2.5 ECOSYSTEM STRUCTURE

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2.5.1 Background

In Skidmore et al. (2016) vegetation height is being mentioned as one of the remotely sensed (RS) EBV candidates (RS-EBVs) to support the measurement of the EBV 'Ecosystem structure', next to ecosystem distribution, fragmentation and land cover. While land cover is already provided as operational RS product since the eighties, vegetation height is currently the most challenging one, and subject of this chapter. Vegetation height can be measured directly or indirectly by specific RS sensors and could support the EBV 'Ecosystem structure' with very valuable information. Vegetation height is valuable information next to spectral information to identify specific ecosystem or vegetation types. Moreover, the regular mapping of vegetation height would help to identify processes such as shrub and tree encroachment. Noss (1990) describes a hierarchy concept for monitoring biodiversity. The different levels of information that can be considered for biodiversity and ecosystem studies are the compositional, structural and functional aspects at multiple levels of ecological complexity. Vegetation height is as such an important component of the structural aspect of ecological complexity. Bunce et al. (2013) emphasises the importance of habitat/vegetation structure in the development of biodiversity policies in their own right and also demonstrates that there are strong links between vegetation structure and occurrence of species. Only a very small part of all species can be monitored while vegetation structure or habitats, as a flagship for many species, are easier to be monitored. As mentioned before, vegetation height is an important aspect as well in the definition of an ecosystem or habitat type. For instance, measuring forest degradation from space requires an agreed definition of a forest. Without a clear definition it is hard to compare forest distribution across large areas or across time. In the 1990s, the Food and Agriculture Organization of the United Nations (FAO) defined forests as ecosystems with a minimum of 10% canopy cover of trees or bamboo associated with wild flora. That definition was updated in 2005 with a minimum height of 5 meters for trees. Such shifts influence perceptions of where forests are, as well as where they used to be (Skidmore et al. 2016).

To enable the measurement of vegetation height, remote sensing can play a crucial role and can become an important information source. Early applications pertained to the stereoscopic visual interpretation of aerial photography were a great step forward in vegetation monitoring. More recently, satellite imagery with a large range of spatial and temporal resolutions is available and enables applications for entire ecosystems. Traditional vegetation mapping methods that use visual interpretation of aerial photography and in combination with field surveys are, and have always been, working very well. But they are often also labour intensive and temporal frequencies are low, while policies are currently demanding higher temporal monitoring frequencies. Therefore, also terrain and nature managers are looking for alternatives that can support the mapping and monitoring of vegetation in more efficient ways.

New developments in remote sensing such as the use of very high resolution (VHR) satellite imagery (passive optical as well RADAR active sensors) and LiDAR (Light Detection And Ranging) techniques, next to the use of UAV platforms (Unmanned Aerial Vehicles), can help to speed up the process of vegetation mapping and monitoring. Nevertheless, som e of these methods are all relatively new and requires ecologists and remote sensing experts to collaborate closely and review the newest methods and technologies. Therefore this chapter discusses the potential use of passive optical sensors, RADAR and LiDAR technology for measuring vegetation height to support the monitoring of the EBV 'ecosystem structure'. See also chapters 4.1 and 5.1 for more information on current and upcoming Earth observation missions, respectively.

2.5.2 Passive sensor technology

Several studies have employed passive satellite sensor data to estimate vegetation height. A wide variety of features have been extracted from passive sensors of spatial resolutions ranging from several centimetres to some tens of metres. For example, the panchromatic channel of Worldview-1 imagery with a 0.5 m spatial resolution has been used to estimate the height of pine forest stands (Mora et al. 2013). The stand median grey-level value and the 90% percentile of crown size distribution in combination with a *k*-nearest neighbour model provided the highest accuracies in terms of the coefficient of determination (R^2 = 0.69) among other predictors and models. Donoghue and Watt (2006) approximated mean vegetation height for plots of 0.02 ha using directly the mean reflectance values from spectral bands of Landsat Enhanced Thematic Mapper Plus (ETM+) and IKONOS images. In particular, a curvilinear regression model with a power function was used to model mean height as $y = ax^b$, where y represents the mean height in a plot, x the mean reflectance, and a and b are real values. They managed to estimate the height of Sitka spruce plantations with R^2 values up to 0.87. Spectral indices from Landsat images, i.e. the Normalized Difference Water Index (NDWI) and the Optimized Soil Adjusted Vegetation Index (OSAVI), have been used to estimate the height of soybean and corn (Anderson et al. 2004) using the biomass development of the crop as main variable. Ahmed et al. (2015) used Landsat time series to approximate the height of conifer and deciduous forest stands. A random forest approach proved more effective than a nonlinear multiple regression model, with Time Since Disturbance (TSD) being the most discriminatory predictor for young (< 30 years) stands and the Normalized Difference Vegetation Index (NDVI) and the Tasseled Cap transformation Angle (TCA) the best ones for mature (> 30 years) stands. In a recent study, Hansen et al. (2016) evaluated Landsat 7 and 8 data both individually and in synergy to estimate tree height in an extensive area in Sub-Saharan Africa. Spectral band reflectance and NDVI values from a large number of images from 2013 and 2014 were collected and sorted for each pixel. Values below the 10^{th} and above the 90^{th} percentiles, i.e. the 20% most extreme values, were discarded. The means for the remaining ranges of values for each image band as well as NDVI were used as predictors in a regression tree approach. Predictors from the integrated Landsat 7 and 8 datasets achieved the lowest Mean Absolute Error (MAE = 2.45 m) suggesting their combined used as well as the potential integration of Sentinel-2 data in future height estimation studies in case LiDAR information is not available or limited. Besides spectral information, texture features extracted from passive sensors have been correlated with vegetation height in several studies. Early studies used simple texture features for the estimation of coniferous tree height, such as the mean (Puhr and Donoghue 2000) and the standard deviation (Franklin et al. 1986) of reflectance values within a 3×3 pixel moving window. Similar features have been calculated from Satellite Pour l'Observation de la Terre 5 (SPOT-5) images and evaluated with different regression models in hardwood and coniferous forests (Wolter et al. 2009). In another study involving SPOT-5 data, a number of first-order and second-order texture features were used together with spectral ones in a tropical forest area (Castillo-Santiago et al. 2010). The variance of the near-infrared (NIR) band in a 9×9 pixel window and the reflectance values in NIR and mid-infrared (MIR) bands were selected as the best predictors by a multiple linear regression model (R^2 = 0.71). Similar second-order grey-level co-occurrence matrix (GLCM) texture features from IKONOS imagery approximated the height of oak, beech, and spruce trees with accuracies up to R^2 = 0.76 (Kayitakire et al. 2006). Chen et al. (2011) used spectral and texture features as well as shadow fraction from a Quickbird image to compare pixel-based and object-based analysis under nonlinear regression. The experimental results from the object-based approach proved more accurate than the pixel-based ones. Instead of a regression problem, as in the previous approaches, vegetation height estimation has also been formulated as a classification problem. In an object-based approach, Petrou et al. (2015) calculated texture features based on local variance, entropy, and local binary patterns from WorldView-2 imagery. The features were used to classify heathland vegetation to six height classes appropriate for habitat studies, ranging from less than 5 cm to 40 m. Filter-based dimensionality reduction and a random forest classifier achieved classification accuracies over 90%, identifying the best performing subsets of features and decreasing the originally extracted features by around 97%.

