs from ALS data or from image matching are the starting point for the detection of individual tree crowns and the calculation of tree parameters, such as height and crown diameter. Depending on the available point density of the DSM, the location of individual trees, the shape of tree crowns or the canopy cover, can be estimated with decreasing point density. The average point density mainly controls the selection of an appropriate smooth or coarse shape model. Robust ITD using ALS data requires a point density of 2 points/m² or higher. Most

approaches start by finding a local height maxima in the DSM. For subsequent processing of local neighborhood region-growings (Solberg et al. 2006), height histogram (Kartinen and Hyypä, 2008), watershed (Straub and Heipke 2001) or cluster analysis (Kartinen et al. 2012) methods are used.

In the case of coarser CHMs, tree crown or canopy shape models can be applied, of which the most common shape approximations use an ellipsoid of rotation (Welles and Norman 1991; Nilson and Peterson 1991; Li and Strahler 1992; Li et al. 1995; Kuusk and Nilson 2000; Garcia-Haro and Sommer 2002; Gerard and North 1997; Gerard 2003). Slightly refined models use a combination of a cone on top of a cylinder (Nilson and Peterson 1991; Chen and Leblanc 1997; Kuusk and Nilson 2000), implement a fixed shape model with adaptive diameter (Vosselman 2003) or use a predefined set of fixed shape models (Rutzinger et al. 2010). For low point densities—which are often the case with large DSMs—less sophisticated shape models are required. A very common terrain shape indicator is curvature (2nd derivative, and has been used in many applications for terrain analysis - Zevenbergen and Thorne 1987). The most prominent disadvantages of the curvature feature are the limited neighborhood (3x3 box), the requirement of an interpolated grid, and the fact that it has no fitting with a shape model. Curvature processing often results in a highly overestimated number of tree crowns and is consequently only of limited use.

For example, in Switzerland, 40% of the coverage area of the Swiss National DSM has a point density of less than 1 point per square meter. As a result, robust detection of ITCs is not possible with the shape models discussed above. Consequently, another model is required, which combines local maxima value with a shape fitting approach. The so-called spider-model (**Figure 13**) implements a non-parametric shape description with few global spatial constraints, mainly to avoid finding a suitable parameter set for the processing of a national dataset. In the first step, a local maxima must exist within a 3x3 neighborhood. In the second step, for each of the 8 directions from the center, the slope values are accumulated for each direction independently. Each slope accumulator contains $(n-1)/2$ values, i.e. 4 slope values for each leg of a 9x9 box. Each slope value in the accumulator must be within the limits of 5 - 85 degrees to be considered valid. In this way, horizontal and vertical slope extremes are rejected. If all slope values are valid, the corresponding direction is classified as a canopy leg candidate (invalid legs are dashed in **Figure 13**). If 6 out of 8 canopy legs are valid and radially contiguous, then the area of the 8 slope accumulators will be defined as a canopy patch. The robustness of shape matching is achieved with the non-parametric evaluation of the slope accumulator and the concept of allowed limited local distortions (invalid legs). Using a moving window, the processing of the DSM results in a point cloud of

canopy patch centers. The result of this detection process is defined as a canopy patch, mainly due to the given Swiss DSM's coarse resolution of 1 m.

Figure 13: The Spider-model which combines local maxima and a minimal shape fitting of an individual tree crown. The height classes of an individual tree are indicated in grey to black. The six canopy legs are yellow, of which the two dashed legs are invalid (the cells of these legs are not within the 5 - 85 degree limits).

The presented shape model requires only a few parameters compared to other shape models, which is a clear advantage with regards to the degree of automation, robustness, and parameter evaluation. With the increasing spatial resolution power of future aerial cameras, the spider-shaped model is still appropriate to extract single tree crowns from low quality digital surface models. On the other hand, the lack of a rigid shape model can be seen as a conceptual disadvantage, which occasionally results in the matching of distorted tree canopies. This compromise, however, achieves the desired degree of robustness.

Fractional tree cover approach

The fractional tree cover approach has been applied to several forest ecosystems in central Europe and involves the continuous representation of probabilities (P woodland) that each image segment is a tree/shrub or not. The fractional tree cover approach is based on logistic regression models and is described in detail in Waser et al. 2008a and 2010. The logistic regression model is a special case of the generalized linear model (GLM). The linear result is run through a *logistic function*, which runs from 0 (negative infinity) and rises monotonically to 1 (positive infinity). Tree probability (P woodland) ranges between 0 and 1 for each pixel that belongs to the class *woodland* (for more details, see Hosmer and Lemeshow 2000). Thus, woodland is continuously mapped in detail and is, therefore, particularly useful for detecting single trees, small trees, and shrubs. Waser (2012) reported that a high degree of automation was achieved with the developed methods, and that trees and shrubs were extracted with a correct classification rate (CCR) of 96-99%. Visual image inspection revealed that the fractional cover approach was also accurate in areas with complex forest structures, such as open forest and gaps, afforestation, and fuzzy borders - especially in steep terrain. The fractional tree cover approach consists of four main steps. **Figure 14** gives an overview of the methodological workflow.

Figure 14. Methodological workflow of extracting woodland using logistic regression models.

First, potential tree crowns are segmented (as described in **Image Segmentation** on page xy) and a high-resolution CHM is generated by subtracting the DTM (derived from LiDAR) from the DSM (derived from image matching). Second, geometric features (height, slope) are generated from the CHM, and spectral features from digital aerial images (original image bands, color transformation, and NDVI). Digitized polygons of woodland/non-woodland samples (as described above in the section **Reference Data**) are used as training and validation data. Third, step-wise feature selection is used as an analytical tool to find redundant features which are then excluded from the model. Fourth, the predictive power of the models is then verified by a 10-fold cross-validation process using different combinations of selected features.

Usually, good mapping results are obtained if all tree segments with P woodland probabilities of greater than 0.5 are included. In the case of overestimated woodland—for example because of grassland on boulders which may be wrongly mapped as trees because of their similarity to real trees and shrubs—the P woodland threshold can be adapted accordingly by lowering it, for example, to 0.3.

