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Characterizing Forest Structure by Means of Remote Sensing: A Review

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1. Introduction

1.1 Forest structural attributes

Forest management comprises of a wide range of planning stages and activities which are highly variable according to the goals and strategies being pursued. Furthermore, those activities often include a requirement for description of condition and dynamics of forests (Koch et al., 2009). Forest ecosystems are often required to be described by a set of general characteristics including composition, function, and structure (Franklin, 1986). Composition is described by presence or dominance of woody species or by relative indices of biodiversity. Forest functional characteristics are related to issues like types and rates of processes such as carbon sequestration. Apart from them, the physical characteristics of forests are essential to be expressed. This description is often accomplished under the general concept of forest structure. However, the entire above-mentioned characteristics are required for timber management/procurement practices, as well as for mapping forests into smaller units or compartments.

The definition by (Oliver & Larson, 1996) can be referred to as one of the basic ones, in which forest structure is defined as 'the physical and temporal distribution of trees in a forest stand'. This definition encompasses a set of indicators including species distribution, vertical and horizontal spatial patterns, tree size, tree age and/or combinations of them. Yet, a more geometrical representation of forest stand was previously presented by e.g. (Franklin, 1986) or later by (Kimmins, 1996). They defined stand structure as the vertical and horizontal association of stand elements. Despite the differences between the above-mentioned definitions, they were later used as basis to derive further representative structural indicators which are mainly derived based on the metrics such as diameter at breast height (DBH). The reason is the straightforwardness and (approximately) unbiasedness of its measurement in terrestrial surveys (Stone & Porter, 1998). The interest in applying geometric derivations e.g. standing volume and aboveground biomass was later accomplished thanks to the progresses in computational facilities and simulation techniques. Those attributes are still of great importance to describe forest stand structure. Nevertheless, (McElhinny et al., 2005) stated that the structural, functional and compositional attributes of a stand are highly interdependent and thus cannot be easily divided to such main categories, since the attributes from either of the groups can be considered as alternatives to each other. Thus a new category was created, according to which the structural attributes were in a group comprising of measures such as abundance (e.g. dead wood volume), size variation (e.g. variation in DBH) and spatial variation (e.g. variation of distance to a nearest neighbour (Table 1) (McElhinny et al., 2005).

Though canopy cover i.e. the vertical projection of tree crowns is often referred to as an attribute characterizing the distribution of forest biomass, there are further attributes such as basal area, standing timber volume and the height of overstory which are considered as the more representative descriptors of forest biomass. Moreover, a combination of those attributes (especially in accordance with species composition) is also reported by e.g. (Davey, 1984) to represent the biomass and vertical complexity of the stands.

Forest stand element	Structural attribute
Foliage	Foliage height diversity Number of strata Foliage density within different strata
Canopy cover	Canopy cover Gap size classes Average gap size and the proportion of canopy in gaps Proportion of crowns with dead and broken tops
Tree diameter	Diameter at Breast Height (DBH) standard deviation of DBH Diameter distribution Number of large trees
Tree height	Height of overstorey Standard deviation of tree height Height classes richness
Tree spacing	Clark - Evans and Cox indices, percentage of trees in clusters Stem count per ha
Stand biomass	Stand basal area Standing volume Biomass
Tree species	Species diversity and/or richness Relative abundance of key species
Overstorey vegetation	Shrub height Shrub cover Total understorey cover Understorey richness Saplings (shade tolerant) per ha
Dead wood	Number, volume or basal area of stags Volume of coarse woody debris Log volume by decay or diameter classes Coefficient of variation of log density

Table 1. Broadly-investigated forest structural attributes, grouped under the stand element under description (after (McElhinny et al., 2005).

In addition, stem count has also been reported as an important indicator of e.g. felled logs or trees with hollows, since they offer potential habitats for the wildlife ((Acker et al., 1998), (McElhinny et al., 2005)). Thus, the frequency of larger stems is considered of more significance as a descriptor of stand structure, as it can mainly characterize the older and mature stems within the overstory of the stands. This attribute (stem count of older trees) has been already studied by e.g. (Van Den Meersschaut & Vandekerkhove, 1998) as a structural feature to distinguish the old-growth stands from the early stages of succession. Although some studies combined stem count with measures of diameter distribution e.g. (Tyrrell & Crow, 1994), some studies e.g. (Uuttera et al., 1997) did not suggest diameter distribution to be essentially helpful for describing forest structure, as comparing the diameter distributions from different stands bears some degree of sophistication.

All in all, the structural features of forest stands, as stated above, are entirely considered to be useful when describing the horizontal and vertical complexity of the forested areas. However, a relatively limited number of those attributes have been attempted to be modelled by means of remote sensing. Only a few studies have focused on other spatially-meaningful characteristics such as gaps or coarse woody debris e.g. (Pesonen et al., 2008) which have been almost entirely conducted across Scandinavian boreal forests, where the homogenous composition, single-story stands (consisting mainly of coniferous species) and topographically-gentle landscape minimise the problems of characterizing more complex descriptors of forest structure.

Since earth observation data has been applied for forestry applications, the majority of modelling tasks have been accomplished by focusing on standing timber volume, stand height, aboveground biomass (AGB), stem count, and diameter distribution as structural attributes. Whereas some compositional characteristics such as species richness/abundance have also been considered as forest structural attributes (Table 1), this article will not review their related literature, as they follow, in the scope of remote sensing, entirely different methodological strategies and thus require separate review studies with more concentration on pixel-based analysis and spectrometry.

Estimation of AGB in forest is obviously of a great importance. The rationale is straightforward: As the available stocks of fossil fuels gradually diminish and the environmental effects of climate change increasingly emerge, a wide range of stakeholders including political, economical and industrial sectors endeavour to adjust to the consequences and adapt the existing energy supply to the ongoing developments. To this aim, a vital step is the assessment of the potential renewable energy sources such as biomass. Germany can be referred as an example, in which approximately 17 million ha of farmland and 11 million ha of forest are potentially reported to be available as bioenergy sources (BMU, 2009). Moreover, according to the results of the German National Forest Inventory, around 1.0 to 1.5 percent of the country's primary energy demand (20 and 25 million m^3) in 2006 was supplied by timber products. The current models even confirm that an additional 12 to 19 million m^3 $year^{-1}$ of timber can be sustainably used for energy production. This can in turn justify the necessity of an efficient monitoring system for assessing the potential biomass resources in regional and local levels.

1.2 Remote sensing for retrieval of forest attributes

In Recent years the general interest in forests and the environmental-related issues has exceedingly increased. This, together with the ongoing technological developments such as improved data acquisition and computing techniques, has fostered progresses in forest monitoring processes, where the assessment of environmental processes has been enabled to be carried out by means of advanced methods such as intensive modelling and simulations

(Guo, 2005). As described above, assessment and mapping of forest attributes have followed a similar progress as an essential prerequisite for forest management practices.

Information within each forest management unit (e.g. sample plots or segments characterising forest stands) often includes attributes that are measured using direct measurement (e.g. field-based surveys) and indirect measurement (e.g. mathematical derivations and modelled/simulated data). Detailed ground-based survey of each unit is reported by e.g. (LeMay & Temesgen, 2005) to be unlikely, particularly in large-area surveys dealing with limited financial resources or in the inventory of small areas, when those areas are under private ownerships. Such areas are usually associated with financial problems for regular plot-based surveys. However, the plot-based inventory data are considered as being essential as representatives of the current forest inventory or as model inputs to project the future conditions. In order to overcome the mentioned limitations in regular terrestrial surveys, one approach is to combine field measurements with airborne and spaceborne remotely-sensed data to retrieve the required information. This can in turn offer combined practical applications of the field data that represent the detailed information on the ground supported by those data which represent the spatial, spectral and temporal merits of satellite or airborne sensors (Figure 1).