2.5.3 RADAR technology

RADAR (Radio Detection And Ranging) is an important tool for detecting the structure and height of vegetation because of its ability to penetrate clouds, to provide a signal from the geometric properties of the vegetation and to generate images over large areas. The RADAR signal, backscatter and interferometric phase, depends on the physical structure and dielectric properties allowing an indirect measurement of vegetation structure. Short wavelength RADAR (X- and C-band; ~2 cm and ~6 cm wavelength) only partially penetrates the vegetation / forest canopy and mainly receives a signal from leaves and small branches. In contrast, long wavelength RADAR (L- and P-band; ~23 and ~60 cm wavelength) penetrates the vegetation / forest canopy and the signal is primarily caused by branches and trunks making it more suitable for mapping ecosystem structure and vegetation height (Ulaby et al. 1986; Woodhouse 2005). Since the early 1990s several studies have demonstrated the relationship between RADAR backscatter and vegetation structure and height (e.g. Dobson et al. 1995, Joshi et al., 2015). Interferometric SAR (InSAR) allows a more direct estimation of height and the vertical distribution of vegetation (Florian et al., 2006, Papathanassiou et al., 2008, Treuhaft and Sinqueira 2004). InSAR derives its sensitivity to vertical vegetation structure from the difference in signal of two RADAR receivers separated in space by a known distance, the so called ‘‘baseline’’. The difference between phases of the signal received at the two ends of the baseline can be translated into a topographic height. The topography measured from InSAR depends on the vegetation characteristics and the RADAR wavelength. Shorter wavelengths provide a signal relatively close to the canopy, while longer wavelength penetrate deeper into the canopy to the ground surface (Rosen et al., 2000). Varying InSAR methods exist to detect the forest height. Some studies compare InSAR height with independent measurements of the ground surface (e.g. national surface height maps) (Kellndorfer et al., 2004, Kellndorfer et al., 2006; Simard et al., 2006). A second approach, uses the difference in between multiple wavelengths (e.g. X-band and P-band) to measure interferometric heights at two frequencies. Height is calculated as the difference in elevation between the two measurements (Wheeler and Hensley, 2000, Sexton et al., 2009). More explorative studies make use of polarimetric InSAR (PolInSAR) technology and use both interferometric height and correlation, along with multiple baselines and/or polarizations in retrieving information on the vertical distribution directly (Cloude and Papathanassiou, 1998; Treuhaft and Siqueira, 2000, Kugler et al., 2007, Garestier et al., 2008, Khati & Singh, 2015). Garestier et al. (2008) used a random volume over ground (RVoG) model to detect forest height from single-pass X-and PolInSAR data set using HH and HV channels over a sparse pine forest. Recently, Khati & Singh (2015) successfully demonstrated the use of space-borne PolInSAR data acquired by TerraSAR-X/TandDEM-X for tree height inversion at a pine forest site. The observed RMSE of 7.6 m relates to an underestimation of the tree heights that is caused by the low penetration capabilities of X-band RADAR into to forest canopy. Garestier et al. (2008) and Wang et al. (2016) found that forest height inversion using short wavelength RADAR (X- and C-band) strongly depends on the forest density. While forest height inversion has been demonstrated at sparse boreal forest, the applicability at dense tropical forest is very limited. Long wavelength PolInSAR (L- and P-band) is much lesser affected, however, current provision of long-wavelength PolInSAR data is limited (Wang et al., 2016).

2.5.4 LiDAR technology

The following subsections deal with LiDAR technology from different platforms that all have their own merits for surveying, they concern respectively, manned and unmanned airborne, spaceborne and terrestrial liDAR scanning.

2.5.4.1 Airborne LiDAR

The use of airborne laser scanning dates back to the 1970s. However, their commercial development is traced back to the mid-1990s only. From the perspective of ecological research, LiDAR can be therefore considered as a relatively new technology (Carson et al. 2004). LiDAR was originally introduced to generate more accurate digital elevation models (DEMs) (Evans et al. 2006) but has recently become an effective tool for natural resources applications (Akay et al. 2008). In the process of creating a DEM, only reflections from the ground level are used, and reflections from vegetation are considered redundant. Recent studies with LiDAR data have explored the possibilities to use these redundant vegetation reflections as a new source of geospatial data that can provide fine-grained information about the 3D physical structure of terrestrial and aquatic ecosystems (Geerling et al. 2007). This result can then be applied in forestry, ecological (habitat) mapping and vegetation monitoring (Hyde et al. 2005). Airborne LiDAR provided most of the applications so far, but Terrestrial LiDAR as well as spaceborne and UAV liDAR will provide more and more applications in the future, since they all have their own merits. Scopus[16] presents very well the steep increase in publications per year between 2000 and 2015, respectively from around 10 in 2000 to 400 publications in 2015 (search "LiDAR AND vegetation"). LiDAR is an active remote sensing technique that measures the properties of emitted scattered light to determine the 3D coordinates (x, y, z) and other properties of a distant target (St-Onge 2005; Mallet et al. 2009). To do so, the LiDAR instrument transmits laser pulses and calculates the distance from a target based on energy that is reflected from the target back to the instrument. The time for laser pulses to return back to the LiDAR sensor is used to calculate the distance to the target (Akay et al. 2008). LiDAR provides geometric data but also radiometric data, such as signal intensity, amplitude, and pulse angle (Hall et al. 2005; Evans et al. 2006). The laser camera measurements are combined with the platform's position and altitude data - measured by a differential global positioning system (GPS) and an inertial navigation unit (INU) - identifying the position and elevation of each collected point (Wehr et al. 1999).The "xy" accuracy of the pulse center is typically 0.05–0.5 m, depending on the flying height. The accuracy in "z" is usually better than 0.2 m. Values range from 0.2 m to 1.0 m for flying heights of 1–5 km (Korpela et al. 2009).

[16] www.scopus.com

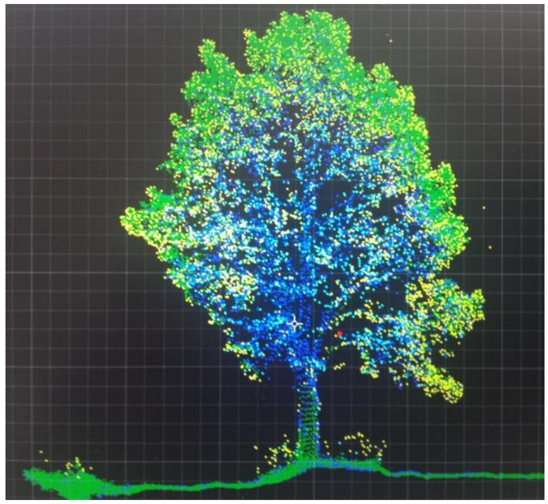

Figure 2.5.4.1.1 Example of a LiDAR point cloud of an individual tree, visualized in 3D, as taken by an UAV LiDAR camera (Acquired with VUX-SYS camera mounted on RiCopter). The colours represent the multiple returns. The first returns are indicated indicated in green and represent leaves or ground, while blues colours represent more the internal woody skeleton or branches of the tree.