This must be done after the first run and is strongly dependent on the individual terrain and vegetation characteristics of the area to be investigated. Thus, the fractional tree cover approach enables the averaging out of possible over- and underestimations, and has high potential to successfully extract shrubs and small single trees. The limitations of this approach include constraints regarding full automation, and the potential lack of sufficient reference data, in particular when mapping large areas with time restrictions or when reference data simply does not exist. Applying the latest image matching algorithms may improve accuracy at forest borders and small openings between them by improving the generation of the geometric features. An example is provided from a mountainous test site in central Switzerland (**Figure 15**: photo of the test site; **Figure 16**: true color orthoimage; **Figure 17**: estimated woodland probabilities).

Figure 15. *Example of mountain woodland where the fractional cover is tested from the center of Figure 16 to the south west. Larch, spruce, and shrubs dominate the area.*

Figure 16. A true color aerial image of woodland in the central Alps of Switzerland.

Figure 17. Mapped woodland (trees and large shrubs) for the same area. The higher the probability for trees and shrubs, the darker the color. Small trees are extracted as well.

Forest mapping

As stressed several times in this chapter, in contrast to mapping woodland, forest mapping implies an unambiguous definition for *forest*. Two highly automated approaches are presented here for forest

mapping which are based on merging the wooded areas with *forest* areas using distance and height criteria. Thus, they can be easily adapted to any forest definition. Each approach includes a short description of method, data, results (tables, but especially figures and illustrations), the use of different definitions for *forest*, and a discussion of pros (potential) and cons. The impact of minimum areas, minimum width, crown coverage, the importance of land use definitions, and their impact on forest areas are also discussed. The results derived from these applications are highly dependent on the fundamental input parameters' size, and position of the delineated forest areas.

Moving window approach

A highly automated workflow based on ArcGIS functions implemented in Python scripts was developed to generate a wall-to-wall forest cover map of Switzerland. The approach is based on the four key criteria (1) minimum tree height; (2) minimum tree crown coverage; (3) minimum width; and (4) land use. The description of this approach below was originally published in Waser et al. (2015) and is only partly modified.

Whereas fairly straightforward and automated methods to obtain criteria 1-3 from remote sensing data exist, the land use criterion is not easily assessable when using remotely sensed data. Due the limitations explained in the *Introduction*, the land use criterion cannot be directly obtained from remotely sensed data. Instead, existing map products must be taken into account, which may have a different scale or level of detail compared to the remote sensing data used for forest mapping. The forest mapping approach is suitable for very high resolution data from airborne laser scanning (ALS) or digital stereo aerial images. The moving window approach is highly automated and uses threshold techniques in combination with the three criteria above and a land use definition. Thus, its suitability for NFI purposes is entirely supported by the application of the land use criterion and its high level of detail, especially regarding forest borders and gaps.

An overview of the main steps and input data sets are shown in **Figure 18**. The four key criteria of the NFI forest definition are explained separately and in more detail below. **Figure 18A** shows a vegetation height model (VHM) based on image-based point clouds with a spatial resolution of 1 m – which was derived from aerial image blocks of 0.5 km x 0.5 km (Ginzler and Hobi 2015). **Figure 18B** shows a preliminary forest cover map based on the criteria of the NFI forest definition (minimum tree height, crown coverage, and minimum width). **Figure 18C** shows the application of the land use criterion in order to remove forest on other land (e.g., orchards, urban parks) while adding temporarily unstocked

forests (e.g., wind throw, harvesting). Finally, in **Figure 18D**, the calculated forest cover map that implements all criteria of the forest definition as used in the stereo-image interpretation of the Swiss NFI is shown.

Figure 18. Workflow of the forest cover map implementing the existing Swiss NFI forest definition. (A) image matching, (B) preliminary forest cover map based on land cover and the thresholds and criteria of the NFI forest definition (minimum tree height, crown coverage, and width), (C) removal of forest on other land and addition of temporarily unstocked forests, (D) final forest cover map (source: Waser et al. 2015).

Height

Terrestrial height measurements are often time consuming for several reasons. In dense forests, it is more challenging to see tree tops from the ground than in open forests. Furthermore, broadleaf trees are even more difficult and ambiguous to measure than coniferous trees, because of the round shape of the crown. Height information—measured remotely using active systems such as ALS or passive systems such as stereo images—can be applied to large areas with high densities. Given a precise DTM from an ALS campaign, the height of objects can be calculated by subtracting the DTM from the elevation above

sea level of the surface model. The result is a CHM with a level of detail which depends on the resolution (point density) of the input DTM and DSM.

To separate trees from other woodland, a height threshold, as specified by a particular forest definition, is used. In the Swiss National Forest Inventory, the minimum tree height is set to three meters (see **Figure 19**). In contrast, in most NFIs and the FAO, the definition of forest specifies a higher minimum tree height of five meters. Regardless of the NFI, height is always clearly defined as “height in situ”, which in fact refers to the height a tree may reach under site-specific conditions in the field and not the actual height. In this way, temporarily un-stocked areas (e.g. harvested areas) retain the classification of *forest* in the framework of a forest inventory, but are not detected as forests when using a CHM.

Figure 19. *Stocked areas in the true color aerial image (left). CHM with extracted trees based on the 3-m height criterion as applied in the Swiss NFI (right).*

Crown coverage

For the calculation of crown coverage, a well-defined reference area is essential, which is usually an interpretation area of a fixed size, as used by forest inventories (an area of 50 m x 50 m is used by the Swiss NFI). Alternatively, forest stand maps can be used to estimate canopy cover. Crown coverage is calculated using a moving window approach, with a rectangle of 51 m x 51 m (odd number in order to obtain the center pixel) which almost corresponds to the interpretation area used in the Swiss NFI terrestrial survey and in the stereo-image interpretation. For each center pixel, the proportion of vegetation greater than or equal to 3 m in height inside the window is calculated and the defined minimum crown coverage of 20% (Swiss NFI definition) is applied. Other definitions of *forest* are in the

range of 10-50 % minimum crown coverage. The results vary substantially if different window sizes are applied (see **Figure 20**).

Figure 20. Extracted tree coverage (crown coverage of 0%-red, 100%-green) based on the moving window approach as applied in Switzerland (left). Example of the same subset after applying a minimal crown coverage threshold of 20 % (right).

