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Applications of Airborne Laser Scanning for the spatial estimation of forest structural parameters in Mediterranean environments

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Chapter 1

1 Introduction and dissertation overview

In this chapter an introduction to the dissertation is given. An overview on the remote sensing technology applied to forestry inventory and on Airborne Laser Scanner role in fuel modeling is presented. The main objectives of this dissertation are also shortly illustrated. Finally, the structure of the dissertation is described.

1.1 Remote sensing and forest inventory

During the past decades, forestry has been focused mainly on the assessment of timber resources and the management practices have been mostly addressed to the production of wood. In the past twenty years, this concept evolved and forests begin to be considered as a complex multi-functional system (Ciancio, 1997). For this reason it is important to acquire more accurate, timely information about their current status and, in particular, changes over time. This information is required for a range of spatial and temporal scales, from local forest inventories used for economic resource management purposes and updated annually, up to global data on carbon, water and energy fluxes required for environmental management over a number of decades (Cohen & Goward, 2004).

Remote sensing, involving the acquisition of information about a surface, object, or other phenomenon from devices that are not in contact with the feature under investigation, can play a crucial role in providing information across these scales. It is a useful tool for assessing forest condition and it notably supports forest monitoring, allowing the generation of data on large scale at regular time intervals.

There are two types of remote sensing devices that can be differentiated in terms of whether they are passive or active. Passive sensors detect only energy emanating naturally from an object, such as reflected sunlight or thermal infrared emissions; active sensors provide their own energy source as radar waves and record its reflection on the target. Each type of sensors has their own specialized purpose or task for which it was designed and often used for. (Franklin, 2001).

Lately, there has been a progressive evolution of remote sensing approaches for the collection of forest resource information: remote sensing with GIS and direct field measurements have shown the potential to facilitate the mapping, monitoring and modeling of the forest resources. Remote sensing provide a systematic, synoptic view of earth cover at regular time intervals and it is useful for detecting changes in land cover and to assess aspect of biological diversity directly (Hall *et al*., 1988; Roughgarden *et al*., 1991; Turner *et al*., 2003; Cohen & Goward, 2004).

The proliferation of low cost, widely available, remotely sensed data has been the basis for many of the important recent technological improvements in forest inventory techniques. Forest inventory is the statistical estimation of the quantitative and qualitative attributes of the forest resources in a given region. The assessment of the relationship between remotely sensed data and the biophysical attributes of forest vegetation (standing wood volume, biomass increment, etc.) allows also the construction of maps of the attributes at the sample inventory units for the whole region of interest, i.e., the attributes can be predicted for all the pixels in the region producing maps. Remotely sensed data have not only contributed to enhance the speed, cost efficiency, precision, and timeliness associated with inventories, but they have facilitated construction of maps of forest attributes with spatial resolutions and accuracies that were not feasible even a few years ago.

In the present dissertation, specific attention will be given on active remote sensing, with a focus on Airborne Laser Scanning, based on a LiDAR system (*Light Detection and Ranging or Laser Imaging Detection And Ranging*) mounted on an airplane or an helicopter. LiDAR is an active remote sensing technique in which a pulse of light is sent to the Earth’s surface; the pulse reflects off of canopy materials such as leaves and branches. The returned energy is collected back at the instrument by a telescope. The time taken for the pulse to travel from the instrument, reflected off of the surface and be collected at the telescope is recorded. From this ranging information various structure metrics can be calculated, inferred or modeled.

1.2 The role of Airborne Laser Scanning in fuel modeling

In recent years, the topic of using of ALS data to describe fuel characteristics has been studied at a certain extent. Fire researchers and managers have long recognized the influence that fuel characteristics have on fire behavior and have attempted to incorporate key characteristics into models used to predict fire dynamics. Biomass estimates are needed to assess fuels, primary productivity, carbon content and budgets, nutrient cycling, treatment effects, and competition within plant communities; they are also needed to assess the effects of different fire regimes on plant communities (Murray & Jacobson 1982, Hierro *et al*. 2000).

Accumulation of fuel loadings in forest stands is an important determinant of fire frequency and severity (Paatalo, 1998; Cochrane *et al*., 1999). Therefore, information regarding the quantification and distribution of fuels in relation to time elapsed since last fire has been used to investigate how rapidly fires will spread, their intensity, and ultimately their ecological effects (Rothermel, 1972; Kauffman *et al*., 1994; Paatalo, 1998).

Fuel characteristics are difficult to measure for a number of reasons. For uniform forest stands, it is assumed that canopy biomass is uniformly distributed vertically, but this assumption does not hold true in a complex forest stand. This is due to multiple layers in the canopy, presence of ladder fuels and variation within tree species and within the forest stand. Although destructive sampling is the most accurate way to measure canopy fuels, it is not a desirable or effective way of acquiring data.

Quantification of vertical structure of the canopy is of importance to wildland fire managers, who are interested in managing the landscape for the reduction of ladder or transitional fuels that facilitate the spread of fire into the canopy (Skowronski *et al*., 2011). Maps of fuel loading can also be used to predict fire behavior and guide operational responses during active fire suppression, to prioritize areas for hazardous fuel reduction treatments, and to evaluate the effects of past fires or other disturbances.

Physical and chemical properties of fuels are characterized by significant variability across space and time. This variability took place according to daily (for example, the moisture content varies according to the weather conditions), seasonal and yearly modifications or in relation to specific processes that occur over decades (successional stages). The quantitative assessment of the fuel characteristics in a given area is generally unsuitable; however, the considerable need to predict fire behavior on a large scale through decision making support tools requires representing this complexity through mapping techniques (Rollins *et al*., 2004; Chirici & Corona, 2006).

LiDAR is a promising technology for generating reliable representation of the horizontal and vertical forest structure, due its capacity to scan wide areas and produce precise vertical and horizontal estimates of forest attributes (Ahokas *et al*., 2003). Recent studies highlight that fire behavior modeling can benefit from such technology because, in combination with optical remotely sensed images, it improves estimation of forest variables (e.g. Riaño *et al*., 2003; Mutlu *et al*., 2008; Erdody & Moskal, 2010). A certain number of studies, conducted mostly in temperate and boreal forests of Europe and North America, indicate the potential of ALS data for estimating tree or forest variables as a component of fuel models. For example, tree height can be readily estimated from the ALS point cloud (e.g. Magnussen *et al*., 1999;

Means *et al*., 1999; Lim *et al*., 2002; Næsset, 2002; Popescu *et al*., 2002; Corona & Fattorini 2008; Barbati *et al.*, 2009). ALS technology appears more limited for predicting the characteristics of ground fuels (grass, shrubs, small trees), especially for low vegetation canopy heights (Riaño *et al.*, 2007). The extraction of data on understory vegetation (e.g. percentage cover and height of the shrub layer) has been investigated in only a few studies (e.g. Harding *et al*. 2001; Riaño *et al*. 2003; Maltamo *et al*., 2005).

The utility of ALS data for characterizing forest ecosystems both for mapping forest classes or forest types and for estimating quantitative variables such as forest biomass, has been confirmed by some studies (e.g. Zhao *et al*., 2011; Corona *et al*., 2012). Many of these studies focused on estimating variables useful for fire management (Arroyo *et al*., 2008) and relied on the combined use of ALS with optical data (Mutlu *et al*., 2008; Koetz *et al*., 2008; Garcia *et al*., 2011).

All these authors identify the need for more research on the use of ALS data for these purposes, especially with reference to Mediterranean forest ecosystems, which are peculiar for their complex structural features.

1.3 Objectives of the dissertation

In this dissertation some of the main questions related to the use of ALS data for the assessment of forest structural parameters, with a special focus on forest stand height and aboveground biomass estimation, have been addressed. The distinctive overall target of this dissertation is to compare different ALS data and methods for assessing forest aboveground biomass under Mediterranean environments.

To accomplish this goal, the research has been set up according to specific objectives that can be summarized as follows:

1. to provide an overview of the current applications of ALS for forestry purposes in Italy, with a special focus on the spatial estimation of forest structural parameters; this objective has been covered by a detailed review literature, to obtain an exhaustive understanding of the topic;
2. to test the potential for innovation offered by ALS data for the spatial estimation of living aboveground biomass through the integration of ALS raw data and ALS-derived information and the application of different remote sensing techniques.

1.4 Structure of the dissertation

The dissertation is organized in five chapters. Chapter 2 provides general considerations, in the form of a scientific review, about ALS applications under alpine, temperate and Mediterranean environments in Italy; the analysis is supported by a remarkable number of case studies and provides special considerations to the common problems in the operational use of ALS systems. Chapters 3 and 4 are focused on the estimation of aboveground biomass using ALS data. Chapter 3 reports an experimental testing of raster Canopy Height Model for the spatial estimation of the aboveground biomass by coupling ALS data and field survey in a riparian forest. Chapter 4 reports an experimental testing of raw ALS data for detecting forest structural variables critical for fuel modeling. Various methods have been analyzed integrating remote sensing techniques with field measurements. The final chapter summarizes main outcomes drawn by the study and provides recommendations for future applications on research development.

Chapter 2

2 Current applications of Airborne Laser Scanning for spatial estimation of forest structural parameters[1]

In this chapter general considerations with reference to selected experiences of ALS applications under alpine, temperate and Mediterranean environments in Italy are provided. The main issues concern the potential use for ALS data exploitation in forest inventories on large territories, their use for silvicultural systems detection and for the estimation of fuel load in forest stands.

2.1 Introduction

Information about the state and changes to forest stands is important for environmental and timber assessment on various levels of forest ecosystem planning and management and for the global change science community (Corona & Marchetti, 2007). Standing volume and above-ground tree biomass are key parameters in this respect. Currently, fine-scale studies have demonstrated the influence of structural characteristics on ecosystem functioning: characterization of forest attributes at fine scales is necessary to manage resources in a manner that replicates, as closely as possible, natural ecological conditions. To apply this knowledge at broad scales is problematical because information on broad-scale patterns of vertical canopy structure has been very difficult to be obtained. Passive remote sensing tools cannot help for detailed height, total biomass, or leaf biomass estimates beyond early stages of succession in forests with high leaf area or biomass (Means *et al.*, 1999). Over the last decades, survey methods and techniques for assessing such biophysical attributes have greatly advanced (Corona, 2010). Among others, laser scanning techniques from space or airborne platforms have developed to the point where they can provide vertical profiles of forest vegetation.

As pointed out in the previous chapter, ALS systems provide a three dimensional point cloud, where over vegetated terrain some of the signals are caused by reflections in the

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vegetation canopy and some by reflections at the ground surface (Hollaus *et al*., 2006). Basic elaboration processes involves the elimination of LiDAR returns identified as below the nominal ground surface or above the expected canopy height, then the remaining LiDAR returns from the ground are separated from those from above ground targets (Donoghue *et al*., 2007).

The airborne LiDAR back-scattered signals can be used as they are (i.e. point data or waveform) or they can be spatially interpolated to produce digital models. Signals from the ground are used to produce Digital Terrain Models (DTM) while above ground returns are used to produce Digital Surface Models (DSM). In areas covered by trees the algebraic subtraction of DTM from DSM corresponds to the Canopy Height Model (CHM), which provides a measure of the height of the upper canopy for each forest pixel in the surveyed area (Kraus & Pfeifer, 1998).

ALS data can convey a rich summary of forest features due to their ability to capture the forest heights: the accuracy of retrievable information is highly dependent on both the extrinsic specifications of the ALS survey as well as the intrinsic effects of the underlying forest structures. Most literature concerns applications under boreal environments (Maltamo *et al*., 2005; Næsset & Gobakken, 2008).

2.2 Data availability

ALS data most commonly used for forestry applications under alpine, temperate and Mediterranean environments are not produced by dedicated flights: forest technicians simply exploit the raster CHM available at low (Clementel *et al*., 2012) or even no cost from ALS surveys carried out for purposes other than forest applications. In Italy around 30% of the land has been covered so far for accurate hydraulic modeling. Laser-scanning data are the best information source for this kind of models, that are necessary to prevent damages by floods, as well to assure water resources for people and agriculture.

However, surveys aimed to generate DTM or topographic measurements, to be used e.g. for land planning or hydrogeological purposes, are frequently characterized by a relatively low density of points per square meter and, above all, they are usually made in winter to minimize the noise by vegetation, since the aim is to achieve a high penetration rate through the vegetation canopy, i.e. to ensure that a high number of pulses reach the ground (Kraus & Pfeifer, 1998). In summer, penetration rates less than 25-30% are normally obtained under forest stands (Kilian *et al*., 1996). In the case of deciduous species (i.e. without green foliage during winter), which are those mostly frequent under temperate and Mediterranean forest environments, these rates can significantly be raised by winter surveys (Ackermann *et al*., 1994): thus, commercial ALS flights for DTM production are almost always made between November and March under temperate and Mediterranean environments and even under alpine environments, at least in those areas not permanently covered by snow in that period. On the contrary the most favorable season to obtain ALS data specifically suitable for forestry applications under temperate and Mediterranean environments is summer, since in winter only the wooden part of the prevalently deciduous canopies generates LiDAR-significant returns (Clementel *et al*., 2012).

Summer and winter CHMs have been compared by Clementel *et al*. (2010) in an alpine site, showing strong correlation but with a systematic, significant stand height underestimation by the winter CHM. A tendency to slightly underestimate the real height is unavoidable with summer flights as well, because the pulse emitted by laser tends to penetrate into the canopy before a significant signal of return can be recorded and also, in the case of raster CHM, the point interpolation on regular cells determines a certain smoothing of tree height (Brandtberg *et al*., 2003). However the stand height underestimation from summer ALS data is negligible for most operative forestry purposes. In general, the most accurate information on the height of the upper canopy in forest areas can be obtained by comparing summer and winter ALS data for canopy height and DTM, respectively.

2.3 Area-based and Individual Tree Crown approaches

Experiences about exploitation of ALS data to support forestry are especially focused on: (i) qualitative and quantitative characterization of forest stands and description of their morphological and structural attributes; (ii) quantitative spatially explicit estimation of forest standing volume and biomass. Data sources and methods for this type of analysis is under evaluation at various scales: the value of LiDAR data derives from their ability to support the monitoring of ecosystem vertical structure which can be used to estimate aboveground ecosystem attributes.

There are two broad categories of ALS data analysis approaches to support forest inventory and management: area-based approaches (AB), called also statistical canopy height distribution approaches, and individual tree crown approaches (ITC).

In the AB approaches, plot level data is related to ALS data aggregated at plot level to estimate stand biophysical attributes; AB approaches relates CHM raster pixels or point ALS data to measured plot characteristics to build parametric (e.g. regression) or non-parametric models to predict the forest attributes of interest. Collective biophysical variables are considered, referred to plots ranging from hundred up to thousand square meters; the established models have been shown to explain the majority of the variation in stand height, volume, and biomass (e.g. Næsset, 1997; Hudak *et al*., 2006; Hollaus *et al*., 2006; Garcia *et al*., 2010).

The ITC approaches include all the methods based on the detection of the individual trees (or at least of the distinguishable trees) in a given forest stand. ITC approaches may use both raster CHM and point ALS data to build individual crown polygons and/or 3-dimensional tree profiles; these individual tree records can then be aggregated to any scale required to create stand-level or ecosystem-level estimates (Akay *et al*., 2009).

AB and ITC approaches to estimating biophysical attributes are not mutually exclusive, and several authors demonstrated how they can be combined (e.g. Lindberg *et al*., 2010; Vastaranta *et al*., 2012).

2.4 ALS - assisted assessment of forest stand and structure

The accuracy and coverage of ALS observations in forestry application is highly dependent on both the extrinsic specifications of the LiDAR survey as well as the intrinsic effects such as the underlying forest structure. Various AB approaches have been used to characterize and classify forest stands in terms of mean height. Floris *et al*. (2010) have observed a correlation coefficient of 0.90 between mean height data measured on the ground (plot size of 1256 m^2) and mean height measured on CHM in an alpine conifer forest. Barilotti *et al*. (2005) and Fusco *et al*. (2008) have obtained similar results in mixed conifers-broadleaves forests, and in mixed broadleaved coppices, respectively. Other features related to hypsometric variables detected by ALS have been proposed by Floris *et al*. (2009), like stand density and canopy roughness identifying the multi-layered or mono-layered structure of the stand: these descriptive features, appropriately combined, can be exploited to guide both the delineation of forest management units and to support forest stand stratification for inventory purposes.

Barilotti *et al.* (2005) have observed that the capability of the laser pulses to reach the ground in forest areas (laser penetration index, LPI) is inversely proportional to tree height and density of the stands; additionally, LPI proves to be closely and inversely proportional to the Leaf Area Index (LAI) measured on the ground, evidencing the potential of ALS data to feed ecological process models that rely on LAI assessment.

ALS data can be used for forest canopy gaps detection, which is relevant both for the ecological studies of stand dynamics and even to exclude the gaps from the sampling process for inventory purposes so to increase the sampling efficiency. Barbati *et al*. (2009) have applied the hot-spot analysis based on the calculation of the local statistic variable Gi* of Getis-Ord (Getis & Ord, 1992) in a coastal Mediterranean pine forest. Bottalico *et al*. (2009) did a comparison between the hot-spot analysis and the morphological functions proposed by Koukoulas & Blackburn (2004) to extract gap boundaries. Floris *et al*. (2009) have adopted a rule of spatial contiguity on a minimum surface under alpine conditions. Barilotti *et al*. (2007a) have developed automated extraction of individual trees from CHM: they have been detected through a sequence of morphological transformations by a Top Hat algorithm implemented under open-source GrassGIS environment (Neteler & Mitašova, 2004). Top Hat is a mathematical function of image processing that allows to highlight the relief structures (Schmidt & Hewitt, 2004), which in the case of forest stands are constituted by the tree apexes. Barilotti *et al*. (2007b) have also developed the automatic delineation of tree crowns by the subsequent use of a segmentation algorithm able to classify the laser points in subsets belonging to the individual crowns. The technique has proved to detect less than 80% of the trees in the examined alpine conifer stands, and even less in stands mainly composed by broadleaved trees. In the latter case, the delineation of individual tree crown contours is generally difficult, due to the frequent high geometric irregularity of crown shapes, high local variation of foliage and branch density and the more pronounced tendency of tree crowns to interpenetrate each other than in conifer stands (Heurich, 2008). Abramo *et al*. (2007) have applied the methods developed by Barilotti *et al*. (2007a, b) in various types of spruce, beech-spruce-fir, spruce-fir, spruce and beech forests, detecting 71% of the trees with a stem diameter at breast height (dbh) greater than 5 cm, 89% of the trees with dbh greater than 17.5 cm and about 94% of the dominant trees. ITC approaches based on segmentation algorithms was also used by Dalponte *et al*. (2011a), exploiting the algorithm developed by Hyyppä *et al*. (2001a, b), and by Forzieri *et al*. (2009), who have obtained acceptable results for stands where the ratio between the mean tree interdistance and the mean tree crown diameter is greater than 0.6.

2.5 ALS - assisted assessment of forest standing volume and biomass

Under alpine, temperate and Mediterranean environments the assessment of the forest standing volume and biomass has been mainly carried out by AB approaches (see 2.3). The strategy is to establish models predicting the stand attributes of interest on the basis of ALS-derived metrics. Such metrics are computed by the raw (point or waveform) ALS data, that allow to calculate plot metrics like number of returns, above ground elevation of highest return, height percentiles, coefficient of variation of return height, skewness and kurtosis of returns height, non-ground percent of total returns, etc., or simply by the raster CHM values, that allow to calculate plot metrics like mean height per pixel, coefficient of variation of the height per pixel or the sum of the heights of all the pixels in the plot.

Corona *et al*. (2008) have examined the correlation between volume measured in circular plots of 314 m^2 and the sum of the CHM heights (raised to a power) within plots in a temperate broadleaved forest. The relationship has proved to be heteroschedastic and linear through the origin, with correlation coefficient equal to 0.78. Starting from this finding, Corona & Fattorini (2008) have subsequently proposed a design-based approach for the AB ALS-assisted estimation of forest standing volume: adopting the height of the upper canopy at pixel level as auxiliary information, a ratio estimator of the total volume is derived, together with the unbiased estimator of its sampling variance and the corresponding confidence interval. With reference to the same above mentioned broadleaved forest, these authors have shown that the use of ALS data as auxiliary information can give rise to a confidence interval of the estimation approximately between half and two-thirds smaller than that obtained by field sampling plots only. Barbati *et al*. (2009) have tested the same estimation approach in a coastal Mediterranean pine forest, finding a correlation coefficient between the volume measured in circular plots of 1256 m^2 and the sum of the CHM heights within the plots equal to 0.88. A study of Fusco *et al*. (2008) on mesophillous coppice stands confirms the relationship between the woody biomass and the sum of CHM heights, with a correlation coefficient equal to 0.87. Extensive AB experimentations for assessing forest standing volume under alpine environments have been carried out by Floris *et al*. (2010): these authors developed regression models between CHM metrics and standing volume measured in sample plots in spruce forests and found that the CHM mean height (excluding those pixels with height less than 2 m) can reliably predict the volume, with a correlation coefficient equal to 0.94. Under alpine conditions, Tonolli *et al*. (2011) have also analyzed the relationship between the standing volume measured on plots with size ranging from 400 m^2 to 3600 m^2 and metrics obtained from point ALS data: the most explicative metrics resulted the mean height of the first return and, with much less importance, the median of the heights of the second return. These authors also found that the relationship is significantly influenced by the plot size, with correlation coefficient increasing from 0.7 to 0.8 in the considered plot size range.