So airborne LiDAR offers the possibility to collect structural information over larger spatial extents than could not be obtained by field surveys (Bradbury et al. 2005). LiDAR, in contrast to optical remote sensing techniques, can be expected to bridge the gap in 3D structural information, including canopy shape, number of vegetation layers and individual tree identification at the landscape scale (Graf et al. 2009).

2.5.4.2 UAV LiDAR (drones)

The use of unmanned airborne vehicles (UAVs) or so-called drones that can carry a LiDAR camera is a recent development. Recently, the use and adoption of UAVs as a flexible sensor platform for monitoring has evolved rapidly. Potential application domains are e.g. agriculture (phenotyping of individual plants), coastal monitoring, dikes, archaeology, corridor mapping (power lines, railway tracks, pipeline inspection), topography, geomorphology, and construction site monitoring (surveying urban environments), next to forestry and vegetation monitoring. Until recently it was not possible to have a LiDAR camera on a UAV since the cameras were too heavy to be carried by a UAV. Before, LiDAR measurements were made only from manned helicopters or airplanes. Attaching a LiDAR sensor to a moving UAV platform allows 3D mapping of larger surface areas. The big advantage of the use of a UAV is its flexibility to be used in space and time. The major limitation compared to manned airborne laser scanning is still limited in its areal coverage, not only due to the technological capabilities but also due to aviation regulations which does not allow in most cases to fly beyond line of sight. The use of unmanned LiDAR Scanning (ULS) has certainly advantages compared to the more static terrestrial laser scanning (TLS) or large-scale systems using manned platforms (Kooistra and Mücher, 2015, business plan prepared for evaluation within CAT Agrofood Program of Wageningen University and Research Centre):

1. In general, the flexible agile deployment is an important asset of UAV data collection especially compared to satellites and manned aircrafts: for example LiDAR observations can be combined with additional camera observation to characterize both the structure and bio-chemistry of 3D objects;

2. Compared to TLS, UAV based LiDAR scanning allows the coverage of a much larger areal extent allowing to investigate relevant processes at local to regional scale (up to 100 ha per day);
3. Compared to manned platforms, UAV based LiDAR scanning allows timing of data acquisition at critical moments and repeated measurements as part of monitoring experiments. The costs for manned platforms for monitoring is often too expensive.

However only a limited number of manufacturers can provide at the moment such integrated UAV-LiDAR systems (ULS).

2.5.4.3 Spaceborne LiDAR

NASA's GLAS instrument (Geoscience Laser Altimeter System) on the spaceborn ICESat platform (Ice, Cloud, and land Elevation satellite), launched on 12 January 2003, is a good example of the promising technique from space. Although the main objective of the GLAS instrument was to measure ice sheet elevations and changes in elevation through time, it was also very successful in measuring forest height. Amongst others Hayashia et al. (2013) showed that ICESat/GLAS data provides useful information on forest canopy height with an accuracy RMSE of 2.8 m. New advanced sensors to be launched in the next couple of years will provide increasingly accurate information on traits such as vegetation height and plant-species characteristics. These include the NASA Global Ecosystem Dynamics Investigation Lidar (GEDI). The scientific goal of the GEDI is to characterize the effects of changing climate and land use on ecosystem structure and dynamics to enable radically improved quantification and understanding of the Earth's carbon cycle and biodiversity. Focused on tropical and temperate forests from its vantage point on the International Space Station (ISS), GEDI uses LiDAR to provide the first global, high-resolution observations of forest vertical structure (http://science.nasa.gov/missions/gedi/).

2.5.4.4 Terrestrial LiDAR

Terrestrial LiDAR, also called terrestrial laser scanning (TLS), is a ground-based remote sensing system that can measure 3D vegetation structure (i.e. the size and location of canopy elements) to centimetre or even millimetre accuracy and precision. Broad scale mapping based on remote sensing (satellite) data rarely, if ever, record the type of forest structural and dynamic information we require directly. Various simplifying assumptions, models and ancillary data are typically required to extract such information. At the fine (sub-ha plot) scale, it has also been difficult to incorporate rapid and robust assessment of accurate ground reference data of 3D forest structure into existing surveying and mapping strategies. This is in part due to the relative newness of such detailed structural data and the consequent lack of consistent methods for processing and analyzing these data in conjunction with more traditional survey and monitoring methods (Calders et al, 2015a).

2.5.5 LiDAR applications supporting EBV ecosystem structure

In this section some examples of LiDAR applications in vegetation monitoring are given, related to the EBV ecosystem structure. The first three subsections are on forest parameters, vegetation structure, and habitat classification, all based on airborne LiDAR. Real LiDAR monitoring applications are so far mainly limited to Terrestrial LiDAR, and these are described in last subsection.

2.5.5.1 Forest structure

Vegetation vertical structure is defined as the bottom to top configuration of above-ground vegetation including for example, canopy cover, tree and canopy height, vegetation layers, and biomass or volume (Bergen et al. 2008). LiDAR remote sensing being capable of providing both horizontal and vertical information at high spatial resolutions and vertical accuracies, allows forest attributes to be retrieved (Dubayah et al. 2000; Akay et al. 2008). Both discrete-return and full waveform devices have been used worldwide for characterizing forest structure (Lefsky et al. 2002a; Lim et al. 2003). These technologies have successfully been used to retrieve tree height (Jan 2005; Wang et al. 2008; Rosette et al. 2009; Heurich et al. 2008), above ground biomass and timber volumes (Calders et al., 2015;Means et al. 2000; Lefsky et al. 2002b; Zimble et al. 2003; Patenaude et al. 2004; Zhao et al. 2009) and leaf area (Roberts et al. 2005;) across various ecosystems such as temperate (Anderson et al. 2006) or tropical forest (Drake et al. 2002). The combination of airborne LiDAR data with other optical remote sensing data also shows promising results for the estimation of forest structural characteristics (Coops et al. 2004), often better that when LiDAR data were used alone (Hudak et al. 2002; Wulder et al. 2003). In some case the intensity recorded by the LiDAR sensors is also used to measure tree metrics and vegetation structure (Lovell et al. 2003; Hall et al. 2005; Evans et al. 2006; Weishampel et al. 2007).Those studies have demonstrated the ability of LiDAR techniques to measure vegetation height, and cover as well as more complex attributes of canopy structure. From those measurements, further analysis can be done related to the vegetation attributes and function.

2.5.5.2 Vegetation structure

Vegetation attributes and structure information generated from airborne LiDAR data have also applications beyond forestry and are of a great help for ecological functions understanding. These canopy metrics and structural data have been proven to be strong predictors of species richness for woodland birds in several studies (Vierling et al. 2008; Mason et al. 2003; Hill et al. 2005), even in difficult terrain (Hyde et al. 2005). Furthermore, the correlation between LiDAR-derived estimates of vegetation structure important to birds have been demonstrated in areas ranging from grasslands to forests (Bradbury et al. 2005; Hinsley et al. 2006). LiDAR have been also demonstrated to be able to identify differently structured habitat units and to quantify variation in vegetation structure within those units (Bradbury et al. 2005). LiDAR can also provide indication about territories and breeding success of several types of birds species (Bergen et al. 2008). Graf et al. (2009) concluded their study on the great potential offered by LiDAR for effective habitat monitoring and management of endangered species. In Korpela et al. (2009) the result obtained using LiDAR for the mire habitat classification accuracy were considered as surpassing earlier results with optical data. Some studies also highlighted that the result of habitat analysis obtained with LiDAR may be enhanced when used in combination with spectral data (Bergen et al. 2007; Clawges et al. 2008; Hyde et al. 2006). In view of those results, LiDAR remote sensing shows considerable efficacy for habitat mapping/characterization and wildlife management in fine detail across broad areas. It may replace many labour-intensive, field-based measurements, and can characterize habitat in novel ways (Vierling et al. 2008). Considering monitoring applications, the repeatable and high absolute “xyz” accuracy is advantageous since changes can be detected at submeter scales and the same measurement units can be monitored over time (Korpela et al. 2009). In that sense, LiDAR constitutes an efficient tool for short and long term monitoring of changes in surface structure and vegetation. For example, Wieshampel et al. (2007) used LiDAR measurements to monitor vegetation recovery after several disturbances and Calders et al (2015) used TLS for phenology monitoring.