Based on this potential cost-effective implications, a range of applications have been developed which enable one to pursue different natural resource planning objectives including retrieval of forest structural attributes. Amongst the most important international forest mapping projects using earth observation data, GMES (Global Monitoring for Environment and Security), TREES (Tropical Ecosystem Environment Observation by Satellite) and FRA (Forest Resource Assessment) can be highlighted (Koch, 2010). Depending on the specific application, the required level of details and especially the required accuracy of output information, variety of remotely sensed data sources can be potentially applied including a wide range of optical data (broadband multispectral and narrowband hyperspectral imagery), Radio Detection and Ranging (RADAR) and recently Light Detection and Ranging (LiDAR) data. Each one of those data sources has been proved to bear potentials and advantages for forestry applications. Whereas LiDAR instruments facilitate collecting detailed information which accurately captures the three-dimensional structure of the earth surface, RADAR data enable one to overcome common atmospheric and shadow effects which often occur in forested areas. Broadband optical data is able to reflect the general spectral responses of natural and manmade objects including vegetation cover over a big scene, while imaging spectroscopy data has been shown to provide a rich source of spectral information for various applications e.g. tree species classification.

Compared to other sources of data, LiDAR data has been successfully validated for studying the structure of forested areas. Laser altimetry is an active remote sensing technology that determines ranges by taking the product of the speed of light and the time required for an emitted laser to travel to a target object. The elapsed time from when a laser is emitted from a sensor and intercepts an object can be measured using either pulsed ranging (where the travel time of a laser pulse from a sensor to a target object is recorded) or continuous wave ranging (where the phase change in a transmitted sinusoidal signal produced by a continuously emitting laser is converted into travel time) (Wehr & Lohr, 1999). LiDAR is capable of providing both horizontal and vertical information with the horizontal and vertical sampling. The quality of sampling depends on the type of LiDAR system used and on whether it is discrete return or full waveform LiDAR system (Lim et al., 2003).

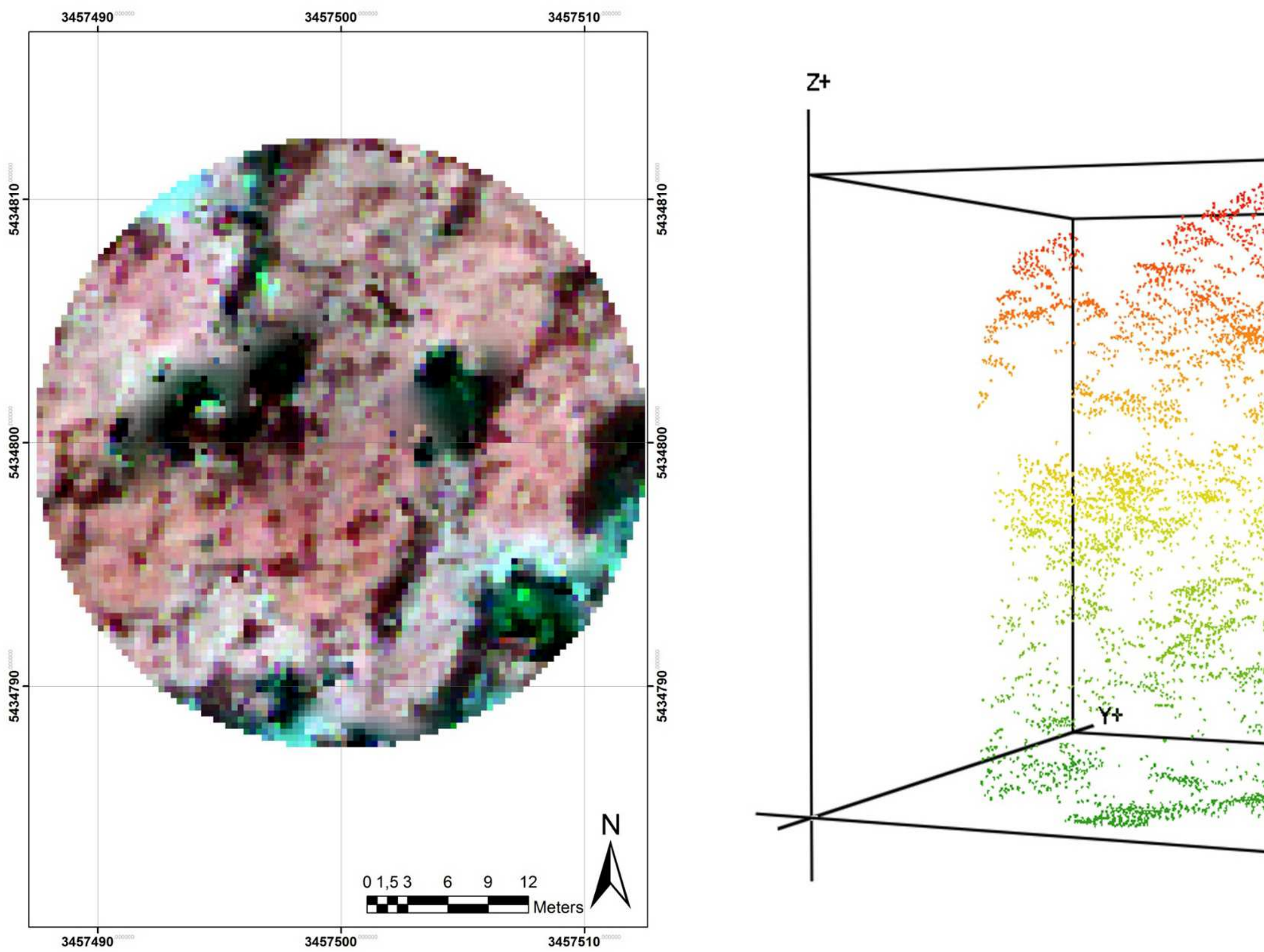

Fig. 1. An example of false colour composite from Colour Infrared (CIR) aerial images (Left) and normal
cloud (right) demonstrating a circular forest inventory plot(452.4 m^2) in a test site in Karlsruhe, German

1.3 Modelling issues

When the aim is to assess the forest attributes by means of remote sensing data, one may note, again, the importance of estimating forest biomass. (Koch, 2010) states that three main factors of forest height, forest closure and forest type are the most meaningful descriptors for AGB. Remote sensing-derived information from the above-mentioned sources will enable one to successfully assess those three factors which can in turn result in reasonable estimation of forest AGB. By using those auxiliary data as descriptors of forest structure (e.g. AGB), Statistical methods are used to model the forest stand attributes in different scales including regional, stand and individual tree levels. So far, the modelling process has been mostly accomplished by means of parametric regression modelling of the response attributes.

Parametric models generally come with strong assumptions of distributions for the parameters and variables which sometimes may not be met by the data. The application of those models is normally subjected to the scientific, technological, and logistic conditions which constrain their application in many cases (Cabaravdic, 2007). A parametric fitting can yield highly biased models resulted from the possible misspecification of the unknown density function (e.g. (Härdle, 1990)). Nevertheless, those modelling procedures have been widely used for building models of forest stand and single tree attributes by several studies (e.g.(Næsset, 2002), (Breidenbach et al., 2008), (Korhonen et al., 2008), and (Straub et al., 2009)).