For professional application purposes and, distinctively, for forest planning, it is interesting to assess the accuracy of the ALS-assisted estimation over forest areas of a certain size (e.g., an entire forest compartment). In this case, if the estimates of standing volume by ALS metrics are unbiased, a compensation of positive and negative errors can be assumed, and good overall accuracy is presumed. Floris *et al*. (2010) have examined this topic for a compartment of 10 ha in an alpine spruce forest where a full callipering was available, observing a difference of the estimate of the total volume less than 3% with respect to the true value. Moreover, ALS-assisted models allow to map the variability of the volume at sub-compartment level: this is an important and innovative issue for forest planning aims (e.g. harvesting planning), not achievable with the traditional forest inventory practices based on field plots only. Overall, the presented results demonstrate that AB approaches have now reached the maturity to be used for mapping forest canopy heights and stand volume and biomass under complex environments throughout large areas.

ITC approaches (see 2.3) to predict forest standing volume or biomass comprise various steps: (i) single tree detection, (ii) ALS measurement of the height of each detected tree, (iii) prediction of dbh of each detected tree by inversion of the height-dbh relationship established in the field, (iv) estimation of the volume of each detected trees through double-entry (height, dbh) volume equations. Beyond the mentioned difficulties to pinpoint single trees (even if this issue is relatively less relevant for stand volume estimation since most volume is due to the bigger trees, which are those normally more reliably detected), this approach significantly involves error propagation across the considered steps. The results by Dalponte *et al*. (2011a) in alpine spruce forests shows that the capability of the ITC approach to assess tree dbh is relatively low (about 6 cm of absolute bias on trees with dbh equal to 45 cm), with overestimation for dbh up to 40 cm and underestimation for larger dbh, and standard errors of volume estimates around 0.7-0.8 m^3 for trees with average volume around 2.3 m^3. However, for the whole 481 examined trees, the bias of the volume estimation is only -5%. A study by Abramo *et al*. (2007) shows that the differences between the volume assessed by field plots and that predicted by the ITC approach is equal to 5-6% for spruce stands (except for a case in which the difference was 11%), 10% for beech high forests and around 19% for beech coppices. On the other hand, it is difficult to infer from the above results the reliability of the prediction over large areas, since in this case species identification of each detected tree is required (distinctive height-dbh and volume models are valid for the different species), making mandatory the tree species reconnaissance, e.g. by fusion of ALS data with multi- or hyper-spectral optical data (Dalponte *et al*. 2008; Tonolli *et al*., 2011).

2.6 Conclusions

In the last years the interest of ALS applications is remarkably increased, because of ALS data ability to capture dimensional information of the Earth's surface. The development of methodologies for ALS data processing has led to an increase of the number of applications also in forestry. Distinctively, in many boreal countries ALS techniques are already under operative use for obtaining information on forest standing volume, biomass and stand structural attributes. The overview presented in this paper highlights the relative suitability of ALS-assisted inventory procedures also with respect to alpine, temperate and Mediterranean environmental and operative conditions in Italy.

Under such conditions AB approaches have been much more applied than the ITC ones. However, these latter may have distinctive relevance when the interest is not only the assessment of forest standing volume or biomass but also the 3-D representation of forest stands, as required e.g. for ecological studies (e.g. habitat suitability studies) or for studies and simulations related to aesthetic preferences.

One of the main outcomes from the ALS area-based literature here considered is that mean height or median height or sum of the heights provides enough information for reliable estimation of forest standing volume, making even the simple auxiliary information provided by CHM very cost-effective to support forest inventories in many situations. This information is often available at low or even no cost from ALS surveys carried out for purposes other than forest inventories, while it is usually much harder or more expensive to get the whole original dataset of backscattered signal returns, as is required to compute metrics from ALS point or waveform data.

The possibility to integrate ALS data in forest inventory over large areas using probability sampling schemes is an aspect to be further developed. In this perspective, the availability of ALS data can range between full coverage over a given territory, where ALS data can be exploited as ancillary data known for the entire population so to adopt e.g. a ratio estimation approach like that proposed by Corona & Fattorini (2008), to a sample of the territory based on transects below the flight lines to spot samples within transects, so to adopt e.g. a multiphase/multistage estimation approach like those proposed by Gregoire *et al*. (2011) and Ståhl *et al*. (2011). Maselli *et al*. (2011) investigated the application of parametric and non parametric methods to Landsat satellite imagery in order to extend stem volume estimation from LiDAR data taken over few strips to the entire forest area.

A critical aspect of all the ALS-assisted procedures is the need for georeferencing and coregistration of both LiDAR measurements and ground truth locations. Ground reference data collection represents an important element in the prediction of ALS-assisted estimation of dendrometrical attributes, and at present it is the most expensive part of such analyses. However, an experiment by Dalponte *et al*. (2011b) in an alpine site, where the presence of a complex landscape increases the uncertainty of the Global Positioning System (GPS) accuracy, has shown that the GPS error did not significantly influence the volume predict accuracy of AB approaches. These results, obtained in a complex mountainous area, allow to infer that similar (or better) results could also be obtained within non mountainous areas.

A poorly investigated topic is the ALS detection of silvicultural systems under temperate and Mediterranean conditions, i.e. the discrimination between high forest and coppice stands. So far, no published paper covers such an issue, that has been long remained unresolved by optical remote sensing: conversely, since ALS can pinpoint the vertical structural properties of a forest stand, it should provide effective support information to such an end. Moreover, it would be likely possible to detect understory in forest or new forest and other wooded lands in rural abandoned spaces rapidly growing. Preliminary evidences seem to indicate that ALS data can distinguish sparsely-distributed individual trees and shrubs on forest-pasture and forest-field ecotones (Sankey & Glenn, 2011).

Another relatively poorly investigated topic is linked to the attributes associated to the forest structure: for example, to what extent ALS information can be used in forest fuel models mapping, which is currently usually based on expensive field surveys. Few studies on this aspect (e.g. Seielstad & Queen, 2003; Mutlu *et al*., 2008) suggest the processing of ALS-derived metrics able to distinguish some fuel models used as input data in fire behavior models, as it improves the forest fuel parameters estimation either by using information processed from ALS point data, when ALS metrics are significant predictors of canopy bulk density and canopy base height for generating maps of canopy fuels for input into fire behavior models, such as in FARSITE (Peterson *et al*., 2007), or combining multispectral passive imagery (e.g. Riaño *et al*., 2003; Mutlu *et al*., 2008; Erdody & Moskal, 2010).

As mentioned, ALS paired with other optical remote sensing data is a well-established approach to spatially estimating forest attributes (Ioki *et al*., 2009; Straub *et al*., 2010; Breidenbach *et al*., 2010). The use of optical remote sensing data in conjunction with ALS data is helpful in both delineating crown boundaries and in differentiating between species. The ability to make species level distinctions is especially important when estimating merchantable timber volumes and biomass, as these attributes differ between species in trees that are the same size.

ALS technology is evolving very quickly and the forestry sector can directly benefit from it, as shown by the selected literature here presented and discussed. It is important to match processing methods with the appropriate scale and scope: some processing methods are valid at the plot scale, whereas other procedures perform well at the regional scale; to be effective, certain ALS data analyses require a minimum point density, whereas other methods perform well using large-footprint sensors (Pirotti, 2011).

Due to the expected technical innovations of ALS systems (e.g., see Koch, 2010), it can be assumed that ALS data will play a even more prominent role in estimation of forest standing volume and biomass in the next years. Multitemporal ALS survey will even be potentially effective to support the assessment of current annual volume increment and the detection of harvesting rates and stand structural degradation. However, it is still particularly important to relatively lower data acquisition costs, so to make ALS data even more accessible for dedicated professional application.

Chapter 3

3 Different applications of multi-temporal monitoring of variation in woody biomass availability for energy production in riparian forest[2]

In this chapter an operational methodology to assess and map the aboveground woody biomass is presented. This approach couples optical remote sensing, ALS (raster CHM values) and field survey data and it is formulated as a case study on a poplar-dominated riparian forest in Central Italy. Experimental results point out the effectiveness of the proposed approach.

3.1 Introduction

As described in Section 2.5, many studies have been published in the literature dealing with the assessment of the aboveground biomass. In riparian forests, the high level of resilience and productivity of riparian tree species like *Populus,* contributes to the rapid biomass accumulation of riparian vegetation making these ecosystems of potential interest for biomass production for energy.

Natural river systems are dynamic bodies that continuously change as a result of their inherent physical conditions. Frequent disturbances like floods, caused by seasonal variation of weather conditions, affect flow patterns on a local scale originating a complex mosaic of landforms and biological communities (Gregory *et al*., 1991; Dècamps, 1996), making rivers the most active component of the rural landscape. Riparian vegetation is adapted to this periodical disturbance. It naturally regenerates on the replenished habitat created by the redistribution of river sediments during floods, playing an important role in the maintenance of stream and riverbank stability (Bradbury *et al*., 1995).

Riparian vegetation has an important function as a source of energy and matter for the aquatic ecosystems. In addition, riparian zones are an essential component of the integrity of river ecosystems, creating ecological corridors between other habitats, such as woodland, and promoting biological diversity at different scales.

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[2]This chapter has been published on Biomass and Bioenergy (2012) http://dx.doi.org/10.1016/j.biombioe.2012.10.023, with the title: “Assessing and mapping biomass potential productivity from poplar- dominated riparian forests: A case study”. Authors: Cartisano R., Mattioli W., Corona P., Scarascia Mugnozza G., Sabatti M., Ferrari B., Cimini D. and Giuliarelli D.

Besides these important ecological functions, riparian vegetation is also characterized by high biomass accumulation rates. Distinctively, riparian tree species like poplars and willows have generally high growth rates and a relevant resilience that allows them to recover ecosystem alterations in short times (Spinelli & Magagnotti, 2007). Because of the relatively high growth rates, riparian forests store large quantities of carbon whose estimation might be of interest for assessing bioenergy production potential in rural areas. In fact, the increasing biomass market is leading to a global re-evaluation of the multiple natural sources of energy. Current interest in biomass potential productivity from riparian forests is greater than in the past, when it was usually neglected due to the alleged poor quality. Nevertheless, very few studies have analyzed the potential of riparian vegetation as source of biomass for energy production and have considered the connected benefits

and drawbacks from the economic, environmental and management points of view (Recchia *et al*., 2010). Monitoring data and methods for assessing the status and the rapid changes of riparian ecosystems over large geographic areas are lacking. In addition, just a few published data are available on the quantification and change of the carbon stock from riparian forests in comparison to other terrestrial ecosystems (Fail *et al*., 1986; Tufekcioglu *et al*., 2001).

In this section, an experimental methodology for assessing and mapping the aboveground woody biomass is presented. The study is carried out on riparian forests that are characterized by rapid dynamics and high biomass accumulation rates. Results from this study provide a map at very high spatial resolution of the woody aboveground biomass that can be used to analyze its spatial distribution and to support the users for planning the harvesting.

3.2 Experimental methodology

Multitemporal land cover mapping is essential to investigate the dynamics of riparian vegetation. The rapid dynamic of riparian vegetation tied with ephemeral morphological and topographic conditions might lead to a quick obsolescence of the information acquired, thus demanding suitable change detection tools. Additional issues are related to human activities and land management (i.e. mineral extraction and agriculture) that can potentially affect biomass availability in riparian forest (Giese *et al*., 2003), making difficult to find an appropriate monitoring strategy. On the other hand, analyzing trends over large areas through a systematic monitoring approach is necessary to assess the conditions of riparian systems and the effectiveness of riparian management programs.

A methodology to quantify changes in riparian forest ecosystems and estimate variation in biomass stock, based on the integration of different remote sensing techniques (Fig. 3.1), is presented:

- land cover change detection by on screen interpretation of multitemporal high resolution orthophotos supported by automatic segmentation, exploited in the case study to quantify changes in the surfaces of riparian forests along a given river tract over a period of seventeen years (see Section 3.2.2);
- mapping aboveground woody biomass using spatialized biomass estimates at selected sampling plots representative of the investigated river tract by means of a spatially explicit model based on tree height canopy measured from ALS data (see Section 3.2.3).

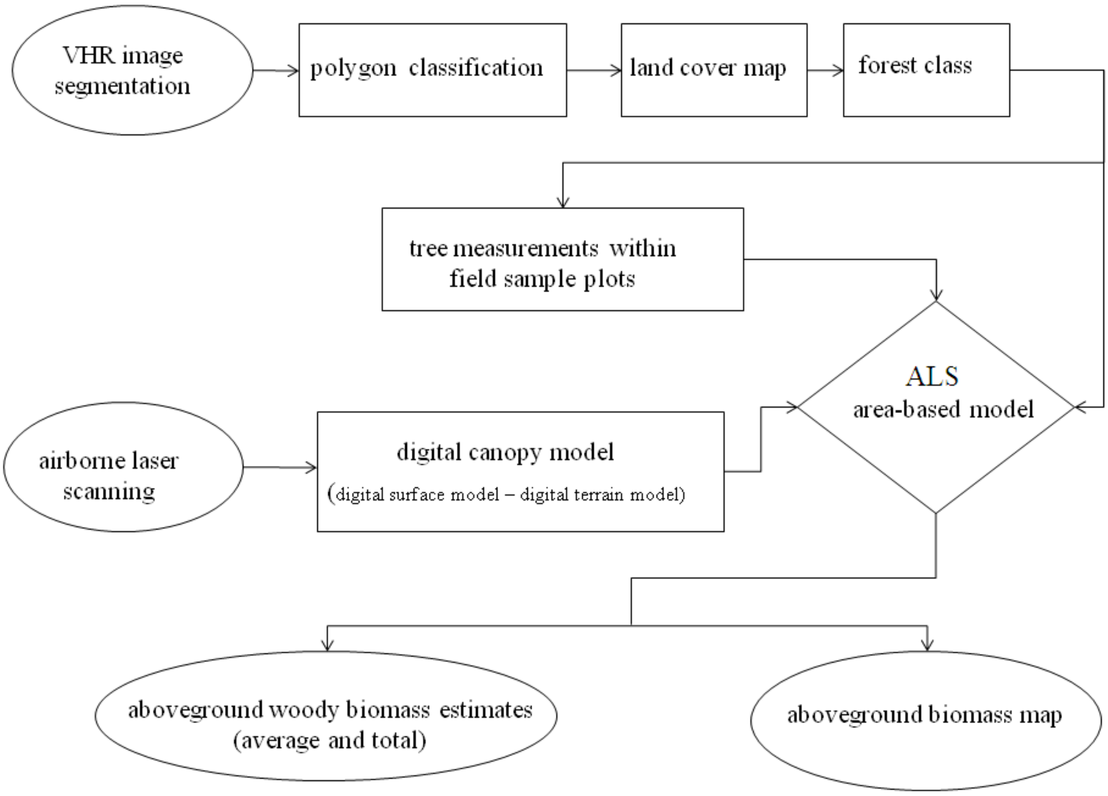


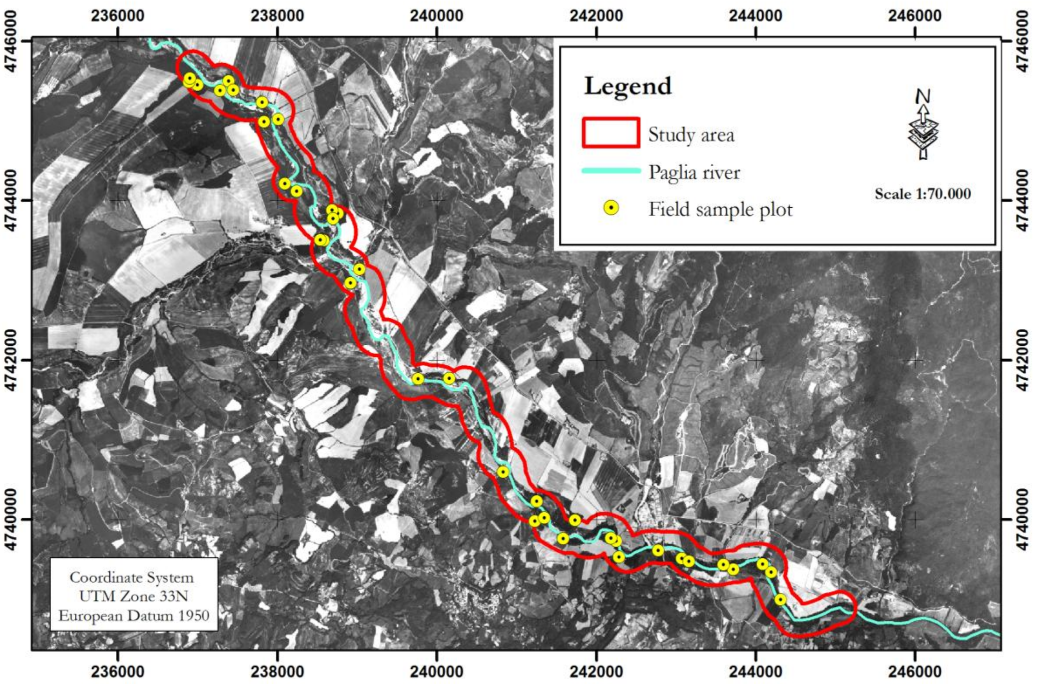
Figure 3.1 - Flow chart of the procedure proposed to assess and map the aboveground woody biomass of forest vegetation.

3.2.1 Study area

The selected case study is located in the Paglia Valley (lat. 42°47'14" N; long. 11°48'44" E), in Central Italy. Paglia river is a western tributary of the Tiber river (Fig. 3.2 bottom). A bottomland two hundreds of meters wide, along a 14.6 km tract of the river was analyzed (total area 560 ha), (Fig. 3.2 upper).

Paglia river drains a watershed of 1338 km^2 (7.8% of the Tiber watershed) and more than 27% of this area is above 900 m a.s.l. The climate is classified as temperate Mediterranean characterized by a gradient in the average annual precipitation within the watershed. Peak flows are reached in 24-48 h with episodic high levels from fall to spring, while low levels are generally present throughout summer. Floods are closely related to snow and rainfall patterns and sediments deposited where the slowing water can no longer move them, provide essential areas for the regeneration of poplars and willows. The forest constantly changes over time as a consequence of natural disturbance caused by frequent flooding and by human activities (gravel extraction, clearcuts). The riparian vegetation is characterized by vertical and horizontal patterning, reflecting the strong influence of flooding and water availability on species distribution.

Tree stocking on the riverbanks is highly variable. Three forest types can be identified in the study area: (a) an uneven-aged poplar forest with abundant natural regeneration, both of gamic and agamic origin (Fig. 3.3), localized in the most dynamic areas of the river in association with willows (*Salix spp*.); (b) scattered groups dominated by alder (*Alnus glutinosa* L.) in the most frequently flooded areas without drainage; (c) Turkey oak (*Quercus cerris* L.) coppices regularly managed for firewood production, located to a greater distance from the river and less disturbed by the river dynamics. Secondary species, like *Acer monspessulanum* L., *Acer campestre* L., *Carpinus betulus* L., *Fraxinus angustifolia* subsp. *oxycarpa* M.Bieb. ex Willd., *Fraxinus ornus* L., *Malus sylvestris* Mill., *Prunus avium* L., *Pyrus piraster* L., *Robinia pseudoacacia* L., *Quercus pubescens* Willd., *Ulmus minor* Mill. can also be found. The shrub layer is represented mostly by *Cornus mas* L., *Prunus spinosa* L., *Ligustrum vulgare* L., *Corylus avellana* L., *Crataegus monogyna* Jacq., *Sambucus nigra* L.



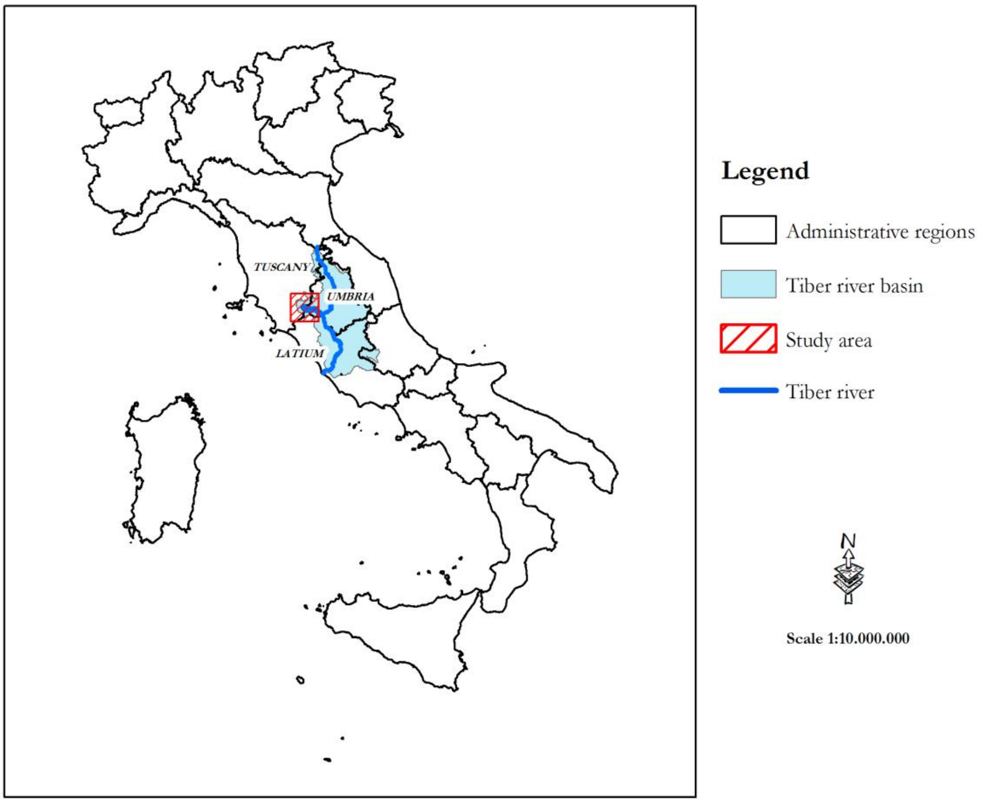


Figure 3.2 - In the upper picture, the 200 m-wide buffer of the Paglia river investigated tract (14.6 km length) is shown with a black line; white dots show the location of field sample plots. On the bottom picture, the location of the study area at the boundary among Latium, Umbria and Tuscany regions (central Italy), within the Tiber river basin.