2.5.5.3 Habitat classification

Studies conducted in order to classify vegetation or habitats using LiDAR showed that discrimination of some types was only possible based on vegetation height and density when they had similar spectral reflectances (Geerling et al. 2007; Geerling et al. 2009). LiDAR appeared to succeed as well in characterizing tree species with the canopy height as the strongest explanatory variables in the vegetation classification (Korpela et al. 2009; Geerling et al. 2007). The integration of spectral information coming from optical remote sensing data and canopy height data generated from LiDAR into the classification has been demonstrated to produce an ecologically meaningful thematic product for a complex woodland environment (Hill et al. 2005). In most of the ecological studies based on LiDAR techniques, the intensity/amplitude is rarely used as it must be calibrated and corrected first (Mallet et al. 2009), even though it appears as a potential important factor for feature extraction or land cover classification. Antonarakis et al. (2008) demonstrate that the combination of intensity and elevation data from LiDAR point clouds can be enough to classify multiple land types using object-based classification method. Other studies using intensity values were conducted and their results imply that the intensity of the laser return signal can be used for classification purposes (Lim et al. 2003; Brennan et al. 2006; Korpela et al. 2009). A biodiversity observation system that is consistent and cost effective is desirable, but its development and implementation remains a significant challenge. Recent advances in Earth Observation (EO) allow inroads to the design of such a system (Mücher et al, 2015). Light Detection and Ranging (LiDAR) and Very High Resolution (VHR) multi-spectral sensors are increasingly becoming available. These images provide opportunities for land cover and habitat mapping with a very high spatial resolution of 1 or 2 meters (mapping scale ~ 1:4000) and a high thematic differentiation in such a way that the derived maps meet the demand of end-users such as terrain and nature conservation managers. The launch of the multi-spectral Worldview-2 (WV-2) sensor with eight spectral bands (including the coastal, yellow and red edge as well as a second (overlapping) NIR channel) and a spatial resolution of 2 meters provides new opportunities for discrimination of land covers/habitats, hence it is preferred for adoption with the EODHaM system (Lucas et al, 2015). A limitation of using optical imagery is that information on vegetation height cannot be retrieved with sufficient reliability unless relationships with, for example, textural measures are provided (Lucas et al, 2015). As such, LiDAR is complementary to optical EO data, since the technology allows for the measurement of vegetation structure (Mücher et al., 2013). LiDAR-derived canopy height models (CHM) represent the calculated height of the woody vegetation above the ground surface (in centimetres) for each individual grid cell. This is critical for the descriptions of woody life forms within the Food and Agricultural Organization (FAO) Land Cover Classification System (LCCS) taxonomy (di Gregorio and Jansen, 2005) and the General Habitat Category (GHC) system for habitat surveillance and monitoring (Bunce et al., 2008). Since vegetation physiognomy and structure are an important diagnostic criteria in the land cover as well as habitat classification system, we put a major emphasis on the exploitation of LiDAR data for CHM in combination with multi-temporal and multi-spectral VHR satellite imagery. The CHM is a result of the difference in height between the calculated Digital Surface Model (DSM), indicating the top of the vegetation, and the Digital Terrain Model (DTM), indicating the ground surface. EODHaM requires in general several satellite images distributed over the growing season (a pre-peak flush image, a peak flush image, and a post-peak flush image) which allows the calculation of a wider range of spectral indices with a sufficient spatial detail. The imagery needs to be acquired for periods that are phenological optimal for the discrimination of land cover and habitat classes (Lucas et al., 2015). An important additional input in the EODHAM system was the CHM with a spatial resolution of 1 by 1 meter and vegetation height indicated in centimetres, as derived from the LiDAR multiple return data. It shows that the combination of LiDAR with VHR satellite imagery is a powerful tool for the identification of plant life forms and associated land covers due to the generic possibilities that it provides in combination with the EODHAM system for any site across the globe. Even though the validation is not showing the highest accuracies (Mücher et al, 2015).

2.5.5.4 Forest Monitoring

The potential of TLS for forest monitoring was first demonstrated more than a decade ago, but has not yet reached its full potential, for the reasons outlined above. Newnham et al.

(2015) & Anderson et al. (2015) provide a full review of the development of TLS as a forest measurement tool.

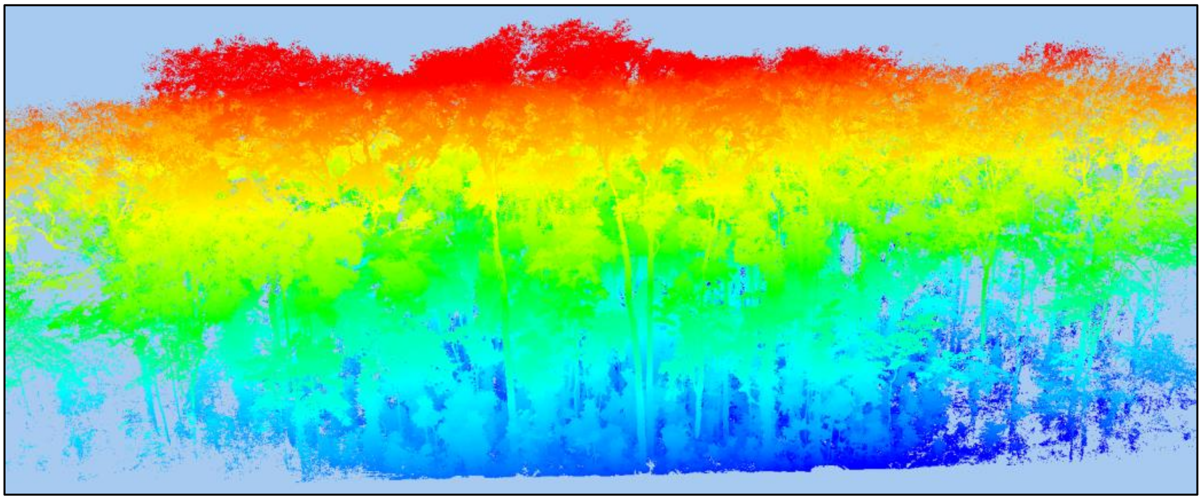

Figure 1.5.5.4.1: Illustration of a 3D terrestrial in-situ laser scanner point cloud of a Maranthaceae forest in Lopé National Park located in central Gabon. The data were collected with a RIEGL VZ-400 LiDAR camera from 7 different scan locations. Coloured by height (blue = 0 m; red = 45 m).