In contrast, the so called âĂIJnonparametric methodsâĂİ allow for more flexibility in using the unknown regression relationships. (Härdle, 1990) and (Härdle et al., 2004) discussed four main motivations to start with nonparametric models: 1)they provide flexibility to explore the relationships between the predictor and response variables, 2)they enable predictions which are independent from reference to a fixed parametric model, 3)they can help to find false observations by studying the influence of isolated points, and 4) they can be considered as versatile methods for imputing missing values or interpolations between neighbouring predictor values. However, they require larger sample sizes than parametric counterparts, as the underlying data in a nonparametric approach simultaneously serves as the model input.

The nonparametric methods include a wide range of model-fitting approaches such as smoothing methods (e.g. kernel smoothing, k-nearest neighbour, splines and orthogonal series estimators), Generalized Additive Models (GAMs) and models based on classification and regression trees (CARTs). The k-nearest neighbour (k-NN) method is known as a group of mostly-applied nonparametric methods. In k-NN method, the value of the response variable(s) of interest on a specific target unit is modelled as a weighted average of the values of the most similar observation(s) in its neighbourhood. The neighbour(s) are defined within an n-dimensional feature space consisted of potentially-relevant predictor variables. The chosen neighbour(s) are selected based on a criterion which quantifies and measures the *similarity* from a database of previously measured observations (Maltamo & Eerikäinen, 2001). In the context of forest inventory, the k-NN method was first introduced in the late 1980's (Kilkki & Päivinen, 1987), applied later for the prediction of standing timber volume by e.g. (Tomppo, 1993) and was later examined in a handful of studies to predict forest stand and individual tree attributes. As stated by e.g. (Haapanen et al., 2004), the k-NN method has been further developed for modelling forest variables and is now operational in Scandinavian countries e.g. in Finnish National Forest Inventory (NFI). It was further integrated as a part of Forest Inventory and Analysis (FIA) program in the Unites States (see (McRoberts & Tomppo, 2007)). The method couples field-based inventory and auxiliary data (e.g. from remote sensing sources) to produce digital layers of measured forest or land use attributes ((Haapanen et al., 2004)). Following the promising results in Scandinavian landscapes achieved by the application of nonparametric methods in prediction/classification of continuous and categorical forest attributes by means of remotely sensed data, the method have recently received a great deal of attention in other parts of the world e.g. in central Europe (Latifi et al., 2011), as the method could be potentially integrated as a cost effective alternative within the regional and national forest inventories.

Apart from the forest inventories conducted in larger scales, the k-NN method has been applied in the context of so-called small-scale forest inventory, in which the accurate and unbiased inventory of small datasets is of major interest. The term 'small area ' commonly denotes a small geographical area, but may also be used to describe a small domain, i.e. a small subpopulation in a large geographical area (Ghosh & Rao, 1994). Sample survey data of a small area or subpopulation can be used to derive reliable estimates of totals and means for large areas or domains. However, the usual direct survey estimators based on the sampled data are often likely to return erroneous outcomes due to the improperly small sample size. This is more crucial in regional forest inventories, where the sample size is typically small since e.g. the overall sample size in a survey is commonly determined to provide specific accuracy at a much higher level of aggregation than that of small areas. In central European forestry context, a small-area domain is of fundamental importance, since the occurrence of multiple forest ownership systems are historically well-established and still frequently occur. This variation bears, in turn, various forest areas which are connected with different requirements in terms of financial and technological resources for forest inventory. In such situations, high expenses are associated with the regular terrestrial surveys (Stoffels, 2009) and the integration of remote sensing and modelling is thus a motivation to reduce the costs. For example, aerial survey with large footprint ALS flights is reported to generate costs to the amount of 1Euro per ha in Germany (Nothdurft et al., 2009). Therefore, an effective strategy of forest inventory should mainly focus on the inventory of such small forest datasets using all the available infrastructures and potentially attainable technological means. The goal should be set to producing reliable (i.e. sufficiently accurate), general (i.e. reproducible) and (approximately) unbiased models of prominent forest attributes which support providing an up-to-date and continuous information database within the bigger framework of periodical state-wide forest inventory system.

However, some issues are crucially required to be taken into consideration, before a remote sensing-supported modelling task of forest attributes can be commenced. These include:

1.3.1 Data combination issues

Remote sensing data provides a valuable source of information to the forest modelling process. The advanced use of 2 and 3D data in both single-tree and area-based approaches of attributes retrieval would offer valuable potentials to characterize the (inherently) 3D structure of the forest stands (particularly vertical structure such as mean or top height). The data combination is specific to the objectives being set within the case study, as well as to the level of details which is required by the analyst. As such, different data including broadband optical (both medium and high spatial resolution), hyperspectral, LiDAR (height as well as intensity), and RADAR data can be combined or fused to reach those goals.

1.3.2 The configuration of models

Depending on what modelling scheme is aimed to be used to retrieve the response forest attributes, a set of parameters are necessary to be set prior to modelling. These parameters can therefore greatly affect issues such as modelling errors and the retrieved values. In case of parametric regression, the underlying distribution of the data, the type of model in use (e.g. Ordinary Least Squares (OLS) or logarithmic models) and model parameters are crucial to be mentioned (see e.g.(Straub & Koch, 2011)). In nonparametric methods, issues like the selection of smoothing parameter for smoothing methods (e.g. (Wood, 2006)), size of neighbourhood for k-NN models, and number of trees per response variable for CART-based methods are necessary to be optimally set. Specifically in terms of k-NN models, the main difference amongst the various approaches is how the distance to the most similar element(s) is measured, which in turn depends on how the *similarity* is quantified within the feature space formed by the multiple predictors. This causes the main difference amongst the diverse distance measures which work based on k-NN approach including the well-known Euclidean and Mahalanobis distances. The neighbourhood size (known also as the number of NNs or k) can be set to any number from 1 to n (the total number of reference units). The single neighbour can, however, contribute to producing more realistic predictions in small datasets, while avoiding major prediction biases in cases where the responses follow skewed (or non-Gaussian) distributions (Hudak et al., 2008). However, one may note that using multiple neighbours would apparently yield more accurate results through averaging values from multiple response units.

1.3.3 Screening the feature space of candidate predictors

When dealing with datasets associated with numerous independent variables, one aim is to reduce the dimensionality of the feature space. Even though heuristic approaches may often be used to deal with highly-correlated variable sets, application of appropriate variable screening methods has recently become an important issue in modelling context. In variable screening, the main objective is to optimize the efficiency of models by achieving a certain performance level with maximum degree of freedom (Latifi et al., 2010). When building models in small scale geographical domains using several (and often strongly inter-correlated) remote sensing metrics, one would most probably come up with the question of how the most relevant information could be extracted from the enormous information content stored in the dataset. This is of major importance when the aim is to build parsimonious models being valid not only across the underlying region of parameterization, but also in further domains which show the (relatively) similar conditions. It also plays a crucial role in k-NN modelling approaches, since the majority of those methods lack an effective built-in scheme for feature space screening. The performances of different deterministic (e.g. forward, backward and stepwise selection methods) and stochastic (e.g. genetic algorithm) have been investigated in various studies available in the literature.