Figure 3.3 - Poplar natural regeneration on the Paglia riverbanks; seeds are produced every year and rapid germination takes place on moist mineral substrates.

3.2.2 Land cover change assessment

The dynamics of riparian vegetation was analyzed by comparing land cover maps produced by photointerpretation of one meter/pixel resolution greyscale aerial orthophotos, taken in summer in 1989 and 2006. The interpretation process was supported by an automatic multitemporal segmentation, using eCognition® software (Definiens Imaging, Germany), allowing the derivation of two multitemporal segmentation levels (i.e. a set of spectrally and spatially coherent objects), identical for both images (Fig. 3.4). The first level, with a scale factor equal to 100, a geometric homogeneity equal to 0.3, and a compactness equal to 0.9, was suitable to distinguish urban/arable areas from natural areas. At the second level of segmentation, the scale factor was reduced to 50 to allow a correct identification of the limit of natural and semi-natural land classes.

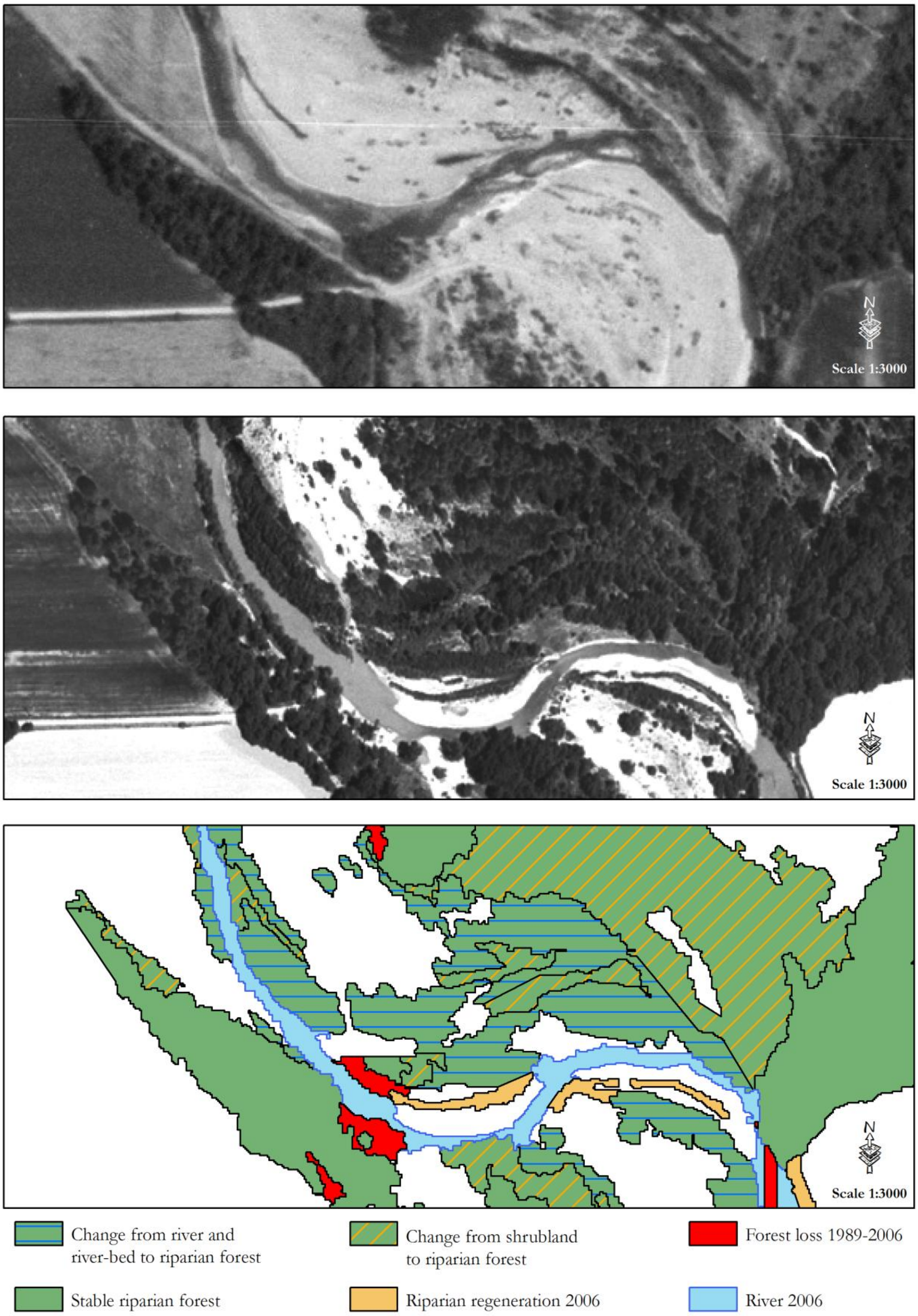


Figure 3.4 - Example of land cover change over the considered period (1989 - 2006); in the upper picture, the summer 1989 aerial orthophoto; in the middle the summer 2006 orthophoto; at bottom, the post-segmentation classification of land cover change (scale 1:3000).

Land cover classes were identified for each polygon created by the second level of segmentation in the years 1989 and 2006: 1. artificial areas (including gravel extraction sites, rural buildings and industrial areas); 2. cropland; 3. riparian forest; 4. shrubland; 5. riparian tree regeneration area (colonized mainly by poplar seedlings); 6. river-bed; 7. river; 8. grassland; 9. Turkey oak coppices; 10. oak reforestation; 11. fruit orchards. Land cover changes from 1989 to 2006 were assessed with reference to minimum mapping units of 5000 m^2 for artificial areas and cropland, and of 500 m^2 for the other classes.

3.2.3 Growing stock and aboveground woody biomass assessment from forest

For 1986 the growing stock and aboveground woody biomass estimation was based on field sample plots. For 2006 the estimation was based on the ALS-assisted area-based approach proposed by Corona & Fattorini (2008), coupling ALS and field plots data.

For the field survey, 37 circular 531-m^2-wide permanent plots were randomly distributed across the area classified as forest. In the second inventory occasion, the center of each plot was geo-referenced applying a post-processing differential correction to the data recorded through a Global Positioning System (GPS) with an estimated accuracy of less than 1 m.

The diameter at breast height (dbh) of all the trees within each plot was measured with a calliper (minimum threshold of 4.5 cm) and, for a subsample, the height was detected. Growing stock (GS) of wood volume from each plot was computed on the basis of allometric equations, based on tree dbh and height, developed within the first Italian National Forest Inventory (Castellani *et al*., 1984). The growing stock of wood volume was converted to aboveground woody biomass (WB, expressed in Mg) by the application of the equation WB = GS*BEF*WBD, where BEFs are the biomass expansion factors and WBDs are the wood basic densities reported in Table 3.1.

The ALS survey was carried out by an ALS ALTM (Airborne Laser Terrain Mapper) Gemini which employed a laser at 1064 nm, installed on I-GIFE plane. The average flying height was 1300 m a.s.l., with a total scan angle of 23°. The swath width was 700 m and the light beam was 1 cm, with a vertical accuracy of 15 cm. A Digital Terrain Model (DTM) and a Digital Surface Model (DSM) with a geometric resolution of 1 m were produced through ALS data elaboration. The raster Digital Canopy Model (DCM) was derived by algebraic subtraction of the DTM from the DSM, providing the height of the upper canopy for each pixel included in the forest survey.

Table 3.1 – Adopted biomass expansion factor and wood basic density for each considered forest type (source: APAT, 2007).

Typology	Forest type	BEF	WBD
Coppices	Hornbeam	1.28	0.66
	Turkey oak	1.23	0.69
	Other oaks	1.39	0.65
	Other broadleaves	1.53	0.53
Protective	Riparian forest	1.39	0.41

For the first inventory occasion, the estimation of the total of the aboveground woody biomass (and of the growing stock) was carried out by the classical estimator of simple random sampling without replacement. For the second occasion, the estimation was carried out according to the mentioned ALS-assisted area-based approach (Corona & Fattorini, 2008). Distinctively, the total (T_A) over a given area A was estimated as

$$\hat{T}_A = \hat{k} T_{xA} \qquad (1)$$

where

$$T_{xA} = \sum_{j=1}^{N} h_j^{\beta} \qquad (2)$$

h_j = height of the upper canopy provided by DCM for the j-th pixel

N = total number of pixels over the given area A

$$\hat{k} = \overline{T} / \overline{P} \qquad (3)$$

$$\overline{T} = \frac{1}{n} \sum_{i=1}^{n} T_i \qquad (4)$$

where T_i is the aboveground woody biomass (or the growing stock) measured in the i-th sample plot and n is the number of sample plots

$$\overline{P} = \frac{1}{n} \sum_{i=1}^{n} P_i \qquad (5)$$

where Pi is the total of the heights (raised to power β) of the upper canopy provided by DCM over the set of the pixels belonging to the i-th sample plot.

The standard error of   was estimated as

$$\hat{e}(\hat{T}_A) = \sqrt{\frac{1}{n(n-1)} \sum_{i=1}^{n} \left(cT_i - c\hat{k}P_i\right)^2} \qquad (6)$$

where c = A/a, with a equal to the sample plot size (expressed in the same measurement unit of A).

The value of the power β was pinpointed on the basis of the observed relationship between T_is and P_is. The highest correlation coefficient and the lowest relative root mean squared error were obtained with a value of β equal to 2.5 (Fig. 3.5), both for the aboveground woody biomass and the growing stock.

The adopted ALS-assisted area-based approach allowed also to map the aboveground woody biomass (and the growing stock) by multiplying by $\hat{k}$ the total of the heights (raised to power β) of the upper canopy provided by DCM for each 531-m^2-wide set of pixels covering the entire investigated area.

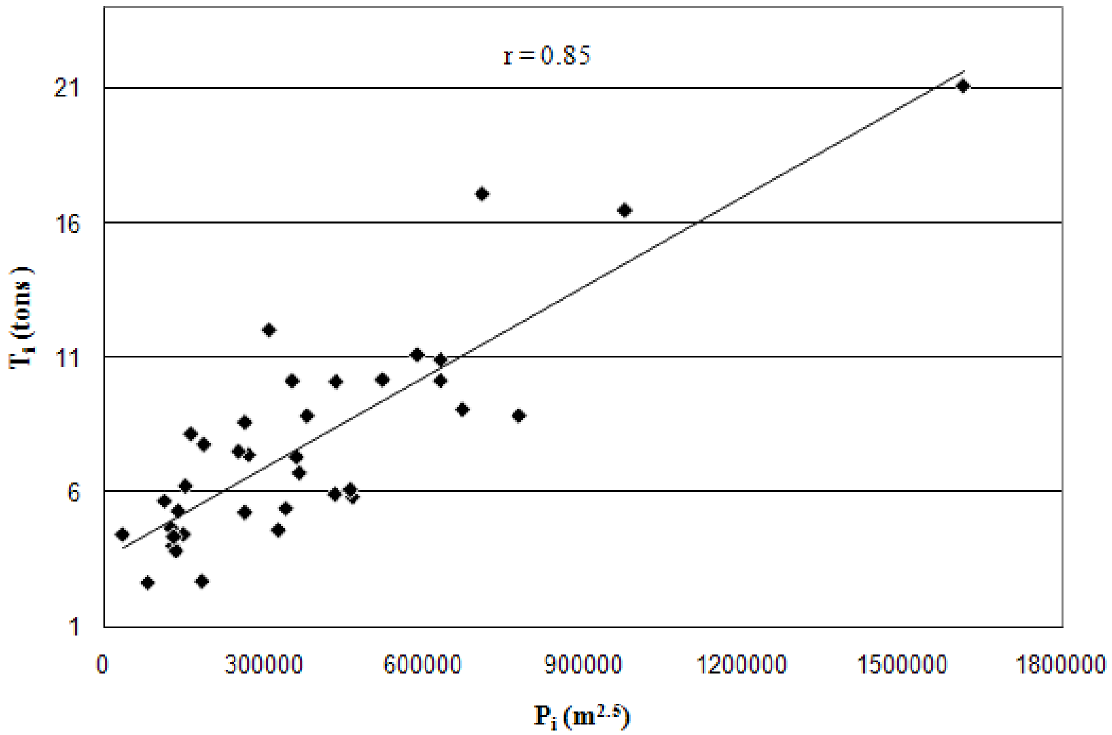


Figure 3.5 - Relationship between the observed aboveground woody biomass in the sample plots and the total of the heights (raised to 2.5) of the upper tree canopy provided by the raster ALS-derived CHM over the set of the pixels belonging to the same plots.

3.3 Results

Land cover change over the observed period is shown in Table 3.2. The most substantial land cover change between 1989 and 2006 concerns riparian forests with a meaningful expansion of the poplar forest area. In spite of a decrease of 7 ha of the riparian forest, 81 ha of poplar forest were created with a mean annual rate of increase of 4.6 percent. Other expanding land cover classes are artificial areas and managed Turkey oak coppices, but both with a moderate increase. There have not been meaningful changes for cropland, while the area of all the other land cover classes has decreased. The highest mean annual rate of area loss was observed in the river-bed class. Shrub vegetation and grassland have also shrunk significantly over the examined period.

Table 3.2 – Land cover classes in 1989 and in 2006 and corresponding mean annual rate ($(\sqrt[17]{A_{2006}/A_{1989}}-1)*100$) of expansion/reduction.

Land cover classes	**Area (ha)**		**Mean annual rate of expansion/reduction (%)**
	1989	**2006**	
Artificial areas	14.3	16.0	0.66
Cropland	255.0	254.1	-0.02
Riparian forests	64.1	137.9	4.61
Shrubland	84.1	58.8	-2.08
Riparian tree regeneration	8.9	4.4	-4.12
River bed	66.7	28.4	-4.90
River	22.9	21.2	-0.45
Grassland	26.4	16.0	-2.90
Turkey oak coppices	16.2	16.5	0.09
Oak reforestation	0	3.1	-
Fruit trees	0	4.8	-

The most significant transition over the 1989-2006 period has concerned the shrubland change to riparian forest. Other main classes contributing to the riparian forest expansion were the river-bed and the river (Fig. 3.6).

Around 10 percent of the riparian forest comes from areas detected as riparian regeneration in 1989 and, finally, a slight increase of the riparian woodland was also due to the change from croplands. There were no substantial transitions from forest to other land cover classes: the river dynamic (expressed by the river and river-bed classes) has led to a loss of 4 percent in terms of area, while another 4 percent of the riparian forest was changed into cropland.

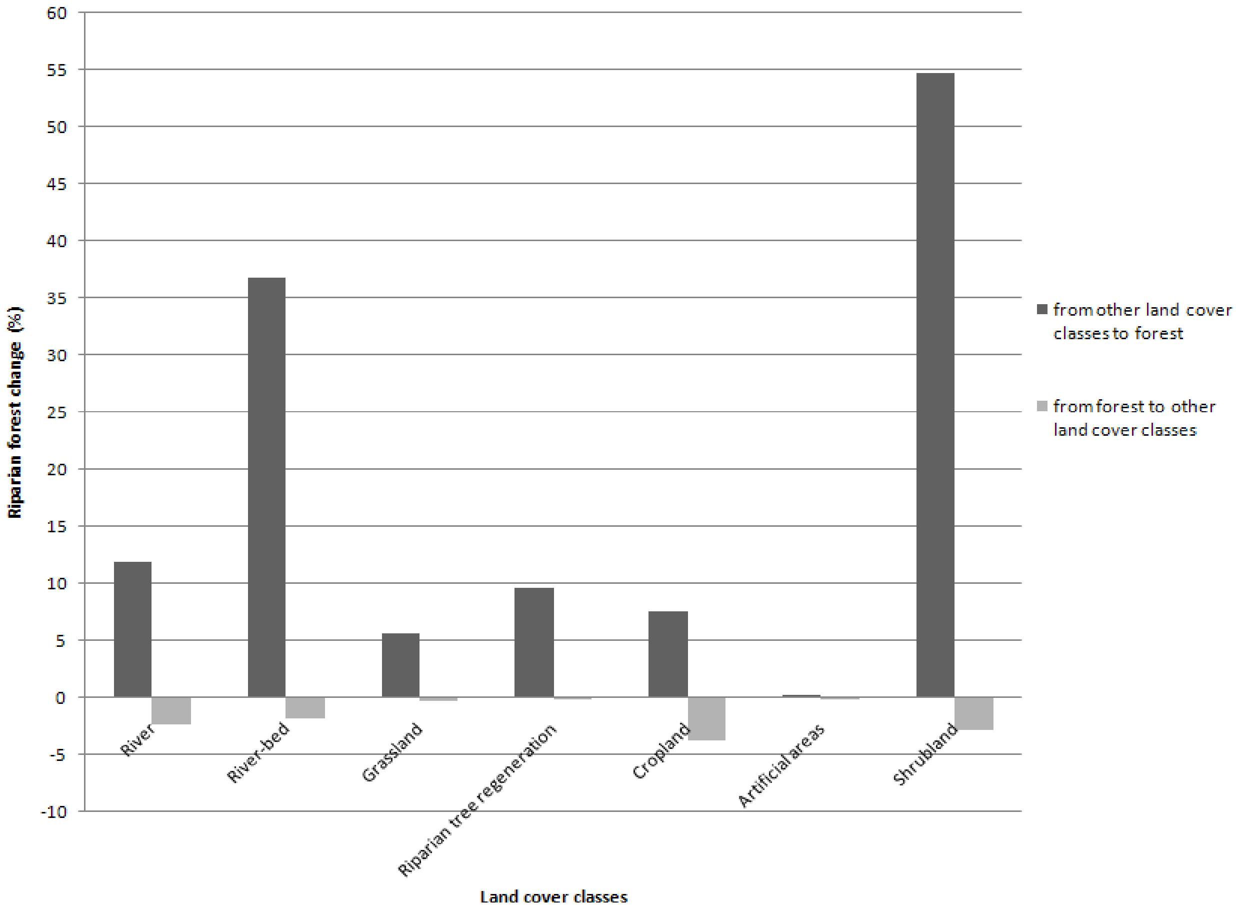


Figure 3.6 - Transition to forest from other land cover classes (in black) and from forest to other land cover classes (in grey) over the 1989 - 2006 period.

The total volumes assessed for the riparian forest and for the Turkey oak coppices in 2006 are 19,452 m^3 (146 m^3 ha^{-1}) and 1650 m^3 (100 m^3 ha^{-1}), respectively. The overall volume in the surveyed area is 137 m^3 ha^{-1}. The total woody aboveground biomass of the riparian forest is 5945 Mg (relative standard error = 21.8%) in 1989 and 11,650 in 2006 (relative standard error = 11.8%). The higher precision of the estimate from the second inventory occasion is due to the contribution by the ancillary ALS data through the adopted model-assisted procedure. Fig. 3.7 shows the map of the aboveground woody biomass in 2006: the highest values were recorded in the lower tract of the river, with a maximum value of around 340 Mg ha^{-1}.

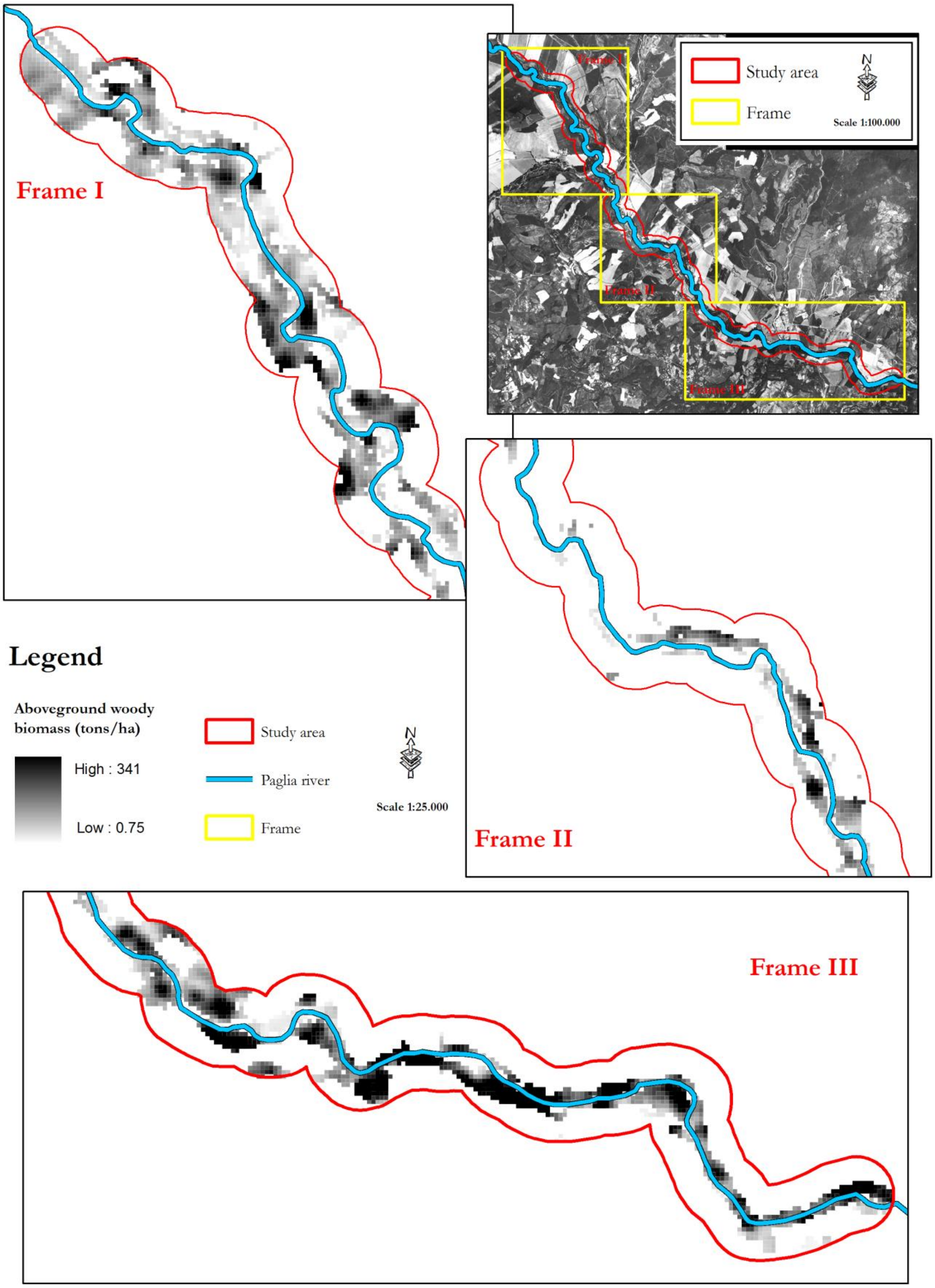


Figure 3.7 - Map of the aboveground woody biomass in the investigated tract of the Paglia river.