Terrestrial LiDAR sensors are usually tripod mounted and record single scans from a fixed location. As such, scans are affected by occlusion, i.e. the near objects in the forest can obscure objects further from the scanner. The effects of occlusion can be significantly reduced by obtaining data from multiple scan locations. Multiple single scans made at different locations can be co-registered (to within mm accuracy depending on instrument and environment) using high reflectivity targets that act as tie-points between different scans (see Figure 2.5.5.4.1). A range of scientific and commercial scanners are currently available. Whereas airborne LiDAR systems have been used in forest measurements since the mid-eighties (Nelson et al., 1984), the first commercial terrestrial laser scanners came to the market in the late 90s with instruments such as the RIEGL LMS Z210 and CYRAX 2200. The first TLS instruments used a time-of-flight ranging principle, with phase-shift based ranging instruments following soon after. The commercial instruments were (and still are) generally developed for precision mapping and survey applications where hard targets (i.e. structurally continuous surfaces) dominate e.g. urban areas and/or mineral and petrochemical exploration. This has implications for their use in forest applications, where many laser hits are partial, and/or from softer targets (i.e. structurally fragmented or dispersed surfaces) with anisotropic reflecting surfaces such as leaves or needles and bark. Of the scientific (i.e. non-commercial) scanners, the Echidna Validation Instrument (EVI) was one of the first laser scanners specifically designed to monitor vegetation (Strahler et al., 2008). Commonly used commercial instruments include the RIEGL VZ-series, Leica C10 and HDS7000, Optech ILRIS-HD and FARO Focus^{3D} X 330 and Trimble TX8. Newnham et al. (2012) provide a detailed independent comparison between some commercial scanners and evaluated their performance for measuring vegetation structure.

2.5.6 Status and outlook

Monitoring ecosystem structure can now be supported by a wide range of remote sensing techniques. The challenge to date is to support the biodiversity community with a global observing system that revolves around the monitoring of a set of agreed variables essential to the tracking of changes in biological diversity on Earth (Pettorelli, 2016), such as EBV ecosystem structure. To achieve this the remote sensing techniques available have to be exploited to a much wider range and should complement each other, so that large parts of the globe can be monitored in reality. LiDAR technique is a tremendously growing remote sensing technique that due to its absolute physical measurements of height and structure has an enormous potential for applications. As we have seen LiDAR instruments can be placed on many different platforms that all have their own merits, ranging from terrestrial to spaceborne LiDAR. Although the LiDAR instruments are still very expensive we see that prices are lowering due to its wide range of applications, and makes it also slowly affordable to mount on UAV platforms. For regular forest monitoring terrestrial LiDAR still has the best credits but will probably change with increasing use of UAV and spaceborne platforms. We have mainly focused on vegetation and more specifically on forest, but it should be stressed that the LiDAR technique has a wide range of applications from terrain, infrastructure and urban applications, to agriculture, archaeology, geology, bathometry, and many other domains. Spaceborne LiDAR is not yet well developed but planned satellite sensors as NASA's GEDI show that this will change. Passive sensor data can be used in certain cases as alternatives of LiDAR data for vegetation height estimation. Although not as accurate as LiDAR overall, satellite passive sensors have provided high precision approximations of height and have been proven particularly useful in cases where LiDAR information was unavailable due to high cost or limited coverage. Several types of predictors have been derived from passive sensor imagery, including reflectance values, spectral indices, texture features, or even temporal and semantic-based information (e.g. time-since-disturbance features in multi-temporal imagery). ESA's upcoming P-band RADAR 'BIOMASS' mission holds promises for accurate space-borne large-area estimation of vegetation structure and height. It is intended to derive vegetation structure and height using POLInSAR globally and at a spatial scale of 100-200 m (Scipal et al., 2010). Due to the long wavelength of ~60 cm a much reduced saturation and underestimation of forest height is expected when compared to results found for shorter wavelength RADAR (e.g. Garestier et al. 2008, Khati & Singh 2015), even over dense tropical forests. Such variety of features is essential in creating non-redundant information between active and passive sensor data and improve height estimation. Experiments involving synergies of LiDAR, RADAR, and passive multispectral data have shown that fusion of data from different sensors can provide increased performance compared with single-sensor data (Hyde et al. 2006). Furthermore, passive optical imagery can indirectly complement LiDAR data in height estimation by spectrally distinguishing vegetation from ground and remove noisy LiDAR measurements from the background that deteriorate accuracy (Riaño et al. 2007). Finally, widely and freely available RADAR and passive optical RS data, think of for example SENTINEL 1 and 2, should be used in synergy with limited but highly accurate LiDAR measurements to increase the spatial coverage of vegetation height measurements.

2.5.7 Acknowledgements

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2.5.8 Key references for section 2.5

Ahmed O.S., Franklin, S.E., Wulder, M.A., White, J.C., 2015. Characterizing stand-level forest canopy cover and height using Landsat time series, samples of airborne LiDAR, and the Random Forest algorithm. ISPRS J. Photogramm. Remote Sens. 101: 89–101.

Akay, A.E., H. Oğuz, et al.,2008. Using LiDAR technology in forestry activities. Environmental Monitoring and Assessment: 1-9.

Anderson, M.C., Neale, C.M.U., Li, F., Norman, J.M., Kustas W.P., Jayanthi, H., Chavez, J., 2004. Upscaling ground observations of vegetation water content, canopy height, and leaf area index during SMEX02 using aircraft and Landsat imagery. Remote Sens. Environ. 92(4): 447–464.

Anderson, J., Martin, M.E., et al., 2006. The use of waveform LiDAR to measure northern temperate mixed conifer and deciduous forest structure in New Hampshire. Remote Sensing of Environment 105(3): 248-261.

Antonarakis, A.S., Richards, K.S. et al., 2008. Object-based land cover classification using airborne LiDAR. Remote Sensing of Environment 112(6): 2988-2998.

Bergen, K.M., Gilboy, A.M. et al., 2007. Multi-dimensional vegetation structure in modeling avian habitat. Ecological Informatics 2(1): 9-22.

Bergen, K.M., Goetz, S.J. et al., 2008. Remote sensing of vegetation 3-D structure for biodiversity and habitat: Review and implications for LiDAR and radar spaceborne missions. Journal of geophysical research 114(G00E06).

Bradbury, R.B., Hill, R.A., et al., 2005. Modelling relationships between birds and vegetation structure using airborne LiDAR data: A review with case studies from agricultural and woodland environments. Ibis 147(3): 443-452.

Brennan, R., and Webster, T. L., 2006. Object-oriented land cover classification of LiDAR-derived surfaces." Canadian Journal of Remote Sensing 32(2): 162-172.

Bunce, R.G.H., Metzger, M.J., Jongman, R.H.G., Brandt, J., De Blust, G., Elena-Rossello,R., Groom, G.B., Halada, L., Hofer, G., Howard, D.C., Kovál, P., Mücher, C.A.,Padoa-Schioppa, E., Paelinx, D., Palo, A., Perez-Soba, M., Ramos, I.L., Roche, P.,Skånes, H., Wrbka, T., 2008. A standardized procedure for surveillance and mon-itoring European habitats and provision of spatial data. Landsc. Ecol. 23 (1),11–25.