2. Remote sensing for modelling forest structure

2.1 Forest attribute modelling using optical data

Due to the lack of required 3D information for characterisation of vertical structure of forest stands, the pure use of multispectral optical remote sensing for forest structure has severe limitations. (Koch, 2010) addresses this issue and states that those data sources have been mainly employed to differentiate amongst e.g. rough biomass classes which show clear distinctions. For example, Simple linear, multiple, and nonlinear regression models were tested by (Rahman et al., 2007) to classify different levels of forest succession in such as primary and secondary forests, where optical band reflectance and vegetation indices from Enhanced Thematic Mapper (ETM+) data were used as predictors. The use of dummy variables was reported to improve the accuracy of forest attribute estimation by ca. 0.3 of R^2 (best R^2 = 0.542 with 10-13 dummy predictors). In an earlier attempt in central Europe, (Vohland et al., 2007) performed parametric classification for a German test site based on a TM image, where 8 forest types were identified with an overall accuracy of 87.5 %. The Linear Spectral Mixture Analysis (endmember method) was also used to predict stem count, in that the fractions extracted from the spectra were linearly regressed with stem count as response variable. This different approach was also reported to introduce an improved calibration of large-scale forest attribute assessment. Although using parametric approaches, the methodology was (truly) stated to be also helpful in case of using nonparametric approaches. Regarding the observed linear correlations between the response variable of interest (stem count) and spectral indices, this assertion seems to be realistic. The usefulness of Landsat-derived features to model forest attributes (species richness and biodiversity indices) has also been discussed and confirmed by (Mohammadi & Shataee, 2010), in which they reported some positive potentials of multiple regressions (adjusted R^2=0.59 for richness and R^2=0.459 for reciprocal of simpson index) in temperate forests of northern Iran.

Attempts toward establishing correlations amongst regional-scale multispectral remote sensing and forest structural attributes in larger scale dates back to some early attempts in the early 1990's, amongst which e.g. (Iverson et al., 1994) can be highlighted. Their empirical regressions between percent forest cover and Advanced Very High Resolution Radiometer (AVHRR) spectral signatures was used based on Landsat-scale smaller calibration centres. Extrapolating forest cover for much bigger scales (state-scale) using AVHRR data resulted in high correlations (r=0.89 to 0.96) between county cover estimates. Those attempts to produce large-scale maps of forest attributes continued up to some later studies e.g. (Muukkonen & Heiskanen, 2007) and (Päivinen et al., 2009). Whereas regression modelling of AGB using Adavanced Spaceborne Thermal Emission and Radiometer (ASTER) and Moderate Resolution Imaging Spectrometer (MODIS) data was pursued in the former study (relative Root Mean Square Error (RMSE)% = 9.9), the latter used AVHRR pixel values which were applied to be regressed with the standing volume to produce European-scale growing stock maps. (Gebreslasie et al., 2010) can be noted as a very recent effort to parametrically model the forest structure in local scale, in which the visible and shortwave infrared ASTER features (original bands and vegetation indices) were investigated to build stepwise regressions of standing volume, basal area, stem count and tree height in *Eucalyptus* plantations. Whereas the spectral data was acknowledged to be an insufficient material to be solely used for modelling (R^2= 0.51, 0.67, 0.65, and 0.52 for standing volume, basal area, stem count and tree height, respectively), integrating age and site index data as predictors showed to notably enhance the models by 42 %, 20.2%, 16.8%, and 42.2% of R^2. The sole application of multispectral data, regardless of the scale within which the data have been used, seems not to fulfil the practical requirements for accurate regression modelling of forest attributes. Except some very few reports showing highly-correlated spectral indices with stem volume (approximate R^2= 0.95 for multiple linear regression using SPOT and AVHRR data in provincial level reported by (Gonzalez-Alonso et al., 2006)), most of other reports state moderate correlations. However, the majority of the studies have acknowledged the potentials in using such spectral data for regression modelling of forest structural attributes.

In context of nonparametric methods, as documented earlier, the initial introduction of k-NN methods to forestry context commenced in the late 1980's and early 1990 's, as a number of preliminary studies were carried out in the Nordic region. The method was initially in use only based on field measurements (Tomppo, 1991) and was later adapted for prediction of stem volume using spaceborne images. At that time, the most feasible satellite image data included Landsat Thematic Mapper (TM) and SPOT images, from which mainly TM and, to a minor extent, SPOT data were employed (Tomppo, 1993). The reported results have confirmed the suitability of the method based on remote sensing data. The method was further developed through various experiences. The further Finnish experiences with pure optical data include a range of studies in which the k-NN method was attempted to be adapted to practical applications in wood and timber industry. Amongst them, (Tommola et al., 1999) used k-NN method as a tool for wood procurement planning to estimate the characteristics of cutting areas in Finland. They found it to be a useful tool compared to the traditional inventory method. (Tomppo et al., 2001) utilized the approach to estimate/classify growth, main tree species, and forest type by means of multispectral TM data in China. The authors found the method to be helpful in classifying tree types and stand ages, though the stand-level predictions were reported to underestimate the growing stock.

As mentioned above, k-NN estimators include a range of distance-weighting approaches such as conventional distances (Euclidean and Mahalanobis) and Most Similar Neighbour (MSN) method. Due to the importance of those methods in the context of spatial modelling, a brief verbal explanation of those distance metrics seems to be essential: In general, the distance between the target units with a vector of predictor variables to any neighbouring unit having the multi-dimensional vector of predictors can be measured by a distance function, in which the weight matrix of predictors plays a central role to weight the predictors according to their predictive power. Whereas this weight matrix turns to be a multi-dimensional identity matrix (in the Euclidian distance) or the inverse of the covariance matrix of the predictor variables (in the Mahalanobis distance), the MSN inference uses canonical correlation analysis to produce a weighting matrix used to select neighbours from reference units. That is, according to (Crookston et al., 2002), the weight matrix is filled with the linear product of the squared canonical coefficients and their canonical correlation coefficients. The MSN method was described by e.g. (Maltamo & Eerikäinen, 2001) as a closely- related method to the basic k-NN based on Euclidean distance, whereas the main difference is that the coefficients of the variables in the distance function are searched using canonical correlations in MSN. Thus, one should bear in mind that a linear correlation between response(s) and predictor(s) can play a key role in the MSN method. The majority of attempts to construct MSN models of forest structure made use of 3D LiDAR data, either alone or in combination with spectral metrics. Therefore, the literature regarding MSN modelling will further be reviewed in the LiDAR section.

To the best of author's knowledge, Efforts to bring the analytical features of k-NN method to the US NFI system (called Forest Inventory and Analysis, FIA) were accomplished by studies such as (Franco-Lopez et al., 2001) who used the method to simultaneously predict basal area, volume and cover types based on FIA field inventory data and TM features. They truly mentioned a common small-scale problem (i.e. the critical performance of k-NN methods in case of small datasets) and acknowledged that "The key to success is the access to (enough) ground samples to cover all variations in tree size and stand density for each cover type".

(Katila, 2002) integrated TM and forest inventory data to model forest parameters including landuse classes. The results were verified using the Leave-one-Out (LOO) cross validation (Efron & Tibshirani, 1993) on the pixel level. The method was assessed to be statistically straightforward comparing to the conventional landcover estimation. (Hölmstrom, 2002) used a set of panchromatic aerial photos and field based information from 255 circular sample plots measured within the boreal forests of Sweden. Stem volume and age were modelled and validated, through which 14 % and 17 % of prediction errors ($RMSE$) for volume and age of the trees were observed, respectively. The k-NN method was thus proposed for stand level applications. However, they highlighted the importance of sufficient and representative reference material and the considerations in selecting the number of neighbours in small datasets as potential drawbacks.