With this technique, forested area is particularly overestimated at the forest border (see **Figure 21**).

Figure 21. Problems related to the forest area at forest borders within the interpretation area (blue line) when its center (dashed line) is clearly outside the forest (**left**) and exactly at the forest border (**right**). Source: Waser et al. (2015).

Figure 21 (left) illustrates that crown coverage is still 20% at the position of the dashed line, even though the center of the interpretation area is clearly outside the desired forested area as defined by the NFI. After the preliminary forest cover map was generated using the 20% crown coverage threshold, the map was shrunk using morphological functions. The number of pixels for the shrinkage process at a specific position i (XY-coordinates of this pixel) is a function of the size of the interpretation area and the minimum crown coverage threshold as described in equation 1.

$$\text{Number of pixels to shrink}_i = \text{window size} \times (0.5 - \text{crown coverage threshold}) \times \text{crown coverage}_i \quad [1]$$

Applying the Swiss NFI forest definition this value is 51 m (window size) $\times$ (0.5-0.2) (20% crown coverage threshold) $\times$ 1 (100% crown coverage at this location inside the forest) = 15.3 pixels (rounded to 15). For the sake of simplification, the crown coverage inside the forest border at any location can be set to 100%, resulting in equation 2.

$$\text{Number of pixels to shrink}_i = \text{window size} \times (0.5 - \text{threshold of crown coverage}) \quad [2]$$

Figure 21 (right) illustrates the example for a 50% crown coverage threshold within the interpretation area. In this case, no shrinkage would be applied.

Minimum area and width

Minimum area and width are two other essential parameters needed for forest mapping. However, both are handled differently by many NFIs. Minimum width is more frequently used to separate areas of narrow tree elements—which do not fulfil the minimum requirements of the forest definition—from clearly defined forest areas. While minimum area is relatively simple to calculate using standard GIS functions, more effort is needed for minimum width. A frequently used method is to place a circle, with the radius of the minimum width inside the stocked area. In this ideal case, the minimum width criteria is fulfilled. If not, another possibility is to calculate these distances with triangulation by setting the length of the minimum triangle to the required width threshold. In the given example (Figure 22 on the left), narrow tree groups below the minimum width of 25 m were removed using morphological functions while preserving the shape and size of larger objects. The forest cover map was first shrunk by half of the minimum width of the forest definition and then expanded by half of the minimum width. Parts smaller than the minimum width criterion were assigned the value zero (non-forest) and thus remain non-forest after the expansion of the shrunk forest cover map.

Figure 22 Removal of narrow tree elements from the forest cover map using morphological filters. Forest cover map after applying the crown coverage threshold of 20% (left). Removed narrow elements (circles) in the expanded forest cover map with half of the minimum width threshold (right) (Source: Waser et al., 2015).

Land use

Since the land use criterion could not be obtained from the VHM or from aerial images, it was implemented using the respective cover from the Topographic Landscape Model (TLM) (for more details see Swisstopo 2016). It is superior to the currently available CORINE 2006 land cover (CLC2006) with respect to the level of detail and updating, and is the best available proxy for the *forestry* land use. Two classes from the TLM were integrated into the present forest mapping approach: the land cover class *closed forest*—which is actually a land use class—to compensate for temporarily unstocked forests, and the land use class *orchards* and *settlement* to eliminate *forest* area on other land uses. In contrast to the three other criteria, additional manual work was necessary since the exact forest definition applied in the TLM is not entirely clear. Both TLM land layers were visually checked and polygons that were obviously wrong or too generalized were manually deleted.

Distance criterion approach

Another often used approach for forest mapping is based on the distance criterion. The approach is highly automated and aggregates point clouds from both image matching or ALS to forest layers within a spatial grouping process as described below. Similar to the moving window approach, the three criteria of height, minimum width, and minimum crown coverage are used from the forest definition. Thus, in the first step, the height criterion of greater than 3 m based on the VHM according to the Swiss NFI forest definition is applied to the woodland. **Figure 22** gives an overview of the distance criterion approach.

Figure 22. Overview of the methodological workflow of the distance criterion approach based on Delaunay triangulation and alpha-shapes.

In the first step, the two criteria of minimum crown coverage and minimum width/area from the NFI forest definition are obtained indirectly using the distance criterion as described below. The previously extracted centers of individual tree crowns (> 3 m) are connected in a non-overlapping mesh using Delaunay triangulation based on a distance criterion (e.g., minimum width of 25 m as defined by the Swiss NFI). In the second step, the shape of the point sample on its surface is reconstructed using alpha shapes. The alpha shapes define a piecewise linear curve around the meshed points. The resulting alpha hull (**Figure 23 on the right**) surrounds the tree crown centers and avoids the overestimation of forest area resulting from the overinclusion of empty areas (Mottus et al. 2006; Vauhkonen et al. 2012; Edelsbrunner 1995).

Figure 23. *The principle of convex and alpha hulls (red line) of points belonging to tree crown centers. Based on the distance criterion, a tree crown lies within a certain distance from its neighbors.*

The triangulation of point clouds and the calculation of the alpha hull is closely related to the problem of correct connectivity within a given point cloud (**Figure 24**).

Figure 24. *Convex (green boundary) and alpha (red boundary) hulls of tree crown centers*

The definition of an appropriate connectivity distance is a crucial point. For the Swiss NFI, this distance corresponds to a minimum width of 25 m. The required control of connectivity can be achieved by a preliminary triangulation with a strict distance constraint. Thus, points within a certain distance metric ($< 25\text{m}$) belong to the same object, and only for these points will the alpha hull be calculated (regions A, B and C in **Figure 25**). The maximum distance is required for all three vertices within each triangle. Therefore, linearly aligned points (narrow tree areas such as tree rows, single trees) do not meet the requirements for a spatial object (region E in **Figure 25**). If the distance is too great from surrounding points, topological holes will be created (region D in **Figure 25**). Thus, forest gaps and clearings are well extracted.