Bunce, R.G.H., Bogers M.M.B., Evans, D., Halada, L., Jongman, R.H.G., Mucher, C.A., Bauch, B., de Blust, G., Parr T.W., and Olsvig-Whittaker L., 2013. The significance of habitats as indicators of biodiversity and their links to species. Ecological Indicators, Special Issue: Biodiversity Monitoring, Vol. 33 (2013) 19-25.

Calders, K., Newnham, G., Burt, A., Murphy, S., Raumonen, P., Herold, M., Culvenor, D., Avitabile, V., Disney, M., Armston, J. and Kaasalainen, M., 2015. Nondestructive estimates of above-ground biomass using terrestrial laser scanning. Methods in Ecology and Evolution 6, 198-208.

Calders, K., Schenkels, T., Bartholomeus, H., Armston, J., Verbesselt, J. and Herold, M., 2015. Monitoring spring phenology with high temporal resolution terrestrial LiDAR measurements. Agricultural and Forest Meteorology 203, 158-168.

Carson, W. W., H. E. Andersen, et al., 2004. LiDAR applications in forestry – An overview, Denver, Colorado.

Castillo-Santiago, M.A., Ricker, M., de Jong, B.H.J., 2010. Estimation of tropical forest structure from SPOT-5 satellite images. Int. J. Remote Sens. 31(10): 2767–2782.

Chen, G., Hay, G.J., Castilla, G., St-Onge, B., Powers, R., 2011. A multiscale geographic object-based image analysis to estimate lidar-measured forest canopy height using Quickbird imagery. Int. J. Geogr. Inf. Sci. 25(6): 877–893.

Clawges, R., Vierling, K., et al.,2008. The use of airborne LiDAR to assess avian species diversity, density, and occurrence in a pine/aspen forest. Remote Sensing of Environment 112(5): 2064-2073.

Cloude, S., Papathanassiou, K.P., 1998. Polarimetric SAR interferometry. IEEE Transactions on Geoscience and Remote Sensing 36, 1551–1565.
Coops, N. C., M. A. Wulder, et al., 2004. Comparison of forest attributes extracted from fine spatial resolution multispectral and LiDAR data. Canadian Journal of Remote Sensing 30(6): 855-866.
di Gregorio, A., Jansen, L.J.M., 2005. Land Cover Classification System (LCCS): Classification Concepts and User Manual for Software. Version 2. Technical Report 8.FAO Environment and Natural Resources Service Series, Rome.
Dobson, M.C., et al., 1995. Estimation of forest biophysical characteristics in northern Michigan with SIR-C/X-SAR, IEEE Trans. Geosci. Remote Sens., 33, 877 – 895, doi:10.1109/36.406674
Donoghue, D.N.M., Watt, P.J., 2006. Using LiDAR to compare forest height estimates from IKONOS and Landsat ETM+ data in Sitka spruce plantation forests. Int. J. Remote Sens. 27(11): 2161–2175.
Drake, J.B., Dubayah, R.O., et al., 2002. Estimation of tropical forest structural characteristics, using large-footprint LiDAR. Remote Sensing of Environment 79(2-3): 305-319.
Dubayah, R.O. and J. B. Drake, 2000. LiDAR Remote Sensing for Forestry. Journal of Forestry 98(6): 44-52.
Evans, D.L., Roberts, S.D., et al., 2006. LiDAR - A new tool for forest measurements? Forestry Chronicle 82(2): 211-218.
Florian, K., Kostas, P. P. Irena, H., Dirk, H., 2006. Forest height estimation in tropical rain forest using Pol-InSAR techniques, paper presented at International Conference on Geoscience and Remote Sensing Symposium, IEEE, Denver
Florian, K., Kostas, P., Irena, H., Angelo, C., 2007. Potential of forest height estimation using X band by means of two different inversion scenarios. In 2007 IEEE international geoscience and remote sensing symposium (pp. 1132-1135). IEEE.
Franklin J, Logan, T.L., Woodcock, C.E., Strahler, A.H., 1986. Coniferous forest classification and inventory using Landsat and digital terrain data. IEEE Trans. Geosci. Remote Sens. GE-24: 139–149.
Garestier, F., Dubois-Fernandez, P.C., Papathanassiou, K.P., 2008. Pine forest height inversion using single-pass X-band PolInSAR data. IEEE Transactions on Geoscience and Remote Sensing, 46(1), 59-68.
Geerling, G.W., Labrador-Garcia, M., et al., 2007. Classification of floodplain vegetation by data fusion of spectral (CASI) and LiDAR data. International Journal of Remote Sensing 28(19): 4263-4284.
Geerling, G.W., M.J., Vreeken-Buijs, et al., 2009. Mapping river floodplain ecotopes by segmentation of spectral (CASI) and structural (LiDAR) remote sensing data." River Research and Applications 25(7): 795-813.
Graf, R.F., Mathys, L., et al., 2009. Habitat assessment for forest dwelling species using LiDAR remote sensing: Capercaillie in the Alps. Forest Ecology and Management 257(1): 160-167.
Hall, S.A., Burke, I.C., et al., 2005. Estimating stand structure using discrete-return LiDAR: An example from low density, fire prone ponderosa pine forests." Forest Ecology and Management 208(1-3): 189-209.
Hansen, A.J., deFries, R.S., Turner, W., 2004. Land use change and biodiversity: A synchapter of rates consequences during the period of satellite imagery. In G. Gutman, A. C. Janetos, C. O. Justice, E. F. Moran, J. F. Mustard, R. R. Rindfuss, ... M. A. Cochrane (Eds.), Land change science: Observing, monitoring and understanding trajectories of change on the Earth's surface (vol. 6) (pp. 277-300). Dordrecht, The Netherlands: Kluwer Academic Publishers.
Hansen, M.C., Potapov, P.V., Goetz, S.J., Turubanova, S., Tyukavina, A., Krylov A., Kommareddy, A., Egorov, A., 2016. Mapping tree height distributions in Sub-Saharan