The application of RADAR data in forest assessments has been reported to be associated with some major constraints due to signal saturation (Imhoff, 1995) which can also occur in optical images when the forest canopy is fully closed (Holmström & Fransson, 2003). However, RADAR reflectance has been reported to be linearly related to standwise stem volume (Fransson et al., 2000). Therefore, multispectral data has been combined, though in relatively few experiences, with active data from RADAR platforms for retrieval of forest attributes. For example, (Holmström & Fransson, 2003) tested the fusion of optical SPOT-4 and airborne CARABAS-II VHF Synthetic Aperture RADAR (SAR) datasets to estimate forest variables in Spruce/Pine stands. The single use of each data was compared to the combined use, and the combined data was expectedly assessed to surpass the single one for modelling stem volume and age ($RMSE$=37 m^3ha^{-1} of combined set compared to $RMSE$=50 m^3ha^{-1} of the best single-data models). The relationship between the reference target units was reported to be "substantially strengthened" when using the two data sources in combination. Later on, (Thessler et al., 2008) investigated the joint application of multispectral and RADAR data in an alternative workflow to the one explained above, in that they applied TM-derived features combined with predictors extracted from the Digital Elevation Model (DEM) of a shuttle RADAR data to classify the tropical forest types in Costa Rica. Some cover type classes were consequently merged to aggregate the classes and improve the results, which led to the overall accuracy of 91 % from the segmented image data based on k-NN classification. (Treuhaft et al., 2003) combined C-band SAR interferometry with Leaf Area Index (LAI) extracted from hyperspectral data to estimate AGB. They introduced their resulted 'forest canopy leaf area density' to be a representative for AGB of forest.

Though the conventional k-NN models of stand-scale forest attributes have been positively supported in the studies like those mentioned above, some other studies e.g. (Finley et al., 2003) acknowledge that the analysts may face the challenge of compromising between increased mapping efficiency and a loss of information accuracy. This is particularly the case when dealing with the question of selecting the optimal number of neighbours (also known as k). Different neighbourhood sizes have been studies in several works ((Franco-Lopez et al., 2001), (Haapanen et al., 2004),(Holmström & Fransson, 2003), (Packalén & Maltamo, 2006), (Packalén & Maltamo, 2007), (Finley & McRoberts, 2008) and (Vauhkonen et al., 2010)), in some of which the optimum number of k were discussed ((Franco-Lopez et al., 2001), (Haapanen et al., 2004), (Finley & McRoberts, 2008)). Whereas the above- mentioned studies reported an improved accuracy of k-NN predictions along with the increment of k (up to a limited number varying amongst the studies), some acknowledge that increasing k leads to a stronger shift of the predictions towards the sample mean which could cause serious biases, particularly in cases where the distribution of observations is skewed ((Hudak et al., 2008), (Latifi et al., 2010)). However, the choice of neighbourhood size is an arbitrary issue in which the expertise of the analyst (e.g. the prior knowledge on the properties and variance of the population) plays a functional role. By using multiple k for imputation, the majority of studies carried out within the framework of FIA program in US (characterized by a cluster sampling design using 4 subplots in each cluster) have shown to yield relatively high accuracies. The study of (Haapanen et al., 2004) can be exemplified, in which three classes of forest, non-forest and water were classified by a conventional k-NN approach (Euclidean distance) and ETM+ features as predictors. They increased the neighbourhood size up to 10 neighbours, which caused an enhancement of overall accuracy up to the use of 4th neighbour, a sudden drop, and a consequent improvement up to k=8. The Majority of other studies in this realm have reported the improvement of accuracy along with increment in the neighbourhood size. Some studies noticed that the selection of other parameters such as weighting distances also depends on the choice of image dates and other associated data ((Franco-Lopez et al., 2001), (Finley & McRoberts, 2008)). (Mäkelä & Pekkarinen, 2004) made a relatively preliminary effort to use field data of stand volume from an inventoried area to make predictions in a neighbouring region which was considered to suffer from lack of field data. However, their poor accuracy yielded from the estimation led them to assess the method as an inappropriate one for stand level predictions. Yet, some of their best volume estimates were reported to be useful for the stands where no (or few) field information is available. In a study conducted in a central Europe, (Stümer, 2004) developed a k-NN application in Germany to model and map basal area (i.e. metric data) and deadwood (i.e. categorical data) using TM, hyperspectral, and field datasets as predictors. The best results showed the RMSE between 35 % and 67 % (for TM data) and 65 % and 67 % (for hyperspectral data). As for the deadwood, the accuracy ranged between 60 % and 73 % (for TM) and 60 % and 63 % (for hyperspectral). The two data sets were separately assessed, in which no combinations were tested.

Using various configurations of k-NN methods, (LeMay & Temesgen, 2005) compared some combinations (e.g. varying number of neighbours) to predict basal area and standing volume in Canadian forests. They reported MSN method (even in a single-neighbour setting) as the most accurate approach compared to the Euclidean distance models based on 3 neighbours. In a relatively similar study in Bosnian forests in Europe, (Cabaravdic, 2007) also achieved relatively accurate k-NN estimates of growing stock using TM-extracted features and a broad range of field survey information. In terms of the configuration, k=5 and Mahalanobis distance were assessed to be optimal for growing stock models. (Kutzer, 2008) tested the selected bands in visible and infrared domain of multispectral ASTER image together with a set of terrestrial data to differentiate the landuse types and the Non Wood Forest Products in Ghana. The results were assessed, though with some exceptions, to be promising for application as a practical forest monitoring tool within the study area.

The majority of forest-related studies using k-NN method have been conducted with the aim of modelling continuous attributes of forest structure, whereas little attention has been paid to predicting categorical forest variables such as site quality or vegetation type. One of the few attempts to introduce such new potentials to the remote sensing society was carried out by (Tomppo et al., 2009), in which TM-derived spectral features were used to predict site fertility, species dominance and coniferous/deciduous dominance as categorical responses across selected test sites in Finland and Italy. Despite the moderate accuracy obtained out of the sole analysis of spectral data (e.g. max. Kappa statistics of approximately 0.65 and relatively higher Kappa values of species dominance compared to soil fertility), this study highlighted the importance of how an efficient strategy for feature space screening can contribute to reducing the prediction errors in k-NN models. Whereas the majority of pearlier studies used deterministic approaches (e.g. stepwise methods) to prune the candidate predictors, this study (which followed an earlier attempt by (Tomppo & Halme, 2004) used an evolutionary Genetic Algorithm (GA) to screen the feature space which reduced the modelling errors in slight rates. The idea of using GA was further applied for a number of LiDAR-supported forest modelling studies by e.g. (Latifi et al., 2010) and (Latifi et al., 2011).

2.2 LiDAR-based models of forest structural attributes

Height information from airborne laser scanner data has been validated to provide the most accurate input data related to the topography of land surface as well as to the structure of forested areas. Whereas (Lim et al., 2003), (Hyyppä et al., 2008) and (Koch, 2010) provide comprehensive reviews on the background and history of LiDAR data application in forest inventories, this section focuses on the methodological background concerning pure LiDAR-based models of forest structure.