Figure 25. Triangulation with the distance-constraint and alpha hulls (red lines) of tree crown centers (dots) with a true color orthoimage as background. Calculated alpha hulls for points within dense forests (A), forest aisles (B), and open forest (C). The building is extracted as a topological hole (D). Tree rows are not extracted due to their linear point alignment.

Grouping methods for forest data are strongly related to the application-defined requirements for connectivity and generalization. This approach makes it possible to control the distance- and shape-related grouping process with only two parameters, and can therefore be easily adapted for a wide range of forest applications. Triangulation enables a more appropriate handling of the spatial distribution of point data compared to cluster approaches. For some applications, it could be necessary to use weighted point data, mainly when specific features of forest data are much more important than spatial distributions (e.g., diameter, health status).

Lessons learned

Nowadays, most existing forest cover maps are still the product of visual interpretation of aerial or satellite images with automation mostly restricted to the processing the input data. While only a few of these automated methods are currently operationalized and applied to large areas, most have been tested within the framework of case studies.

In this chapter, the potential of remote sensing data and techniques towards automated woodland and, in particular, forest mapping has been illustrated. The presented approaches are promising and, because of their automation potential, superior to existing approaches. Because they make use of airborne or spaceborne sensors, and optical data sets can be applied entailing lower costs and less complex data processing and handling, they can be regarded as state-of-the art, and may be used to gather accurate up-to-date information on forest areas at different scales, including small wooded patterns and single trees. The most likely interest groups that could benefit from the presented mapping approaches are public or private authorities with environmental or forest-related concerns, private environmental agencies, forest districts, private forest owners, and NFIs.

The approaches illustrated here are straightforward from a methodological point of view (well-defined input and output data, with several processing steps), facilitating handling at the operational level and not only at the case study level. They are also highly automated and applicable to larger areas. However, each of the illustrated approaches still consist of steps that need some manual adaptation of parameters. This applies both regarding the processing of data sets, such as the segmentation of images, and the checking of existing training data, or, if not available, the generation of such training data (e.g., digitizing polygon samples).

Automation is reduced when mapping forest is entirely based on a NFI definition, less because of the calculation of geometric parameters (minimum height, minimum crown coverage, and minimum

width/area), but more because of the implementation of a land use criterion. The latter may require the appropriate collection of relevant land use information.

From a technical point of view, current handling of large data sets is no longer a problem. In theory, processing and data storage can be done using standard personal computers. However, for wall-to-wall forest cover maps, multi-core computers with large physical memories are recommended. This is not only in order to minimize processing time but also to optimize and speed up each step of the applied mapping approach because most software packages enable the use of clusters for faster calculations.

There are, however, several significant constraints that remain. First, the implicit term *forest* is not always correctly used by the remote sensing community and is confused with *woodland*, since it only comprises a minimum height criterion. Thus, prior to the use of any mapping approach, unambiguous definitions of forest and non-forest are indispensable. Regardless of the applications, the FAO definitions seem to be reliable. Problems regarding automation increase for cross-border mapping approaches because harmonization of existing forest definitions are additionally necessary. Manual interactions and processing steps are also required, such as merging different remote sensing data sets, and harmonizing different forest definition criteria (minimum height, crown coverage and width/area).

A second area of concern is the implementation of a *land use* criterion, which, in turn, has an impact on the definition of *forest*. Although remote sensing methods enable woodland mapping, the limitations of forest mapping increase if land use is incorporated. Although land cover can be easily and directly assessed using remote sensing data and techniques, for land use it is less straightforward, requiring a combination of image classification expertise and external knowledge. Interviewing foresters or performing *in situ* field visits of the areas under examination are recommended. Problems also arise if remote sensing-based mapping products are combined with statistically estimated NFI products. In addition to the decreased processing automation, comparisons of the extracted mapped forest areas must be handled with care.

A third concern is that forest mapping may also be challenging because of the huge variety of existing remote sensing data and methods. However, the value of the final map product strongly depends on the requirements of the end user. Thus, in order to maximize automation, a precise understanding of these requirements—that incorporates the end user's needs, budget, availability of training, and the validation, quality, and handling of the remote sensing data must be worked out. In addition, weather conditions (clouds) may also affect the planning process, and a certain degree of flexibility may be needed if alternative data material must be used. Furthermore, the time span between data sets should be kept to a minimum.

A fourth issue is that automation strongly depends on the collection of training data which—although a labor intensive part of the mapping process—will substantially reduce future work by the implementation of existing NFI sample plot data, such as tree/non-tree information (based on stereo-image interpretation), and terrestrial information (obtained from field visits) within the framework of a NFI.

Future perspectives

Technical developments in remote sensing data and collection methods in the near future, and the increasing need and demand for long-term forest cover maps, will further push and improve the automation of such products.

Current trends in spaceborne remote sensing also appear promising in a number of ways for the land use and land cover assessment community. The provision of larger swath-widths in combination with more bands and high temporal resolution (on the order of a few days) will significantly enhance the operational forest monitoring capabilities of entire countries. Sustainability of such applications is currently supported by the Landsat data continuity mission and systems that are being promoted by the European Space Agency (ESA) and the European Commission (EC) Global Monitoring for Environment and Security (GMES) program. The ESA's Sentinels program—which provides dedicated spaceborne satellite missions that address the operational user and institutional needs within the wider European Copernicus (former GMES) initiative—represents a major step forward. Dedicated to Copernicus, Sentinel-1 already ensures the continuity of C-band SAR data collection (planned launch of Sentinel-2 in April 2016, building on ESA's and Canada's heritage SAR systems on ERS-1, ERS-2, ENVISAT and RADARSAT). Full-waveform LiDAR data (as presented in *Mapping Forest 3D Heterogeneity Using Waveform Lidar*) also has great potential. These programs provide high quality 3D information as required by many processing steps in the derivation of CHM or geometric features for forest definitions. Moreover, they are the current standard in many countries and acquired in cycles of 3-6 years.

A higher degree of automation can be achieved by simplifying the methodological workflow using modern machine learning algorithms, scripting, and entire process chains. Focusing on a remote sensing-based derivation of land use by using additional existing information on land use (e.g., from stand maps or forest inventories), can substantially increase the degree of automation for forest mapping. Additionally, newer information and information provided within shorter timespans on the extent of woodland/forest areas by NFIs—which combine terrestrial sampling with remotely sensed estimations—may be used with positive results.