Africa using Landsat 7 and 8 data. Remote Sens. Environ. doi:10.1016/j.rse.2016.02.023.
Hayashia, M., Saigusaa, N., Ogumab, H., Yamagataa, Y., 2013. Forest canopy height estimation using ICESat/GLAS data and error factor analysis in Hokkaido, Japan. ISPRS Journal of Photogrammetry and Remote Sensing Volume 81, July 2013, pp 12–18.
Heurich, M. and F. Thoma, 2008. Estimation of forestry stand parameters using laser scanning data in temperate, structurally rich natural European beech (Fagus sylvatica) and Norway spruce (Picea abies) forests." Forestry 81(5): 645-661.
Hill, R.A. and Thomson, A.G., 2005. Mapping woodland species composition and structure using airborne spectral and LiDAR data. International Journal of Remote Sensing 26(17): 3763-3779.
Hinsley, S.A., Hill, R.A., et al., 2006. The application of LiDAR in woodland bird ecology: Climate, canopy structure, and habitat quality. Photogrammetric Engineering and Remote Sensing 72(12): 1399-1406.
Hudak, A.T., Lefsky, M.A., et al., 2002. Integration of LiDAR and Landsat ETM+ data for estimating and mapping forest canopy height. Remote Sensing of Environment 82(2-3): 397-416.
Hyde, P., Dubayah, R., et al., 2005. Mapping forest structure for wildlife habitat analysis using waveform LiDAR: Validation of montane ecosystems." Remote Sensing of Environment 96(3-4): 427-437.
Hyde, P., R. Dubayah, et al., 2006. Mapping forest structure for wildlife habitat analysis using multi-sensor (LiDAR, SAR/InSAR, ETM+, Quickbird) synergy." Remote Sensing of Environment 102(1-2): 63-73.
Jan, J.F., 2005. Comparison of forest canopy height derived using LiDAR data and aerial photos. Taiwan Journal of Forest Science 20(1): 13-27.
Joshi, N.P., Mitchard, E.T.A., Schumacher, J., Johannsen, V.K., Saatchi, S., Fensholt, R, 2015. L-Band SAR Backscatter Related to Forest Cover, Height and Aboveground Biomass at Multiple Spatial Scales across Denmark. Remote Sens., 2015, 7, 4442-4472.
Kayitakire., F., Hamel, C., Defourny, P., 2006. Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery. Remote Sens. Environ. 102(3–4): 390–401.
Kellndorfer, J., Walker, W., Pierce, L., Dobson, C., Fites, J.A., Hunsaker, C., Vona, J., Cutter, M., 2004. Vegetation height estimation from Shuttle Radar Topography Mission and National Elevation Datasets. Remote Sensing of Environment 93, 339–358.
Kellndorfer, J., Walker, W., LaPoint, E., Hoppus, M., Westfall, J., 2006. Modeling height, biomass, and carbon in U.S. Forest from FIA, SRTM, and Ancillary National Scale Data Sets.In: IEEE International Conference on Geoscience and Remote Sensing Symposium. pp. 3591–3594.
Khati, U., and Singh, G., 2015. Bistatic PolInSAR for forest height estimation: results from TanDEM-X. In Synthetic Aperture Radar (APSAR), 2015 IEEE 5th Asia-Pacific Conference on (pp. 214-217). IEEE.
Korpela, I., Koskinen, M., et al., 2009. Airborne small-footprint discrete-return LiDAR data in the assessment of boreal mire surface patterns, vegetation, and habitats. Forest Ecology and Management 258(7): 1549-1566.
Kugler, F., Papathanassiou, K.P., Hajnsek, I., Angelo, C., 2007. Potential of forest height estimation using X band by means of two different inversion scenarios. In 2007 IEEE international geoscience and remote sensing symposium (pp. 1132-1135).
Lefsky, M.A., Cohen, W.B., et al., 2002a. LiDAR remote sensing for ecosystem studies. BioScience 52(1): 19-30.

Lefsky, M.A., Cohen, W.B., et al., 2002b. LiDAR remote sensing of above-ground biomass in three biomes. Global Ecology and Biogeography 11(5): 393-399.
Lim, K., P. Treitz, et al., 2003. LiDAR remote sensing of forest structure. Progress in Physical Geography 27(1): 88-106.
Lovell, J.L., Jupp, D.L.B., et al., 2003. Using airborne and ground-based ranging LiDAR to measure canopy structure in Australian forests. Canadian Journal of Remote Sensing 29(5): 607-622.
Lucas, R.M., Blonda, P., Bunting, P.F., Jones, G., Inglada, J., Arias, M., Kosmidou, V., Petrou, Z., Manakos, I., Adamo, M., Charnock, R., Tarantino, C., Mücher, C.A., Kramer, H. Jongman, R., Honrado, J., Mairota, P., 2015. The Earth Observation Data for Habitat Monitoring (EODHaM) System. International Journal of Applied Earth Observation and Geoinformation 37 (2015) 17–28.
Mallet, C. and Bretar, F., 2009. Full-waveform topographic LiDAR: State-of-the-art. ISPRS Journal of Photogrammetry and Remote Sensing 64(1): 1-16.
Mason, D.C., Anderson, G.Q.A., et al., 2003. Measurement of habitat predictor variables for organism-habitat models using remote sensing and image segmentation. International Journal of Remote Sensing 24(12): 2515-2532.
Means, J.E., Acker, S.A. et al., 2000. "Predicting forest stand characteristics with airborne scanning LiDAR." Photogrammetric Engineering and Remote Sensing 66(11): 1367-1371.
Mora, B., Wulder, M.A., Hobart, G.W., White, J.C., Bater, C.W., Gougeon, F.A., Varhola, A., Coops, N.C., 2013. Forest inventory stand height estimates from very high spatial resolution satellite imagery calibrated with lidar plots. Int. J. Remote Sens. 34(12): 37–41.
Mücher, C.A., Roupioz, L., Kramer, H., , Bogers, M.M.B., Jongman, R.H.G., Lucas, R.M., , Petrou, Z., Kosmidou, V.E., Manakos, I., Padoa-Schioppa, E., Adamo, M., Blonda., 2015. Synergy of Airborne LiDAR and Worldview-2 satellite imagery for land cover and habitat mapping: a BIO_SOS-EODHaM case study for the Netherlands. International Journal of Applied Earth Observation and Geoinformation 37 (2015) 48–55.
Mücher, C.A., Kooistra, L. Vermeulen, M., Vanden Borre, J. Haest, B. Haveman, R., 2013 Quantifying structure and function of Natura 2000 heathland habitats using spectral mixture analysis and segmentation techniques on hyperspectral imagery. Ecological indicators, Special Issue: Biodiversity Monitoring, Vol. 33 (2013) 71-81.
Nelson, R., Krabill, W. and MacLean, G., 1984. Determining forest canopy characteristics using airborne laser data. Remote Sensing of Environment, 15: 201-212.
Newnham, G., Armston, J., Muir, J., Goodwin, N., Tindall, D., Culvenor, D., Puschel, P., Nystrom, M., & Johansen, K., 2012. Evaluation of terrestrial laser scanners for measuring vegetation structure. CSIRO Sustainable Agriculture Flagship.
Newnham, G.J., Armston, J.D., Calders, K., Disney, M.I., Lovell, J.L., Schaaf, C.B., Strahler, A.H., and Danson, F.M., 2015. Terrestrial Laser Scanning For Plot Scale Forest Measurement. Current Forestry Reports, 1: 239-251.
Noss, R.F., 1990. Indicators for monitoring biodiversity: A hierarchical approach. Conservation Biology, 4(4), 355-364.
Papathanassiou, K.P., Kugler, F., Lee, S., Marotti, L., Hajnsek, I., 2008. Recent advances in Polarimetric SAR Interferometry for forest parameter estimation, paper presented at Radar Conference 2008, IEEE, Rome.
Patenaude, G., Hill, R.A., et al., 2004. Quantifying forest above ground carbon content using LiDAR remote sensing. Remote Sensing of Environment 93(3): 368-380.
Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R., et al. 2013. Essential biodiversity variables. Science 339, 277–278.

Petrou, Z.I., Manakos, I., Stathaki, T., Mücher, C.A., Adamo, M., 2015. Discrimination of vegetation height categories with passive satellite sensor imagery using texture analysis. IEEE J. Sel. Top. Appl. 8(4): 1442-1455.