LiDAR instruments include three main categories of profiling, discrete return, and waveform devices. Profiling devices record one return at low densities along a narrow swath (Evans et al., 2009) and were mainly used in the earlier studies such as (Nelson et al., 1988). Later, discrete-return (Pulse form) laser scanners enabled to use LiDAR in remote sensing where scanning over large areas was needed (Næsset, 2004). Such devices collect multiple returns (often three to five returns) based on intensity of the emitted laser energy from the earth surface. In terms of waveform data, the devices digitize the total amount of emitted energy in intervals and therefore are able to characterize the distribution of emitted laser from the objects. Although small footprint waveform sensors are most commonly available, they are reported to be computationally intensive and thus associated with restrictions when used in fine-scale (i.e. high resolution) environmental applications (Evans et al., 2009). They provide data featuring high point densities and enable one to broader representation of the surface and forest canopy. The importance of using pulse form data for studies concerning forest structure is already stated in the relevant literature e.g. (Sexton et al., 2009).

LiDAR data can be used in two main approaches to retrieve forest structural attributes. In ”area-based methods”, the statistical metrics and other nonphysical distribution-related features of LiDAR height measurements are extracted either from the laser point clouds or from a rasterized representation of laser hits. They are then used to predict forest attributes e.g. mean tree height, mean DBH, basal area, volume and AGB at an area-level such as the plot or stand level (Yu et al., 2010). This method enables one to retrieve canopy height information by means of a relatively coarse resolution LiDAR data e.g. satellite or airborne data featuring <5 measurements per m^2 e.g. (Korhonen et al., 2008), (Jochem et al., 2011), though data with higher point density can also be used to derive the metrics at an aggregated level (e.g. (Maltamo, Eerikäinen, Packalén & Hyyppä, 2006) (Heurich & Thoma, 2008), (Straub et al., 2009) and (Latifi et al., 2010)). A key to success in area-based methods, when the metrics are extracted from a rasterized form of LiDAR data such as normalized Digital Surface Model (nDSM), has been stated to be the quality of extracted Digital Terrain Model (DTM) and Digital Surface Model (DSM) (Hyyppä et al., 2008).

The focus in the so called ”Single tree-based methods” is on the recognition of individual trees. Here, the tree attributes e.g. tree height, crown dimensions and species information are measured. The measured attributes can further be applied to retrieve other attributes such as DBH, standing volume and AGB by means of various modelling approaches (Yu et al., 2010). The retrieved attributes are either presented as single-tree attributes or can be aggregated into a higher level e.g. stand or sample plot level.

In some earlier studies, one of the main goals in applying 3D data was to facilitate an accurate estimation of stand height, in which correlating the laser-derived height information to those measured in the field was of major interest. This often yielded notably promising results which strongly supported the accuracy of LiDAR instruments for precise height measurements. For example, (Maltamo, Hyyppä & Malinen, 2006) used airborne laser data to retrieve crown height information i.e. basal area, mean diameter and height at both tree and plot levels using linear regression methods in Finland. The results indicated the superiority of LiDAR-based attributes over the field-based ones in area-level, though a contrasting result was reported in single-tree level. Better result was hypothesized to be achieved when data with higher point density would be obtained with large swaths. The roughly similar result was later reported by (Maltamo, Eerikäinen, Packalén & Hyyppä, 2006), in which the plot-level stem volume estimates calculated from field assessments were reported to be less accurate than the methods in which volume had been predicted by LiDAR measures.(Maltamo et al., 2010) further studied different methods including regression models to retrieve crown height information. Regardless of the differences amongst the methods, they all yielded RMSEs between 1.0 and 1.5 m in predicting crown height.

Application of laser scanner data to enhance volume and AGB models dates back to some preliminary experiments in 1980 ’s e.g. (MacLean & Krabill, 1986), (Nelson et al., 1988) which demonstrated the usefulness of LiDAR-extracted canopy profiles to improve stem volume and AGB estimates (e.g.R^2=0.72 to 0.92 achieved in regression analysis by (MacLean & Krabill, 1986)). In the recent years, except some cases, the investigations on further developments in the retrieval of model-derived volume and AGB attributes has considerably grown. (Heurich & Thoma, 2008) built linear models to predict plot-level stem volume, height, and stem count in Bavarian National Park, where they reported $RMSE\% = 5$, 10 and 60 for LiDAR-estimated height, volume and stem count, respectively. The forest areas were stratified into three main deciduous, coniferous, and mixed strata. Despite achieving relatively accurate results in their models, they acknowledged that factors such as occurrence of deadwoods and complexities in forest structure constrain the achievement of better results. As stated earlier, derivation of model-based estimates of stem volume (in different assortments) have recently formed a major field of research in LiDAR-related studies. The Sawlogs can be exemplified as vital timber assortments in Nordic forest utilization context. Therefore, the accurate estimation of their volume can lead to an added value in forest management. (Korhonen et al., 2008) studied this by using parametric models, in that they used LiDAR canopy height metrics i.e. percentiles to make linear models of sawlog volume, which yielded relatively favourable accuracies ($RMSE\%$=9.1 and 18 for theoretical and factual volumes). In other examples, regression modelling of individual trees using the multi-return, pulse-form LiDAR metrics has been reported to be accurate for standing volume (R^2=0.77) (Dalponte et al., 2009) as well as for AGB (Max. R^2=0.71) (Jochem et al., 2011).

In terms of the type of metrics extracted from laser scanner data, one important issue cannot be neglected: In addition to height metrics, the LiDAR intensity data is reported to contain some information in infrared domain which may potentially share some values to the modelling of forest attributes e.g. (Boyd & Hill, 2007), especially when dealing with species-specific models (Koch, 2010). Regardless of some exceptions e.g. (Vauhkonen et al., 2010),(Latifi et al., 2010), most of the pure LiDAR-based models of forest attributes solely made use of height metrics as input variables for modelling.

Using nonparametric methods greatly contributed to the studies aiming at retrieval of forest attributes by means of LiDAR metrics. Those methods have been applied in various scales, using numerous metrics, and combined, in some cases, with additional methods for screening the high-dimensional feature space or for estimating the prediction variance. (Falkowski et al., 2010) evaluated k-NN imputation models to predict individual tree-level height, diameter at breast height, and species in northeastern Oregon in USA. Topographic variables were added to LiDAR-extracted height percentiles and other descriptive statistics to accomplish the task. Whereas 5 and 16 m^3ha^1 of $RMSE$ were achieved for basal area and volume estimates, occurrence of small trees or the dense understory showed to be the main source of prediction errors. Similarly, promising results have been reported by e.g.(Nothdurft et al., 2009) in central Europe for area-based models of stem volume using LiDAR height metrics (approximately 20 % of$RMSE$ for MSN models of stem volume in Germany).