3.4 Discussion

This study synthesizes the main outcome of a methodological exercise to test the assessment and mapping of aboveground biomass dynamics of a poplar-dominated riparian forest along a 14.6 km tract of the Paglia river, in Central Italy. The results show that the surface of riparian vegetation has significantly changed over the considered seventeen-years period. More than 70 hectares of new poplar-dominated forest were naturally regenerated during the 1989-2006 period, evidencing the rapid changes characterizing these environments. Shrub vegetation and grassland have decreased in favour of the riparian forest. Surfaces covered by river and river-bed in 1989 have been colonized by riparian forest as redistribution of river sediments during floods has favored the re-colonization of the newly replenished habitat. Over the examined period there were no substantial transitions from forest to other land cover classes. In the study area, the land cover changes have been probably influenced by human operations causing the variation of the hydrological regime due to flood protection measures and extraction activities impacting the morphology of the riverine system. This has determined the presence of locations where silt and clay settle out and poplar seedlings find suitable conditions for a quick establishment.

The main motivation of this work was to gather reliable information at high spatial resolution on the biomass potential from riparian forest environments, for which very few data can be found in the literature. Multitemporal optical remote sensing data, combined with the imagery segmentation process and improved by ALS data in the second inventory occasion, have allowed the rapid identification and quantification of the surfaces affected by the dynamics of riparian vegetation. Distinctively, the survey approach here proposed, based on the ALS-derived CHM, has proved to be highly effective to support the assessment of the riparian forest wood volume and biomass, providing comparable results in terms of accuracy to previous experiments carried out under different forest environments (Corona & Fattorini, 2008; Corona *et al.*, 2008). Using solely canopy height, instead of more sophisticated ALS metrics, leaves out some information, but this survey approach is truly feasible from a practical point of view: first of all, full coverage of raster CHM is often available at low or no cost (as a byproduct from ALS surveys on large territories committed, mainly by public administrations, for purposes other than forest applications) while it proves to be much more expensive (or harder when public administrations are the data owners) for forest professionals to get the whole original data sets of back-scattered LiDAR signal returns, as is required to calculate more sophisticated ALS metrics; furthermore, the handling of raster CHM is much more straightforward for forest professionals than the handling of the original data sets of back-scattered LiDAR signal returns.

A map of the aboveground woody biomass, as produced in this study, can be used to analyze its spatial distribution so to support the users for planning the precision harvesting of aboveground woody biomass of riparian stands, whose distribution is usually not homogeneous, as demonstrated by the case study: in the examined river, a maximum value of about 340 Mg ha^{-1} was found in the last tract of the sampled area while much lower values were assessed in the middle tract where the proximity of the extraction quarries has continuously influenced negatively the regeneration of the riparian forest.

Coupling the cleaning of the river bed for hydraulic maintenance to the utilization of the obtained biomass for energy production may offer relevant opportunities for the energy biomass supply: harvesting practices can be safely encouraged given the assessed high regeneration capacity of riparian forests. Nearby the case study, harvesting rates of 80-85% (around 70 Mg ha^{-1}) of available biomass in poplar-dominated riparian areas managed with clearcut did not have a negative impact on the preservation of the riparian forest; these areas, in fact, appear to be immediately recolonized by poplar regeneration. However, the percentage of the deliverable biomass has to be modulated depending of the levels of the hydraulic risk, affecting the different tracts of the river. Despite this, such interventions appear to be economically sustainable for the energy production (Spinelli & Magagnotti, 2007; Spinelli, 2005) and for the actual working conditions, generally favorable to the harvesting operations.

3.5 Conclusions

Woody biomass from riparian forests may constitute an important source of biomass for the small-scale energy production. In the examined case study, an average aboveground woody biomass of about 90 Mg ha^{-1} was assessed within poplar-dominated riparian forest, corresponding to an amount of available biomass of 800 Mg km^{-1} along the river axis. For comparison, in Italy the riparian forests, which cover nearly 0.3 million hectares (i.e. 1% of the national land area), are characterized, on average, by woody biomass around 60 Mg ha^{-1} (INFC, 2005). A recent study by Spinelli & Magagnotti (2007) estimated the biomass available from the cleaning of river beds to be higher than 400 Mg km^{-1}, assuming a selective wood removal: such an amount, albeit lower than those usually exploitable from specialized forest crops, highlights the unnegligible woody biomass harvesting potential within riparian environments.

Under such a perspective, the innovative strategy here proposed to assess and map at a very high spatial resolution the aboveground woody biomass of riparian forest meets the monitoring requirements to support energy production based on modern, non-conventional biomass harvest planning options (Lasserre *et al*., 2010).

Chapter 4

4 Analysis of the spatial variability of Mediterranean fuel models

In this chapter an experimental test for investigating the structural variability of Mediterranean fuel models is presented. An analysis of the effectiveness of ALS raw and raster data in the estimation process is performed and two different methodological approaches coupling ALS data processing with field sampling are presented . Experimental results from this analysis highlight the potential of ALS data to provide detailed map of the spatial distribution of forest fuels and the quantification of the structural parameters able to characterize fuel types.

4.1 Introduction

An accurate description of the forest in terms of fuel conditions is essential to support fire management and to predict fire risk (Chuvieco *et al*., 2004).

The description of fuels is extremely complex because multiple variables must be considered. The total amount of biomass in the different forest components (herbs, shrubs, trees), fuel structural characteristics (surface-area-to volume ratio, fuel density, fuel loading, height and stratification of fuel strata), fuel chemical composition and moisture content all affect fire behavior. To simplify the description of a forest area in terms of these characteristics, vegetation types with similar fuel conditions are grouped together under "fuel types". Forest areas classified within the same fuel type have similar fire hazard and/or fire propagation behavior (Hardy, 2005; Pyne *et al*., 1996).

Several fuel type classification systems are used worldwide (Arroyo *et al*., 2008). One of the most widely used is the system of 13 standard fuel types developed by the Northern Forest Fire Laboratory (NFFL), Rocky Mountain Research Station, U.S. Forest Service (Burgan & Rothermel, 1984) and used for input by the most common fire simulation models (Behave, Farsite). These fuel type models, known as standard Fire Behavior (Albini, 1976; Burgan & Rothermel, 1984), were designed to describe the characteristics of surface fuels over large areas. Fuel types associated with the different forest cover types may fall into grassland, shrubland or ground litter types depending on the vertical structure of fuelbeds and, accordingly, the fuelbed stratum identified as the main vector for surface fire propagation (grass/shrub understory, ground litter); thus, the same fuel model can identify different forest stands in terms of species composition, management and silvicultural treatments. In Mediterranean areas, landscapes are usually characterized by a fragmented distribution of remnant vegetation with high heterogeneity and complex mixed structures (Agee & Skinner, 2005). For this reason, the parameters of the fuel models can be significantly different if compared to standard models. In this direction, specific adjustments of NFFL models to Mediterranean conditions have been proposed, in particular through a calibration of parameters like surface area-to-volume ratio, fuel load and fuel structure (Rodríguez y Silva & Molina Martìnez, 2012).

In Europe the Prometheus system (Chuvieco *et al.*, 2003) is an adaptation of the NFFL classification to Mediterranean conditions and comprises seven fuel types based on the type and height of the propagation element divided into three major groups: grasses, shrubs and ground litter (Fig. 4.1).

Semi-empirical fire behavior modeling programs such as FARSITE (Finney, 1998) and FlamMap (Finney, 2006) integrate input spatial data including fuel types and their structural attributes (crown height, canopy cover), topography and weather to predict wildfire growth and crown fire initiation and propagation (Fig. 4.2). Most of these input data are derived from layers of coarse spatial resolution which leads the pixels to be spatially homogeneous over relatively large areas (Finney & Andrews, 1994).

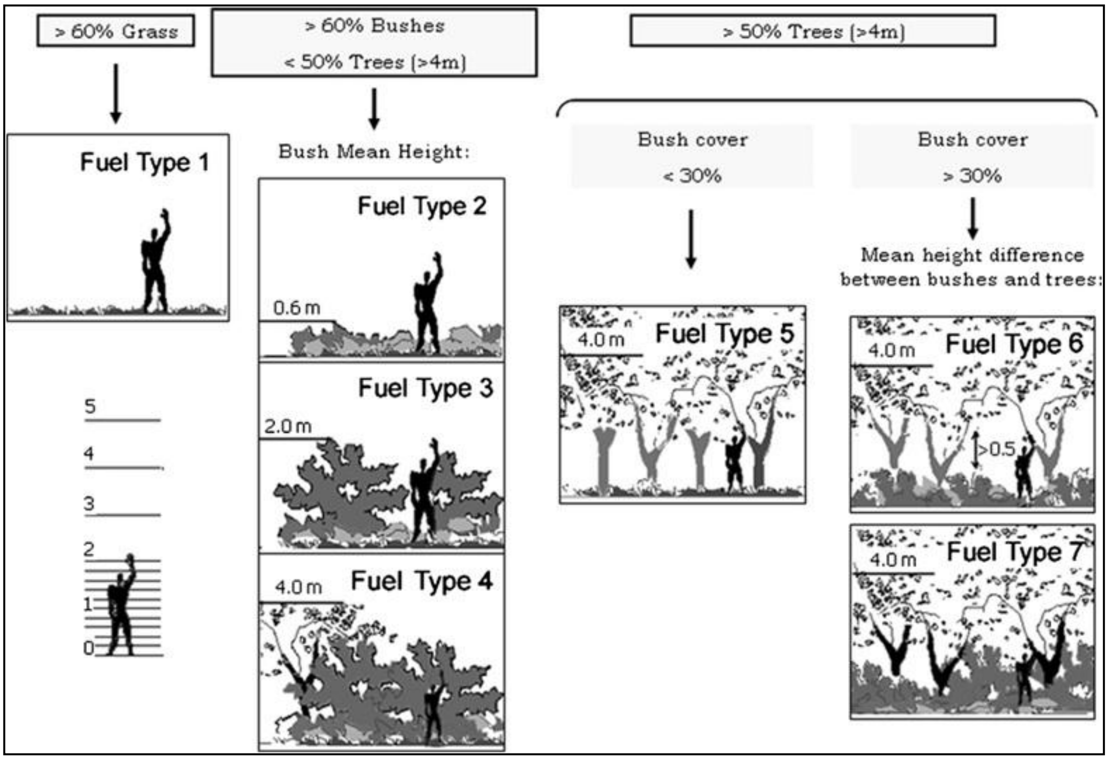


Figure 4.1 - PROMETHEUS fuel types (Arroyo *et al.*, 2006).

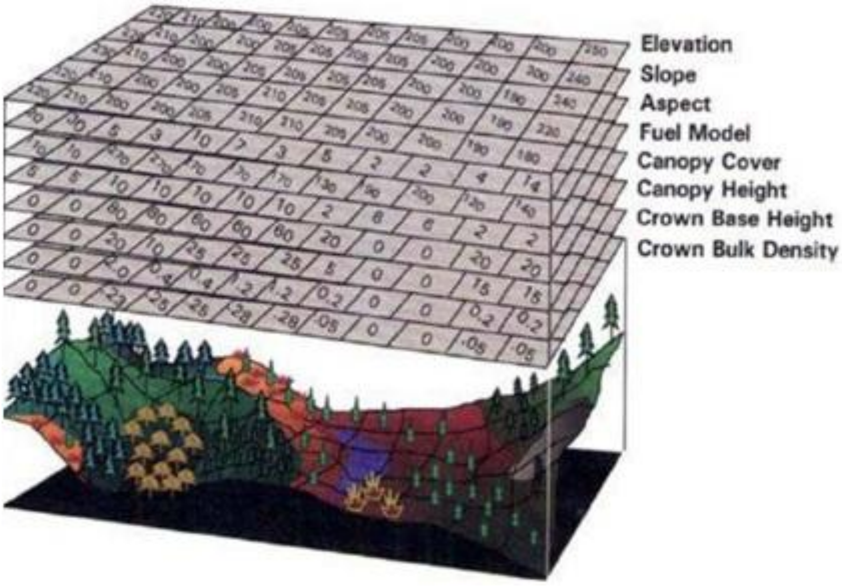


Figure 4.2 - FARSITE input layers for landscape topography and vegetation (from Finney, 2007).

As pointed out in Chapter 2, ALS technology provides high spatial resolution data that can effectively improve the spatial estimation of fuel structural parameters for fire behavior modeling. In this perspective, a key issue is to investigate to what extent ALS information can be used for the structural characterization of forest fuel models, currently based on expensive field surveys, and for mapping key structural attributes (canopy height, volume, aboveground biomass) for fire behaviour simulation.

Continuous maps of a given attribute can be potentially derived by coupling remotely-sensed data over the whole region of interest and ground plot data collected by field surveys (Corona, 2010). Notably, finding robust statistical relationships between ALS data and ground measurements of forest structural variables allows the statistical reliability of the ground sampling to be combined with the high spatial resolution of ALS data. In this direction, the field data collection has an important role and, when performed according to a defined sampling design, permits to generate maps over the entire extent of the ALS data coverage, through the statistical analysis of the relationship between ALS metrics and structural attributes (Montaghi *et al*., 2012).

The spatial localization of the sampling points should be performed according to specific sample schemes able to provide an adequate representation of the fuel models in the investigated area. In this context, the reference point is given by systematic or stratified sampling designs (Corona & Marchetti, 2007). The accuracy of the sampling points positioning is crucial for the development of estimation procedures based on ALS data processing. Current Global Positioning Systems (GPS) limit the positional error within 1-2 m making possible a comparison of field measurements with ALS data in a neighborhood of a magnitude higher (e.g. circular sampling plots with 12-20 m radius). The sampling plot can be structured according to the third phase ground plot of the Italian National Forest Inventory of Forests and Forest Carbon Sinks (INFC, 2005; Tabacchi *et al*., 2006) in order to derive quantitative estimates of forest fuels in a standardised way. In this perspective, the sample unit can be constituted by circular concentric plots including different size areas around the sample point.

These considerations have motivated the experiments presented in this chapter whose aim is to propose a methodological approach based on the integration of ALS data and field surveys to:

- investigate which ALS metrics can be selected for the structural characterization of fuel types;
- perform the spatial estimation of key structural parameters of forest fuels (canopy height, volume, aboveground biomass).

The expected outcome should help future implementations of ALS data in forest fire prevention by providing input data for decision support system for planning fuel treatments at forest stand and landscape scales.

This chapter is organized as follows: section 4.2 describes the study area and data used; section 4.3 presents the methodological approach through two experiments focusing on the integration of ALS data processing and field sampling. Section 4.4 illustrates experimental results and, finally, section 4.5 discusses the outcomes of the experiments providing some conclusions.

4.2 Dataset description

Two areas of 487 km^2 and 165 km^2, located in Sicily in the provinces of Palermo and Agrigento respectively, were considered (Fig. 4.3). Both study areas are characterized by typical Mediterranean climate (meso - and termo Mediterranean climate), with a bi-seasonal regime of hot/dry summers and cold/wet winters. Elevation ranges from 2 m to 1879 m a.s.l. in the largest area and from 198 to 1434 m a.s.l. in the smaller area. A mosaic of land cover types is found in both study areas, including agricultural lands, grasslands, shrublands and forest land.

A digital fuel map was available for both the study sites (source: Sicily Forest Inventory). The map was recently developed by manual on-screen delineation of high resolution (1 x 1 m) digital orthophotos supported by an intensive field campaign for all Sicily. With an overall accuracy of 85%, the fuel type map was assumed to be error free for this study. Details concerning the map features can be found in Hoffman *et al*. (2011). The map depicts a classification of fuel complexes with respect to the NFFL fuel types (Burgan & Rothermel, 1984) for forest stands, open shrublands and grasslands of the Sicily island with a nominal geometric resolution of approximately 0.1 ha. Fuel types associated with the different forest cover types may fall into grassland, shrubland or ground litter types depending on the vertical structure of fuelbeds and, accordingly, the fuelbed stratum identified as the main vector for surface fire propagation (grass/shrub understory, ground litter). A full description of the nomenclature system is reported in Table 4.1.

ALS data were available for both the areas and were acquired during July and August 2010 by an Optech Pegasus system on board of a Piper Navajo I-BGFE with a scan angle of 20° at 100 KHz resulting in an average density of 1.5 points per square meters.

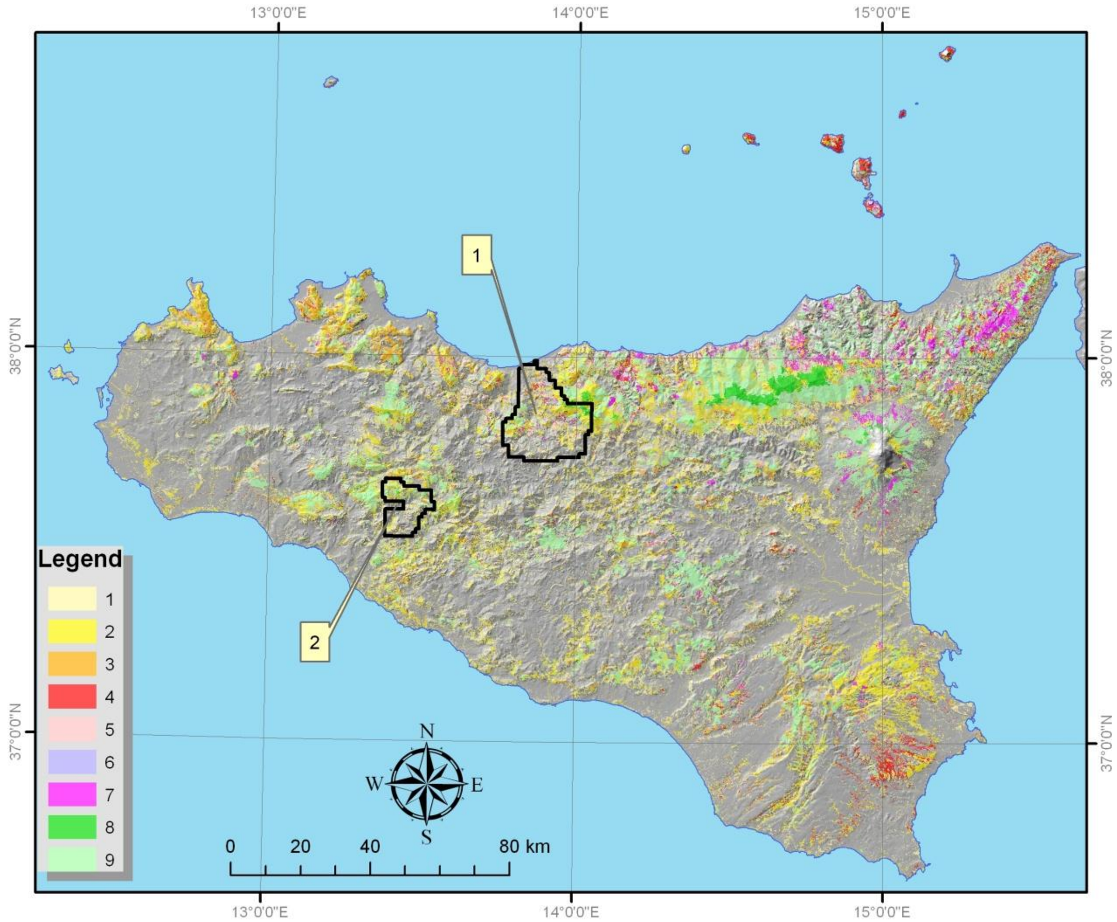


Figure 4.3 - Location of the study sites on the basis of the fuel type map (the legend of the system of nomenclature is reported in Table 4.1).

Table 4.1 - Fuel characteristics of the fuel types mapped in Sicily.