With a higher degree of automation, high-quality forest maps based on remote sensing can be derived more frequently and help provide the latest information on forest resources for entire countries and continents in the future. In turn, retrospective analysis of changes in these areas will become feasible and increasing interest will lead to the development of wall-to-wall forest maps that will become standard in many countries. While future NFIs will be based on both terrestrial surveys and remotely sensed parameter estimations, mapped forest area will play a key role. It is expected that the future of NFIs will be characterized by a complementary combination of diverse types of information and sources of information, such as remotely sensed parameters—e.g., forest cover and trees outside forest (TOF)—enquiries by the local forest service, stereo-image interpretation, and, of course, terrestrial information.

References

- Alford J (1993) Towards a new public management model: beyond "managerialism" and its critics. *Aust J Publ Admin* 52(2):135-148
- APEX (2011) Airborne Prism Experiment. <http://www.apex-esa.org> Accessed 28 March 2016
- Baatz M, Schäpe A (2000) Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. In: Strobl J, Blaschke T, Griesebner G (eds) *Angewandte Geographische Informationsverarbeitung XII. Beiträge zum AGIT Symposium*, Wichmann, Heidelberg, Germany, pp 12-23
- Barrett F, McRoberts RE, Tomppo E, Cienciala E, Waser LT (2016) A questionnaire-based review of the operational use of remotely sensed data by national forest inventories. *Remote Sens Environ*, 174:279-289
- Bartholomé E, Belward AS (2005) GLC2000: a new approach to global land cover mapping from Earth observation data. *Int J Remote Sens* (26):1959-1977
- Brandtberg T (2002) Individual tree-based species classification in high spatial resolution aerial images of forests using fuzzy sets. *Fuzzy Set Sys* 132(3):371-387
- Chen JM, Leblanc S (1997) A four-scale bidirectional reflectance model based on canopy architecture. *IEEE T Geosci Remote* 35:1316-1337
- Cheng YZ (1995) Mean Shift, Mode Seeking, and Clustering. *IEEE T Pattern Anal* 17: 790-799
- Chubey M, Stehle K, Albricht R, Gougeon F, Leckie D, Gray S, Woods M, Courville P (2009) Semi-Automated Species Classification in Ontario Great Lakes - St. Lawrence Forest Conditions. Final Report: Great Lakes - St. Lawrence ITC Project (2005/2008). Ontario Ministry of Natural Resources, January 2009, p 71

966 Dalponte M, Orka HO, Ene LT, Gobakken T, Naesset E (2014) Tree crown delineation and tree species
 967 classification in boreal forests using hyperspectral and ALS data. *Remote Sens Environ* 140:306-317

968 Darvishsefat A, Kellenberger T, Itten K (2002) Application of hyperspectral data for forest stand
 969 mapping. *Int Arch Photogram Rem Sens Spatial Inform Sci* 34 (4)

970 Dees M, Koch B, Pelz D (1998) Integrating satellite based forest mapping with Landsat TM in a concept
 971 of a large scale forest information system. *PFG* 4:209-220

972 Dong J, Xiao X, Sheldon S, Biradar C, Zhang G, Dinh Duong N, et al. (2014) A 50-m Forest Cover Map in
 973 Southeast Asia from ALOS/PALSAR and Its Application on Forest Fragmentation Assessment. *PLoS ONE*
 974 9(1): e85801. doi:10.1371/journal.pone.0085801

975 Edelsbrunner H (1995) Smooth surfaces for multi-scale shape representation. *Lecture Notes in*
 976 *Computer Science* 1026:391-412

977 Eysn L, Hollaus M, Schadauer K, Pfeifer N (2012) Forest delineation based on airborne LiDAR data.
 978 *Remote Sens* 4:762-783

979 Eysn L, Hollaus M, Lindberg E, Berger F, Monnet J, Dalponte M, Kobal M, Pellegrini M, Lingua E, Mongus
 980 D, Pfeifer N (2015) A Benchmark of Lidar-Based Single Tree Detection Methods Using Heterogeneous
 981 Forest Data from the Alpine Space. *Forests* 6:1721-1747

982 FAO (1997) Food and Agriculture Organization. *State of the World's Forests*. Food and Agriculture
 983 Organization, Rome, Italy, 200 pp

984 FAO (1999) Food and Agriculture Organization. *UNEP Terminology for Integrated Resources Planning*
 985 *and Management*. Food and Agriculture Organization/United nations Environmental Program, Rome,
 986 Italy and Nairobi, Kenya

987 FAO (2000) Food and Agriculture Organization. *FRA 2000: On definitions of forest and forest change*.
 988 Working paper 33, Forest Resource Assessment, Rome, 14 p

989 FAO (2001) Food and Agriculture Organization. *Global Forest Resources Assessment 2000 Main Report*.
 990 FAO Forestry Paper 140. FAO, Rome, Italy

991 FAO (2010) Food and Agriculture Organization. *Global Forest Resources Assessment 2010 Main Report*.
 992 FAO Forestry Paper 163, Rome

993 FAO (2012) Food and Agriculture Organization. *Global forest land-use change 1990–2005*. FAO Forestry
 994 Paper 2012, Rome

995 Fisher P, Comber A, Wadsworth R (2005) Land Use and Land Cover: Contradiction or Complement. In: P
 996 Fisher P, DJ Unwin DJ (eds) *Re-presenting GIS*, Wiley, pp 199-209

997 Förster M, Kleinschmit B, Walentowski H (2005) Monitoring NATURA 2000 forest habitats in Bavaria by
 998 the use of ASTER, SPOT5 and GIS data – an integrated approach. In: *Proceedings of the ForestSAT 2005*
 999 *conference*, 31th May – 2nd June 2005, Borås, Sweden

1000 Förster M, Kleinschmit B (2008) Object-based classification of QuickBird data using ancillary information
 1001 for the detection of forest types and NATURA 2000 habitats. In: Blaschke T, Lang S, Hay G. (eds) *Object-*
 1002 *Based Image Analysis*, Springer, pp 275-290