(Hudak et al., 2008) compared different imputation methods to impute a range of forest inventory attributes in plot level using height metrics from LiDAR data and additional topographical attributes in Idaho, USA. They found the Random Forest (RF) to be superior to other imputation methods such as MSN, Euclidean distance and Mahalanobis distance. They used the selected RF outputs for final wall-to-wall mapping of forest structural attributes at pixel level. The dominance of RF model was further confirmed by studies such as (Latifi et al., 2010) and (Breidenbach, Nothdurft & Kändler, 2010) and led to a wider application of RF as a leading nonparametric method in combination with LiDAR metrics e.g. (Yu et al., 2011). The RF method (Breiman, 2001) works based on ensembles of CARTs for resampled predictor variable sets. It starts with evolving bootstrap samples from the original data. It then grows, for each bootstrap sample, an unpruned regression tree. The best splits are chosen from the randomly sampled variables at each node or the trees. The new predictions are then made by aggregating the predictions of the total number of trees. That is, the mode votes (the most frequent values) from the total trees will be the predicted value of the respective variable ((Liaw & Wiener, 2002), (Latifi et al., 2011)). Though the former studies e.g. (Hudak et al., 2008) and (Vauhkonen et al., 2010) have shown that the RF approach generally surpasses other imputation methods including MSN, (Breidenbach, Nothdurft & Kändler, 2010) reported an approximately similar performance of RF and MSN, as their study yielded e.g. the $RMSE$ of 32.41 % (for MSN) and 32.81 % (for RF) when predicting the total standing timber volume by averaging k=8.

In addition to those stated above, the nonparametric methods were also tested to predict further structural characteristics of forest stands e.g. diameter distributions by the sole use of laser scanner data (e.g. (Maltamo et al., 2009)), yielding some potentials towards further application of 3D topographic remote sensing for forest monitoring.

2.3 Combining LiDAR and optical data for modelling

As explained earlier, the application of ALS-extracted metrics (height and intensity features) has been validated as a being helpful and thus required for most practices regarding forest inventory. This is because the data has previously been proved to be potentially applicable in several environmental and natural resource planning tasks, particularly where the vertical structure of the respective phenomena is dealt with. Nevertheless, the use of multi-sensorial data may enable one to make use of advanced methods of data analysis and thus overcome some problems faced by using single datasets (Koch, 2010). The use of multispectral data can contribute to the analysis of vegetation cover by adding spectral information from visible and infrared domains. In this way, the information required for species-specific tasks will be provided by the spectral data, while the LiDAR data contributes an enormous amount of information in terms of 3D structural attributes (see e.g. (Packalén & Maltamo, 2007), (Heinzel et al., 2008), (Straub et al., 2009)).

When combining spectral and LiDAR data, the parametric models have been quite rarely used for predicting forest attributes. In contrast, relatively more studies were carried out using combined data made use of nonparametric methods (especially MSN and RF), probably as the models are generally assumed as rather 'distribution-free methods' which can potentially be applied regardless of the underlying distribution of the population. A further reason could be the ability of more advanced methods such as MSN and RF to handle high-dimensional feature spaces. However, examples of the joint use of spectral and laser scanner data for parametric modelling can be e.g. (Fransson et al., 2004) and (Hudak et al., 2006), in both of which the magnitude of candidate predictors were notably less than those making use of nonparametric methods. (Fransson et al., 2004) built regression models to predict stem volume using SPOT5 data aided by TopEye laser scanner data in Swedish coniferous landscapes. The SPOT5 data was used to develop features including multi-spectral bands, ditto squared, and the band ratios. LiDAR- derived features included height and forest density measures at stand level. The single as well as combined datasets were tested, from which the combined use of laser height data with the spectral features surpassed the individual use of the datasets. Later on,(Hudak et al., 2006) linearly regressed basal area and tree density on 26 predictors derived from height/intensity of LiDAR and Advanced Land Imager (ALI) multispectral data. They found laser height (to a higher extent) added by laser intensity metrics as most relevant predictors of both responses (The LiDAR-dominated models explained around 90 % of variance for both response variables).

In terms of applying conventional distance-based k-NN methods, (McInerney et al., 2010) can be referred who combined airborne laser scanner and spaceborne Indian Remote Sensing (IRS) multispectral data to model stand canopy height using k-NN method. They apparently reported laser height data as the major means of canopy height retrieval, and achieved a relative $RMSE$ between 28 and 31 %. (Maltamo, Malinen, Packalén, Suvanto & Kangas, 2006) applied a k-MSN (MSN using multiple k) method to combine the LiDAR data with aerial images and terrestrial stand information in Finland. The laser-based models were reported to outperform aerial photography in stand volume estimation, and the combination improved the models at plot and stand levels. (Wallerman & Holmgren, 2007) have also highlighted the combined application of predictive features derived from optical (SPOT) and laser (TopEye) data, according to which the combined dataset yielded the mean standing volume and stem density models with $RMSE = 20\%$ and $RMSE = 22\%$, respectively. Combining satellite-based (TM) spectral features with laser metrics was also carried out by (Latifi et al., 2010) who reported that TM-extracted metrics can be used as alternatives to those derived from aerial photography for area-based models. Using k-MSN approach, (Packalén & Maltamo, 2006) conducted a survey to achieve species-specific stand information using sets of aerial photography and ALS data. The procedure consisted of two methods including 1) simultaneous k-MSN estimation and 2) a two- phase prediction (prediction of the responses using regression analysis of ALS data and then allocation of the variables using a fuzzy classification approach). The k-MSN achieved better results than the fuzzy classifications. Although the study still proposed some further developments of the predictor variables from both datasets, the results were assessed satisfactory in cases of Norway spruce (*Picea abies* L.) and Scots pine (*Pinus sylvestris* L.). Soon after, (Packalén & Maltamo, 2007) made stand level models of volume and height using the similar dataset as before. A set of Haralick textural features(Haralick, 1979) from the optical data were additionally combined with the calculated ALS height features to produce predictive models. Accuracy of the predicted responses was finally found to be comparable to stand-level field assessments, though the attributes of conifers were estimated more accurately than those from the deciduous stands. In a further study by those authors, (Packalén & Maltamo, 2008) made use of the similar data to develop k-MSN models of diameter distribution by tree species. Based on the results of growing stock estimation in the previous research work(s), two approaches were compared including 1) field-based modelling using the Weibull distribution and 2) k-MSN prediction, in which the latter was assessed to outperform the former method. Nevertheless, the need to have more comprehensive reference field data (i.e. a common small-scale problem) to cover the spectral variations of the remote sensing data was highlighted as a major concern which supports those already acknowledged by precedent studies. (Nothdurft et al., 2009) represents an attempt towards solving this, in which bootstrap-simulated prediction errors of MSN inferences of volume based on sole use of LiDAR height metrics were smaller than those of design-based sampling.

Few studies e.g. (Straub et al., 2010) and (Latifi et al., 2011) compared parametric and nonparametric methods for forest attribute estimation in presence of both LiDAR and multispectral datasets. Whereas the former study compared Ordinary Least Squares (OLS) regression and a yield table-estimated stem volume with that from Euclidean distance-based k-NN method, the latter made a comparison between RF and OLS outputs. Nevertheless, both studies made relatively similar conclusions, in that they stated that using nonparametric methods cannot b expected to remarkably contribute to the improvement of forest attribute estimates. Besides, it supports (Yu et al., 2011)who also tested pure LiDAR metrics and achieved a similar performance of RF and OLS in a single tree scale. The rationale behind this is that non-parametric imputations do not share the same mix of error components as regression predictions. Imputation errors are often greater than regression errors because the errors do not result from a least-squares minimisation, but from selection of a most similar element in a pool of neighbouring observations (Stage & Crookston, 2007). However, K-NN methods (especially in single- neighbour setting) yield predictions with similar variance structure to that of the observations (Moeur & Stage, 1995), and are thus advantageous over the higher accuracies achievable by the use of OLS (Hudak et al., 2008).