NFFL Fuel type N.°	***Main propagation element***	***Fuelbed structure***	***Associated forest types***	***Fuel load (t ha^{-1})***
1	Grassland	Dry short grass (< 1 m) Sparsely wooded grassland (tree cover < 50%)	Quercus ilex Fagus sylvatica	1-2
2	Grassland	Scrubby land with mainly herbaceous vegetation Low cover woodland/shrubland (< 50%) with grass understory Forest plantations with grass understory	Eucalyptus plantations	5-10
3	Grassland	Dry tall grassland (1 m)		4-6
4	Shrubland	Continuous tall shrubland (2 m)		25-35
5	Shrubland	Continuous low open shrubland (<1 m) Forest with low shrubland understory (< 1m)		5-8
6	Shrubland	Open shrubland (0,6-1,2 m) with cover > 50% Low (< 2m) deciduous woodland with shrubland understory		10-15
7	Shrubland	Open high flammable shrubland (0,5-2m) Forest with high flammable shrubland understory	Quercus suber Quercus pubescens Pinus halepensis, Pinus pinea, Pinus pinaster	10-15
8	Ground litter	Broadleaved dominated forest with compact litter Short-needle (<5 cm) coniferous plantations with undecomposed litter	Fagus Robinia Abies Cedrus Cupressus	10-12
9	Ground litter	Deciduous broadleaved dominated forest with not compact litter Thermophilous pinewoods	Quercus ilex Quercus suber Quercus petraeae and Quercus pubescens Quercus cerris Castanea sativa Pinus halepensis, P. pinea, P. pinaster	7-9

4.3 Experimental design

Two main experiments were performed in the study areas:

1) Experiment 1: analysis of the potential use of ALS-based metrics for structural characterization of fuel types using the bagging/boosting classification tree method characterized as Stochastic Gradient Boosting (SGB). This experiment was carried out in both study areas described in Section 4.2 using a tessellated stratified sampling scheme for the extraction of ALS metrics in different fuel types. Results obtained using SGB are compared to results obtained using traditional CART and Random Forests methods.

2) Experiment 2: spatial estimation of forest structural parameters (canopy height, volume, aboveground biomass assisted by ALS-based metrics). The focus for this experiment was the study area 1, located in the Oriented Natural Reserve "Bosco Favara and Granza", in the Madonie Regional Natural Park. The parameters have been assessed through an integrated approach that couples ALS data and field surveys. The methodology allowed to map canopy height and the aboveground woody biomass for the areas where ALS coverage and field surveys were available.

4.3.1 Experiment 1: use of ALS-derived metrics for the characterization of fuel types

The study areas were sampled using a tessellation stratified sampling scheme (Barabesi & Franceschi, 2011). The areas were divided into 100 x 100 m squares, a point was randomly selected in each square, and a 30 x 30 m plot with random orientation was centred at each point. This procedure produced 12,772 plots in Area 1 and 3989 plots in Area 2. The plots were intersected with the fuel types map, and only those entirely contained in a single fuel type were retained for further investigation; the result was a total of 16,761 plots (Fig. 4.4).

ALS data, in LAS- file format (Graham, 2005), were filtered and classified through appropriate techniques in order to eliminate data errors (e.g., low points, isolated and air points). A Progressive Triangular Network (TIN) densification method, developed by Axelsson (1999; 2000) and implemented in Terrascan software (Soininen, 2010), was used to classify the point cloud into ground and non-ground returns. These filtered ground returns were used to generate a 1 x 1 m pixel resolution Digital Terrain Model (DTM) using an Inverse Distance Weight (IDW) interpolation method (Andersen *et al*., 2005; Vepakomma *et al*., 2008).

Figure 4.4 - Example of the sampling design adopted on the basis of the fuel type map (colors refer to the legend in Figure 4.3 and labels to Table 4.1) and the digital orthophoto originally used for its delineation. Sampling points (in yellow) inside systematic squares of 100 m x 100 m (in grey). Around each sampling point one squared plot 30 m x 30 m (in white) is generated with random orientation.

Based on previous reported research results (e.g. Næsset, 2002; Andersen *et al*., 2005; Evans *et al*., 2009; Falkowski *et al*., 2009; Tesfamichael *et al*., 2010; Estornell *et al*., 2011), 31 ALS-based metrics were calculated from the normalized height returns for each 30 x 30 plot, to investigate structural differences among fuel types.

Descriptions of the selected ALS-based metrics are reported in Table 4.2. The metrics are either pure numbers or "heights above ground level" measured in meters. The majority are statistics characterizing the distributions of the "heights" of the returns of ALS pulses within the plots. Because stratified structures characterize Mediterranean vegetation, some metrics have been derived by splitting the returns into three, equally spaced, vertical levels and computing statistics for each level. The "Canopy coverage" metric is calculated as returns percentage where pulses with height greater than 0 m are considered as non-crown returns.

Table 4.2 - Definition and main statistical parameters for the ALS-based metrics calculated in the study areas. *Metric* in the short name of the metric. *1stQU*, *Median*, *3rdQU* and *Max* (the first quintile), are the statistical parameters in the study sites.

	Metric	Mean	Min	1stQu	Median	3rdQu	Max	M.unit	Definition
1	*Returns*	.	10	157	492	1066	13509	count	number of returns from the plot
2	*Hmax*	6,5	0,1	1.9	5.1	9.5	50.1	m	above ground elevation of highest return
3	*Hmean*	2.2	0.0	0.4	1.2	3.2	17.9	m	mean height of all returns
4	*Hmin*	0.0	0.0	0.0	0.0	0.0	0.3	m	lowest height among all returns
5	*CV*	80.0	19.6	60.7	76.0	95.1	303.5	p.n.	CV of returns height
6	*texture*	0.2	0.0	0.2	0.2	0.3	0.4	m	standard deviation of non-ground returns [0 m < h <= 1 m];
7	*Skewness*	0.9	-2.4	0.2	0.8	1.4	8.1	p.n.	skewness of returns height
8	*Kurtosis*	1.2	-1.9	-0.7	0.1	1.8	82.3	p.n.	kurtosis of returns height
9	*relHmean*	0.3	0.0	0.2	0.3	0.4	0.8	p.n.	relative mean height [(mean-min)(max-min)]
10	*CanopyC*	34.3	0.5	10.3	30.5	56.4	91.8	p.n.	non-ground percent of total returns
11	*Pct10*	0.5	0.0	0.1	0.1	0.3	13.6	m	percentile 10 of heights distribution
12	*Pct20*	0.9	0.0	0.1	0.3	0.6	15.8	m	percentile 20 of heights distribution
13	*Pct30*	1.3	0.0	0.2	0.4	1.3	17.1	m	percentile 30 of heights distribution
14	*Pct40*	1.7	0.0	0.2	0.5	2.3	18.0	m	percentile 40 of heights distribution
15	*Pct50*	2.1	0.0	0.3	0.7	3.0	18.6	m	percentile 50 of heights distribution
16	*Pct60*	2.5	0.0	0.4	1.0	3.7	19.3	m	percentile 60 of heights distribution
17	*Pct70*	2.9	0.0	0.5	1.4	4.5	25.8	m	percentile 70 of heights distribution
18	*Pct80*	3.5	0.0	0.6	2.1	5.2	31.2	m	percentile 80 of heights distribution
19	*Pct90*	4.2	0.1	0.9	2.9	6.3	37.0	m	percentile 90 of heights distribution
20	*Pct99*	5.7	0.1	1.6	4.4	8.4	46.5	m	percentile 99 of heights distribution
21	*Density1*	0.4	0.0	0.2	0.4	0.6	1.0	p.n	cumulative density of returns above Hmax/3
22	*Density2*	0.1	0.0	0.0	0.1	0.2	0.9	p.n.	cum. dens. returns between 1 and 2 times Hmax/3
23	*Rets1pct*	58.9	1.6	41.7	62.1	77.6	99.3	p.n.	percent of returns above Hmax*2/3
24	*Hmean1*	0.9	0.0	0.2	0.5	1.1	5.3	m	mean height of returns above Hmax*2/3
25	*CV1*	69.2	0.2	55.7	66.1	79.8	333.4	p.n.	CV of heights above Hmax*2/3
26	*Rets2pct*	28.8	0.2	15.8	27.5	40.8	81.5	p.n.	percent of returns between 1 and 2 times Hmax/3
27	*Hmean2*	3.2	0.1	0.9	2.5	4.6	31.4	m	mean height of returns between 1 and 2 times Hmax/3
28	*CV2*	18.6	0.1	17.7	18.8	20.0	45.4	p.n.	CV of heights between 1 and 2 times Hmax/3
29	*Rets3pct*	11.7	0.2	4.2	8.6	16.1	84.5	p.n.	percent of returns below Hmax/3
30	*Hmean3*	5.1	0.1	1.5	4.0	7.4	41.7	m	mean height of returns below Hmax/3
31	*CV3*	10.2	0.0	9.0	10.1	11.4	28.2	p.n.	CV of heights below Hmax/3

Note: p.n. = pure number

Observations for a random 10% sample of the 16,761 plots were extracted for each fuel type and used as a training dataset for developing CART models. The remaining observations were used as a validation dataset to calculate classification accuracies (Congalton & Green, 2008). The analyses focused on testing three non-parametric classification algorithms based on the CART approach. The first algorithm is a simple CART (Breiman *et al*., 1984); the second is based on a trees ensemble constructed using the Random Forests procedure (Breiman, 2001); and the third is a stochastic gradient boosting (SGB) model (Friedman, 2002). All three algorithms are implemented in the Salford Systems Predictive Modeling Suite (SPM) and are commercially known as CART®, RandomForest® and TreeNet™, respectively (http://www.salford-systems.com/spminfo.html).

For each classification method, the importance of each predictor variable was assessed on the basis of the improvement in classification accuracy that could be attributed to the variable. For each method, improvement values were scaled relative to the best performing predictor. The scores in percentages reflect the contribution each variable makes in classifying or predicting the response variable (Tolliver, 2009). In the cases of Random Forest and SGB, the values were averaged across all trees.

The models were constructed using the training datasets and then applied to predict the response variable for the validation data set. The resulting classifications were evaluated by cross-tabulating predictions and observations using a confusion matrix and calculating traditional accuracy indexes: overall accuracy, producer's and user's accuracies, and commission and omission errors (Congalton & Green, 2008).

4.3.2 Experiment 2: integration of raster ALS data and field survey for spatial estimation of target forest structural parameters

The experiment was carried out only the study area 1, located in the province of Palermo. In the selected area, different forest occur: *Quercus pubescens*, *Quercus suber* and *Quercus ilex* located between 400 and 600 m a.s.l. in the Oriented Natural Reserve "Bosco Favara and Granza"; high forests of *Fagus sylvatica* between 1000 and 1800 m a.s.l. in the Madonie Regional Natural Park. The aim of the study was to assess some of the most relevant parameters characterizing the forest fuels, such canopy height, woody volume and aboveground biomass using an experimental approach that couples raster ALS data and field survey and to produce high resolution maps of the considered variables. For the field survey, 41 sample plots were distributed throughout the study area according to a non-aligned sampling scheme to discriminate the different fuel types and to derive the quantitative parameters for each fuel model (Table 4.3). In order to standardize field data collection, sample unit (Fig. 4.5) follows INFC design with two concentric circles, respectively of 13

(Ads13) and 4 (Ads4) m, for measurement of the attributes reported in table 4.3. Four 1-m^2 squared-shaped subplots are designated to assess ground fuel load.

Table 4.3 - Attributes detected in the sampling units for the characterization of forest fuel (dbh = diameter at breast height of the tree; H = tree height).

Plot sample sub-unit	Measured elements	Size threshold	Attributes	Main assessed parameters
Ads13	Standing trees	dbh≥ 9,5 cm H≥130 cm	specie, $D_{1,30}$, height, azimuth, distance from the center of the area	volume aboveground woody biomass
Ads4	Standing trees	dbh≥ 2,5 cm H≥130 cm	specie, $D_{1,30}$, height, azimuth, distance from the center of the area	volume aboveground woody biomass
Subplot	Trees	dbh≤ 2,5 cm	Canopy cover, mean height	aboveground biomass
Subplot	Shrubs		Canopy cover, mean height	aboveground woody biomass
Subplot	Herbaceous species		Canopy cover, mean height	aboveground woody biomass

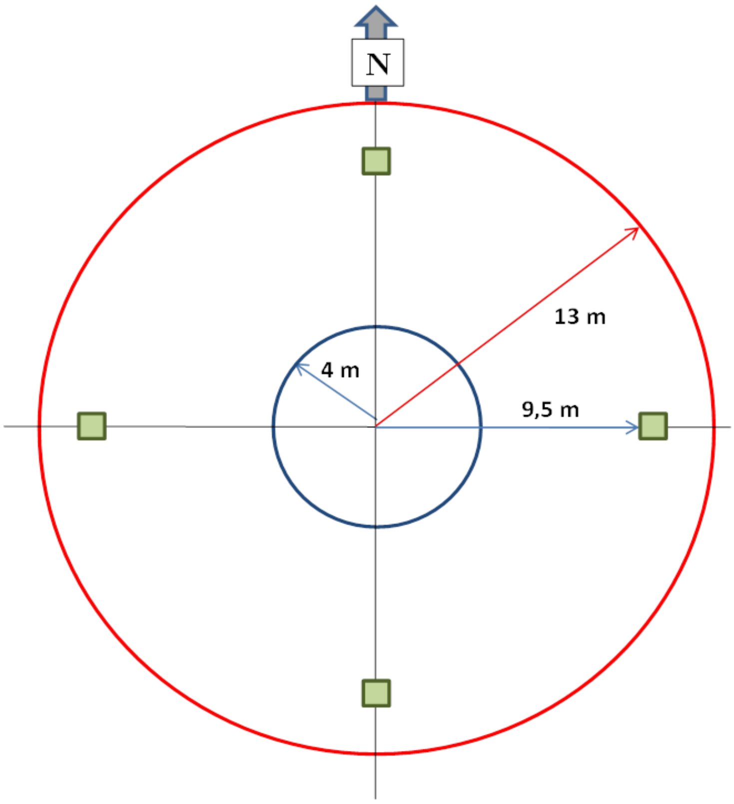


Figure 4.5 - Layout of the field sample plot components. Each circle represents a different sampling unit with specific measurement (see table 4.3).

Within each plot, the dbh and the trees height were measured and the height curve was calculated. The volume per hectare was computed on the basis of allometric equations (Tabacchi *et al*., 2011) following the same methodology used in section 3.2.3.

As detailed in Section 2.1, by the algebraic subtraction of the DSM from the DTM a raster CHM at the corresponding location of the sample plots (Fig. 4.6) was obtained and used as primary information to retrieve the forest attributes (mean height, volume, aboveground biomass). For each sampling plot the mean height from CHM was calculated using two thresholds heights above 2 meters and above 5 meters.

The ALS-derived mean height was then related with key structural variables measured in the plot (canopy height, volume, aboveground woody biomass) through regression analysis. This relationship was used to map canopy height and the aboveground woody biomass variables in the investigated area.

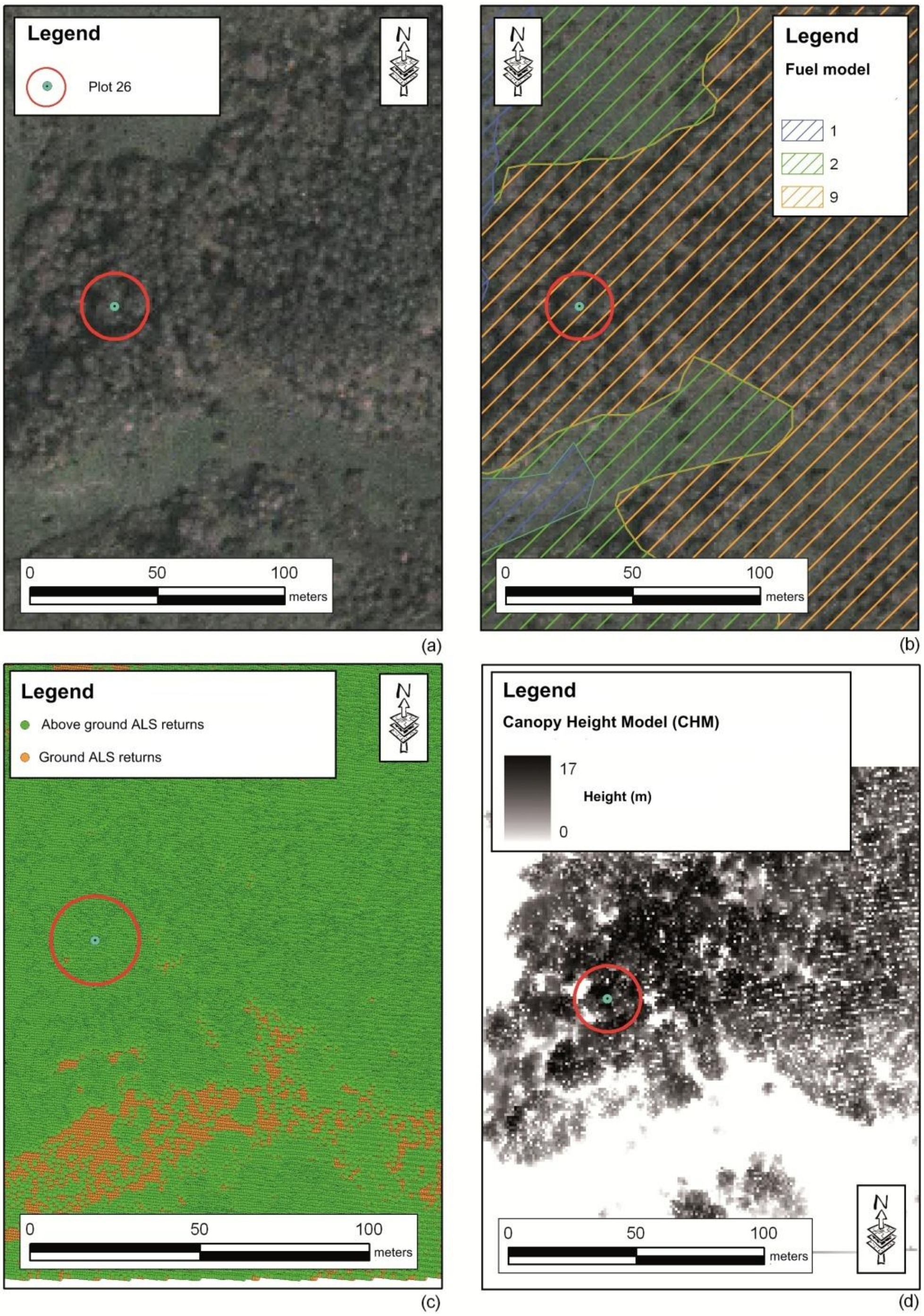


Figure 4.6 - Example of ALS data classification in the sample plot located in a mixed oak forest, NFFL fuel model n.9: (a) sample plot localization on aerial orthophoto; (b) NFFL fuel model map; (c) ALS return classification; (d) Canopy Height Model.

4.4 Experimental results

Experiment 1

The experiment conducted helps to provide an accurate description of the spatial heterogeneity of fuel in the analyzed areas. As depicted in Figure 4.7, the distribution of fuel type absolute frequencies features great heterogeneity among classes and between the two areas. Comparing the relative frequencies separately for each study area, three fuel types were prominent: type 2, observed in approximately 40% of the plots, dominates the largest study area, Area 1; type 9 dominates the smaller Area 2; and type 1 has similar incidence, approximately 20%, in the two areas; with all other types have much smaller frequencies.

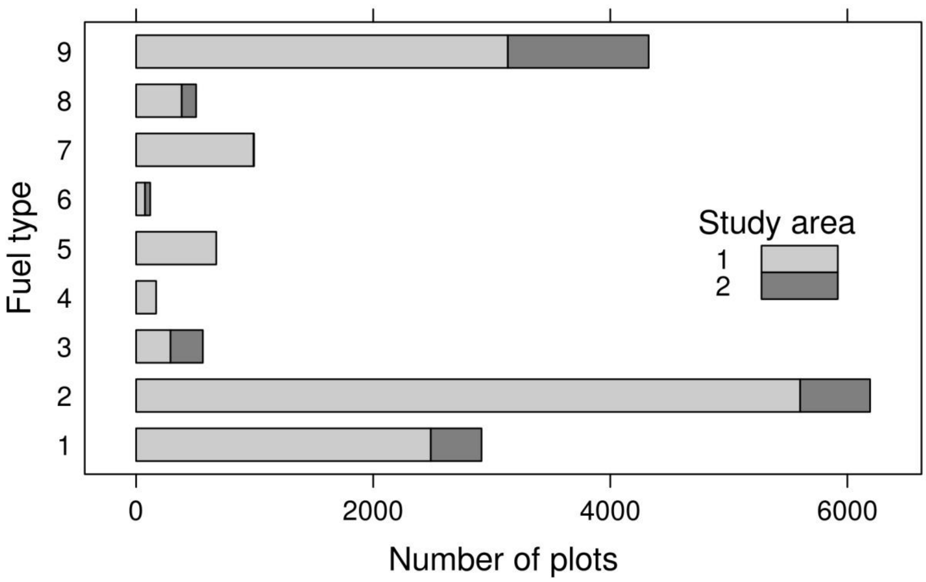
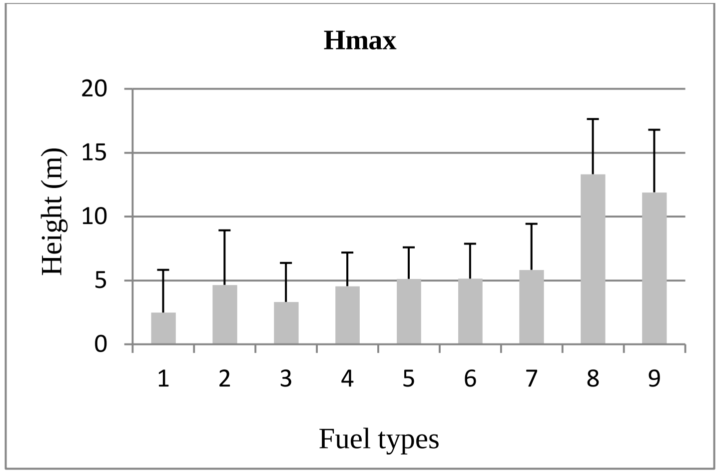


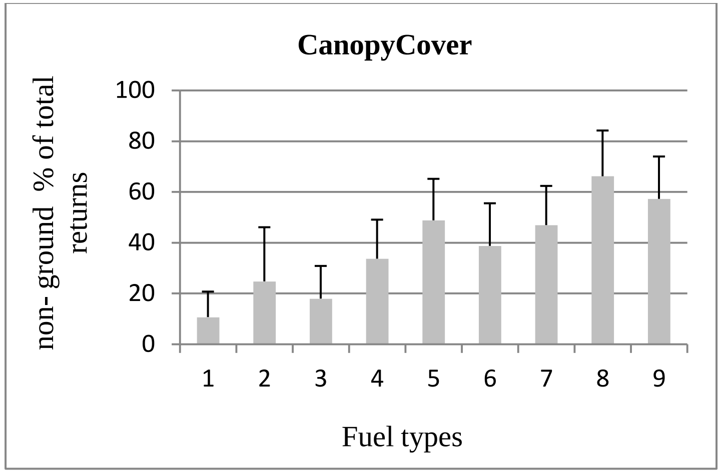
Figure 4.7 - Frequency distributions of fuel types in the study areas. Nomenclature of fuel types is reported in Table 4.1.