1003 Fransson JES, Magnusson M, Folkesson K, Hallberg B, Sandberg G, Smith-Jonforsen G, Gustavsson A,
 1004 Ulander LMH (2007) Mapping of wind-thrown forests using VHF/UHF SAR images. In: Proceedings of the
 1005 Geoscience and Remote Sensing Symposium, IGARSS 2007, 23-28th July 2007, Barcelona, Spain, pp
 1006 2350-2353

1007 Fukunaga K, Hostetler LD (1975) Estimation of Gradient of a Density-Function, with Applications in
 1008 Pattern-Recognition. IEEE Trans Inform Theory 21:32-40

1009 Garcia-Haro FJ, Sommer S (2002) A fast canopy reflectance model to simulate realistic remote sensing
 1010 scenarios. Remote Sens Environ 81(2-3):205-227

1011 Gebhardt S, Wehrmann T, Ruiz M, Maeda P, Bishop J, Schramm M, Kopeinig R, Cartus O, Kelldorfer J,
 1012 Ressler R *et al.* (2014) MAD-MEX: Automatic wall-to-wall land cover monitoring for the Mexican REDD-
 1013 MRV program using all Landsat data. Remote Sens (6):3923-3943

1014 Gerard F (2003) Single angle, dual angle and multi-temporal viewing: assessing through modelling the
 1015 implications for forest structure variable extraction. Int J Remote Sens 24(6):1317-1334

1016 Gerard FF, North, PRJ (1997) Analyzing the effect of structural variability and canopy gaps on forest
 1017 BRDF using a geometric-optical model. Remote Sens Environ 62(1):42-62

1018 Gillis M, Leckie D (1996) Forest inventory update in Canada. Forest Chron 72(2):138-156

1019 GFW (2016) The Global Forest Watch.
 1020 [http://www.globalforestwatch.org/map/3/15.00/27.00/ALL/grayscale/loss,forestgain?begin=2001-01-](http://www.globalforestwatch.org/map/3/15.00/27.00/ALL/grayscale/loss,forestgain?begin=2001-01-01&end=2015-01-01&threshold=30)
 1021 [01&end=2015-01-01&threshold=30](http://www.globalforestwatch.org/map/3/15.00/27.00/ALL/grayscale/loss,forestgain?begin=2001-01-01&end=2015-01-01&threshold=30) Accessed 28 March 2016

1022 Ginzler C, Hobi M (2015) Countrywide stereo-image matching for updating digital surface models in the
 1023 framework of the Swiss national forest inventory. *Remote Sens* 7:4343-4370

1024 Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz
 1025 SJ, Loveland TR, Kommareddy A, Egorov A, Chini L, Justice CO, Townshend JRG (2013) High-Resolution
 1026 Global Maps of 21st-Century Forest Cover Change. Science 342(6160):850-853

1027 Hajnsek I, Kugler F, Lee SK, Papathanassiou KP (2009) Tropical-Forest-Parameter Estimation by means of
 1028 Pol-InSAR: The INDREX II Campaign. IEEE T Geosci Remote 47(2):81-493

1029 Hirschmugl M, Weninger B, Raggam H, Schardt M (2007) Single Tree Detection in Very High Resolution
 1030 Remote Sensing Data. Remote Sens Environ 110(4):533-544

1031 Hirschmüller H (2008) Stereo Processing by Semi-Global Matching and Mutual Information. IEEE T
 1032 Pattern Anal 30(2):328-341

1033 Hosmer DW, Lemeshow S (2000) Applied logistic regression, 2nd edition, Wiley, New York

1034 Immitzer M, Atzberger C, Koukal, T (2012) Tree Species Classification with Random Forest Using Very
 1035 High Spatial Resolution 8-Band WorldView-2 Satellite Data. Remote Sens 4(9):2661-2693

1036 JAXA (2016) World's First High-Resolution Global Forest/Non-Forest Map.
 1037 http://global.jaxa.jp/article/special/geo/shimada_e.html Accessed 28 March 2016

1038 Jensen JR (2005) Introductory digital image processing: A remote sensing perspective. Prentice Hall,
 1039 Upper Saddle River, New York

1040 JRC (2016) European Joint Research Center JRC. [http://forest.jrc.ec.europa.eu/activities/forest-](http://forest.jrc.ec.europa.eu/activities/forest-mapping/forest-cover-map-2006/)
 1041 [mapping/forest-cover-map-2006/](http://forest.jrc.ec.europa.eu/activities/forest-mapping/forest-cover-map-2006/) Accessed 28 March 2016

1042 Kaartinen H, Hyyppä J, Yu X, Vastaranta M, Hyyppä H, Kukko A, Holopainen M, Heipke C, Hirschmugl M,
 1043 Morsdorf F, Næsset E, Pitkänen J, Popescu S, Solberg S, Wolf BM, Wu J-C (2012) An International
 1044 Comparison of Individual Tree Detection and Extraction Using Airborne Laser Scanning. *Remote Sens*
 1045 *4*(4):950-974

1046 Kaartinen H, Hyyppä J (2008) EuroSDR/ISPRS Project, Commission II “Tree Extraction” Final Report.
 1047 EuroSDR (European Spatial Data Research): Dublin, Ireland, 2008

1048 Keil M, Schardt M, Schurek A, Winter R (1990) Untersuchung und Kartierung von Waldschäden mit
 1049 Methoden der Fernerkundung. DLR-Abschlussdokumentation, Kapitel Auswertung von Satellitendaten,
 1050 pp 71-131

1051 Kennedy P, Bertolo F (2002) Mapping sub-pixel forest cover in Europe using AVHRR data and national
 1052 and regional statistics. *Can J Remote Sens* *28*(2):302-321

1053 Koch B, Dees M, van Brusselen J, Eriksson L, Fransson J, Gallaun H, Leblon B, McRoberts RE, Nilsson M,
 1054 Schardt M, Seitz R, Waser LT (2008) Forestry applications. In: Li Z, Chen J, Baltsavias E (eds) *Advances in*
 1055 *Photogrammetry, Remote Sensing and Spatial Information – ISPRS 2008 Congress Book*, Taylor & Francis
 1056 Group, London, pp 439-468