Pettorelli, N., Martin Wegmann, Andrew Skidmore, Sander Mücher, Terence P. Dawson, Miguel Fernandez, Richard Lucas, Michael E. Schaepman, Tiejun Wang, Brian O'Connor, Robert H.G. Jongman, Pieter Kempeneers, Ruth Sonnenschein, Allison K. Leidner, Monika Böhm1, Kate S. He, Harini Nagendra, Grégoire Dubois, Temilola Fatoyinbo, Matthew C. Hansen, Marc Paganini, Helen M. de Klerk, Greg Asner, Jeremy Kerr, Anna B. Estes, Dirk S. Schmeller, Uta Heiden, Duccio Rocchini, Henrique M. Pereira, Eren Turak, Nestor Fernandez, Angela Lausch, Moses A. Cho, Domingo Alcaraz-Segura, Mélodie A. McGeoch, Woody Turner, Andreas Mueller, Véronique St-Louis, Johannes Penner and Gary N. Geller, 2015. Framing the concept of Satellite Remote Sensing Essential Biodiversity Variables: challenges and future directions. Online 25th of March 2016 at onlinelibrary.wiley.com/doi/10.1002/rse2.15/pdf Remote Sensing in Ecology and Conservation (Open Access).

Puhr, C.B., Donoghue, D.N.M., 2000. Remote sensing of upland conifer plantations using Landsat TM data: A case study from Galloway, south-west Scotland. Int. J. Remote Sens. 21(4): 633–646.

Riaño, D., Chuvieco, E., Ustin, S.L., Salas, J., Rodríguez-Pérez, J.R., Ribeiro, L.M., Viegas, D.X., Moreno, J.M., Fernández, H., 2007. Estimation of shrub height for fuel-type mapping combining airborne LiDAR and simultaneous color infrared ortho imaging. Int. J. Wildland Fire 16: 341–348.

Roberts, S.D., Dean, T. J., et al., 2005. Estimating individual tree leaf area in loblolly pine plantations using LiDAR-derived measurements of height and crown dimensions. Forest Ecology and Management 213(1-3): 54-70.

Rosen, P.A., Hensley, S., Joughin, I.R., Li, F.K., Madsen, S.N., Rodriguez, E., Goldstein, R., 2000. Synthetic aperture radar interferometry. In: Proceedings of the IEEE, vol. 88. pp. 333–382.

Rosette, J. A., North, P. R. J., et al., 2009. A comparison of biophysical parameter retrieval for forestry using airborne and satellite LiDAR. International Journal of Remote Sensing 30(19): 5229-5237.

Scipal, K., Arcioni, M., Chave, J., Dall, J., Fois, F., LeToan, T., Saatchi, S., 2010, July. The BIOMASS mission—An ESA Earth Explorer candidate to measure the BIOMASS of the earth's forests. In Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International (pp. 52-55). IEEE.

Sexton, J.O., Bax, T., Siqueira, P., Swenson, J. J., Hensley, S., 2009. A comparison of lidar, radar, and field measurements of canopy height in pine and hardwood forests of southeastern North America. Forest Ecology and Management, 257(3), 1136-1147.

Simard, M., Zhang, K., Rivera-Monroy, V. H., Ross, M. S., Ruiz, P. L., Castañeda-Moya, E. & Rodriguez, E. (2006). Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. Photogrammetric Engineering & Remote Sensing, 72(3).

Skidmore, A.k., Pettorelli, N., Coops, N.C., Geller, G.N., Hansen, M., Lucas, R., Mücher, C.A., O'Connor, B., Paganini, M., Pereira, H.M., Schaepman, M.E., Turner, W., Wang, T., Wegmann, M., 2015. Agree on biodiversity metrics to track from space. Nature, 23 July 2015, Vol. 523, pp 403-405.

Slatton, K.C., Crawford, M.M., Evans, B.L., 2001. Fusing interferometric radar and laser altimeter data to estimate surface topography and vegetation heights. IEEE Trans. Geosci. Remote Sens. 39(11): 2470–2482.

St-Onge, B., 2005. LiDAR remote sensing: Overview of technology and applications. Proceedings of the 26th Canadian Symposium on Remote Sensing.

Strahler, A. H., Jupp, D. L. B., Woodcock, C. E., Schaaf, C. B., Yao, T., Zhao, F., Yang, X., Lovell, J., Culvenor, D., Newnham, G., Ni-Meister, W. and Boykin-Morris, W., 2008. Retrieval of forest structural parameters using a ground-based lidar instrument (Echidna). Canadian Journal of Remote Sensing, 34: 426-440.

Treuhaft, R.N., Siqueira, P.R., 2000. The vertical structure of vegetated lad surfaces from interferometric and polarimetric radar. Radio Science 25, 141–177.

Treuhaft, R.N., Law, B.E., Asner, G.P., 2004. Forest attributes from radar interferometric structure and its Fusion with optical remote sensing. BioScience 54(6): 561–571.

Treuhaft, R.N., Siqueira, P.R., 2004. The calculated performance of forest structure and biomass estimates from interferometric radar, Waves Random Complex Media, 14, S345– S358, doi:10.1088/0959-7174/14/2/013.

Ulaby,T.F., Moore, R.K., Fung, A.K., 1986. Microwave remote sensing - Active and Passive., Norwood, USA: Artech House.

Vierling, K.T., Vierling, L.A., et al., 2008. LiDAR: Shedding new light on habitat characterization and modeling. Frontiers in Ecology and the Environment 6(2): 90-98.

Wang, C., and Glenn, N.F., 2008. A linear regression method for tree canopy height estimation using airborne LiDAR data. Canadian Journal of Remote Sensing 34(SUPPL. 2): S217-S227.

Wang, C., Wang, L., Fu, H., Xie, Q., & Zhu, J., 2016. The Impact of Forest Density on Forest Height Inversion Modeling from Polarimetric InSAR Data. Remote Sensing, 8(4), 291.

Wehr, A. and Lohr, U., 1999. Airborne laser scanning - An introduction and overview. ISPRS Journal of Photogrammetry and Remote Sensing 54(2-3): 68-82.

Weishampel, J. F., J. B. Drake, et al., 2007. Forest canopy recovery from the 1938 hurricane and subsequent salvage damage measured with airborne LiDAR. Remote Sensing of Environment 109(2): 142-153.

Wheeler, K., Hensley, S., 2000. The GeoSAR Airborne mapping system. In: IEEE International Radar Conference Proceedings. pp. 831–835.

Wolter P.T., Townsend, P.A., Sturtevant, B.R. (2009) Estimation of forest structural parameters using 5 and 10 meter SPOT-5 satellite data. Remote Sens. Environ. 113(9): 2019–2036.

Woodhouse, I.H., 2005. Introduction to Microwave Remote Sensing., CRC Press.

Wulder, M.A., Norman, P., et al., 2003. Special Issue: LiDAR remote sensing of forest structure and terrain." Numéro spécial: La télédétection LiDAR de la structure de la forêt et du terrain 29(5): ii-iii.

Zhao, K., Popescu, S. et al., 2009. LiDAR remote sensing of forest biomass: A scale-invariant estimation approach using airborne lasers. Remote Sensing of Environment 113(1): 182-196.

Zimble, D.A., Evans, D.L., et al. 2003. Characterizing vertical forest structure using small-footprint airborne LiDAR. Remote Sensing of Environment 87(2-3): 171-182.