The selection of proper predictor variables for a k-NN model (i.e. an absent element of conventional k-NN approaches) is a time-consuming task which and needs to be automated. (Packalén & Maltamo, 2007) used an iterative cost- minimizing variable selection algorithm which aimed at minimizing the weighted average of the relative $RMSE$. In contrast, studies like (Hudak et al., 2008) and (Straub et al., 2009)applied stepwise selection methods, where the former study based its stepwise iteration on the *Gini* index of variable importance used by (Breiman, 2001) as a built-in feature in RF. As such, other variable screening methods such as parametric univariate correlation analysis (Breidenbach, Næsset, Lien, Gobakken & Solberg, 2010), Built-in schemes of RF such as stepwise iterative method (Vauhkonen et al., 2010) and forward selection (Breidenbach, Nothdurft & Kändler, 2010)were also used to complete this task in the recent literature. Each of those screening methods has been reported to be satisfying in terms of reducing the dimensionality of the feature space, though no rationale (e.g. comparison to other methods) has been presented. (Latifi et al., 2010) used a GA on categorised response variables to optimise the high-dimensional feature space formed by numerous correlated predictors. Even though this GA prototype was evaluated to efficiently reduce the relative RMSE of standing volume and AGB compared to the stepwise selection of predictors, the method was reported to produce unstable subsets attributed to strong correlations amongst the predictors. By using a Tau-squared index on continuous responses, GA was later shown to yield stable parsimonious variable subsets (Latifi et al., 2011). GA is a search algorithm which works via numerous solutions and generations and thus explores the entire possible combinations of candidate predictor variables. It provides the consequent NN models with the optimum range of refined, pre-processed feature space formed of relevant (and uncorrelated) remote sensing descriptors and is shown to be able to be adjusted to the k-NN modelling approaches (e.g. (Tomppo & Halme, 2004)). In this context, fitness functions to optimise continuous responses are preferable for regression scenarios. Those functions can even be linear as long as no highly non-linear trend/prediction is observed in the entire underlying dataset.

In a review by (Koch, 2010), the importance of combined use of laser and optical data for such purposes was highlighted. She stated that combining the altimetric height information with physical values derived from laser intensity is appropriate for modelling forest structure. As 3D data has already been shown to be plausible for AGB modelling, and due to the expected future technical innovations of those data for biomass assessments, it is assumed that it will further play a prominent role in major forest monitoring tasks e.g. those related to AGB modelling.

3. Conclusion

Amongst the available active/passive remote sensing instruments, information derived from laser scanner (especially the height information) is definitely of major importance for studies regarding forest structure. According to (Koch, 2010), the significance of using LiDAR data for biomass assessment has been confirmed by variety of investigations which repeatedly showed comparatively higher performance of those data. However, the use of LiDAR intensity data is still limited. The intensity data has been shown to be able to add useful complementary information to LiDAR height data for forest attribute modelling (e.g. (Hudak et al., 2006)). Yet, a direct physical connection between those intensity metrics and forest structure still cannot be drawn. The reason for this complication is stated to be the dependency of intensity on a range of factors affecting reflected laser data including range, incidence angle, bidirectional reflectance function effects, and transmission of atmosphere (Hyyppä et al., 2008).

Apart from few exceptional studies which reported the incapability of spectral data for explaining the variation beyond the variation that could be explained by laser metrics (Hudak et al., 2008), adding spectral information to pure LiDAR-based models has been confirmed to be useful, as they provide continuous information over long time series and are spectrally sensitive for differentiating tree species. The ability of multispectral data, even in regional-scale spatial resolution such as Landsat images, has been constantly approved to bear practical values when combined with laser scanner data ((Fransson et al., 2004), (McInerney et al., 2010)) and even as an alternative to aerial photography for area-based applications (Latifi et al., 2010). Furthermore, image spectroscopy data showed positive potentials for forest modelling ((Foster et al., 2002), (Schlerf et al., 2005)) and could potentially complement LiDAR-based models. However, one should bear in mind that the experimental results of surveys is by no means an eventual justification for the small- scale end users to take the acquisition of (relatively) expensive airborne hyperspectral data for granted.

In terms of various modelling methods used, both parametric and nonparametric modelling categories were frequently employed to describe the forest structural attributes. However, the latter approaches received more attention during the recent years to be run for high dimensional predictor datasets as well as for simultaneous predictions. The k-NN methods (especially MSN and RF) have been successfully coupled with LiDAR information and thus caused a rapid increase in the number of research projects during recent years. As it was shown here, much work has been done on area-based methods e.g. stand and plot levels, whereas single-tree approaches still lack some research, mainly due to high computational requirements and the need for high resolution data.

In terms of handling predictor feature space induced by remote sensing features, some examples were previously referred. Whereas studies such as (Breidenbach, Nothdurft & Kändler, 2010)made the general necessity of variable screening in k-NN context questionable, some other studies acknowledge the requirement to selecting an effective strategy of pruning of predictor dataset (e.g. (Hudak et al., 2008), (Latifi et al., 2010)) and showed some decisive influences on the outcomes of the forest attribute models. The proper pruning of predictor feature space has been proved to help producing robust models (Latifi & Koch, 2011). Reducing the sensitivity of models has been also shown to greatly contribute to increasing the robustness of the models. Using resampling methods e.g. bootstrapping to reproduce the underlying population (e.g. (Nothdurft et al., 2009),(Breidenbach, Nothdurft & Kändler, 2010), and (Latifi et al., 2011) increases the potential and robustness of applying nonparametric models in small-scale forest inventory, where the shortage of reference data for validating the models is a major constraint. Robust models enable the analyst to apply them under other natural growing conditions except of the underlying test site, and can thus open up new operational applications for the yielded models (e.g. (Koch, 2010)).

Along with the rapid advancements in launching the active/passive remote sensing instruments, the general access to high resolution products (particularly to laser scanner data) at reasonable costs is increasing. Therefore, the efforts towards thorough description of tree and forest stand structure are currently following a boosting trend all over the world. However, it is necessary to emphasize, again, that much care should be taken in terms of producing valid and robust results, as well as to get the best out of the available data and modelling facilities. Whereas the rapid and accurate modelling of standing volume, biomass and tree density is still important, some remaining open areas of research still require further research. These include, for example, efforts towards advanced classification tasks (especially on single-tree level or in complicated mixed stands), modelling understory and regenerations (e.g. important for intermediate silvicultural practices), and modelling rare and ecologically-valuable populations.

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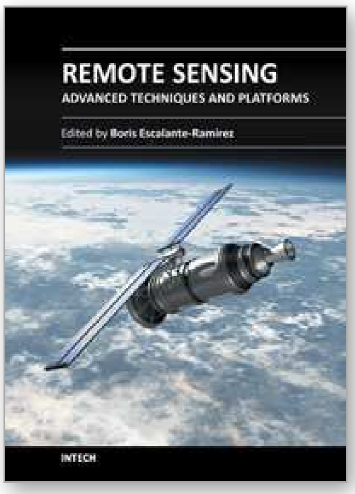

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This dual conception of remote sensing brought us to the idea of preparing two different books; in addition to the first book which displays recent advances in remote sensing applications, this book is devoted to new techniques for data processing, sensors and platforms. We do not intend this book to cover all aspects of remote sensing techniques and platforms, since it would be an impossible task for a single volume. Instead, we have collected a number of high-quality, original and representative contributions in those areas.

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