1057 Koch B, Straub C, Dees M, Wang, Weinacker H (2009) Airborne laser data for stand delineation and
 1058 information extraction. *Int J Remote Sens* *30*(4):935-963

1059 Kuusk A, Nilson T (2000) A directional multispectral forest reflectance model. *Remote Sens Environ*
 1060 *72*(2):244-252

1061 Lamonaca A, Corona P, Barbati A (2008) Exploring forest structural complexity by multi-scale
 1062 segmentation of VHR imagery. *Remote Sens Environ* *112*(6):2839-2849

1063 Laliberte AS, Rango A, Havstad KM, Paris JF, Beck RF, McNeely R (2004) Object-oriented image analysis
 1064 for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sens Environ*
 1065 *93*(1-2):198–210

1066 Leckie DG, Gougeon FA, Walsworth N, Paradine D (2003) Stand delineation and composition estimation
 1067 using semi-automated individual tree crown analysis. *Remote Sens Environ* *85*(3):355-369

1068 Leckie DG, Tinis S, Nelson T, Burnett Ch, Gougeon FA, Cloney E, Paradine D (2005) Issues in species
 1069 classification of trees in old growth conifer stands. *Can J Remote Sens* *31*(2):175-190

1070 Lindberg E, Hollaus M (2012) Comparison of Methods for Estimation of Stem Volume, Stem Number and
 1071 Basal Area from Airborne Laser Scanning Data in a Hemi-Boreal Forest. *Remote Sens* *4*(4):1004-1023

1072 Li XW, Strahler AH (1992) Geometric-Optical Bidirectional Reflectance Modeling of the Discrete Crown
 1073 Vegetation Canopy - Effect of Crown Shape and Mutual Shadowing. *IEEE T Geosci Remote* *30*(2):276-292

1074 Li XW, Strahler AH, Woodcock CE (1995) A hybrid geometric optical–radiative transfer approach for
 1075 modeling albedo and directional reflectance of discontinuous canopies. *IEEE Trans Geosci Remote*
 1076 33:466-480

1077 Lund, H.G. rev*. Definitions of Forest, Deforestation, Afforestation, and Reforestation. Gainesville, V.A.:
 1078 Forest Information Services. [Online] Note this paper has been continuously updated since 1998. DOI:
 1079 10.13140/RG.2.1.2364.9760

1080 Magdon P, Fischer C, Fuchs H, Kleinn C (2014) Translating criteria of international forest definitions into
 1081 remote sensing image analysis. *Remote Sens Environ* (149):252-262

1082 McRoberts RE, Tomppo EO (2007) Remote sensing support for national forest inventories. *Remote Sens*
 1083 *Environ* 110(4):412-419

1084 McRoberts RE (2012) Satellite image-based maps: Scientific inference or pretty pictures? *Remote Sens*
 1085 *Environ* 115(2):715-724

1086 McRoberts RE, Liknes GC, Domke, GM (2014) Using a remote sensing-based, percent tree cover map to
 1087 enhance forest inventory estimation. *Forest Ecol Manage* (331):12–18

1088 Mottus, M, Sulev M, Lang M (2006) Estimation of crown volume for a geometric radiation model from
 1089 detailed measurements of tree structure. *Ecol Model* (198):506-514

1090 Næsset E (2007) Airborne laser scanning as a method in operational forest inventory: Status of accuracy
 1091 assessments accomplished in Scandinavia. *Scand J Forest Res* 22(5):433-442

1092 Næsset E, Gobakken T (2005) Estimating forest growth using canopy metrics derived from airborne laser
 1093 scanner data. *Remote Sens Environ* 96(3-4):453-465

1094 Nilson T, Peterson U (1991) A forest canopy reflectance model and a test case. *Remote Sens Environ*
 1095 37:131–142

1096 Pekkarinen A, Reithmaier L, Strobl P (2009) Pan-European forest/non-forest mapping with Landsat ETM+
 1097 and CORINE Land Cover 2000 data. *ISPRS J Photogramm* 64(2): 171-183

1098 Petrie G, Walker AS (2007) Airborne digital imaging technology: A new overview. *Photogramm Rec*
 1099 22(119):203-225

1100 Rahman M, Sumantyo J (2010) Mapping tropical forest cover and deforestation using synthetic aperture
 1101 radar (SAR) images. *Appl Geomat* 2:113–121

1102 **Reitberger J**, Krzystek P, Heurich M (2006) Full-waveform analysis of small footprint airborne laser
 1103 scanning data in the Bavarian forest national park for tree species classification. In: Koukal T, Schneider
 1104 W. (eds) *Proceedings of the International Workshop 3D Remote Sensing in Forestry*, 14 -15th February
 1105 2006, University of Natural Resources and Applied Life Sciences, Vienna, Austria, pp 218-228

1106 Rosenquist Å, Shimada M, Ito N, Watanabe M (2007) ALOS PALSAR: A pathfinder mission for global-scale
 1107 monitoring of the environment. *IEEE Trans Geosci Remote* 45(11):3307-3316

1108 Rutzinger M, Pratihast AK, Elberink SO, Vosselman G (2010) Detection And Modelling Of 3D Trees From
 1109 Mobile Laser Scanning Data. *Int Arch Photogram Rem Sens Spatial Inform Sci* 38(5), pp. 520-525