Analyzing in detail the distribution of the metrics within the fuel models in both study areas, we can identify ALS-derived metrics characterizing the general structure and the stratification of the stands. *Hmax, Canopy Cover* and *Hmean* (Figg. 4.8 a, b, c) are the metrics that can give preliminary information about the structure of the fuel types. The distribution of the *Hmax* metric within the nine fuel model (Fig. 4.8 a), shows that the above ground elevation of highest return for the fuel types describing the grassland group (1-3) is between 3 and 4.2 meters while for the fuel models of the shrubland group (4-7) this value ranges from 4.5 and 5.8 meters. For the models 8 and 9 (tree component) the aboveground height of the highest return is between 11.5 and 13 meters. Similar trend is observed for *Canopy Cover* metric (Fig. 4.8 b) in which the non-ground percent of total returns ranges between 10 -17% for the models 1 and 3 and is around 25% for the model 2; the 33-48% of the non-ground returns is located in the shrub layer (models 4 to 7) while the 57-66% is observed in the models 8 and 9. Finally, *Hmean* distribution (Fig. 4.8 c) shows that the mean height of all returns ranges between 0.6 and 0.7 meters for the models 1 and 3 while is around 1.31 meters for the model 2. For the tree component the value ranges between 4.7 and 6.4 meters.

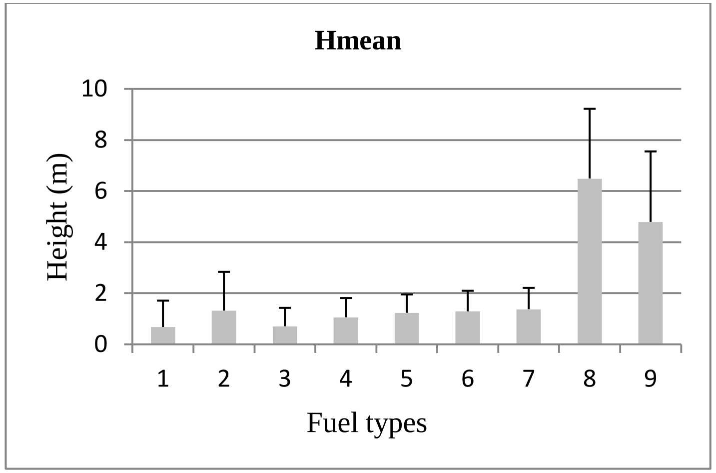
Concerning the stratification metrics, Figure 4.8d shows the distribution of percentile 70 of heights. For grassland and shrubland groups the value is lower than 2 meters while for the tree layer it ranges between 6.3 and 8 meters. As showed in Figure 4.9, for the grassland and shrubland groups, a greater number of ALS returns is observed in the height interval below Hmax/3. This percentage decrease as we reach the maximum height of the canopy and the mean height observed for the returns within this interval (Fig. 4.10) ranges between 2 and 4 meters; the tree component shows an high percentage of ALS returns within in the height interval between 1 and 2 times Hmax/3 and below this interval with a mean height 8 and 10 meters. ALS metrics, thus, indicate the vertical fuel structure for each fuel model considered.



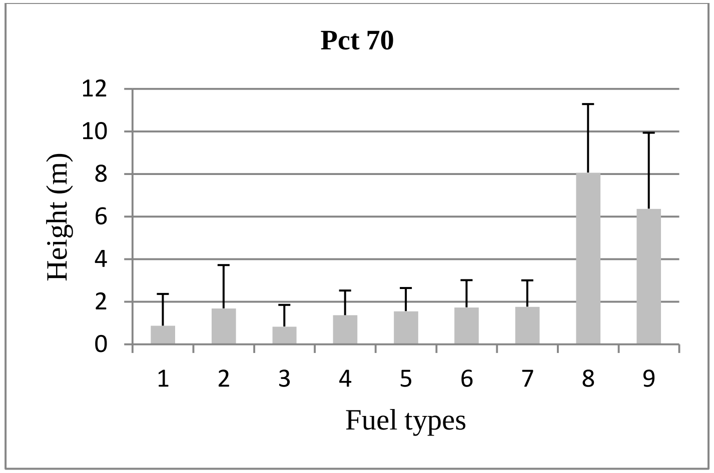
a)



b)



c)



d)

Figure 4.8 - Average values with standard deviation of above ground elevation of highest return (a), non-ground percent of total returns (b), mean height of all returns (c) and percentile 70 of heights distribution (d).

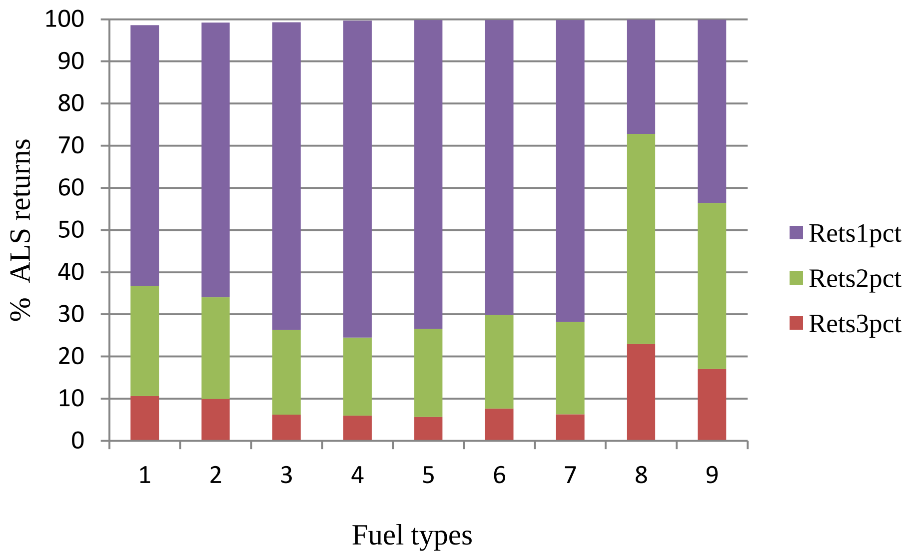


Figure 4.9 - Percent of returns above Hmax*2/3 , between 1 and 2 times Hmax/3 and below Hmax/3.

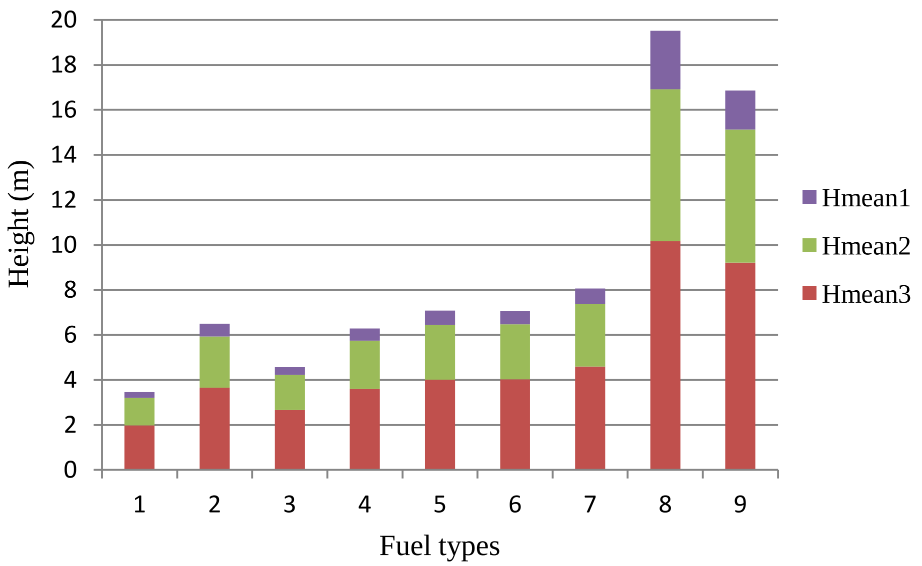


Figure 4.10 - Mean height of returns above Hmax*2/3, between 1 and 2 times Hmax/3 and below Hmax/3.

The relevance of ALS-based metrics as fuel type predictors for the traditional CART approach, the CART approach with bagging called Random Forests, and the CART with bagging/boosting called Stochastic Gradient Boosting are reported in Table 4.4. The most relevant metric was canopy cover, defined as the percent of non-ground returns. Other relevant metrics included percentiles of the height distribution, the mean height of all returns, and the number of returns.

CART and Random Forests with overall accuracies of only 38% and 37%, respectively, were not able to achieve sufficiently accurate classifications. However, SGB with overall accuracy of 73% produced substantially more accurate classifications for the two study areas (Table 4.5). In terms of omission errors, the three models did not differ although SGB limited commission errors to an average 16% across the nine fuel types, whereas the average errors were 65% and 66%, respectively, for CART and Random Forests. The most evident advantage of SGB was the ability to maintain an acceptable classification accuracy, especially from the producer’s perspective, for fuel types with relatively small numbers of observations (from type 3 to type 8), (Fig. 4.11). On the other hand, all the classifiers were able to achieve comparably accurate results for the most widespread fuel types (types 1, 2 and 9) which, in the validation datasets, represent 82% of total number of observations.

Table 4.4 - Relevance of the ALS-based metrics in the different models tested. Metrics are ranked top to down on the basis of the sum of the three relevances. The description of the metrics is in Table 4.2.

Metric	CART	Random Forest	TreeNet
CanopyC	93.5	52.6	100.0
Pct30	100.0	91.1	28.6
Pct70	17.2	94.7	83.7
Pct50	4.8	100.0	42.6
Pct60	3.1	94.0	42.9
Hmean	4.7	76.5	50.9
Pct10	17.3	66.4	45.8
CV	23.9	58.8	46.5
Pct20	7.9	86.2	34.3
Pct80	7.1	68.0	49.8
Returns	19.8	43.6	60.6
Hmean1	6.3	64.4	46.7
Texture	30.4	33.7	52.8
CV1	37.4	15.9	43.7
Pct90	4.8	42.1	34.4
Pct99	11.5	25.2	35.2
Kurtosis	10.3	28.1	30.2
Rets2pct	14.3	13.9	37.6
Hmean3	11.8	18.4	34.6
CV2	13.1	10.1	34.3
Hmin	11.9	4.1	37.1
CV3	3.4	3.4	35.5
Density2	5.1	7.1	28.8
Hmax			34.9
Hmean2			33.1
Skewness			32.9
Pct40			32.4
relHmean			31.2
Rets3pct			26.4
Density1			22.6
Rets1pct			19.1

Table 4.5 - Confusion matrix based on the classification by SGB.

	Fuel Types	VALIDATION 1	2	3	4	5	6	7	8	9	Total	User Accuracy	Commission Error
CLASSIFICATION	1	1436	404	30	1	2	3	7	0	18	1902	75.5%	24.5%
	2	1154	4728	314	44	210	22	320	53	396	7242	65.3%	34.7%
	3	14	8	156	0	0	0	2	0	0	180	86.6%	13.4%
	4	0	0	0	100	0	0	0	0	0	100	100.0%	0.0%
	5	1	37	0	0	326	3	16	0	25	409	79.8%	20.2%
	6	0	0	0	0	0	76	1	0	0	77	98.5%	1.5%
	7	2	84	6	2	25	1	462	0	20	603	76.6%	23.4%
	8	1	14	0	0	0	0	0	269	12	296	90.8%	9.2%
	9	51	422	8	7	53	2	99	158	3476	4276	81.3%	18.7%
	Total	2660	5697	514	154	617	109	908	480	3946			
	Producer Accuracy	54.0%	83.0%	30.3%	64.7%	52.9%	70.1%	50.9%	56.1%	88.1%			
	Omission Error	46.0%	17.0%	69.7%	35.3%	47.1%	29.9%	49.1%	43.9%	11.9%			

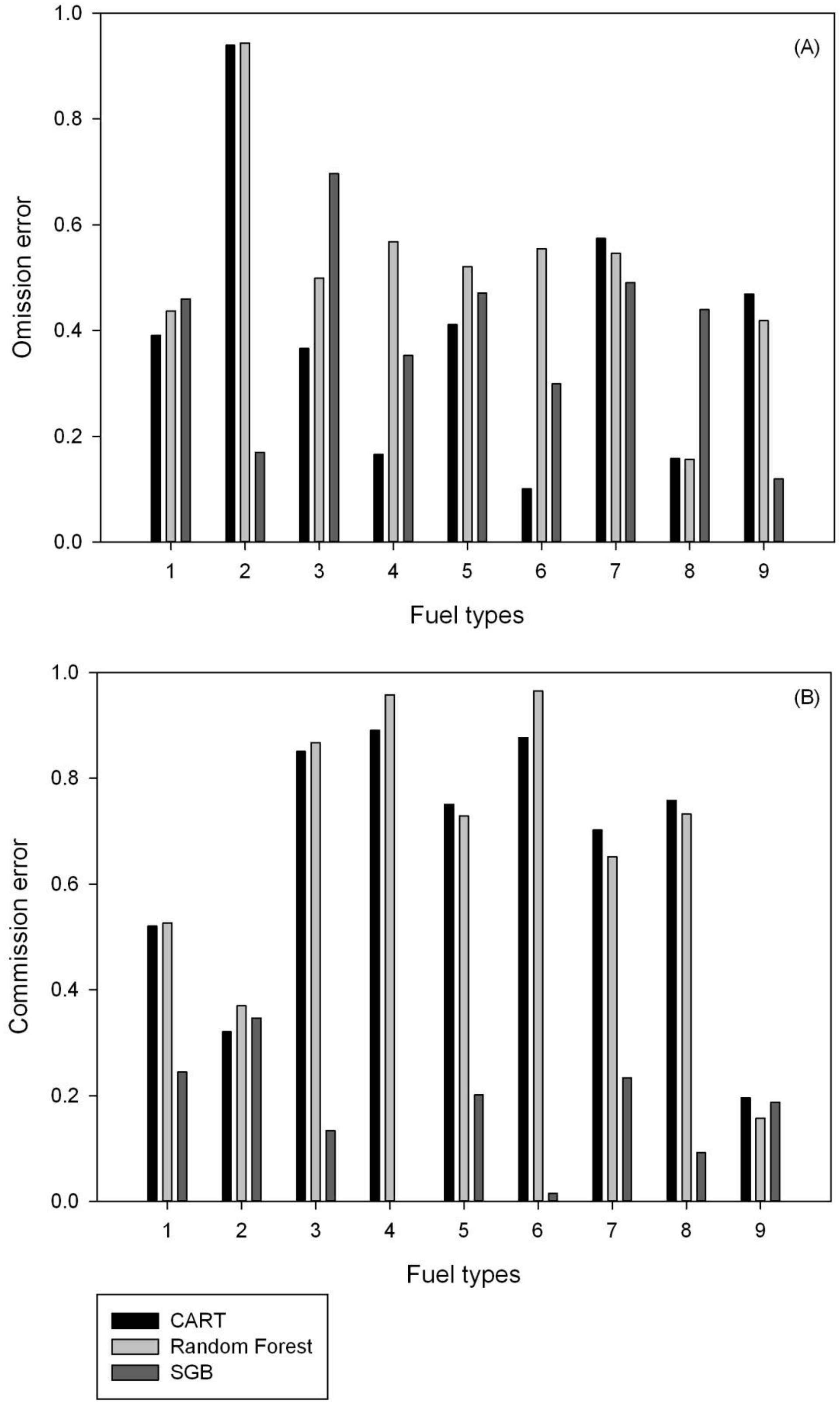


Figure 4.11 - Omission (A, above) and commission errors (B, below) for the three tested classification algorithms for the nine fuel types.

Experiment 2

Figure 4.12 shows the distribution of the sample plots in the study area. Two main zones are identified: (a) mixed oak forests where the highest number of sample plots is located; (b) beech forests belonging to different fuel models (respectively FM2 and FM8). Table 4.4 shows how the structural variability of the forest stands belonging the same fuel model is relative large.

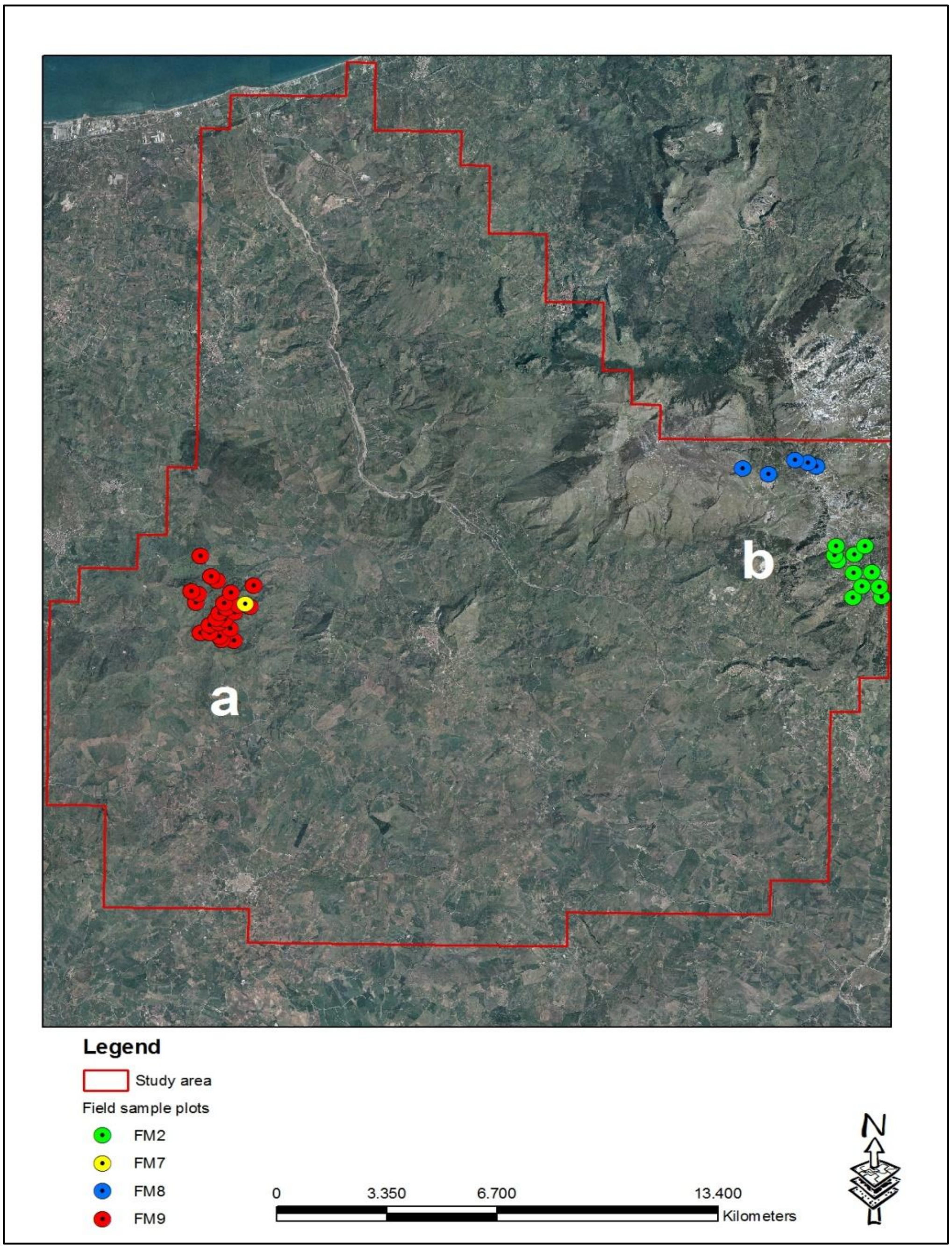


Figure 4.12 - Location of the field sample plots. Coloured dots show the distribution of the field plots according to the different fuel models.

Table 4.6 - Main dendrometric characteristics of the sample plots.

NFFL Fuel model number	Number of sample units	Forest type	Min and max values of crown mean height (m)	Min and max values of standing volume(m^3 ha^{-1})
2	11	Beech forest	6.2 - 15.2	9 - 294
7	1	Mixed oak forest	7.5	36
8	5	Beech forest	12.1 - 17.2	115 - 475
9	23	Mixed oak forest	5.1 - 11.8	11 - 212
9	1	Mixed oak forest with new spontaneous groups of Calicotome spinosa	6.3	10

The relationship between the mean height and the woody volume assessed in the plots (Fig. 4.13 b) provides good results (R^2= 0.60) even if not excellent.