1110 Schepaschenko D, See L, Lesiv M, McCallum I, Fritz S, Salk C, Moltchanova E, Perger C, Schepashchenko
 1111 M, Shvidenko A et al. (2015) Development of a global hybrid forest mask through the synergy of remote
 1112 sensing, crowdsourcing and FAO statistics. *Remote Sens Environ* 162:208–220
 1113 Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R, Lucas R (2014) New global forest/non-
 1114 forest maps from ALOS PALSAR data (2007–2010). *Remote Sens Environ* 155:13–31
 1115 Solberg S, Naesset E, Bollandsas OM (2006) Single tree segmentation using airborne laser scanner data
 1116 in a structurally heterogeneous spruce forest. *Photogramm Eng Rem S* 72:1369-1378
 1117 Stibig HJ, Achard F, Fritz S (2004) A new forest cover map of continental southeast Asia derived from
 1118 SPOT-VEGETATION satellite imagery. *Appl Veg Sci* 7(2):153-162
 1119 Spurr SH (1960) *Photogrammetry and photo-interpretation*, 2nd edition. Ronald Press, New York
 1120 Stoffels J, Mader S, Hill J, Werner W, Ontrup G (2012) Satellite-based standwise forest cover type
 1121 mapping using a spatially adaptive classification approach. *Eur J Forest Res* 131(4):1071-1089
 1122 Straub BM, Heipke, C (2001) Automatic extraction of trees for 3D city models from images and height
 1123 data. *Automatic Extraction of Man-Made Objects from Aerial and Space Images*, 3:267-277
 1124 Straub C, Weinacker H, Koch B (2008) A fully automated procedure for delineation and classification of
 1125 Forest and Non-Forest Vegetation based on full-waveform Laser Scanner Data. *Int Arch Photogram Rem*
 1126 *Sens Spatial Inform Sci* 37(8) pp. 1013-1019
 1127 Straub C, Stepper C, Seitz R, Waser LT (2013) Potential of UltraCamX stereo images for estimating timber
 1128 volume and basal area at the plot level in mixed European forests. *Can J Forest Res* 43(8):731-741
 1129 Swisstopo (2016) The topographic landscape model TML. Available online:
 1130 <http://www.swisstopo.admin.ch/internet/swisstopo/en/home/topics/geodata/tlm.html> Accessed 28
 1131 March 2016
 1132 Thiel C, Drezet P, Weise C, Quegan S, Schmullius C (2006) Radar remote sensing for the delineation of
 1133 forest cover maps and the detection of deforestation. *Forestry* 79(5):589-597
 1134 Tomppo E, Halme M (2004) Using coarse scale forest variables as ancillary information and weighting of
 1135 variables in k-NN estimation: a genetic algorithm approach. *Remote Sens Environ* 92(1):1-20
 1136 Tomppo E, Haakana M, Katila M, Peräsaari J (2008) *Multi-source national forest inventory-methods and*
 1137 *applications*. Managing Forest Ecosystems 18; Springer Science and Business Media B.V., Berlin,
 1138 Germany.
 1139 Tomppo E, Gschwantner Th, Lawrence M, McRoberts RE (eds) (2010) *National Forest Inventories -*
 1140 *Pathways for common reporting*, 1st edition. Springer, Berlin
 1141 Vauhkonen J, Seppänen A, Packalén P, Tokola T (2012) Improving species-specific plot volume estimates
 1142 based on airborne laser scanning and image data using alpha shape metrics and balanced field data.
 1143 *Remote Sens Environ* 124: 534-541
 1144 Vosselman G (2003) 3d reconstruction of roads and trees for city modeling. *Int Arch Photogram Rem*
 1145 *Sens Spatial Inform Sci* 34(3), W13, Dresden, Germany, pp 231-236

1146 Wagner W, Luckman A, Vietmeier J, Tansey K, Balzter H, Schmullius C, Davidson M, Gaveau D, Gluck M,
 1147 Le Toan T, Quegan S, Shvidenko A, Wiesmann A, Yu JJ (2003) Large-scale mapping of boreal forest in
 1148 SIBERIA using ERS tandem coherence and JERS backscatter data. *Remote Sens Environ* 85(2):125–144
 1149 Wang Z, Boesch R, Ginzler C (2007.) Color and LIDAR Data Fusion: Application to automated forest
 1150 boundary delineation in aerial images. *Int Arch Photogram Rem Sens Spatial Inform Sci* 36(1)
 1151 Wang Z, Ginzler C, Waser LT (2015) A novel method to assess short-term forest cover changes based on
 1152 digital surface models from image-based point clouds. *Forestry* (88):429-440
 1153 Waser LT, Baltsavias E, Ecker K, Eisenbeiss H, Feldmeyer-Christe E, Ginzler C, Kuchler M, Thee P, Zhang L
 1154 (2008a) Assessing changes of forest area and shrub encroachment in a mire ecosystem using digital
 1155 surface models and CIR-aerial images. *Remote Sens Environ* 112(5):1956-1968
 1156 Waser LT, Baltsavias E, Ecker K, Eisenbeiss H, Ginzler C, Kuchler M, Thee P, Zhang L (2008b) High-
 1157 resolution digital surface models (DSM) for modeling fractional shrub/tree cover in a mire environment.
 1158 *Int J Remote Sens* 29(5):1261-1276
 1159 Waser LT, Klonus S, Ehlers M, Kuchler M, Jung A (2010) Potential of Digital Sensors for Land Cover and
 1160 Tree Species Classifications - A Case Study in the Framework of the DGPF-Project. *PFG* 2:141-156
 1161 Waser LT, Ginzler C, Kuechler M, Baltsavias E, Hurni L, (2011) Semi-automatic classification of tree
 1162 species in different forest ecosystems by spectral and geometric variables derived from Airborne Digital
 1163 Sensor (ADS40) and RC30 data. *Remote Sens Environ* 115(1):76-85
 1164 Waser LT (2012) Airborne remote sensing data for semi-automated extraction of tree area and
 1165 classification of tree species. Dissertation, ETH Zürich, 153 p. [http://e-](http://e-collection.library.ethz.ch/view/eth:6087)
 1166 [collection.library.ethz.ch/view/eth:6087](http://e-collection.library.ethz.ch/view/eth:6087)
 1167 Waser LT, Kuchler M, Jütte K, Stampfer T (2014) Evaluating the Potential of WorldView-2 Data to Classify
 1168 Tree Species and Different Levels of Ash Mortality. *Remote Sens* (6):4515-4545
 1169 Waser LT, Fischer C, Wang Z, Ginzler C (2015) Wall-to-Wall Forest Mapping Based on Digital Surface
 1170 Models from Image-Based Point Clouds and a NFI Forest Definition. *Forests* 6:4510-4528
 1171 Zevenbergen, LW, and C. R. Thorne, LW (1987) Quantitative Analysis of Land Surface Topography. *Earth*
 1172 *Surf Processes* 12:47-56
 1173
 1174