Figure 4.14 shows the map of the mean stand height for the areas in which ALS data and field sample plot are available. The mean height ranges between 5 and 22 meters in the zone a) while in the zone b) it is between 5 and 24 meters. Figure 4.15 shows the map of the distribution of the aboveground woody biomass. The highest values were recorded within the models 8 and 9 with a maximum value of around 507.2 Mg ha^{-1} while lower values were observed within the model 3 (on average, 182.5 Mg ha^{-1}).

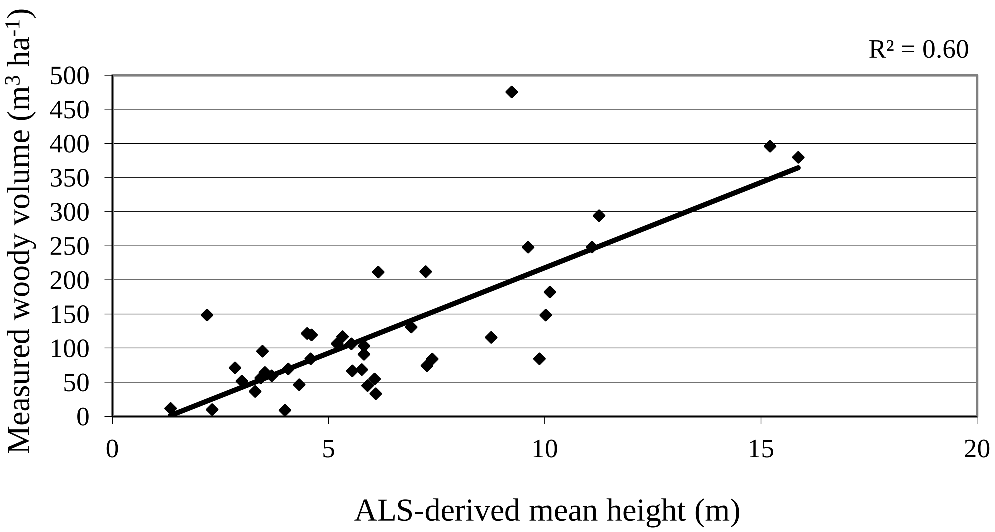


Figure 4.13 - Relationship between ALS-derived mean height and ground truth values of woody volume within the sample plots.

Table 4.7 shows the coefficients and the relative standard errors and confidence intervals of the linear regression used for assessing the woody volume. From the statistical point of view the relationships are very different both if we use a threshold of 5 meters and 2 meters. The linear regression is better adapted to beech forests (R^2= 0.87; 0.86) respect to mixed oak forests (R^2= 0.10; 0.03).

Table 4.7 - Coefficients, standard error and confidence intervals of the linear regression used to assess the woody volume.

Threshold	Forest type	Coefficients		Std. Error	95% Confidence Interval for B	
					Lower Bound	Upper Bound
2 meters	Beech forest	Intercept	-177,76	37,81	-263,29	-92,23
		β	37,47	4,69	26,86	48,09
	Mixed oak forest	Intercept	36,99	38,61	-43,30	117,29
		β	10,64	6,67	-3,23	24,51
5 meters	Beech forest	Intercept	-227,02	45,71	-330,43	-123,62
		β	40,46	5,29	28,49	52,43
	Mixed oak forest	Intercept	46,19	57,86	-74,13	166,51
		β	7,41	8,38	-10,01	24,84

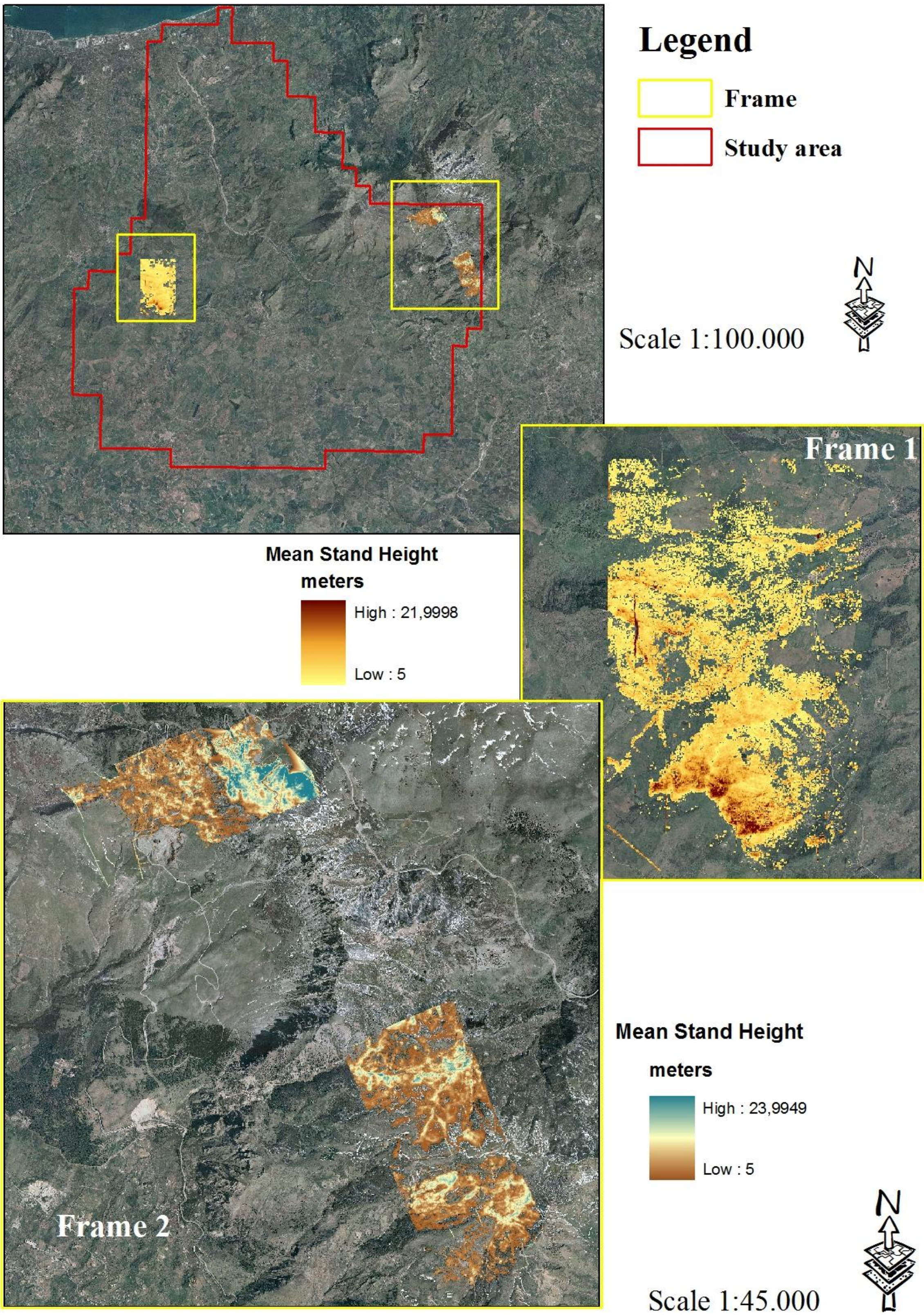


Figure 4.14 - Map of the mean stand height in two zones of the investigated areas.

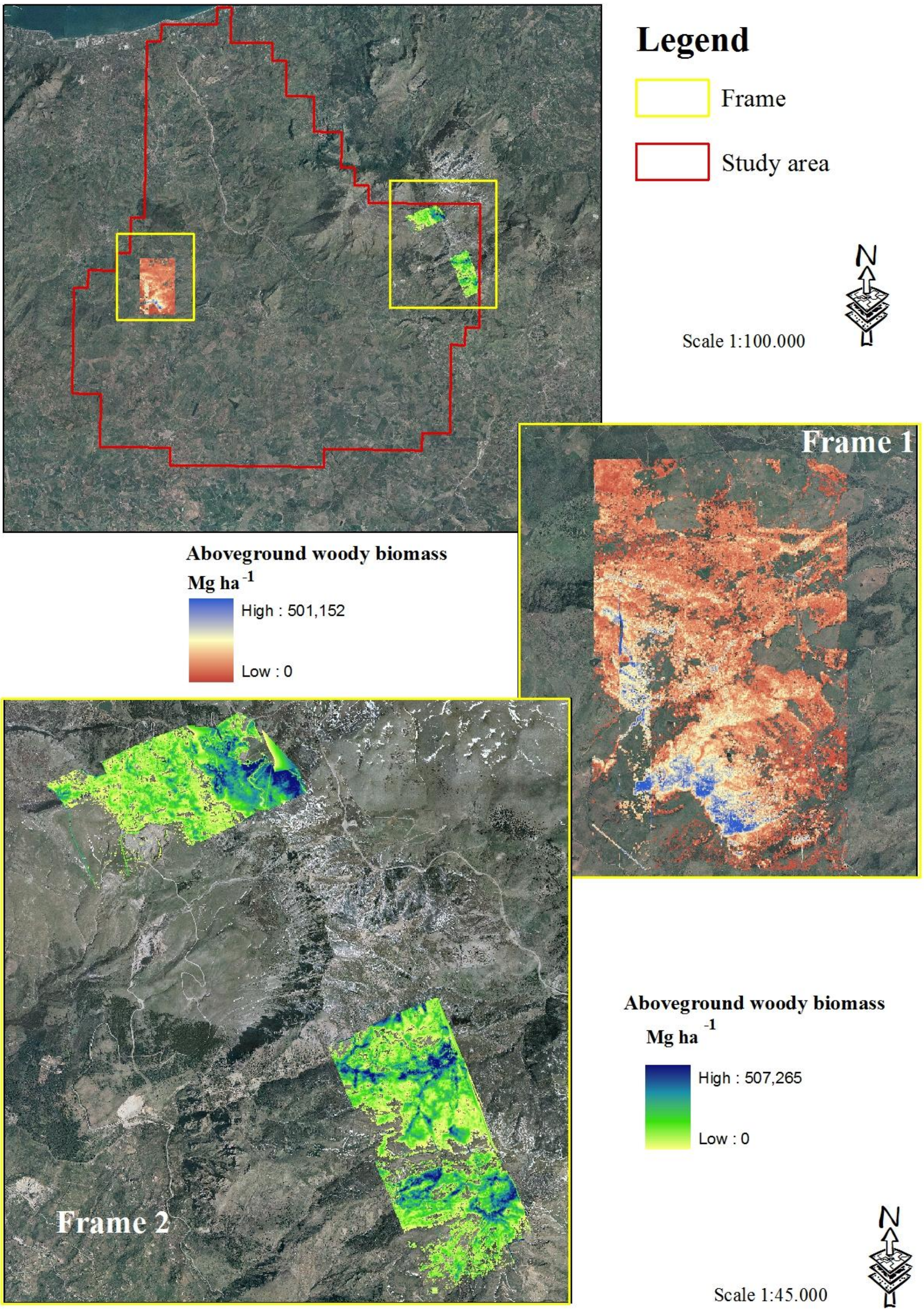


Figure 4.15 - Map of the standing aboveground woody biomass in the investigated areas. The map was computed using the mean tree height derived by the relationship between field and ALS data.

4.5 Discussions

In this chapter, an experimental analysis of the spatial variability of Mediterranean fuel models has been presented. This analysis has focused on two forest areas characterized by different fuel types and was aimed to: i) explore the potential of ALS data for characterizing fuel types by using ALS metrics derived from the height values of laser points; ii) use raster ALS data to assess the structural parameters of fuel models in order to obtain detailed maps to be used in forest fire prevention planning. In particular, the maps produced can be exploitable for fire behavior modeling constituting the input layers of fuel management simulation decision making support tools as FARSITE.

The analysis conducted in the experiment 1 resulted in interesting conclusions on the characterization of the general structure of the study areas providing interesting information about the vertical stratification of the vegetation. Different cover types can affect the density of ALS returns and the results obtained by this experimentation confirm that ALS data, even if with low pulse density (1.5 points per square meters), are at least able to better characterize the tree component from grass and shrub layers. Within the grassland group the *Canopy Cover* metric is even able to characterize the model 2 in respect with the models 1 and 3. Referring to the NFFL classification (Table 4.1), Model 2, in fact, also includes forest types in which some residual trees still may exist. Additionally, the descriptive statistics of these metrics show coherence with PROMETHEUS classification and help to quantify where most of the fuel load is located. In consideration of these results it would be possible a rational treatments planning aimed at the reduction of forest fuels in the areas prone to fire.

With reference to the results obtained through the experiment 2, that tested ALS data, even if with low pulse density, showed a good predictive ability for spatial extraction of the mean height of the stands and the aboveground biomass of the forest types representative of Mediterranean and temperate environments. As previously stated, the maps derived can significantly improve the data layer creation process for wildfire simulation models (as FARSITE) enabling a realistic and accurate prediction of fire behavior.

Comparing the results of the two experiments it is possible to draw some considerations. First, the analysis of descriptive statistics of ALS metrics within a delimited area makes possible a preliminary characterization of fuel models without the field survey, a time and cost consuming activity. Moreover, the spatial variability of forest fuels requires the implementation of new methodologies able to satisfy the information needs linked to its classification and characterization on large scale. In this direction, the integration of the traditional field surveys with innovative remote sensing technologies, as ALS data, could be an effective way to produce detailed maps.

Chapter 5

5 Conclusions

The dissertation addressed key questions related to the use of ALS data for the assessment of forest structural parameters, with a special focus on aboveground woody biomass estimation. The main contribution of this dissertation to the literature are: i) a detailed scientific review of the current applications of ALS for forestry purposes in Italy; ii) an experimental testing of raster CHM-derived for the spatial estimation of the aboveground biomass by coupling ALS data and field survey; iii) an experimental testing of raw ALS data for detecting forest structural variables critical for fuel modeling.

The scientific review produced in chapter 2, provided general considerations with reference to selected experiences of ALS applications under alpine, temperate and Mediterranean environments in Italy. The main issues concern the potential use for ALS data exploitation in forest inventories over large territories, their use for silvicultural systems detection and for the estimation of fuel load in forest stands.

Regarding the estimation part of the work, the dissertation focused on the estimation of the aboveground biomass and on the characterization of forest fuels.

The survey approach proposed in chapter 3, based on the ALS-derived CHM, has proved to be highly effective to support the assessment of the riparian forest wood volume and biomass, providing comparable results in term of accuracy to previous experiments carried out under different forest environments (Corona & Fattorini, 2008; Corona *et. al.*, 2008). In addition, a map of the aboveground woody biomass, as produced in this study, can be used to analyze its spatial distribution so that to support the users for planning the precision harvesting of aboveground woody biomass of riparian stands, whose is usually not homogeneous. In the examined case study, an average aboveground woody biomass of about 90 Mg ha^{-1} (R^2= 0.85) was assessed within poplar-dominated riparian forest, corresponding to an amount of available biomass of 800 Mg km^{-1} along the river axis.

The second analysis performed in chapter 4 was aimed to analyze the effectiveness of ALS raw and raster data in the estimation process. Findings from the first experiment demonstrate that ALS metrics, without the use of optical data, would be sufficient to discriminate among different fuel types. The non-parametric procedures tested were based on classification and regression trees. Good accuracy (73%) was obtained for only the stochastic gradient boosting (SGB) method, whereas traditional CART and Random Forests produced poor results. The second approach showed a good predictive ability (R^2 = 0.60) for spatial extraction of tree attributes, in particular the mean height of the stands and the aboveground woody biomass of the forest types representative of Mediterranean environments. Therefore, experimental results from this analysis confirm the potential of ALS data to provide detailed map of the spatial distribution of forest fuels and the quantification of the structural parameters able to characterize fuel types.

References

Abramo E., Barilotti A., Sepic F. (2007) - Dalla dendrometria diametrica alla dendrometria ipsometrica: stima del volume degli alberi da rilievi laser-scanning. *Forest@* 4 (4): pp. 373-385.

Ackermann F., Englich M., Kilian J. (1994) - Die Laser-Profil-Befliegung Gammertingen. *ZfV* 119 (5): pp. 264-277.

Agee J. K., Skinner C. N. (2005) - Basic principles of forest fuel reduction treatments. *Forest Ecology and Managemen*t 211, (11): pp. 83-96.

Ahokas E., Kaartinen H. & Hyyppä J. (2003) - A quality assessment of airborne laser scanner data. In*: Proceeding of the IAPRS*, Dresden (Deutschland), Vol. XXXIV-3/W13, p. 7.

Akay A., Oðuz H., Karas I., Aruga K. (2009) - Using LiDAR technology in forestry activities. *Environmental Monitoring and Assessment*, 151: pp. 117-124.

Albini F. A. (1976) - Estimating wildfire behavior and effects. *Gen. Tech. Rep*. INT-GTR-30. U.S. Department of Agriculture, Forest Service, Ogden, USA.

Andersen H. E., McGaughey R. J., Reutebuch S. E. (2005) - Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment*, 94: pp. 441-449.

APAT. Italian Greenhouse Inventory 1990-2005. *National Inventory Report 2007.* Annual Report for submission under the UN Framework Convention on Climate Change and the European Union's Greenhouse Gas Monitoring Mechanism, LULUCF sector, 2007.

Arroyo L. A., Healey S. P., Cohen W. B., Cocero D. (2006) - Using object-oriented classification and high-resolution imagery to map fuel types in a Mediterranean region. *Journal of Geophysical Research* 111, G04S04.

Arroyo L.A., Pascual C., Manzanera J. A. (2008) - Fire models and methods to map fuel types: the role of remote sensing. *Forest Ecology and Management*, 256: pp. 1239-1252.

Axelsson P. E. (1999) - Processing of laser scanner data - algorithms and applications. *Isprs Journal of Photogrammetry and Remote Sensing*, 54: pp. 138-147.

Axelsson P. E. (2000) - DEM Generation from Laser Scanner Data Using Adaptive Models. *International Archives of Photogrammetry and Remote Sensing*, 33: pp. 110-117.

Barabesi L. & Franceschi S. (2011) - Sampling properties of spatial total estimators under tessellation stratified designs. *Environmetrics*, 22: pp. 271-278.

Barbati A., Chirici G., Corona P., Montaghi A., Travaglini D. (2009) - Area-based assessment of forest standing volume by field measurements and airborne laser scanner data. *International Journal of Remote Sensing.* 30 (19): pp. 5177-5194.

Barilotti A., Turco S., Napolitano R., Bressanc E. (2005) - La tecnologia LiDAR per lo studio della biomassa negli ecosistemi forestali. *Proceedings of 15th Meeting of the Italian Society of Ecology*, 12-14 September 2005, Torino.

Barilotti A., Sepic F., Abramo E., Crosilla F. (2007a) - Improving the morphological analysis for tree extraction: a dynamic approach to LiDAR data. *ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007*, Espoo, September 12-14, 2007, Finland.

Barilotti A., Sepic F., Abramo E., Crosilla F. (2007b) - Assessing the 3D structure of the single crowns in mixed alpine forests. In: Stilla U., Meyer H., Rottensteiner F., Heipke C., Hinz S. (eds). (2007). PIA07 - Photogrammetric Image Analysis 2007. *International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences*, 36, Part 3/W49A.

Bottalico F., Montaghi A., Travaglini D. (2009) - Identificazione dei gaps nella copertura forestale con dati LiDAR. *Atti 13a Conferenza Nazionale ASITA,* Bari, 1-4 Dicembre 2009.

Bradbury J, Cullen P, Dixon G, Pemberton M. (1995) - Monitoring and management of streambank erosion and natural revegetation on the lower Gordon River, Tasmanian Wilderness World Heritage Area, *Australia. Environmental Management*; 19 (2): pp. 259-272.

Brandtberg T., Warner T. A., Landenberger R. E., McGraw J. B. (2003) - Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density LiDAR data from the eastern deciduous forest in North America. *Remote Sensing of Environment* 85: pp. 290-303.

Breidenbach J., Næsset E., Lien V., Gobakken T., Solberg S. (2010) - Prediction of species specific forest inventory attributes using a nonparametric semi individual tree crown approach based on fused airborne laser scanning and multispectral data. *Remote Sensing of Environment*, 114: pp. 911-924.

Breiman L. (2001) - Random Forests. *Machine Learning*, 45 (1): pp. 5-32.

Breiman L., Friedman J. H., Olshen R. A., Stone C. J. (1984) - Classification and Regression Trees. *Chapman and Hall* (Wadsworth, Inc.), New York.

Burgan R. & Rothermel R. C. (1984) - BEHAVE: Fire Behaviour Prediction and Fuel Modeling System-FUEL Subsystem. *Rep. No. GTR INT-167*. Intermountain Forest and Range Experiment Station, Ogden, UT.

Castellani C., Scrinzi G., Tabacchi G., Tosi V. Inventario Forestale Nazionale Italiano (1984). Tavole di cubatura a doppia entrata*. Ministero dell'Agricoltura e delle Foreste*, *Istituto Sperimentale per l'Assestamento Forestale e per l'Alpicoltura*.

Chirici G. & Corona P. (2006) - Utilizzo di immagini satellitari ad alta risoluzione nel rilevamento delle risorse forestali. *Aracne Editrice*, Roma.

Chuvieco E., Riano D., van Wagtendonk J., Morsdorf F. (2003) - Fuel loads and fuel type mapping. In: Wildland Fire Danger Estimation and Mapping. The Role of the Remote Sensing Data (Chuvieco E. ed). *World scientific*, Singapore, pp. 119-142.

Chuvieco E., Cocero D, Riaño D., Martin P., Martínez-Vega J., Riva J. D. L., Pérez F. (2004) - Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sensing of Environment*, 92: pp. 322-331.

Ciancio O. (1997) - La selvicoltura ritrovata. *L'Italia Forestale e Montana*, 52 (3): pp. 161-191.

Clementel F., Colle G., Farruggia C., Floris A., Scrinzi G., Torresan C. (2010) - Stima operativa di parametri dendrometrici forestali con riprese LiDAR invernali a bassa risoluzione. *Atti 14a Conferenza Nazionale ASITA*, Brescia, 9-12 Novembre 2010.

Clementel F., Colle G., Farruggia C., Floris A., Scrinzi G., Torresan C. (2012) - Estimating forest timber volume by means of “low-cost” LiDAR data. *Italian Journal of Remote Sensing*, 44 (1): pp.125-140.

Cochrane M. A., Alencar A., Schulze M. D., Souza C. M., Nepstad D. C., Lefebvre P., Davidson E. A. (1999) - Positive feedbacks in the fire dynamic of closed canopy tropical forests. *Science* 284: pp.1832-1835.

Cohen W. B. & Goward S. N. (2004) - Landsat role in ecological applications of remote sensing. *BioScience*, 54: pp. 535-545.

Congalton R. G. & Green K. (2008) - Assessing the accuracy of remotely sensed data: Principles and practices, 2nd Edition. *CRC Press*, Taylor and Francis group. Boca Raton, FL, USA.

Corona P. (2010) - Integration of forest mapping and inventory to support forest management. *iForest*, 3: pp. 59-64.

Corona P. & Marchetti M. (2007) - Outlining multi-purpose forest inventories to assess the ecosystem approach in forestry. *Plant Biosystem*, 2: pp. 243-251.

Corona P. & Fattorini L. (2008) - Area-based LIDAR-assisted estimation of forest standing volume. *Canadian Journal of Forest Research* 38: pp. 2911-2916.

Corona P., Lamonaca A., Chirici G., Travaglini D., Marchetti M., Minari E., *et al*. (2008) - Estimation of growing stock of broadleaved forests by airborne laser scanning. In: Gianelle D, Travaglini F, Mason E, Minari E, Chirici G, Chemini C, editors. Canopy Analysis and dynamics of a flood-plain forest. *CIERRE Edizioni* Verona: pp. 39-44.

Corona P., Cartisano R., Salvati R., Chirici G., Floris A., Di Martino P., Marchetti M., Scrinzi G., Clementel F., Travaglini D., Torresan C. (2012) - Airborne Laser Scanning to support forest resource management under alpine, temperate and Mediterranean environments in Italy. *European Journal of Remote Sensing* 45: pp. 27-37.

Dalponte M., Bruzzone L., Pianelle D. (2008) - Fusion of hyperspectral and LiDAR remote sensing data for classification of complex forest areas. *Transactions on geosciences and remote sensing*, 46 (5): pp. 1416-1427.

Dalponte M., Bruzzone L., Gianelle D. (2011a) - A system for the estimation of single tree stem diameters and volume using multireturn LiDAR data. IEEE *Transactions on Geoscience and Remote Sensing,* 49 (7): pp. 2479-2490.

Dalponte M., Martinez C., Rodeghiero M., Gianelle D. (2011b) - The role of ground reference data collection in the prediction of stem volume with LiDAR data in mountain areas. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66: pp. 787-797.

Décamps H. (1996) - The renewal of floodplain forests along rivers: a landscape perspective. *Verh. Int. Verein. Limnol*; 26 (1): pp.35-59.

Donoghue D. N. M., Watt P. J., Cox N. J., Wilson J. (2007) - Remote sensing of species mixtures in conifer plantations using LiDAR height and intensity data. *Remote Sensing of Environment*, 110: pp. 509-522.

Erdody T. L. & Moskal L. M. (2010) - Fusion of LiDAR and imagery for estimating forest canopy fuels. *Remote Sensing of Environment*, 114: pp. 725-737.

Estornell J., Ruiz L. A., Velàzquez-Martì B., Fernández-Sarría A. (2011) - Estimation of shrub biomass by airborne LiDAR data in small forest stands. *Forest Ecology and Management*, 262: pp. 1697-1703.

Evans J. S., Hudak A. T., Faux R., Smith A. M. (2009) - Discrete Return Lidar in Natural Resources: Recommendations for Project Planning, Data Processing, and Deliverables. *Remote Sensing*, 1: pp. 776-794.

Fail J. L, Hamzah M. N., Haines B. L., Todd R. L. (1986) - Above and belowground biomass, production, and element accumulation in riparian forests of an agricultural watershed. In: Correll DL, editor. *Watershed Research Perspectives*, Washington, DC.: Smithsonian Press: pp.193-223.

Falkowski M. J., Evans J. S., Martinuzzi S., Gessler P. E., Hudak A. T. (2009) - Characterizing forest succession with lidar data: An evaluation for the Inland Northwest, USA. *Remote Sensing of Environment*, 113: pp. 946 - 956.

Finney M. A. (1998) - FARSITE: Fire Area Simulator - model development and evaluation. *Res. Pap. RMRS-RP-4*, Ogden,UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: p. 47.

Finney M. A. (2006) - An overview of FlamMap modeling capabilities. In: P.L. Andrews, B.W. Butler (comps.). *Fuels Management – How to measure success: Conference Proceedings*. RMRS-P-41: pp. 213-219.

Finney M. A. (2007) - A computational method for optimising fuel treatment locations. *International Journal of Wildland Fire* 16: pp. 702-711.

Finney M. A. & Andrews P. L. (1994) - The farsite fire area simulator: Fire management applications and lessons of summer 1994. In: *Proceedings of Interior West Fire Council Meeting and Program*.

Floris A., Clementel F., Farruggia C., Scrinzi G. (2009) - Il LiDAR nella stratificazione tematica dei soprassuoli forestali: applicazioni in Trentino. *Atti 13a Conferenza Nazionale ASITA*, Bari, 1-4 dicembre 2009.

Floris A., Clementel F., Farruggia C., Scrinzi G. (2010) - Stima su base LiDAR delle provvigioni legnose forestali: uno studio per la Foresta di Paneveggio. *Rivista Italiana di Telerilevamento*, 42 (3): pp.15-32.

Forzieri G., Guarnieri L., Vivoni E. R., Castelli F., Preti F. (2009) - Multiple attribute decision making for individual tree detection using high-resolution laser scanning. *Forest Ecology and Management*, 258: 2501-2510.

Franklin S. E. (2001) - Remote sensing for sustainable forest management. *Lewis publishers,* DC.

Friedman J. H. (2002) - Stochastic gradient boosting. *Computational Statistics and Data Analysis*, 38 : pp. 367-378.

Fusco S., Pflugmacher D., Kirschbaum A., Cohen W., Chiatante D., Montagnoli A. (2008) - Uso di dati LiDAR per stima della biomassa forestale in un bosco misto di latifoglie: un caso studio in Valsassina (LC). *Atti 12a Conferenza Nazionale ASITA*, L'Aquila, 21-21 Ottobre 2008.

García M., Riaño D., Chuvieco E., Danson F. M. (2010) - Estimating biomass carbon stocks for a Mediterranean forest in central Spain using LiDAR height and intensity data. *Remote Sensing of Environment*, 114: pp. 816-830.

García M., Riano D., Chuvieco E., Salas J., Danson F. M. (2011) - Multispectral and LIDAR data fusion for fuel map type mapping using Support Vector Machine and decision rules. *Remote Sensing of Environment* 115: pp. 1369-1379.

Getis A. & Ord K. (1992) - The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24: pp. 189-206.

Giese L. A. B., Aust W. M., Kolka R. K., Trettin C. C. (2003) - Biomass and carbon pools of disturbed riparian forests. *Forest Ecology and Management*; 180 (1-3): pp. 493-508.

Graham, L. (2005) - The LAS 1.1 standard. *Photogrammetric Engineering & Remote Sensing*, 71 (7): 777-780.

Gregoire T. G., Ståhl G., Næsset E., Gobakken T., Nelson R., Holm S. (2011) - Model-assisted estimation of biomass in a LiDAR sample survey in Hedmark county, Norway. *Canadian Journal of Forest Research*, 41: pp. 83-95.

Gregory S. V., Swanson F. J., McKee W. A., Cummins K. W. (1991) - An ecosystem perspective of riparian zones. *BioScience*; 41 (8): pp. 540-551.

Hall G. F., Strebel D. E., Sellers P. J. (1988) - Linking knowledge among spatial scales: vegetation, atmosphere climate and remote sensing. *Landscape Ecology*, 2: pp. 3-22.

Harding D., Lefsky M., Parker G., Blair J. (2001) - Laser altimetry canopy height profiles - Methods and validation for closed-canopy, broadleaf forests. *Remote Sensing of Environment*, 76: pp. 283-297.

Hardy C. (2005) - Wildland fire hazard and risk: problems, definitions, and context. *Forest Ecology and Management,* 211: pp. 73-82.

Heurich M. (2008) - Automatic recognition and measurement of single trees based on data from airborne laser scanning over the richly structured natural forests of the Bavarian national park. *Forest Ecology and Management*, 255: pp.2416-2433.

Hierro J. L., Branch L. C., Villarreal D., Clark K. L. (2000) - Predictive equations for biomass and fuel characteristics of Argentine shrubs. *Journal of Range Management* 53: pp. 617-621.

Hoffmann A., Cibella R., Bertani R., Miozzo M., Fantoni I., Luppi S. (eds.), (2011) - Strumenti conoscitivi per la gestione delle risorse forestali in Sicilia. Sistema Informativo Forestale Regionale. *Regione Siciliana*, Palermo.

Hollaus M., Wagner W., Eberhöfer C., Karel W. (2006) - Accuracy of large-scale canopy heights derived from LiDAR data under operational constraints in a complex alpine environment. *ISPRS Journal of Photogrammetry and Remote Sensing*, 60 (5): pp. 323-338.

Hudak A. T., Crookston N. L., Evans J. S., Falkowski M. J., Smith A. M. S., Gessler P. E., Morgan P. (2006) - Regression modeling and mapping of coniferous forest basal area and tree density from discrete-return LiDAR and multispectral satellite data. *Canadian Journal of Remote Sensing*, 32: pp. 126-138.

Hyyppä J., Schardt M., Haggrén H., Koch B., *et al*. (2001a) - High-scan: the first European-wide attempt to derive single-tree information from laserscanner data. *The Photogrammetric Journal of Finland*, 17: pp. 58-68.

Hyyppä J., Kelle O., Lehikoinen M., Inkinen M. (2001b) - A segmentation-based method to retrieve stem volume estimates from 3-D tree height models produced by laser scanner. *IEEE Transactions on Geoscience and Remote Sensing*, 39: pp. 969-975.

INFC (2005) - Inventario nazionale delle foreste e dei serbatoi forestali di carbonio. *Ministero delle Politiche Agricole Alimentari e Forestali*, Ispettorato Generale-Corpo Forestale dello Stato. CRA-Istituto Sperimentale per l’Assestamento Forestale e per l’Alpicoltura.

Ioki K., Imanishi J., Sasaki T., Morimoto Y., Kitada K. (2009) - Estimating stand volume in broad-leaved forest using discrete-return LiDAR: plot-based approach. *Landscape and Ecological Engineering*, 6: pp. 29-36.

Kauffman J. B., Cummings D. L., Ward D. E. (1994) - Relationships of fire, biomass and nutrient dynamics along a vegetation gradient in the Brazilian cerrado. *Journal of Ecology*. 82 (3): pp. 519-531.

Kilian J., Haala N., Englich M. (1996) - Capture and evaluation of airborne laser scanner data. *International Archive of Photogrammetry and Remote Sensing*, 31, Part B3: pp. 383-388.

Koch B. (2010) - Status and future of laser scanning, synthetic aperture radar and hyperspectral remote sensing data for forest biomass assessment. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65: pp. 581-590.

Koetz B., Morsdorf F., van der Linden S., Curt T., Allgöwer B. (2008) - Multi-source land cover classification for forest fire management based on imaging spectrometry and LiDAR data. *Forest Ecology and Management*, 256: pp. 263-271.

Koukoulas S. & Blackburn G. A. (2004) - Quantifying the spatial properties of forest canopy gaps using LiDAR imagery and GIS. *International Journal of Remote Sensing*, 25 (15): pp. 3049-3071.

Kraus K. & Pfeifer N. (1998) - Determination of terrain models in wooded areas with airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 53 (4): pp. 193-203.

Lasserre B., Chirici G., Chiavetta U., Garfì V., Tognetti R., Drigo R., *et al*. (2010) - Assessment of potential bioenergy from coppice forests trough the integration of remote sensing and field surveys. *Biomass and Bioenergy* 35 (1): pp. 716-724.

Lim K., Treitz P., Baldwin K., Morrison I., Green J. (2002) - Lidar remote sensing of biophysical properties of northern tolerant hardwood forests. *Canadian Journal of Remote Sensing*, 29: pp. 658-678.

Lindberg E., Holmgren J., Olofsson K., Wallerman J., Olsson H. (2010) - Estimation of tree lists from airborne laser scanning by combining single-tree and area-based methods. *International Journal of Remote Sensing*, 31: pp. 1175-1192.

Magnussen S., Eggermont P, Lariccia V. (1999) - Recovering tree heights from airborne laser scanner data. *Forest Science*, 45: pp. 407-422.

Maltamo M., Packalén P., Yu X., Eerikäinen K., Hyyppä J., Pitkänen J. (2005) - Identifying and quintifying structural characteristics of heterogeneous boreal forests using laser scanner data. *Forest Ecology and Management*, 216: pp. 41-50.

Maselli F., Chiesi M., Montaghi A., Pranzini E. (2011) - Use of ETM+ images to extend stem volume estimates obtained from LiDAR data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66: pp. 662-671.

Means J. A., Acker S. A., Harding D. J., Blair J. B., Lefsky M. A., Cohen W. B., *et al*. (1999) - Use of large-footprint scanning airborne LiDAR to estimate forest stand characteristics in the western Cascades of Oregon. *Remote Sensing of Environment*, 67 (3): pp. 298-308.

Montaghi A., Corona P., Dalponte M., Gianelle D., Chirici G., Olsson H. (2012) - Airborne Laser Scanning of Forest Resources: an overview of research in Italy as a commentary case study. *International Journal of Applied Earth Observation and Geoinformation*, 23 : pp. 288-300.

Murray R. B. & Jacobson. M. Q. (1982) - An evaluation of dimension analysis for predicting shrub biomass. *Journal of Range Management*, 35: pp. 451-454.

Mutlu M., Popescu S., Stripling C., Spencer T. (2008) - Mapping surface fuel models using LiDAR and multispectral data fusion for fire behavior. *Remote Sensing of Environment*, 112: pp. 274-285.

Næsset E. (1997) - Estimating timber volume of forest stands using airborne laser scanner data. *Remote Sensing of Environment*, 61: pp. 246-253.

Næsset E. (2002) - Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*, 80: pp. 88-99.

Næsset E. & Gobakken T. (2008) - Estimation of above- and below-ground biomass across regions of the boreal forest zone using airborne laser. *Remote Sensing of Environment*, 112: pp. 3079-3090.

Neteler M. & Mitašova H. (2004) - Open Source GIS: A GRASS GIS Approach. Second Edition. Boston: *Kluwer Academic Publishers/Springer*.

Paatalo M. L. (1998) - Factors influencing occurrence and impacts of fires in northern European forests. *Silva Fennica*, 32: pp.185-202.

Peterson B., Dubayah R., Hyde P., Hofton M., Blair J. B., Fites-Kaufman J. (2007) - Use of LiDAR for forest inventory and forest management application. In: McRoberts R., Reams G., Van Deusen P., McWilliams W. H. (eds.) *Proceedings of the seventh annual forest inventory and analysis symposium*, October 3-6, 2005;

Portland, ME. Gen. Tech. Rep. WO-77. Washington, DC: U.S. Department of Agriculture, Forest Service: pp. 193-202.

Pirotti F. (2011) - Analysis of full-waveform LiDAR data for forestry applications: a review of investigations and methods. *iForest*, 4: pp. 100-106.

Popescu S. C., Wynne R. H., Nelson R. H. (2002) - Estimating plot-level tree heights with LIDAR: Local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture*, 37 (1-3): pp. 71-95.

Pyne S. J., Andrews P. L., Laven R. D. (1996) - Introduction to wildland fire. *John Wiley and Sons, Inc.*

Recchia L., Cini E., Corsi S. (2010) - Multicriteria analysis to evaluate the energetic reuse of riparian vegetation. *Applied Energy*; 87 (1): pp. 310-319.

Riaño D., Meier E., Allgower B., Chuvieco E., Ustin S. (2003) - Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. *Remote Sensing of Environment*, 86: pp. 177-186.

Riaño D., Chuvieco E., Ustin S., Salas F., Rodriguez-Perez J., Ribeiro L., Viegas D., Moreno J., Fernandez H. (2007) - Estimation of shrub height for fuel type mapping combining airborne lidar and simultaneous colour infrared images. *International Journal of Wildland Fire*, 16: pp. 341-348.

Rodríguez y Silva F., Molina-Martínez J. R. (2012) - Modeling Mediterranean forest fuels by integrating field data and mapping tools. *European Journal of Forest Research*, 131: pp. 571-582.

Rollins M. G., Keane R. E., Parson R. A. (2004) - Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modeling. *Ecological Applications*, 14: pp. 75-95.

Rothermel R. C. (1972) - A mathematical model for predicting fire spread in wildland fuels. *USDA Forest Service Research Paper INT-115*: Intermountain Forest and Range Experiment Station.

Roughgarden J., Running S. W., Matson P. A. (1991) - What does remote sensing do for ecology? *Ecology*, 72: pp. 1981-1982.

Sankey T. & Glenn N. (2011) - Landsat-5 TM and LiDAR fusion for sub-pixel Juniper tree cover estimates in a western rangeland. *Photogrammetric Engineering & Remote Sensing*, 77 (12): pp. 1241-1248.

Schmidt J. & Hewitt A. (2004) - Fuzzy land element classification from DTMs based on geometry and terrain position. *Geoderma*, 121: pp. 243-256.

Seielstad C. & Queen L. (2003) - Using airborne laser altimetry to determine fuel models for estimating fire behaviour. *Journal of Forestry*, 101: pp. 10-15.

Skowronski N. S., Clark K. L., Duveneck M., & Hom J. (2011) - Three-dimensional canopy fuel loading predicted using upward and downward sensing LiDAR systems. *Remote Sensing of Environment*, 115 (2): pp. 703-714.

Soininen A. (2010). TerraScan User's Guide. *TerraSolid Ltd*.

Spinelli R. (2005) - Biomassa legnosa e manutenzione degli alvei fluviali. *Alberi e Territorio*, 6: pp. 18-22.

Spinelli R. & Magagnotti N. (2007) - Manutenzione degli alvei fluviali, ambiente e biomassa. *Alberi e Territorio*, 1-2: pp. 47-51.

Ståhl G., Holm S., Gregoire T. G., Gobakken T., Næsset E., Nelson R. (2011) - Model-based inference for biomass estimation in a LiDAR sample survey in Hedmark County, Norway. *Canadian Journal of Forest Research*, 41: pp. 96-107.

Straub C., Weinacker H., Koch B. (2010) - A comparison of different methods for forest resource estimation using information from airborne laser scanning and CIR orthophotos. *European Journal of Forest Research*, 129: pp. 1069-1080.

Tabacchi G., Scrinzi G., Tosi V., Floris A., Paletto A., Di Cosmo L., Colle G. (2006) - Inventario Nazionale delle Foreste e dei Serbatoi Forestali di Carbonio (INFC). Procedure di posizionamento e di rilievo degli attributi di terza fase con istruzioni per l'impiego degli applicativi NAV3 e RAS3. *MiPAF - Ispettorato Generale del Corpo Forestale dello Stato*, CRA-ISAFA, Trento.

Tabacchi G., Di Cosmo L., Gasparini P., Morelli S. (2011) - Stima del volume e della fitomassa delle principali specie forestali italiane. Equazioni di previsione, tavole del volume e tavole della fitomassa arborea epigea. *Consiglio per la Ricerca e la*

Sperimentazione in Agricoltura - Unità di Ricerca per il Monitoraggio e la Pianificazione Forestale, Trento.

Tesfamichael S. G., Ahmed F. B., Van Aardt J. A. N. (2010) - Investigating the impact of discrete-return lidar point density on estimations of mean and dominant plot-level tree height in Eucalyptus grandis plantations. *International Journal of Remote Sensing*, 31: pp. 2925-2940.

Tolliver D. (2009) - What is the variable importance measure? Available on line at http://www.salford-systems.com/blog/company/what-is-the-variable-importance-measure.html. Last accessed 17 Apr. 2012.

Tonolli S., Dalponte M., Vescovo L., Rodeghiero M., Bruzzone L., Gianelle D. (2011) - Mapping and modeling forest tree volume using forest inventory and airborne laser scanning. *European Journal of Forest Research*, 130: pp. 569-577.

Tufekcioglu A., Raich J. W., Isenhart T. M., Schultz R. C. (2001) - Soil respiration within riparian buffers and adjacent crop fields. *Plant and Soil*, 229 (1): pp. 117-124.

Turner B. L., Kasperson R. E., Matson P. A., McCarthy J. J., Corell R. W. *et al*. (2003) - A framework for vulnerability analysis in sustainability science. *Proc. Natl. Acad. Sci*. USA, 100: pp. 8074-8079.

Vastaranta M., Kankare V., Holopainen M., Yu X., Hyyppä J., Hyyppä H. (2012) - Combination of individual tree detection and area-based approach in imputation of forest variables using airborne laser data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67: pp. 73-79.

Vepakomma U., St-Onge B., Kneeshaw D. (2008) - Spatially explicit characterization of boreal forest gap dynamics using multi-temporal lidar data. *Remote Sensing of Environment*, 112: pp. 2326 - 2340.

Zhao K., Popescu S., Meng X., Pang Y., Agca M. (2011) - Characterizing forest canopy structure with lidar composite metrics and machine learning. *Remote Sensing of Environment,* 115: pp. 1978-1996.